Computers in Biology and Medicine 134 (2021) 104457

Contents lists available at ScienceDirect

Computers in Biology and Medicine

journal homepage: www.elsevier.com/locate/compbiomed

Automated detection of coronary artery disease, myocardial infarction and congestive heart failure using GaborCNN model with ECG signals

V. Jahmunah [a], E.Y.K. Ng [a,*], Tan Ru San [b], U. Rajendra Acharya [c,d,e,f,g,**]

[a] Department of Mechanical and Aerospace Engineering, Nanyang Technological University, Singapore
[b] National Heart Centre, Singapore
[c] School of Engineering, Ngee Ann Polytechnic, Singapore
[d] Biomedical Engineering, School of Social Science and Technology, Singapore University of Social Sciences, Singapore
[e] International Research Organization for Advanced Science and Technology (IROAST), Kumamoto University, Kumamoto, Japan
[f] Department Bioinformatics and Medical Engineering, Asia University, Taiwan
[g] School of Management and Enterprise, University of Southern Queensland, Australia

ARTICLE INFO

Keywords:
Cardiovascular disease
Convolutional neural network
Gabor filter
Gabor convolutional neural network
Ten-fold validation
Deep learning
Multi-class classification

ABSTRACT

Cardiovascular diseases (CVDs) are main causes of death globally with coronary artery disease (CAD) being the most important. Timely diagnosis and treatment of CAD is crucial to reduce the incidence of CAD complications like myocardial infarction (MI) and ischemia-induced congestive heart failure (CHF). Electrocardiogram (ECG) signals are most commonly employed as the diagnostic screening tool to detect CAD. In this study, an automated system (AS) was developed for the automated categorization of electrocardiogram signals into normal, CAD, myocardial infarction (MI) and congestive heart failure (CHF) classes using convolutional neural network (CNN) and unique GaborCNN models. Weight balancing was used to balance the imbalanced dataset. High classification accuracies of more than 98.5% were obtained by the CNN and GaborCNN models respectively, for the 4-class classification of normal, coronary artery disease, myocardial infarction and congestive heart failure classes. GaborCNN is a more preferred model due to its good performance and reduced computational complexity as compared to the CNN model. To the best of our knowledge, this is the **first study** to propose GaborCNN model for automated categorizing of normal, coronary artery disease, myocardial infarction and congestive heart failure classes using ECG signals. Our proposed system is equipped to be validated with bigger database and has the potential to aid the clinicians to screen for CVDs using ECG signals.

1. Introduction

The heart pumps blood through the circulatory system [1], and any abnormality in the cardiovascular system can give rise to cardiovascular disease (CVD) [2]. Although death rates from CVDs are abating, CVDs continue to be the main cause of death in the United States. About 9.2 million or 44% of adults in the United States are projected to have at least one type of CVD by 2030. Globally, CVDs are the main causes of death, exacting an annual death toll of 17.9 million according to the World Health Organization [3].

1.1. Etiology of CAD

Coronary artery disease (CAD) is the most common type of CVD. CAD occurs when at least one of the left anterior descending (LAD), left circumflex (LCX) and right coronary (RCA) arteries is stenotic. In CAD, extracellular matrix in the inner lining of the coronary arterial wall combine with lipoproteins, exposing them for more lipoprotein modification and inflammation, resulting in the formation of vulnerable atherosclerotic plaques [4]. As inflammation progresses, there is cell death and accumulation of extracellular lipid in the artery wall of the lesion as well as calcium deposition [5]. The atherosclerotic plaque thickens, causing stenosis of the coronary lumen [6], which results in restriction of blood flow and delivery of oxygenated blood to the heart muscles, causing ischemia.

