Big Data Research 26 (2021) 100271

Contents lists available at ScienceDirect

Big Data Research

www.elsevier.com/locate/bdr

CardioNet: An Efficient ECG Arrhythmia Classification System Using Transfer Learning

Anita Pal [a], Ranjeet Srivastva [b,*], Yogendra Narain Singh [a]

[a] Department of Computer Science and Engineering, Institute of Engineering and Technology, Dr. A. P. J. Abdul Kalam Technical University, Uttar Pradesh, Lucknow, India

[b] Department of Information Technology, Babu Banarasi Das Northern India Institute of Technology, Dr. A. P. J. Abdul Kalam Technical University, Uttar Pradesh, Lucknow, India

ARTICLE INFO

Article history:
Received 30 October 2020
Received in revised form 13 May 2021
Accepted 21 August 2021
Available online 30 August 2021

Keywords:
Electrocardiogram
Cardiac arrhythmia
Transfer learning
DenseNet

ABSTRACT

The electrocardiogram (ECG) is a noninvasive test used extensively to monitor and diagnose cardiac arrhythmia. Existing automated arrhythmia classification methods hardly achieve acceptable performance in detecting different heart conditions, especially under imbalanced datasets. This paper presents a novel method of heartbeat classification from ECG using deep learning. An automated system named 'CardioNet' is devised that employs the principle of transfer learning for faster and robust classification of heartbeats for arrhythmia detection. It uses pre-trained architecture of DenseNet that is trained on ImageNet dataset of millions images. The weights obtained during training of DenseNet are used to fine-tune CardioNet learning on the ECG dataset, resulting a unique system providing faster training and testing. The ECG dataset is prepared using augmentation process to provide a comprehensive learning of heartbeat morphology in the presence of intraclass variations. Two benchmark datasets of ECG recordings *e.g.*, MIT-BIH arrhythmia and PTB are used to classify 29 types of heartbeats for arrhythmia classification. The proposed CardioNet system achieves higher classification accuracy of 98.92% outperforming other methods and shows robustness to different irregular heartbeats or arrhythmias.

1. Introduction

Cardiovascular diseases (CVDs) are a group of disorders present in the heart and blood vessels. It affects the structure or function of the heart that includes several heart diseases and arrhythmias. According to a report of world health organization (WHO), CVDs are the leading cause of deaths all over the world [1]. About 17.9 million people died from CVDs in 2016, representing 31% of the deaths worldwide, whereas 85% are due to heart attack and stroke.

The early diagnosis of cardiac diseases is crucial to improve its treatment. The conventional CVD determination standards depend on the patient's clinical history and clinical assessments [2]. The outcomes are deciphered by a lot of quantitative clinical boundaries to classify arrhythmias dependent on the scientific categorization of clinical ailments. The conventional rule-based diagnosis models are inefficient because of managing the immense amount of heterogeneous information. It requires a huge examination and clinical ability to accomplish sufficient exactness in diagnosis. The issue turns out to be more articulated in places, where there are absence of clinical specialists and clinical equipments, particularly in developing and poor countries. Therefore, a reliable and effortless technique for automated monitoring and diagnosis is required. It paves the path to use computer-aided diagnosis systems (CADS). The CADS are composed of automated monitoring procedures of health conditions dependent on the investigation of physiological signs to assess the usefulness of the related organ [3]. It provides individuals with portable and straightforward solutions to keep them informed about their diseases.

The easiest and prime source of monitoring the heart function is electrocardiogram (ECG). The ECG is the bioelectrical signal that shows the propagation of electrical conduction of the heart [4]. Therefore, many cardiac structural or electro-physiological abnormalities have their signatures on the ECG. Clinicians widely use it as a routine modality in hospitals to identify cardiac arrhythmias. The characterization and recognition of arrhythmias by manual means can be inconvenient because it is important to observe each heartbeat of the ECG records. For example, an adult's normal resting heart generates about 72 beats per minute while a Holter ECG recording acquires signal over a longer period of time. Thus, clinicians have to investigate thousands of heartbeats and due to

* Corresponding author.
E-mail addresses: anitapal13@gmail.com (A. Pal), ranjeetbbdit@gmail.com (R. Srivastva), singhyn@gmail.com (Y.N. Singh).

https://doi.org/10.1016/j.bdr.2021.100271
2214-5796/

exhaustion the arrhythmia misclassification might occur. Therefore, several computational methods have been utilized for automated arrhythmia classification using ECG [2], [3], [5], [11], [15–53].

For automated arrhythmia classification the morphological patterns and frequency components of individual heartbeats are examined. However, an ECG-based automated arrhythmia classification is typically confronted with several significant challenges. ECG signal may change due to physiological artifacts and interferences. It may diminish the viability of the automated arrhythmia diagnosis. Further, due to ECG signals' non-stationary nature, the symptoms of disease may occur randomly at irregular intervals [5]. The majority of arrhythmia classification methods use ECG waveforms either in temporal or frequency domain. The recognition of beat type is done by specifying several features from this ECG representation. Briefly, major challenges of ECG arrhythmia classification are summarized as follows:

- The need of a robust method for heartbeat annotation and feature measurement is essential. The arrhythmia manifestations probably won't be seen during the ECG signal acquisition [5].
- ECG signal differs among individuals due to their unique intrabeat and interbeat temporal-amplitude features [6–10]. It relies upon various factors *e.g.*, age, gender, physical conditions and lifestyle. The need of a generalized framework of heartbeat classification that is scalable to a larger population is challenging [5].
- The reflection of arrhythmia is random in the temporal-frequency domain. Therefore, the ECG signal analysis may have to be carried out over a larger duration, resulting in larger information. Consequently, there is a higher likelihood of false diagnosis of arrhythmia.
- The noise and other undesired components can mash and overlap morphological patterns making the heartbeat classification harder [11].

We develop a computer-assisted diagnostic system that helps cardiologists by providing ingenious, cost-effective and efficient arrhythmia diagnostics using ECG. To accomplish this objective, the characterization of ECG arrhythmia patterns is done using the state-of-the-art deep learning methods. The proposed method can explicitly characterize and recognize 29 different types of heartbeats that are classified among 28 distinct cardiovascular arrhythmias, and the rest is normal. Apparently, our method is the first to work upon such a colossal number of heartbeat classification, particularly cardiac arrhythmia.

This paper presents a novel method for arrhythmia classification from ECG using the state-of-the-art pre-trained deep neural network *i.e.*, DenseNet [12]. The architecture is named 'CardioNet' that works on the principle of transfer learning. The DenseNet architecture is initially trained on millions of images of ImageNet dataset. The learned model is trained using 2D images augmented from the ECG signals of publicly available datasets. Thus, the learning of CardioNet starts from an elevated point that reduces the training and testing time. The approach of transfer learning used in designing the CardioNet system makes it novel and robust than other methods of arrhythmia classification present in literature. Briefly, the principal contributions of this work are as follows:

1. A novel ECG arrhythmia classification system is developed using transfer learning, which we called 'CardioNet'. It performs training and testing comparatively faster than other learning models. Further, the pre-trained model provides good starting point for convergence of the classification algorithm.
2. Our CardioNet system successfully classifies a deeper level classification up to 29 different types of heartbeats of five major classes as recommended by Association for the Advancement of Medical Instrumentation (AAMI) [13].
3. To mitigate the heartbeat features deformation across sessions, ECG signal data augmentation is also investigated. Augmented dataset forces the model to learn the intraclass variations within arrhythmia classes.
4. The proposed CardioNet system classifies arrhythmia in computationally efficient manner and is highly sensitive to the variations in heartbeat brought about by types of arrhythmia.

The remainder of the paper is organized as follows: The related studies conducted on arrhythmia classification and their achievements are presented in Sec. 2. The descriptions of ECG basics, preprocessing and feature representation along with their analysis are given in Sec. 3. The highlight of this section is the proposed model of transfer learning named 'CardioNet' for arrhythmia classification using ECG. The experimental details including datasets used, classification results and their comparative analysis are given in Sec. 4. Finally, the conclusion is drawn in Sec. 5.

2. Related work

The surge of computing technology has embraced the use of computers in medicine, especially cardiology. The electronic health records of patients are used in monitoring, care and diagnostic using intelligent tools devised on machine learning and transfer learning techniques [33], [46–49], [51–53]. These computing technologies analyse and learn health records to make predictions about cardiac arrhythmia based on input datasets *e.g.*, ECG. Andrew Wallace was among the first who has identified the potential role of computers in cardiology. The computing system may assist the medical practitioners to increase their efficiency for providing better patient care. The electronic health records, including diagnostic results, image analysis for pattern classification and automated monitoring of vital signs are the prime objectives of a computer-assisted health system. Further, the capability and potential of computing technologies for developing intelligent softwares using machine learning along with computer-assisted patient monitoring and treatment certainly open the new avenues for researchers.

The work of automated cardiac arrhythmia classification has begun two decades ago [34]. These methods employ different approaches of feature extraction *i.e.*, ECG morphology, temporal and frequency based features. The methods have used a combination of handcrafted features and statistical classifiers *i.e.*, linear discriminant analysis (LDA) [50], hidden Markov models [40], k-nearest neighbor [39]. Further, machine learning methods that relax the feature engineering process *e.g.*, support vector machine (SVM) [46], [47], [48], path forest [49] *etc.* are also used. Recently, the use of deep neural networks (DNNs) has been growing with a potential effect on the precision of classification. Several arrhythmia classification systems leverage DNNs to distinguish heartbeats using ECG signals. It leads to adaptation of cost-effective heart monitoring, minimum-effort feature engineering and high-quality predictions. A brief description of the significant deep networks and their utilization for automated arrhythmia classification is presented in Table 1.

An extensive literature on arrhythmia classification that has utilized a combination of handcrafted features and statistical classifiers or advanced deep learning methods that do not involve feature engineering is available [2], [3], [5], [11], [15–53]. The techniques used for arrhythmia detection using ECG signals essentially require preprocessing, segmentation, feature extraction, and classification. Preprocessing of the signal is an essential step for improving the quality and noise removal that yields correct determination and delineation of morphological features of heartbeats, respectively in the ECG signal [8]. The heartbeat features in

Table 1
Arrhythmia classification methods using deep learning.