* Corresponding author. School of Mechanical and Aerospace Engineering, Nanyang Technological University, 639798, Singapore.
** Corresponding author. School of Engineering, Ngee Ann Polytechnic, Singapore.
E-mail addresses: mykng@ntu.edu.sg (E.Y.K. Ng), aru@np.edu.sg (U.R. Acharya).

https://doi.org/10.1016/j.compbiomed.2021.104457
Received 9 February 2021; Received in revised form 22 April 2021; Accepted 26 April 2021
Available online 7 May 2021

1.2. Etiology of MI

Atherosclerotic lesions with thick fibrous caps and calcification but with relatively smaller lipid cores can slowly induce ischemia due to progressive plaque volume increase that encroaches the coronary lumen diameter. In contrast, some atherosclerotic lesions with larger lipid cores and thinner fibrous caps are vulnerable to rupture, in which the contents are suddenly spilled into the coronary lumen, triggering the thrombus formation which can occlude the lumen and completely disrupt myocardial blood flow [5]. This leads to acute myocardial infarction (MI) [7,8] in which heart muscles die due to a lack of oxygen for an extended time duration.

1.3. Etiology of CHF

There are many causes for congestive heart failure (CHF), the most common being CAD-induced ischemia or MI. Heart muscle damage from chronic repeated episodes of ischemia or after MI can induce adverse remodelling of the heart chamber and impair contractility of the heart muscle. In addition, mechanical complications of MI such as mitral regurgitation from papillary muscle dysfunction or rupture and, ventricular septal rupture can aggravate cardiac embarrassment leading to heart failure [9]. Timely diagnosis of CAD and MI is important for the early treatment and to avert the possible development of CHF.

1.4. Electrocardiography for diagnosis

The current diagnostic methods of CVDs such as blood tests or cardiac catheterization are invasive. Additionally, other noninvasive cardiac testing methods have other disadvantages ranging from uncertainties on the suitable choice, order and frequency of cardiac imaging tests to perform in varying medical situations [10]. Furthermore, other tests such as cardiac magnetic resonance imaging (MRI) or echocardiography are expensive and require expert professionals to screen the ultrasound and MRI images [11]. Machine learning techniques have been employed more successfully for the classification of CVDs in recent years [12–16]. Hence in this study, the authors propose to develop a cost-effective, non-invasive and user-friendly tool for the automatic diagnosis of CVDs using electrocardiograms.

The ECG is the electrical activity of the heart which gets altered due to CAD, MI and CHF [17]. These diagnostic ECG alterations are often small amplitudes and for short durations. Hence visual interpretation by medical experts is subjective and prone to intra and/or inter-observer variabilities [18]. Automated systems incorporating machine learning algorithms can be used to improve the diagnostic sensitivities [19] and can be deployed to assist the clinicians in ECG screening to find CVDs in at-risk populations. In this study, an automated system based on a novel deep learning algorithm has been developed to classify ECG signals into normal (N), CAD, MI and CHF classes.

2. Deep learning versus conventional machine learning

In machine learning, models are trained with subsets of data to solve specific tasks [20]. The models employ a range of statistical, probabilistic and optimization methods to learn from previous experience and identify useful patterns from big, unstructured and intricate datasets [21]. In supervised learning, the data is split into training, testing and validation. As the model is being trained for classification tasks, it uses patterns in the training data to represent features to the target such that it is able to forecast based on future data [22]. The training and validation data are used to update the model about the link between features and target, whereas the test dataset is used to gauge the performance of the model in making predictions on unseen data [20]. Conventional classifiers commonly used for disease classification include support vector machines, random forest, naïve Bayes, decision tree and k-nearest neighbor [23].

Advanced classifiers such as artificial neural networks (ANN) are built using synthetic neurons to emulate biological neurons [22]. An ANN typically comprises an input data layer and an output data layer, with some hidden data layers (0–3) in between, whereas in a deep neural network, the number of hidden layers are in the ranges of ten to hundreds [24]. As input data goes through each layer in sequence, they are successively modified at each layer such that at the last layer, they differ substantially from the original state. This transformation is triggered by rectified linear activation functions in deep models [24]. A single node in the last layer with sigmoidal activation relates to binary classification; and multiple nodes, to the predicted number of classes for multi-class classification [20]. Examples of deep models commonly used for disease classification include convolutional neural network (CNN) [25,26], long short-term memory network (LSTM) [27], recurrent neural network (RNN) [28] and autoencoders [29].

Deep learning models are generally preferred for disease classification due to several advantages over traditional machine learning methods. In the latter, feature extraction and selection are not automated and need to be handcrafted. In deep learning, these processes are fully automated [15]. Furthermore, deep models can be trained by very large data, unlike machine learning models which perform well with smaller datasets [30]. Recently, Shakib et al. [31] used Gabor filters with CNN model to train the model with lesser time complexity. They reported that Gabor filters were able to reduce a significant amount of time during the back-propagation training of the model, hence achieving a substantial reduction in training time of the model. Additionally, in another study, Alekseev et al. [32] reported that CNN models with Gabor layers showed improved performance on several datasets (6% improvement in accuracy), as compared to the conventional CNN model. Hence, from the two studies, it is clear that CNN model with Gabor filters performs well, yielding good accuracy and reduces computational complexity at the same time. Thus, the Gabor filter is used in this study to classify N, CAD, MI and CHF classes using ECG signals.

Table 1 and Table 2 summarise studies that employed machine learning for binary and multi-class classification into N/abnormal and N/CAD/MI/CHF classes, respectively.

From Table 1, it is observable that most authors developed deep CNN models [35,37,40,41,43,46,47,57,59,61] for the automated classification of MI/CAD/CHF and normal classes while few authors developed hybrid deep models using CNN [18,39,42,45,51,53]. Fewer authors employed other deep models such as the deep belief model [48], autoencoders [49], deep multilayer perceptron [52], deep ensemble models [56], deep neural network [60] and long-short term memory model (LSTM) [54] and conventional machine learning classifiers such as artificial neural networks [33,34,36,39,58] for the classification. High classification accuracies of about 95% were achieved when integral features were extracted using neural networks in Ref. [33] and from CNN models [35,47].

Higher classification accuracies (more than 95%) were obtained in the following studies; the bat algorithm was employed with neural network in Ref. [34], feature fusion technique was explored with neural network in Ref. [44], Hilbert transform technique was employed with deep belief network in Ref. [48], extraction of multiscale features from the CNN model in Ref. [40], extraction of features from hybrid CNN models in Refs. [42,45,51,53], extraction of features from CNN models in Refs. [35,40,46,47,57,59,61], and extraction of features from LSTM model in Refs. [54,62], and from deep ensemble model in Ref. [56]. Additionally, the highest accuracy of 100% was obtained in Ref. [58] wherein autoregressive burg features were extracted from the random forest classifier. In Table 2, the CNN-LSTM hybrid model obtained a relatively high classification accuracy of 98.5% for the categorization of CAD, MI, CHF and normal classes.

Table 1
a: Summary of studies that employed machine learning techniques for automated detection of normal and MI classes using ECG signals.

Year	Method	Participant information	Findings/Results (%)
[33], 2014	• Artificial neural network • T-wave and total integral features • Classifiers	MI: 290 patients	**Naïve Bayes:** **AC**: 94.74
[34], 2015	• Enhanced Bat algorithm • Classifiers • Neural networks	N: 52 subjects MI: 148 patients	**Bat algorithm + Levenberg-Marquardt Neural Network:** **AC**: 98.90
[35], 2017	• 1D CNN model • K-fold (k = 10) validation	N: 52 subjects MI: 148 patients	**AC**: 95.22
[36], 2017	• Classifier + Recursive Feature Eliminator + Artificial neural network • K-fold (k = 10) validation	N: 52 subjects MI: 148 patients	**AC**: 80.60 **SN**: 86.58 **SP**: 64.71
[37], 2018	• CNN model • Separability index	N: 52 subjects MI: 148 patients	**AC**: 84.54 **SN**: 85.33 **SP**: 84.09
[38], 2018	• Optimal biorthogonal filter bank • Nonlinear features • 10-fold validation	N: 52 subjects MI: 148 patients	**KNN classifier:** AC: 99.74%
[39], 2018	• CNN-LSTM model • K-fold (k = 10) validation technique • Sample shuffling	PhysioNet: MI: 148 patients N: 52 subjects Others: 90 patients Noisy signals: 278 records	**SN**: 92.4 **SP**: 97.7 **Ppv**: 97.2 **F1 score**: 94.6
[40], 2018	• Multi-lead CNN model • Multiscale features	N + MI + other CVDs: 290 participants (549 records)	**AC**: 96.0 **SN**: 95.40 **SP**: 97.37
[41], 2019	• CNN model • K-fold (k = 10) validation technique	N: 52 subjects MI: 127 patients	**SN**: 93.0 **SP**: 89.7
[42], 2019	• CNN + LSTM model • Oversampling	N: 52 subjects MI: 148 patients	**AC**: 95.54 **SN**: 98.2 **SP**: 86.5 **F1 score:** 96.8
[43], 2019	• CNN model built from 12 leads ECG data	N: 52 subjects MI: 148 patients	**AC**: 99.78
[44], 2019	• Neural network • Feature fusion technique • K-fold (k = 5) validation technique	N: 52 subjects MI: 112 patients	**AC**: 99.92 **F1 score:** 99.94
[45], 2019	• CNN + BLSTM hybrid model • Class-based five-fold validation technique	N: 52 subjects MI: 148 patients	**Class-based:** **AC**: 99.9
[46], 2019	• CNN model • End-to-end structure	N: 125 652 beats MI: 485 752 beats (10 types of MI data)	**AC**: 99.78