Deep Networks	Contributors	Feature Characterization	Heartbeat Classes	Performance (%) SN/Recall	SP	ACC	MSE	F-Score	PP/Precision
	Zeraatkr *et al.* [15]	4 Interval, Morphological	3	96.77	88.5	-	-	-	-
	Jadhav *et al.* [16]	RR Interval	2	93.75	93.1	86.67	-	-	-
MLP	Kumari *et al.* [17]	RR Interval	2	95.1	-	-	-	-	95.1
	Srivastava *et al.* [18]	QRS amplitude, RR interval	2	80	90	85	-	-	-
	Khazaee *et al.* [19]	RR Interval	3	-	-	-	0.76	-	-
	Kiranyaz *et al.* [39]	Temporal+Morphological	5	-	-	96.4	-	-	-
	Acharya *et al.* [20]		5	-	-	94.03	-	-	-
	Acharya *et al.* [21]		2	-		95.53	-	-	-
CNN	Xiong *et al.* [22]		4	-	-	-	-	82	-
	Xia *et al.* [23]	Temporal+Morphological	4	-	-	95.8	-	-	-
	Jun *et al.* [24]	Raw gray scale images	8	97.8	99.5	99.05	-	-	-
	Zhai *et al.* [25]	Dual beat Coupling Matrix	5	-	-	96.05	-	-	-
	Andreotti *et al.* [26]	QRS-T segment	4	-	-	-	-	83	-
	Huanhuan *et al.* [27]	Temporal+DBN	6	-	-	98.49	-	-	-
DBN	Wu *et al.* [28]	Temporal	5	-	-	99.5	-	-	-
	Wu *et al.* [29]	Temporal+Morphological	4	-	-	97.9	-	-	-
	Singh *et al.* [30]	ECG Block	2	-	-	85.4 (RNN)	-	-	-
				-	-	82.5 (RNN+GRU)	-	-	-
RNN				-	-	88.1 (RNN+LSTM)	-	-	-
	Gao *et al.* [31]	R-peak Centered ECG	8	-	-	99.26	-	-	-
	Pandey *et al.* [32]	Temporal+Morphological	5	94.89	99.14	99.37	-	-	-
	Salem *et al.* [33]	ECG Spectrogram	4	-	-	97.23	-	-	-
Transfer Learning	Isin *et al.* [53]	AlexNet	3	-	-	92	-	-	-

ACC = Accuracy, CNN = Convolutional Neural Network, DBN = Deep Belief Network, GRU= Gated Recurrent Units, LSTM = Long Short-Term Memory, MLP = Multi-layer Perceptron, MSE = Mean Squared Error, PP = Positive Predictivity, RNN = Recurrent Neural Network, SN= Sensitivity, SP = Specificity.

the temporal-amplitude domain are usually needed for classifying arrhythmia. Therefore, an effective method of heartbeat segmentation is needed.

The effective strategies of signal processing and heartbeat segmentation make the feature extraction of heartbeat in the temporal-amplitude domain easier. Among various feature extraction techniques used for arrhythmia classification, some of them are prominent. These methods have used Fourier transform to highlight the frequency variations of the ECG signal [35]. Discrete Fourier transform is also utilized for effective feature engineering in different work [36]. To account for non-linearity and non-Gaussian noise, the higher order statistics can be effectively utilized for feature extraction from non-stationary signals [37], [38].

The feature vectors consist of attributes are classified on the basis of general characteristics or patterns. The machine learning based classifiers are proved to be very effective in many classification problems. The existing methods have utilized classifiers *e.g.*, k-nearest neighbor [39], hidden Markov models [40], artificial neural networks (ANN) [41], [42], recurrent neural networks (RNN) [43], probabilistic neural networks (PNN) [44], [45], support vector machines (SVM) [46], [47], [48], path forest [49], linear discriminant analysis (LDA) [50] *etc.* for arrhythmia classification.

The recent pattern recognition methods utilize deep learning, particularly convolutional neural networks (CNNs). It urges analysts to implement these methods to the field of medical image and signal processing. Utilization of deep learning techniques even to the most perplexing clinical pattern recognition tasks end up being exceptionally encouraging, acquiring cutting edge results. Generally, extracting highly representative features from the data in hand has the most significant impact on the performance of automated classification systems. However, this is a tedious job that requires expert knowledge. Further, the selected features may not be robust enough to accommodate the variations present in the data. When compared to conventional characterization strategies, CNNs naturally extract complex features from data, consequently, the requirement for handcrafting features is effectively eliminated.

Recently, Jun *et al.*, proposed a method to classify normal and premature ventricular contraction (PVC) beats [51]. They have used six handcrafted features that are fed to six hidden layers of deep neural network. The discrimination between normal beats and paroxysmal atrial fibrillation (PAF) is performed by Pourbabaee *et al.* [52]. The features are extracted directly from raw ECG signal using deep convolutional neural network.

The training of a deep convolutional neural network requires a larger dataset to achieve high network performance to make the network deeper [53]. Regardless of whether an extremely large dataset is accessible, the network's depth increases the computation cost due to the complexity of convolutional operations. In view of limited training data, and moderate computer resources, the principle of transfer learning and its variation for fine-tuning provides a useful solution to address these issues [33], [53].

3. Method and material

The schematic of CardioNet system for ECG arrhythmia classification using transfer learning is shown in Fig. 1. The method consists of a generic patient data acquisition stage, signal preprocessing and signal analysis applying transfer learning stage followed by classification. In the first step, the raw ECG signal is preprocessed for noise removal and segmentation of heartbeats. Next, the ECG signal is transformed into 2D images. The DenseNet model is trained for feature representation using 2D images prepared from ECG recordings. The model learns the features from ECG images while utilizing its previous learning done on ImageNet dataset. After training, the system is ready to test the ECG signal for the presence of abnormal heartbeats; thus, predicting corresponding arrhythmia class.

3.1. ECG basics

The ECG is a recording of heart electrical activity representing the repetitive pattern of heartbeats consisting P-QRS-T waveforms as shown in Fig. 2. In the mid 1900s, Willem Einthoven built up the ECG acquisition method. The muscle fibers of the heart depolarize and repolarize while the electrical potential flows through them. The atrial and ventricle depolarization forms P-wave and

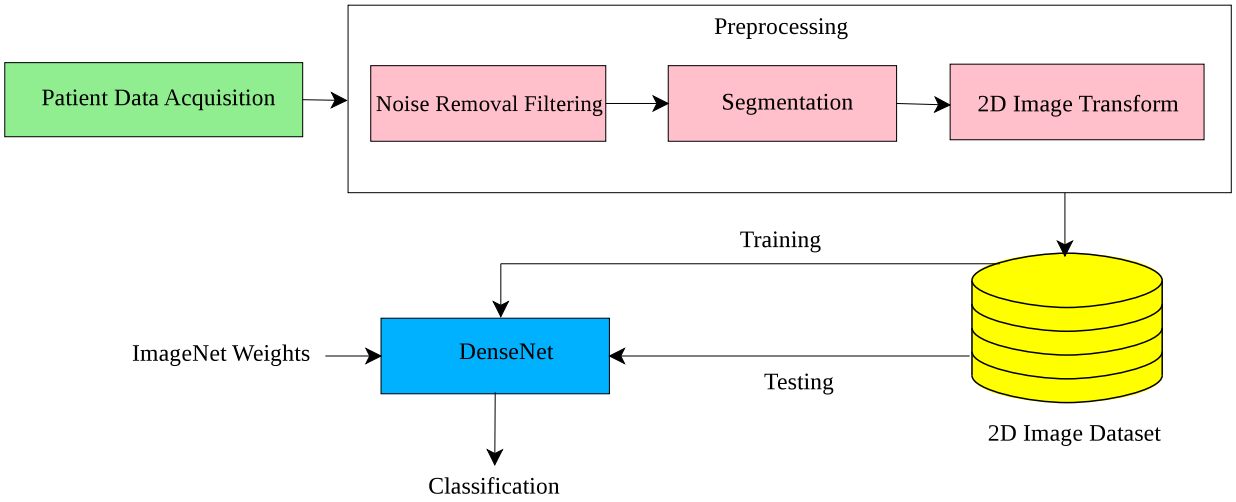


Fig. 1. Schematic of CardioNet system for ECG arrhythmia classification using transfer learning.

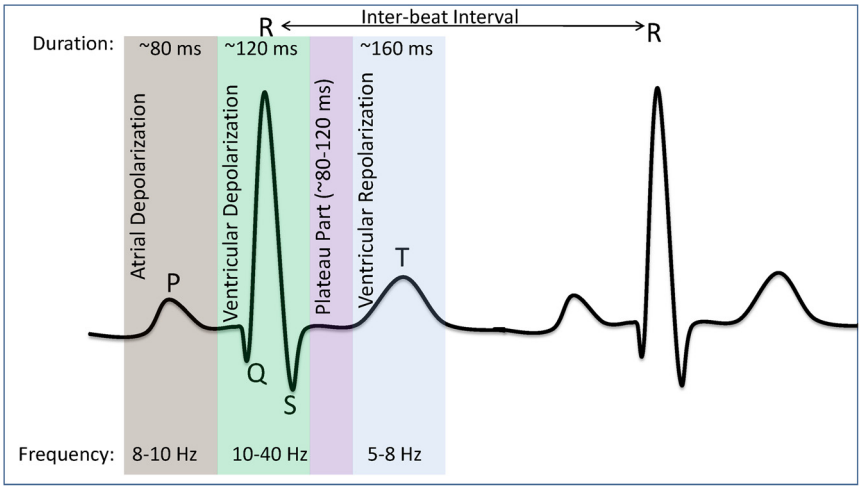


Fig. 2. ECG waveforms and characterization.

QRS-wave, respectively [4]. The T-wave is generated due to ventricular repolarization. Each P-QRS-T cycle represents a heartbeat. The heartbeat contains temporal and frequency domain features in particular, intrabeat and interbeat features are shown in Fig. 3. These features are computed using dominant fiducials (P, Q, R, S, T) present in heartbeat morphology.

The ECG waveforms represent the sequential polarization and depolarization of the cardiac cells that are shown in Fig. 2. The P wave is generated when the right and left atria of the heart are depolarized. It corresponds to low-frequency spectral components *i.e.*, $10-15$ Hz that has a duration of $60-100$ ms and low amplitude morphology of $0.1-0.25$ mV, usually found at the beginning of heartbeat. The QRS complex is a short duration wave of $80-120$ ms and high amplitude, normally of 0.5 and 1.0 mV. The time taken for the ionic potential to spread from the sinus node, through the atrial muscle and entering the ventricles ranges from $120-200$ ms that is known as PR interval. The ventricles have relatively long ionic potential duration of $300-420$ ms known as the QT interval. The plateau part of the ionic potential of $80-120$ ms after the QRS is known as the ST segment. The return of the ventricular muscle to it's resting state causes the T wave that has an amplitude of $0.1-0.5$ mV and a duration of $120-180$ ms. The duration from resting of ventricles to the beginning of the next cycle of atrial contraction is known as the TP segment which is a long plateau part of the negligible elevation. The temporal duration between successive R peaks is known as the RR interval.

3.2. ECG signal preprocessing

The ECG signal is acquired from individuals that may be contaminated with noise and other artifacts. The cause of noise and artifacts are power line interference, baseline drift, motion of electrodes, improper contact to electrodes or muscle contraction. The unwanted information may affect the inherent distinctiveness of features present in the heartbeats. Therefore, the conditioning of the ECG signal is important to improve its quality for data representation. During ECG signal acquisition, the noise is contaminated and distributed over different frequency bands. Therefore, filters of different frequency bands are usually applied to prepare a good quality ECG signal. Thus, the signal is passed through a band pass filter that requires only integer coefficients. A band pass filter is designed by combining a low pass filter and a high pass filter. The actual ECG signal with reduced noise level lies in the range of 5 Hz to 15 Hz. To restrict the frequency of ECG signal below 15 Hz, the system is first passed through low pass filter of order two [54].

$$y_{nT} = 2y_{(n-1)T} - y_{(n-2)T} + x_{nT} - 2x_{(n-6)T} + x_{(n-12)T} \quad (1)$$

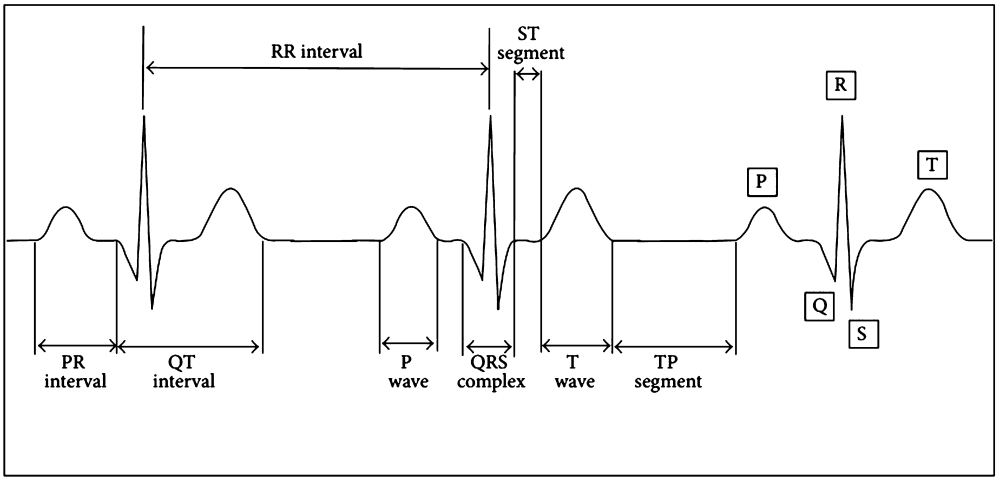


Fig. 3. Typical intrabeat and interbeat temporal features and the information lying in P, Q, R, S and T waves [8].

where, y_{nT} is the output signal generated from input signal x_{nT}. It represents the data sample of size n at discrete instance of time T. The signal is then passed through a system of high pass filter to reduce the edge effect with the following difference equation. Where the cutoff frequency of this filter is set to 5 Hz [54].

$$y_{nT} = 32x_{(n-16)T} - (y_{(n-1)T} + x_{nT} - x_{(n-32)T}) \tag{2}$$

3.3. Heartbeat segmentation

The heartbeats are detected from the filtered signal using Pan & Tompkins's method that is one of the best methods known till date for QRS detection from ECG signal [54]. The signal is differentiated to provide the slope information for QRS complex. The method computes five-point derivative using following transfer function and difference equation as shown in Eq. (3) and Eq. (4), respectively.

$$H(z) = (1/8T)(-z^{-2} - 2z^{-1} + 2z^{1} + z^{2}) \tag{3}$$

$$y_{nT} = (1/8T)\big[-x(nT-2T) - 2x(nT-T) + 2x(nT+T) + x(nT+2T)\big] \tag{4}$$

The derivative operation is followed by squaring function that squares the signal point-by-point. To obtain the waveform information along with the R slope, a moving window integrator with N samples window, is calculated as follows,

$$y_{nT} = (1/N)\big[x(nT-(N-1)T) + x(nT-(N-2)T) + \ldots + x(nT)\big] \tag{5}$$

Finally, using adaptive thresholding technique QRS complex is detected from each heartbeat. After detecting the R-peak, a window of size 700 ms around R-peak is set for heartbeat segmentation. The beats are normalized using z-score normalization [55]. The segmented heartbeats are converted into one channel 2D ECG images. Further, these one channel images are transformed to three channel images by reproducing them and reshaped to size 150×150.

3.4. ECG signal data augmentation

In order to do the effective training, the deep learning models require larger datasets. The learning models may suffer either from over-fitting or under-fitting if the data is imbalance and insufficient, respectively. Data imbalance refers a situation where number of samples varies among classes, largely. Consequently, the classes having more samples may dominate over other classes with smaller data samples, *i.e.*, over-fitting. In case of data insufficiency, there are very few samples per class. It leads to poor learning of model and termed as under-fitting. In order to address the issues of over-fitting and under-fitting the data augmentation is a most preferred technique. It expands and equalizes the data samples among classes.

The heartbeats of a person can be varied across sessions due to different stressful conditions known as intraclass variations. The heart rate varies due to temporal conditions *e.g.*, physical, psychological, and behavioral. It causes inappropriate learning of the model thus, resulting in misclassification of the signal during training-testing. To overcome the heartbeat morphing from frequency variations, the signal data augmentation provides different views for a comprehensive study of input data source. The signal data augmentation technique is adopted to train the model that is robust enough to morphological shift of the ECG. The rationale behind using ECG data augmentation is forcing the model to learn heartbeats even in the presence of intraclass variations.

The available dataset used in this study was imbalanced *i.e.*, some classes had insufficient samples to train the CardioNet, as shown in Table 2. Therefore, the augmentation of data is performed to increase the sample size by performing different operations *e.g.*, feature-wise center, channel, shift, shear, standard normalization, zoom-in and zoom-out operations. These operations are performed to each sample of ECG such that the total number of images per class increases to 1000. The augmentation operation is fine-tuned repeatedly in case of less number of images within a class. For example, the zoom-in operation is performed on an image at different levels within the interval of 1 to 100. Thus, a large number of augmented images are generated using at different levels. Therefore, we equalize the number of images per class and get sufficient data samples to learn the complex patterns of heartbeats.

3.5. Transfer learning architecture

The concept of transfer learning is employed to overcome under-fitting that generally occurs during training of a model using smaller dataset [60]. The weights of a pre-trained model are utilized for training of a new model using a different dataset. Thus, the learning starts from an elevated point that avoids data insufficiency. Moreover, the identical distributions of training and test datasets are not required while using the transfer learning.

Formally, let, ζ_1 be the learning curve of a model that is pre-trained on dataset χ_1. The aim is to improve the learning curve, ζ_2 for a new model with a new dataset χ_2. The learnt behavior

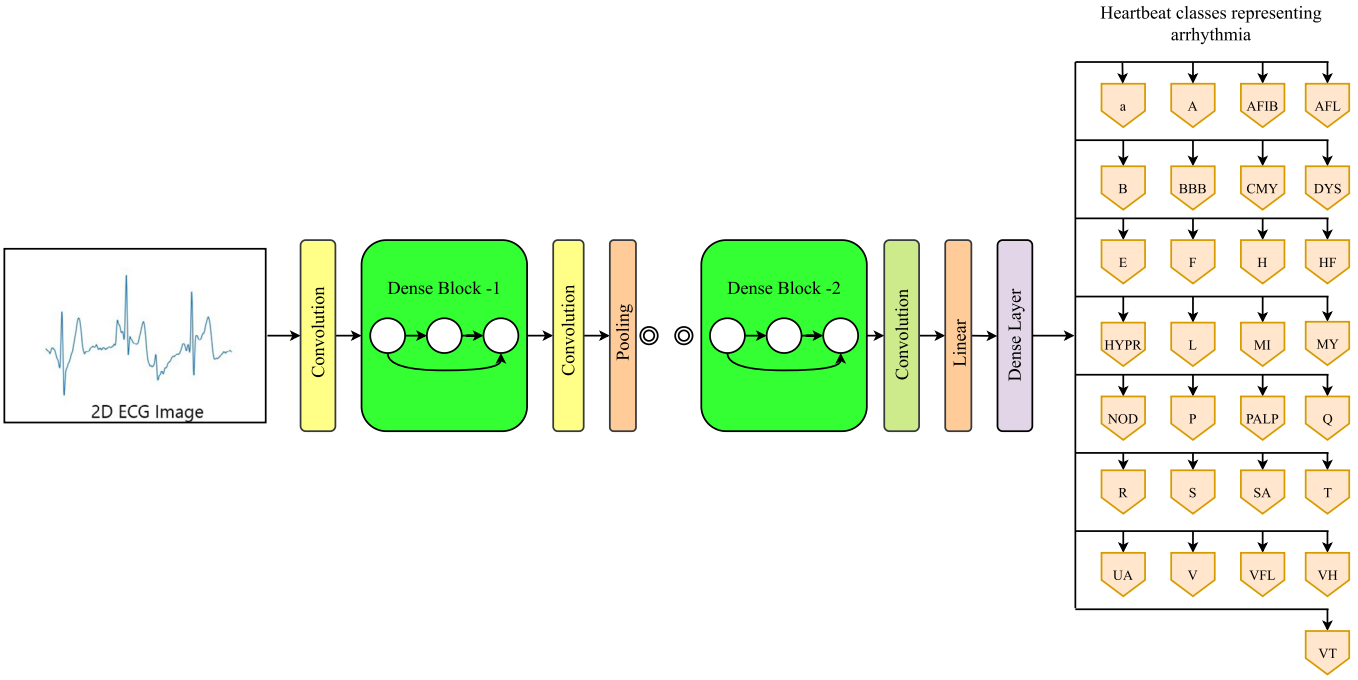


Fig. 4. Heartbeat classification for arrhythmia prediction using DenseNet.

of model pre-trained on, χ_1 is transferred to the predictive function, ϕ. The function ϕ in turn, improves the learning curve, ζ_2 on dataset χ_2. Several state-of-the-art image classification methods are devised using transfer learning [60]. Different models are pre-trained on ImageNet that contains millions of images of over 1000 categories. The upper layers of these pre-trained models can be fine tuned to match the current model working on the new dataset. This work utilizes the DenseNet architecture [12]. It is selected among other architectures of deep learning based on the performance reported for arrhythmia classification. Moreover, DenseNet architecture provides solution to vanishing gradient problem [12]. The vanishing gradient problem makes it harder to train deep networks. If the network depth is increased simply by stacking several layers together, the back-propagated gradient becomes infinitely small due to repeated multiplication. Hence, the performance of the architecture degrades with an increase in the network depth.

DenseNet comprises of several blocks that are densely connected together. The features generated by one block is input to the next dense block, as shown in Fig. 4. In larger CNN models, there may be feature loss before it reaches to output layer. DenseNet overcomes this issue with the use of repeated blocks. Further, the DenseNet requires fewer number of parameters. More formally, consider an ECG image Y_0 that is passed through a convolutional network. Let the network contains n layers, each of which executes on a non-linear transformation $K_n(.)$, where n indexes the layer. The $K_n(.)$ can be a composite function of operations such as batch normalization (BN), rectified linear units (ReLU), pooling, or convolution. The output of the n^{th} layer, Y_n, is denoted as follows,

$$Y_n = K_n([Y_0, Y_1, ..., Y_{n-1}]), \tag{6}$$

where $[Y_0, Y_1, ..., Y_{n-1}]$ refers to the concatenation of the feature-maps produced in layers $(0, 1, ..., n-1)$. Since the architecture is densely connected, therefore it referred as dense convolutional network (DenseNet).

The recursive concatenation operations may generate massive redundant features at graphics processing unit during training, if not implemented properly. Here, the 1×1 convolution is introduced as a bottleneck layer to reduce the number of input feature-maps. Many other architectures adopt this design choice to improve computational efficiency, and we find it effective especially for DenseNet. Unless otherwise specified, each bottleneck layer reduces the input to 4 times the number of feature maps produced by the subsequent 3×3 convolutional layer.

The concatenation operation used in Eq. (6), is not viable when the size of feature-maps change. However, an essential part of convolutional networks is pooling that changes the size of feature-maps. To facilitate pooling in our architecture, we divide the network into multiple densely connected blocks. The layers between blocks are referred as transition layers, which do convolution and pooling. The transition layers used in this experiment consist of a batch normalization layer and a 1×1 convolutional layer followed by a 2×2 average pooling layer. The transition layers are much wider than other basic layers, unlike using the expensive 3×3 convolution with stride 2 to perform downsampling in a DenseNet.

3.6. Classes of cardiac arrhythmia

Arrhythmia (also known as dysrhythmia) is a group of heart ailments in which the heartbeat is abnormal or irregular. Arrhythmia occurs due to change in heart tissues and the electrical conduction system that controls the heartbeat. The ECG is one of the most noninvasive tests used globally to diagnose arrhythmia. The ECG morphology contains essentially two types of information. Firstly, by estimating the time spans of a heartbeat temporal features, the cardiologist can decide the amount of time the electrical wave traverses through the heart's electrical conduction system. Thus, diagnoses the irregularity in the electrical activity of the heart. Second, a practitioner can also measure the potential of electrical activity to know whether the heart is exhausted or too large. Therefore, cardiac arrhythmia can be detected by finding any disorder in the electrical activity of heart muscles.

According to the standard developed by the Association for the Advancement of Medical Instrumentation (AAMI) described in ANSI/AAMI EC57:1998, a heartbeat can be categorized as normal (N), ventricular ectopic beat (VEB), supraventricular ectopic beat

(SVEB), fusion of a normal and a VEB (F), or unknown beat (Q) [13], [14]. These five super classes include a total of 15 types of arrhythmia. Normal class includes normal (N), left bundle branch block (L), right bundle branch block (R), atrial escape beat (e) and nodal (junctional) escape beat (j). The premature beats such as atrial (A), aberrated atrial (a), nodal (junctional) (J) and supraventricular premature (S) corresponds to SVEB class. Whereas the VEB class of heartbeat includes premature ventricular contraction (V) and ventricular escape beat (E). The paced beat (P), fusion of paced and normal beat (f) and unclassified beat (U) are categorized as unknown beat (Q). The arrhythmias recognized in this work include heartbeat types recommended by AAMI and others taken collectively from PTB and MIT-BIH datasets described below [13].

Atrial fibrillation (AFIB): AFIB is an arrhythmia characterized by an irregular and rapid heartbeat. It occurs when action potentials fire quickly inside the atrium, bringing a fast atrial rate $\sim 400-600$ bpm. The fast atrial rate with low amplitude level, causes the absence of P waves. It is the most commonly encountered clinical arrhythmia that may have the symptoms like, irregular heartbeat, heart palpitations, extreme fatigue, shortness of breath and chest pain [56].

Bundle Branch Block (BBB): BBB is a defect of the fascicles in the heart's electrical conduction system. It interrupts the normal cardiac conduction system that prompts the QRS morphology. It can be of two types *i.e.*, left bundle branch block (L) and right bundle branch block (R). Typically, left ventricles (LV) and right ventricles (RV) depolarized by left and right bundle, respectively. When impulses of right bundle depolarize LV it results in L, whereas if left bundle depolarizes RV then it causes R. In both cases the QRS morphology becomes irregular [59].

Ectopic Beats (EB): It appears when the action potentials are generated faster from outside of the sinus node. Consequently, the P wave is no longer has its normal sinus appearance. These may occur due to anxiety, stress or consumption of alcohol [59]. There are two types of ectopic beats *i.e.*, premature atrial contraction (PAC) and premature ventricular contraction (PVC). PAC and PVC are the common cardiac arrhythmias characterized by premature heartbeats originating in the atria and ventricle, respectively. A premature or early beat may interrupt the regular rhythm of the heart that results in either PAC or PVC [59]. In this work, four types of premature beats *i.e.*, atrial premature (A), aberrated atrial premature (a), supraventricular premature (S), and PVC (V) are recognized.

Bigeminy (B) and Trigeminy (T): If a PVC shortly follows a sinus beat, a pause, another normal beat, and then another PVC then it is known as begeminy that is a heart rhythm problem [58]. When PVC happens in a pattern of three beats, it is termed as trigeminy. Ventricular Escape Beats (E): Normally, heart rhythm starts in the atria and subsequently transmitted to the ventricles. Unlike to this, the contraction of ventricles initiated by self-generated electrical discharge produces escape beats. It indicates that electrical impulse is unable to reach the ventricles [57]. The sensation of skipping a beat or adding an extra beat are heart palpitations (PALP). A person may feel like his/her heart is racing, pounding, or fluttering.

Myocardial Infarction (MI): Occurs when blood flow decreases or stops in a part of the heart, inflicting everlasting injury to the coronary heart muscle or arteries. It may include a T-wave inversion due to ST-segment depression or a new BBB because of ST-segment elevation. Heart Failure (HF): In case of weaker heart function, the heart may not pump enough blood to the body [56]. It may become chronic gradually over time. If it is harder to pump blood throughout the body due to heart muscles' disease, it is called cardiomyopathy (CMY). It may lead to heart failure. The inflammation of the heart muscle that affects the heart's electrical system and reduces the pumping ability of the heart is known as myocarditis (MY). It may form clots in the heart leading to a stroke or heart attack [56].

Fusion of Ventricular and Normal Beats (F): If the ventricles depolarize due to coinciding of impulses from both ectopic and normal conduction system, it generates fusion beats. It is ventricular fusion beat (VFB) if it follows up on the ventricular chambers, while colliding impulses in the atrial chambers produce atrial fusion beats (AFB) [57]. Stable Angina (SA) and Unstable Angina (UA): Due to the lack of blood flow, the heart may not get enough oxygen. It results in chest pain that is termed as angina. A predictable pattern of chest pain is stable angina, whereas unstable angina occurs suddenly and gets worse over time that may lead to a heart attack [57].

Dysrhythmia (DYS): Changes in normal sequence of electrical impulses may result in irregular rhythm of heartbeat. Heart may beat too slowly (bradycardia), too fast (tachycardia) or with an irregular pattern. Ventricular Tachycardia (VT): A heart rate over 100 beats per minute in adults is acknowledged as tachycardia [58]. It may be normal (due to exercise) or abnormal. If a faster heart rate starts in the upper heart chambers, it referred to as atrial or supraventricular tachycardia (SVT). When the heart rate increases due to the faster flow of impulses from the heart, it is known to be sinus tachycardia. More than three abnormal QRS complex occurring consecutively with duration more than 120 ms and ST-T vector points opposite the QRS deflection is considered as ventricular tachycardia.

Atrial Flutter (AFL): The irregular circuitry within the atria may cause an atrial flutter. It is a common unusual heart rhythm that begins in the atrial chambers of the heart. At the point when it initially happens, it is normally connected with a fast heart rate and is classified as a kind of SVT [59]. Ventricular Flutter (VFL): It is an unstable arrhythmia in which a tachycardia affecting the ventricles with a rate over $150-300$ beats per minute. VFL is a possible transition stage between VT and fibrillation that can cause sudden cardiac death. A sinusoidal waveform characterizes it without a clear definition of the T-waves and QRS [58].

Myocardial Hypertrophy (HYPR): The chronic and increased stress on the heart may enlarge cardiac muscle fibres' thickness termed hypertrophy. It may be due to physiological (intense exercise) or pathological *e.g.*, hypertension or valvular heart disease (VH). VH is characterized by damage to or a defect in one of the four heart valves: the mitral, aortic, tricuspid or pulmonary [57].

Nodal (A-V Junctional) Rhythm (NOD): It occurs when the electrical impulses originate near or within the atrioventricular node, rather than from the sinoatrial node. It may cause narrow QRS complex, unseen P wave usually buried within the QRS complex [57]. Paced Rhythm (P): when electrical conduction system is dangerously disturbed, a pacemaker is indicated. Vertical signals or pacemaker spikes identify the electrical activity of the pacemaker. It may generate atrial or ventricular paced rhythm when atria or ventricles are paced, respectively [59].

AAMI also recommended standard database and evaluation criteria. The MIT-BIH database is most utilized among other recommended databases such as EDB (The European Society of Cardiology ST-T Database), AHA (The American Heart Association Database), CU (The Creighton University Sustained Ventricular Arrhythmia Database) and NST (The Noise Stress Test Database). The automated arrhythmia classification methods' evaluation is recommended by AAMI using sensitivity (Se), positive predictivity (+P), false positive rate (FPR) and overall accuracy (Acc). Positive predictivity is generally known to be precision and sensitivity is termed as recall in the literature.

Table 2
Number of subjects per arrhythmia class from PTB and MIT-BIH datasets.

Datasets	Type of Arrhythmia	Representation	Number of Subjects	Number of Heartbeats Examined
	Bundle Branch Block	BBB	15	846
	Cardiomyopathy	CMY	15	651
	Dysrhythmia	DYS	14	447
	Healthy	H	52	953
	Heart Failure	HF	3	82
PTB	Myocardial Hypertrophy	HYPR	7	326
	Myocardial Infarction	MI	148	916
	Myocarditis	MY	4	158
	Palpitation	PALP	1	40
	Stable Angina	SA	2	74
	Unstable Angina	UA	1	25
	Valvular Heart Disease	VH	6	133
	Aberrated Atrial Premature	a	3	48
	Atrial Premature Beat	A	8	231
	Atrial Fibrillation	AFIB	6	87
	Atrial Flutter	AFL	3	71
	Ventricular Bigeminy	B	4	93
	Ventricular Escape Beat	E	1	105
	Fusion of Ventricular and Normal Beat	F	7	105
	Left Bundle Branch Block	L	3	258
MIT-BIH	Nodal (A-V Junctional) Rhythm	NOD	2	34
	Paced Rhythm	P	3	56
	Unclassifiable Beat	Q	4	27
	Right Bundle Branch Block	R	2	243
	Supraventricular Premature	S	1	2
	Ventricular Trigeminy	T	5	58
	Premature Ventricular Contraction	V	10	271
	Ventricular Flutter	VFL	1	6
	Ventricular Tachycardia	VT	7	39

4. Experimental setup and evaluation metrics

4.1. Dataset

The ECG acquisition method plays an important role in determining the performance of arrhythmia classification system. Generally, on-the-person ECG acquisition methods are used in clinical applications. It requires placement of electrodes on the chest, leg or hand through the conductive gel. Most of the ECG arrhythmia classification methods use on-the-person ECG dataset. To validate the performance of the proposed CardioNet system for arrhythmia classification, two benchmark datasets *i.e.*, PTB and MIT-BIH arrhythmia are used in this study [61].

4.1.1. PTB dataset

Physikalisch-Technische Bundesanstalt (PTB) dataset consist of 549 records acquired in five sessions from 290 subjects [61]. The PTB dataset consists of healthy as well as unhealthy records. The 2D ECG images are prepared through ECG signal data augmentation from the recordings of 268 subjects. Rest of the recordings of 22 subjects are left from the experiment as they didn't contain the information about any arrhythmia. The number of subjects suffering from different arrhythmias are shown in Table 2. Thus, a total of 4651 ECG images are created initially. The data augmentation is done in such a way that a total of 1000 2D ECG images are prepared for each arrhythmia class. Therefore, a total of 12000 ECG images are prepared from PTB dataset for twelve classes of arrhythmia. The types of arrhythmia present in the PTB dataset and their representative heartbeats are shown in Table 3.

4.1.2. MIT-BIH dataset

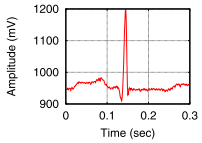
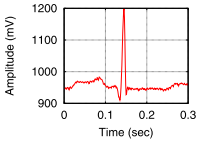
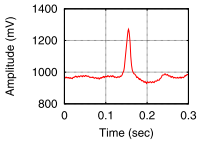
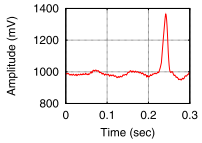
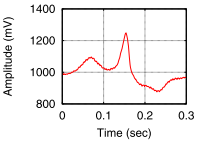
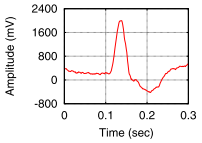
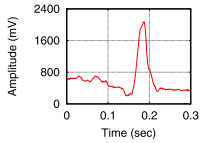
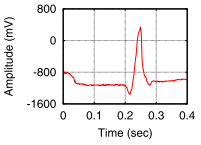
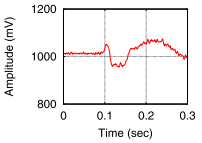
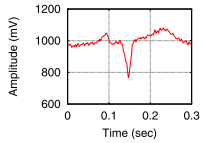
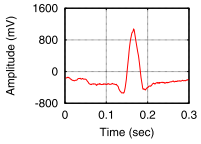
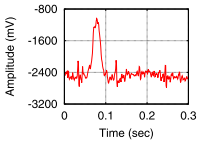
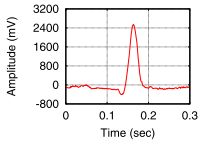
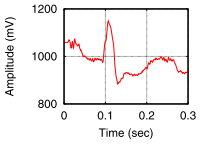
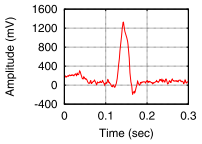
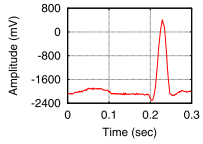
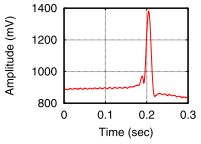
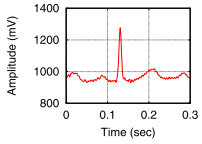
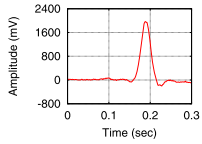
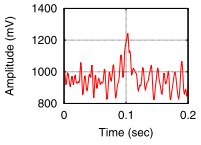
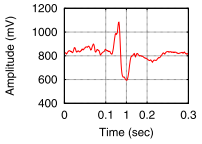
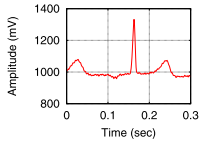
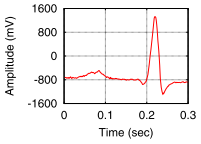
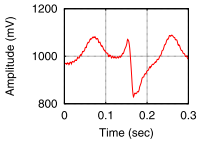
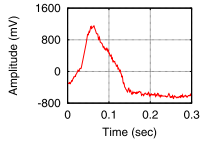
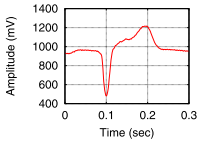
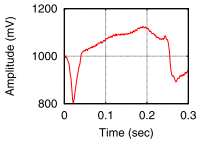
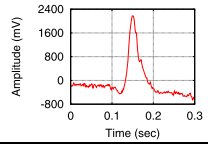
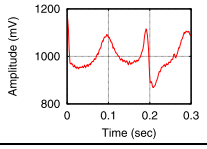
The MIT-BIH arrhythmia dataset consists 30 minutes recording of two-channel ambulatory system acquired from 48 subjects. A minimum of two cardiologists were involved in annotating each record and recorded the issues and corresponding solutions needed to reach to the computer-readable outcome. Heartbeats are collected from different subjects under seventeen arrhythmia classes. About 1734 2D ECG images are initially prepared from all the arrhythmia classes, collectively. The number of subjects involved and heartbeats taken for preparing 2D ECG images is given in Table 2. The representative heartbeats for each arrhythmia class are shown in Table 3. Using ECG signal data augmentation a total of 17000 2D ECG images are prepared for 17 classes of arrhythmia. Thus, the efficacy of proposed CardioNet is evaluated on 29,000 2D ECG images containing 28 different arrhythmia types and a single normal class.

4.2. Evaluation metrics

The performance of the CardioNet system is evaluated using following primitive metrics *i.e.*, number of true positives (TP), false negatives (FN), false positives (FP) and true negatives (TN). Using these primitive metrics other performance metrics are also computed:

- False Positive Rate (FPR): It measures the likelihood of incorrect prediction of unauthorized samples.It is the ratio of number of false positive (FP) to the total number of classification attempts.
- False Negative Rate (FNR): It measures the likelihood of incorrect rejection of authorized samples. It is ratio of number of false negative (FN) to the total number of classification attempts.
- Accuracy: It is the most natural performance metric and it is simply a ratio of number of correct predictions to the total observations.
- Precision: It is the ratio of the number of correct positive (TP) predictions to the total number of positive predictions.
- Recall: It is the ratio of the number of correct positive (TP) predictions to the total number of TP and FN. It is known to be true positive rate (TPR) or sensitivity.
- F1-score: It is the weighted average of precision and recall. F1-score is proved to be better than accuracy as it takes both false positives and false negatives into consideration in case of uneven class distributions.

Table 3
Arrhythmia classes and their heartbeat morphology.

Type of Arrhythmia	Representation	Type of Arrhythmia	Representation	Type of Arrhythmia	Representation
Aberrated Atrial Premature (a)		Atrial Premature Beat (A)		Atrial Fibrillation (AFIB)	
Atrial Flutter (AFL)		Ventricular Bigeminy (B)		Bundle Branch Block (BBB)	
Cardiomyopathy (CMY)		Dysrhythmia (DYS)		Ventricular Escape Beat (E)	
Fusion of Ventricular and Normal Beat (F)		Healthy (H)		Heart Failure (HF)	
Myocardial Hypertrophy (HYPR)		Left Bundle Branch Block (L)		Myocardial Infarction (MI)	
Myocarditis (MY)		Nodal (A-V Junctional) Rhythm (NOD)		Paced Rhythm (P)	
Palpitation (PALP)		Un classifiable Beat (Q)		Right Bundle Branch Block (R)	
Supra ventricular Premature (S)		Stable Angina (SA)		Ventricular Trigeminy (T)	
Unstable Angina (UA)		Premature Ventricular Contraction (V)		Ventricular Flutter (VFL)	
Valvular Heart Disease (VH)		Ventricular Tachycardia (VT)			

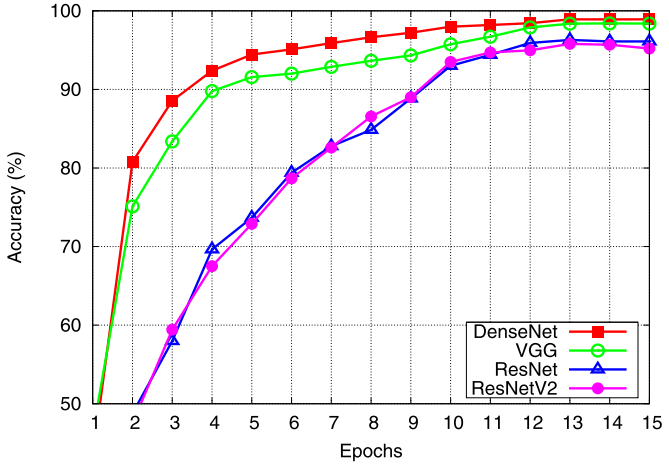


Fig. 5. Classification accuracies for different pre-trained architectures.

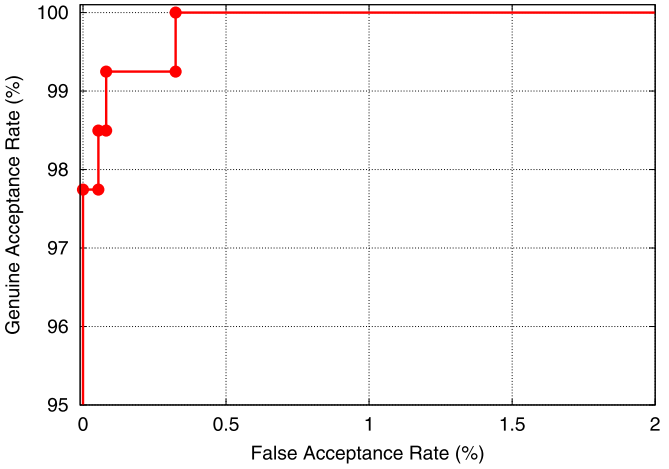


Fig. 6. ROC curve for arrhythmia classification using CardioNet.

4.3. CardioNet system learning

The ECG images of size 150×150 containing heartbeat morphological features are feed-forwarded to network layers of the model. It uses weights obtained during pre-training on ImageNet. The rationale behind is that the network learns in a faster way from an elevated starting point. The layers in CardioNet represents one or more operations *i.e.*, convolution, pooling, rectification, stride and normalization. The convolutional filter is applied with ReLU activation function and the stride is selected as one to capture maximum features of the heartbeats. The size of feature vector decreases by increasing the stride. Therefore, the stride can be taken greater than one, if the small feature vector is sufficient for effective classification. The max pooling is performed at pooling layers. The last layer used for classification is to be fully connected. It employs softmax loss function having the number of channels equal to the number of classes. For model training, stochastic gradient descent optimization is used. It randomly selects a subset of samples from the whole dataset at each iteration to make the training computationally efficient. In each iteration, the total number of selected samples is ensured to be in minibatches. We set the minibatch size as 30, it provides maximum utilization of the available video random access memory (VRAM) of the graphics processing units (GPU). Increasing the size of minibatch may cut down the training time, but requires a larger VRAM. The gradient direction is guided with a momentum that accumulates it to the past steps that help determine the gradient's optimal direction. The momentum coefficient is set to 0.92 that assists in fast convergence of learning algorithm. The value of momentum coefficient is chosen heuristically. For 15 training epochs, the model converges to return with maximum accuracy. Zero mean Gaussian distribution with deviation of 10^{-2} is used as initial weights of the filters.

4.4. Arrhythmia classification results

The experimental dataset prepared from PTB and MIT-BIH ECG recordings consists 29 known types of heartbeats. The experiment is conducted on the dataset with a training and testing ratio of 80:20 and reports the best results compared to training and testing ratios of 90:10 and 70:30. The selection of DenseNet architecture for CardioNet system is based on the classification performance reported on the prepared dataset and found to be the best compared to other architectures such as VGG, ResNet and ResNetV2 those are pre-trained on ImageNet. The classification accuracies of different pre-trained architectures is shown in Fig. 5. The advantage of these architectures' pre-training is that they converge faster and achieve optimal accuracy within 10 epochs. After 10 epochs, there is a minor variation in accuracy and system achieves highest accuracy within 15 epochs. Although, the classification accuracies of all architectures are found to be nearly same at first epoch. The DenseNet outperforms other architectures from second epoch onwards. The testing accuracies of DenseNet architecture are found to be 43.11%, 80.79%, 92.38%, 95.89%, 97.98%, 98.42% and 98.92% at 1, 2, 4, 7, 10, 12 and 15 epochs, respectively. The highest accuracy achieved by DenseNet architecture is 98.92%. Whereas the highest accuracies reported by other architectures *i.e.*, VGG, ResNet and ResNetV2 are 98.38%, 96.1% and 95.2%, respectively.

The classification performance of CardioNet system for different arrhythmia classes represented through following metrics of precision, recall and F1-score are given in Table 4. These results also prove the efficacy of the proposed method and its robustness in heartbeats classification irrespective to their arrhythmia types. The result of performance metrics shows less variation and reported higher for all classes further, proves the robustness of CardioNet. The higher values of precision for different arrhythmia classes show that the number of false positives is negligibly small compared to the number of true positives. Likewise, the number of true positives is reportedly higher than the number of false negatives, therefore recall values are higher for each arrhythmia class. Further, the value of F1-score is also reported higher that validates the lower number of FP and FN. Finally, the overall values of precision, recall and F1-score for different arrhythmia classes are found to be 98.62%, 98.68% and 98.65%, respectively. Thus, CardioNet avoids FP (Type I error) and FN (Type II error).

The effectiveness of a proposed CardioNet system for classifying arrhythmia using ECG is also evaluated in terms of genuine acceptance rate (GAR). To achieve better visualization of the accuracy of the CardioNet, a receiver operating characteristic (ROC) curve is drawn and shown in Fig. 6. The ROC curve plots false acceptance rate (FAR)-vs-GAR in a 2D plane. Thus, a relationship is established between FAR and GAR that can be utilized while deciding a threshold for FAR to attain optimal GAR. The CardioNet achieves 97.74% GAR at 0% FAR, using experimented dataset prepared from PTB and MIT-BIH ECG recordings. The GAR values reported to 98.5%, 99.2% and 100% at the lower values of FAR to 0.03%, 0.05% and 0.3%, respectively.

Alike accuracy, the collective representation of true positives (TP), true negatives (TN), false positives (FP) and false negatives (FN) can be seen in a confusion matrix as drawn in Fig. 8. The confusion matrix as the name suggests displays the confusion of a model in predicting classes. Although, the number of TP, TN, FP and FN, can not be directly calculated as there is no positive or

Table 4
CardioNet classification performance for different arrhythmias.

Heartbeat/Arrhythmia	Presision (%)	Recall (%)	F1-score (%)	Accuracy (%)
Aberrated Atrial Premature Beat (a)	100	100	100	100
Atrial Premature Beat (A)	97.09	96.15	96.62	97.45
Atrial Fibrillation (AFIB)	100	100	100	100
Atrial Flutter (AFL)	98.43	98.43	98.43	98.89
Ventricular Bigeminy (B)	100	100	100	100
Bundle Branch Block (BBB)	99.07	98.17	98.62	98.27
Cardiomyopathy (CMY)	100	100	100	100
Dysrhythmia (DYS)	94.87	96.73	95.79	94.9
Ventricular Escape Beat (E)	100	100	100	100
Fusion of Beats (F)	100	100	100	100
Healthy (H)	100	100	100	100
Heart Failure (HF)	100	100	100	100
Hypertrophy (HYPR)	98.41	100	99.20	99.21
Left Bundle Branch Block (L)	100	100	100	100
Mycordial Infarction (MI)	100	95.59	97.74	96.58
Myocarditis (MY)	100	100	100	100
A-V Junctional Rhythm (NOD)	96.30	100	98.11	97.19
Paced Rhythm (P)	100	100	100	100
Palpitation (P)	100	100	100	100
Unclassified Beat (Q)	100	100	100	100
Right Bundle Branch Block (R)	97.96	98.17	98.56	98.68
Supraventricular Premature Beat (S)	94.37	93.06	93.71	98.4
Stable Angina (SA)	97.44	95.80	96.61	98.5
Ventricular Trigeminy (T)	99.19	100	99.60	99.19
Unstable Angina (UA)	98.88	98.88	98.88	97.79
Premature Ventricular Contraction (V)	94.96	97.41	96.17	97.62
Ventricular Flutter (VFL)	98.46	98.46	98.46	98.96
Valvular Heart disease (VH)	97.81	96.40	97.10	98.36
Ventricular Tachycardia (VT)	97.01	98.74	97.38	98.89

negative class in a multiclass problem. These values can be calculated for each class individually. For example, these metrics for a particular class of arrhythmia 'AFIB' are calculated as shown in Fig. 7. The actual and predicted class labels are shown in x, y plane, respectively. Each square in confusion matrix shows the probability of matching the predicted class to their genuine class. The TP for the arrhythmia class 'AFIB' is equal to the total number of correct predictions for the class *i.e.*,

$$TP_{AFIB} = AFIB_{AFIB} \tag{7}$$

The sum of probabilities in all squares of confusion matrix that does not belong to class 'AFIB' in either predicted or actual label, is the number of TN for the class.

$$\begin{aligned} TN_{AFIB} = {} & a_a + a_A + a_{AFL} + a_B + \ldots + a_{VT} + \\ & A_a + A_A + A_{AFL} + A_B + \ldots + A_{VT} + \\ & AFL_a + AFL_A + AFL_{AFL} + AFL_B + \ldots + AFL_{VT} + \\ & \ldots + VT_a + VT_A + VT_{AFL} + VT_B + \ldots + VT_{VT} \end{aligned} \tag{8}$$

The sum of matching probabilities for all genuine classes with predicted class 'AFIB', is the number of FP for class 'AFIB'. Similarly, the number of FN for class 'AFIB' can be calculated by adding all the predictions of the actual class 'AFIB' with other predicted classes as follows,

$$\begin{aligned} FP_{AFIB} = {} & AFIB_a + AFIB_A + AFIB_{AFL} \\ & + AFIB_B + \ldots + AFIB_{VT} \end{aligned} \tag{9}$$

and,

$$\begin{aligned} FN_{AFIB} = {} & a_{AFIB} + A_{AFIB} + AFL_{AFIB} \\ & + B_{AFIB} + \ldots + VT_{AFIB} \end{aligned} \tag{10}$$

Using these metrics, the performance of the CardioNet system is assessed by measuring FPR_{AFIB}, $precision_{AFIB}$, $recall_{AFIB}$ and Acc_{AFIB}, as shown in Fig. 7. Likewise, these metrics are calculated for each 29 classes of heartbeats considered for classification.

The confusion matrix drawn for CardioNet system trained for 29 heartbeat classes using prepared dataset is shown in Fig. 8. The x-y plane of the confusion matrix represents actual and predicted classes. The square corresponding to a class at x-axis represents the probability of matching with the corresponding class at y-axis. The probabilities for matching of a class in predicted and actual are found higher except for the class 'supraventricular premature (S)' *i.e.*, 0.88. All other matching probabilities are approaching towards diagonal and close to 1, whereas the matching probabilities other than diagonal are closer to 0. Therefore, CardioNet gets hardly any chance of confusion to perform incorrect prediction.

4.5. Comparative analysis

The proposed CardioNet system accomplishes outstanding results and outperforms other methods of arrhythmia classification known till date. This section exhibits a comparison of best known recent machine learning methods of arrhythmia classification. The method in [62] has reported the arrhythmia classification performance to 97.06%. However, method utilized for the classification of only two classes *e.g.*, supraventricular ectopic beat (SVEB) and ventricular ectopic beat (VEB). An ensemble of bootstrap aggregated decision trees has been used to achieve 96.15% accuracy over 16 classes of arrhythmia [63]. Their study also proposed two other feature extraction methods that increase the dimension of the feature vectors, consequently raising the training and testing time required by the classifier. A general regression neural network (GRNN) is used by Li *et al.*, for classifying 5 classes of arrhythmia [64]. They have achieved 88% detection accuracy using 8 temporal and slope features. Huang *et al.*, utilized short-time Fourier transform (STFT) and image spectrogram with 1D and 2D CNN, respectively [65]. The average accuracy of 90.93% has been achieved for five arrhythmia classes. Although, the higher accuracy of 99.81% is accomplished by Wang *et al.*, they also considered only 5 classes of arrhythmia [66]. The classification of arrhythmia

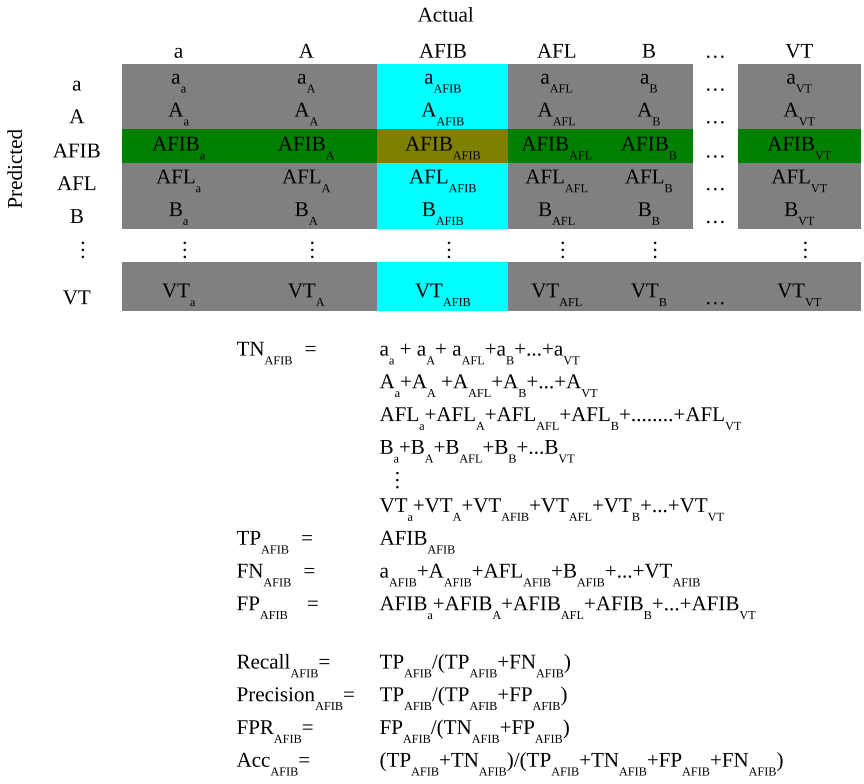


Fig. 7. Computation of different performance metrics using confusion matrix.

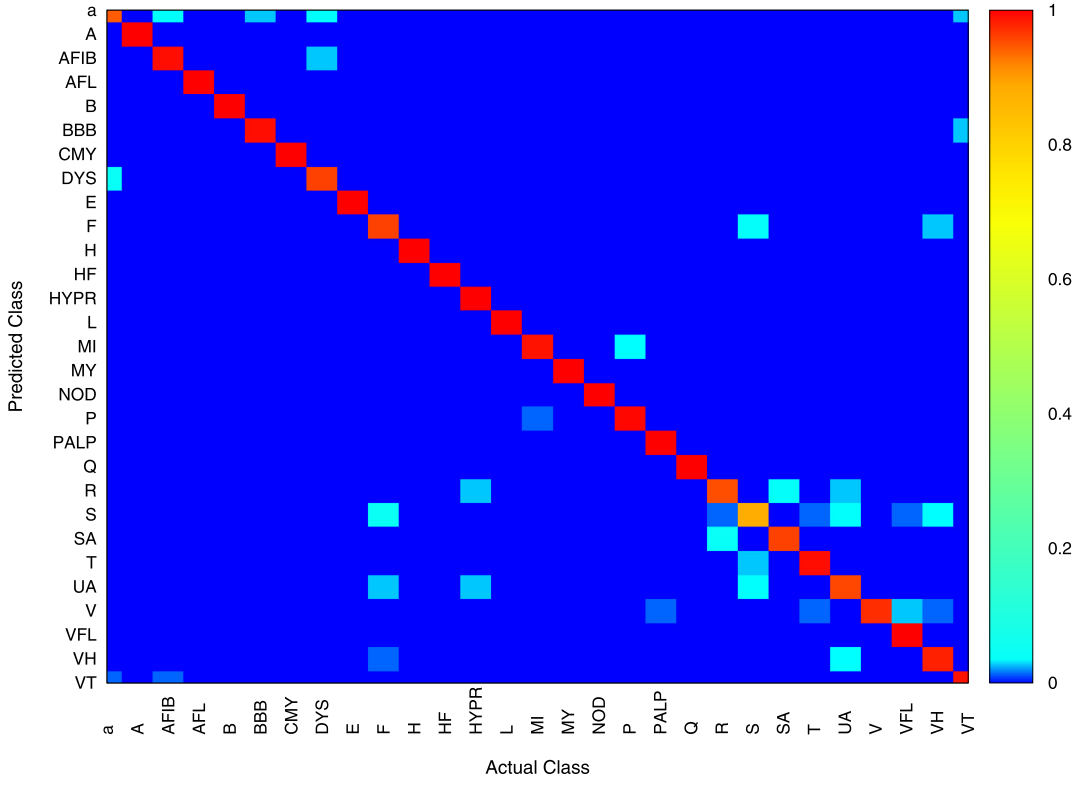


Fig. 8. Confusion matrix for arrhythmia classification using CardioNet. (For interpretation of the colors in the figure, the reader is referred to the web version of this article.)

is performed using morphological features with residual network and long short-term memory (LSTM). A bidirectional LSTM is used by He *et al.*, for three arrhythmia classes and achieves the classification accuracy to 92.07% [67]. Zhu *et al.*, have used a combination of 13 temporal features, DWT and PCA with SVM classifier and achieves an accuracy of 97.8% for four arrhythmia classes [68].

The work of Salem *et al.* and Isin *et al.*, used transfer learning for heartbeat classification but limited to a very few classes and experimented smaller datasets [33], [53]. Isin *et al.*, used AlexNet architecture for feature extraction from 416 images of size $256 \times 256 \times 3$ each [53]. Using larger size images generate more parameters that may increase processing time and cost. The AlexNet being a shallow network compared to current state-of-the-art models, struggles to learn features from complex images. Therefore, classification accuracy is rather poor to 92.4% for only three classes of heartbeats. Salem *et al.*, used DenseNet model for feature extraction and support vector machine (SVM) for classification [33]. The SVM performs poorly, if feature size exceeds the number of training samples. Therefore, feature size needs to be reduced (dimensionality reduction) prior classification. In case of complex datasets, dimensionality reduction sometimes leads to loss of significant features resulting to lower classification accuracy. Therefore, this work uses artificial neural network (ANN) for classification as it handles larger feature set compared to traditional machine learning models. Also, the ANN can be customized according to the nature and complexity of the feature set. Since, there are 29 classes of heartbeats with complex feature set need to be classified and the machine learning model hardly lead to promising results. Therefore, the CardioNet system using transfer learning is proposed. The method converges faster as compared to machine learning models and performs better than a custom built CNN. The proposed CardioNet system is trained faster and highly sensitive to heartbeat variations. Thus, the CardioNet system is robust and cost-effective compared to other existing method of arrhythmia classification.

Finally, the potential of proposed method of arrhythmia classification using ECG with CardioNet architecture is proved and found to be the best among other similar methods. For the first time, an arrhythmia classification system is developed that classifies a large number of heartbeat types. In a nutshell, this paper contributes to developing an intelligent, reliable and robust system for arrhythmia classification *i.e.*, CardioNet.

5. Conclusion

The ECG is a bioelectrical signal that records the electrical activity of the heart. It is a representation of the depolarization and repolarization of cardiac muscles in temporal-frequency domain. An ECG is a non-invasive, inexpensive and extensively used test for medical diagnostic by clinicians to detect cardiac arrhythmia. An abnormal or irregular heartbeat can characterize an arrhythmia. There are several conditions in which the heart rhythm is irregular. A group of conditions representing different irregular heartbeats are called cardiac arrhythmia. Most of the arrhythmias are harmless and some can be life-threatening. Therefore, their detection and classification are essentially needed for the diagnosis of heart disease. The arrhythmias are essentially diagnosed by observing the electrical activity of the heart using ECG.

The computer-assisted cardiology is discovered in the recent past from last couple of decades. This domain aims to discover intelligent and novel algorithms with computer-assisted data acquisition devices for patient treatment modalities. In particular, the use of machine learning and deep learning techniques make possible the detection, diagnostic and predictions of diseases based on clinical data, efficiently. This work is motivated by this aim and has developed a computer assisted system for diagnosing heart disease or arrhythmia.

This paper has presented a novel method of arrhythmia classification from ECG signal using deep learning. A fine-tuned architecture named 'CardioNet' has been developed by using the state-of-the-art pre-trained deep neural networks. The proposed architecture has used the principle of transfer learning, thus making a novel framework that does the faster and robust classification of heartbeats than other methods. Our proposed framework is unique such that the initial pre-trained model provides a good starting point that enables classification algorithm to converge faster. The testing time is also reduced through fine-tuning and thus, CardioNet has achieved optimal accuracy within ten epochs. The efficacy of the proposed method is evaluated on the combination of benchmarked datasets. The CardioNet system has successfully reported higher accuracy values on all tested classes of 29 different heartbeats consisting 28 arrhythmia types along with one normal beat. Thus, the proposed transfer learning model *i.e.*, CardioNet has performed better and shown robustness to different arrhythmias. For the first time, the arrhythmia classification system is developed that classifies many arrhythmias to different 28 classes.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

References

[1] Cardiovascular diseases (CVDs), online at: https://www.who.int/news-room/fact-sheets/detail/cardiovascular-diseases-(cvds). (Accessed 13 May 2021).
[2] Z. Ebrahimi, M. Loni, M. Daneshtalab, A. Gharehbaghi, A review on deep learning methods for ECG arrhythmia classification, Expert Syst. Appl., X 7 (September 2020) 100033.
[3] M.M.A. Hadhoud, M.I. Eladawy, A. Farag, Computer aided diagnosis of cardiac arrhythmias, in: 2006 International Conference on Computer Engineering and Systems, Cairo, 2006, pp. 262–265.
[4] Y.N. Singh, P. Gupta, ECG to individual identification, in: 2008 IEEE Second International Conference on Biometrics: Theory, Applications and Systems, Arlington, VA, 2008, pp. 1–8.
[5] R. Ceylan, Y. Ozbay, Comparison of FCM, PCA and WT techniques for classification ECG arrhythmias using artificial neural network, Expert Syst. Appl. 33 (2) (2007) 286–295.
[6] Y.N. Singh, S.K. Singh, Evaluation of electrocardiogram for biometric authentication, Int. J. Inf. Secur. 3 (2012) 39–48.
[7] Y.N. Singh, S.K. Singh, P. Gupta, Fusion of electrocardiogram with unobtrusive biometrics: an efficient individual authentication system, Pattern Recognit. Lett. 33 (2012) 1932–1941.
[8] Y.N. Singh, Human recognition using Fisher's discriminant analysis of heartbeat interval features and ECG morphology, Neurocomputing 167 (2015) 322–335.
[9] R. Srivastva, Y.N. Singh, ECG analysis for human recognition using nonfiducial methods, IET Biometrics 8 (5) (2019) 295–305.
[10] R. Srivastva, A. Singh, Y.N. Singh, PlexNet: a fast and robust ECG biometric system for human recognition, Inf. Sci. 558 (3) (2021) 208–228.
[11] S.M.P. Dinakarrao, A. Jantsch, M. Shafique, Computer-aided arrhythmia diagnosis with bio-signal processing: a survey of trends and techniques, ACM Comput. Surv. (CSUR) 52 (2) (2019) 23.
[12] G. Huang, Z. Liu, L. Van Der Maaten, K.Q. Weinberger, Densely connected convolutional networks, in: 2017 IEEE Conference on Computer Vision and Pattern Recognition (CVPR), Honolulu, HI, 2017, pp. 2261–2269.
[13] Recommended practice for testing and reporting performance results of ventricular arrhythmia detection algorithms, in: Association for the Advancement of Medical Instrumentation, Arlington, VA, USA, 1987.
[14] ST segment measurement algorithms, American National Standards Institute, Inc. (ANSI), Association for the Advancement of Medical Instrumentation (AAMI), ANSI/AAMI/ISO EC57,1998-(R)2008, 2008.
[15] E. Zeraatkar, S. Kermani, A. Mehridehnavi, A. Aminzadeh, E. Zeraatkar, H. Sanei, Arrhythmia detection based on morphological and time-frequency features of T-wave in electrocardiogram, J. Med. Signals Sensors 1 (2) (2011) 99–106.
[16] S.M. Jadhav, S.L. Nalbalwar, A.A. Ghatol, Artificial neural network models based cardiac arrhythmia disease diagnosis from ECG signal data, Int. J. Comput. Appl. 44 (15) (2012) 8–13.
[17] V.S.R. Kumari, P.R. Kumar, Cardiac arrhythmia prediction using improved multilayer perceptron neural network, Res. Develop. (IJECIERD) 3 (4) (2013) 73–80.
[18] V.K. Srivastava, D. Prasad, DWT-based feature extraction from ECG signal, Am. J. Eng. Res. 2 (3) (2013) 44–50.

[19] A. Khazaee, Heart beat classification using particle Swarm optimization, Int. J. Intell. Syst. Appl. 5 (6) (2013) 25–33.
[20] U.R. Acharya, S.L. Oh, Y. Hagiwara, J.H. Tan, M. Adam, A. Gertych, T.R. San, A deep convolutional neural network model to classify heartbeats, Comput. Biol. Med. 89 (2017) 389–396.
[21] U.R. Acharya, H. Fujita, S. Lih, Y. Hagiwara, J. Hong, M. Adam, Application of deep convolutional neural network for automated detection of myocardial infarction using ECG signals, Inf. Sci. 415–416 (2017) 190–198.
[22] Z. Xiong, M.K. Stiles, J. Zhao, Robust ECG signal classification for the detection of atrial fibrillation using novel neural networks, Comput. Cardiol. 44 (1) (2017) 1–4.
[23] Y. Xia, Y. Xie, A novel wearable electrocardiogram classification system using convolutional neural networks and active learning, IEEE Access 7 (2019) 7989–8001.
[24] T.J. Jun, H.J. Park, N.H. Minh, D. Kim, Y.H. Kim, Premature ventricular contraction beat detection with deep neural networks, in: Proc. of IEEE International Conference on Machine Learning and Applications, 2017, pp. 859–864.
[25] X. Zhai, C. Tin, Automated ECG classification using dual heartbeat coupling based on convolutional neural network, IEEE Access 6 (2018) 27465–27472.
[26] F. Andreotti, O. Carr, M.A.F. Pimentel, A. Mahdi, M. De Vos, Comparing feature-based classifiers and convolutional neural networks to detect arrhythmia from short segments of ECG, Comput. Cardiol. 44 (2017) 1–4.
[27] M. Huanhuan, Z. Yue, Classification of electrocardiogram signals with deep belief networks, in: 2014 IEEE 17th International Conference on Computational Science and Engineering, Chengdu, 2014, pp. 7–12.
[28] Z. Wu, X. Ding, G. Zhang, A novel method for classification of ECG arrhythmias using deep belief networks, Int. J. Comput. Intell. Appl. 15 (4) (2016).
[29] Z. Wu, et al., A novel features learning method for ECG arrhythmias using deep belief networks, in: 2016 6th International Conference on Digital Home (ICDH), Guangzhou, 2016, pp. 192–196.
[30] S. Singh, S.K. Pandey, U. Pawar, R.R. Janghel, Classification of ECG arrhythmia using recurrent neural networks, Proc. Comput. Sci. 132 (2018) 1290–1297.
[31] J. Gao, H. Zhang, P. Lu, Z. Wang, An effective LSTM recurrent network to detect arrhythmia on imbalanced ECG dataset, in: Special Issue on Big Data Intelligence in Healthcare Applications Based on Physiological Signals, J. Healthc. Eng. 2019 (2019) 6320651.
[32] S.K. Pandey, R.R. Janghel, Automatic arrhythmia recognition from electrocardiogram signals using different feature methods with long short-term memory network model, Signal Image Video Process. 14 (2020) 1255–1263.
[33] M. Salem, S. Taheri, J. Yuan, ECG arrhythmia classification using transfer learning from 2-dimensional deep CNN features, in: 2018 IEEE Biomedical Circuits and Systems Conference (BioCAS), Cleveland, OH, 2018, pp. 1–4.
[34] T.H. Yeap, F. Johnson, M. Rachniowski, ECG beat classification by a neural network, in: Proc. Twelfth Annual International Conference of the IEEE Engineering in Medicine and Biology Society, Philadelphia, PA, USA, 1990, pp. 1457–1458.
[35] K. Najarian, R. Splinter, Biomedical Signal and Image Processing, CRC Press, 2005.
[36] P. Plawiak, Novel methodology of cardiac health recognition based on ECG signals and evolutionary-neural system, Expert Syst. Appl. 92 (2018) 334–349.
[37] J.M. Mendel, Tutorial on higher-order statistics (spectra) in signal processing and system theory: theoretical results and some applications, Proc. IEEE 79 (3) (March 1991) 278–305.
[38] Y. Park, I.D. Yun, Arrhythmia detection in electrocardiogram based on recurrent neural network encoder-decoder with Lyapunov exponent, IEEJ Trans. Electr. Electron. Eng. (2019) 1273–1274.
[39] S. Kiranyaz, T. Ince, J. Pulkkinen, M. Gabbouj, Personalized longterm ECG classification: a systematic approach, Expert Syst. Appl. 38 (4) (Apr. 2011) 3220–3226.
[40] D.A. Coast, R.M. Stern, G.G. Cano, S.A. Briller, An approach to cardiac arrhythmia analysis using hidden Markov models, IEEE Trans. Biomed. Eng. 37 (9) (Sep. 1990) 826–836.
[41] I. Guler, E.D. Ubeyli, ECG beat classifier designed by combined neural network model, Pattern Recognit. 38 (2005) 199–208.
[42] S.C. Matta, Z. Sankari, S. Rihana, Heart rate variability analysis using neural network models for automatic detection of lifestyle activities, Biomed. Signal Process. Control 42 (2018) 145–157.
[43] E.D. Ibeyli, Recurrent neural networks employing Lyapunov exponents for analysis of ECG signals, Expert Syst. Appl. 37 (2) (Mar. 2010) 1192–1199.
[44] J.S. Wang, W.C. Chiang, Y.L. Hsu, Y.T.C. Yang, ECG arrhythmia classification using a probabilistic neural network with a feature reduction method, Neurocomputing 116 (Sep. 2013) 38–45.
[45] S.N. Yu, Y.H. Chen, Electrocardiogram beat classification based on wavelet transformation and probabilistic neural network, Pattern Recognit. Lett. 28 (2007) 1142–1150.
[46] S. Osowski, T. Hoai, T. Markiewicz, Support vector machine-based expert system for reliable heartbeat recognition, IEEE Trans. Biomed. Eng. 51 (4) (Apr. 2004) 582–589.
[47] M.H. Song, J. Lee, S.P. Cho, K.J. Lee, S.K. Yoo, Support vector machine based arrhythmia classification using reduced features, Int. J. Control. Autom. Syst. 3 (4) (2005) 571–579.
[48] M. Hammad, A. Maher, K. Wang, F. Jiang, M. Amrani, Detection of abnormal heart conditions based on characteristics of ECG signals, Measurement 125 (2018) 634–644.
[49] E.J. da, S. Luz, T.M. Nunes, V.H.C. De Albuquerque, J.P. Papa, D. Menotti, ECG arrhythmia classification based on optimum-path forest, Expert Syst. Appl. 40 (9) (Jul. 2013) 3561–3573.
[50] P. Chazal, M. O'Dwyer, R.B. Reilly, Automatic classification of heartbeats using ECG morphology and heartbeat interval features, IEEE Trans. Biomed. Eng. 51 (2004) 1196–1206.
[51] T.J. Jun, et al., Premature ventricular contraction beat detection with deep neural networks, in: 15th IEEE International Conference on Machine Learning and Applications, 2016, pp. 859–864.
[52] B. Pourbabaee, M.J. Roshtkhari, K. Khorasani, Feature learning with deep convolutional neural networks for screening patients with paraoxysmal atrial fibrillation, IEEE Int. Joint Conf. Neural Netw. (2016) 5057–5064.
[53] A. Isin, S. Ozdalili, Cardiac arrhythmia detection using deep learning, Proc. Comput. Sci. 120 (2017) 268–275, 2017.
[54] J. Pan, W.J. Tompkins, A real-time QRS detection algorithm, IEEE Trans. Biomed. Eng. 32 (3) (1985) 230–236.
[55] Y.N. Singh, P. Gupta, Quantitative evaluation of normalization techniques of matching scores in multimodal biometric systems, in: S.W. Lee, S.Z. Li (Eds.), Advances in Biometrics. ICB 2007, in: Lecture Notes in Computer Science, vol. 4642, Springer, Berlin, Heidelberg, 2007, pp. 574–583.
[56] Heart Disease, Center for disease control and prevention, online at: https://www.cdc.gov/heartdisease/. (Accessed 13 May 2021).
[57] M.B. Conover, Understanding Electrocardiography, Elsevier Health Sciences, 2002.
[58] E. Awtry, C. Jeon, M.G. Ware, Blueprints Cardiology, Lippincott Williams & Wilkins, 2006.
[59] E.J. Otten, Cecil textbook of medicine, 22nd edition, J. Emerg. Med. (2005), https://doi.org/10.1016/j.jemermed.2004.10.006.
[60] C. Tan, F. Sun, T. Kong, W. Zhang, C. Yang, C. Liu, Survey on deep transfer learning, in: 27th International Conference on Artificial Neural Networks, Rhodes, Proceedings, Part III, 2018.
[61] A. Goldberger, et al., PhysioBank, PhysioToolkit, and PhysioNet: components of a new research resource for complex physiologic signals, Circulation [Online] 101 (23) (2000) e215–e220.
[62] A.I. Rahhal, M.M. Bazi, H.Y. Alhichri, N. Alajlan, F. Melgani, R.R. Yager, Deep learning approach for active classification of electrocardiogram signals, Inf. Sci. 345 (2016) 340–354.
[63] R.G. Afkhami, G. Azarnia, M.A. Tinati, Cardiac arrhythmia classification using statistical and mixture modeling features of ECG signals, Pattern Recognit. Lett. 70 (2016) 45–51.
[64] P. Li, et al., High-performance personalized heartbeat classification model for long-term ECG signal, IEEE Trans. Biomed. Eng. 64 (1) (Jan. 2017) 78–86.
[65] J. Huang, B. Chen, B. Yao, W. He, ECG arrhythmia classification using STFT-based spectrogram and convolutional neural network, IEEE Access 7 (2019) 92871–92880, https://doi.org/10.1109/ACCESS.2019.2928017.
[66] P. Wang, B. Hou, S. Shao, R. Yan, ECG arrhythmias detection using auxiliary classifier generative adversarial network and residual network, IEEE Access 7 (2019) 100910–100922.
[67] R. He, et al., Automatic cardiac arrhythmia classification using combination of deep residual network and bidirectional LSTM, IEEE Access 7 (2019) 102119–102135.
[68] W. Zhu, X. Chen, Y. Wang, L. Wang, Arrhythmia recognition and classification using ECG morphology and segment feature analysis, IEEE/ACM Trans. Comput. Biol. Bioinform. 16 (1) (2019) 131–138.