Table 1b: **Summary of studies that employed machine learning techniques for automated detection of normal and CAD classes using ECG signals.**

Year	**Method**	**Participant information**	**Findings/Results(%)**
[47], 2017	• CNN model with 11 layers • K-fold (k = 10) validation	N: 40 subjects CAD: 7 patients	**AC**: 95.11 **SN**: 91.13 **SP**: 95.88
[48], 2017	• Deep Belief model • Hilbert transform • K-fold (k = 10) validation	N: 25 subjects CAD: 60 patients	**AC**: 98.05 **SN**: 98.88 **SP**: 96.02
[49], 2017	• 2 deep autoencoder models and SoftMax classifier • 4 varying datasets • K-fold (k = 10) validation	CAD: 303 patients	**Switzerland data:** **AC**: 92.20
[50], 2017	• Higher order spectra features • Principal component analysis • Traditional classifiers	N: 40 subjects CAD: 7 patients	**Decision tree classifier:** **AC**: 98.99%
[51], 2018	• LSTM + CNN model • Blindfold validation	N: 40 subjects CAD: 7 patients	**AC**: 99.85
[52], 2018	• Deep neural network (multilayer perceptron) • Accuracy of diagnosis computed	CAD: 303 patients	**AC**: 83.67 **SN**: 93.51 **SP**: 72.86

(*continued on next page*)

Table 1 (*continued*)

Year	Method	Participant information	Findings/Results (%)
[53], 2018	• CNN-LSTM model • K-fold (k = 10) validation	47 subjects (arrhythmia)	**AC:** 98.10 **SN:** 97.50 **SP:** 98.70
[54], 2019	• LSTM with focal loss, LSTM model	93371 ECG beats (arrhythmia)	**AC:** 99.26
[55], 2019	• Features from deep coding • Convolutional auto-encoder deep model	100 022 signals (5 beat types)	**AC:** more than 99
[56], 2019	• Deep ensemble models • Spectral power density K-fold (k = 10) validation	744 segments (29 subjects)	**AC:** 99.37 **SN:** 94.62 **SP:** 99.66
[57], 2020	• CNN model • K-fold (k = 10) cross validation	PhysioNet: N, atrial premature beat, premature ventricular contraction: 48 recordings	**AC:** 98.33 **SN:** 98.33 **SP:** 98.35
Table 1c: **Summary of studies that employed machine learning techniques for automated detection of normal and CHF classes using ECG signals.**			
Year	**Method**	**Participant information**	**Findings/Results(%)**
[58], 2016	• Traditional classifiers • Artificial neural network • Autoregressive (AR) Burg features	N: 13 subjects CHF: 15 patients	**Random forest classifier:** **AC: 100**
[59], 2019	• CNN model with 11 layers • 4 datasets • K-fold (k = 10) validation technique	**Dataset B** N: 110 000 signals CHF: 30 000 signals	**AC:** 98.97
[60], 2019	• Deep neural network • Traditional classifiers	N: 19 836 subjects CHF: 1391 HFrEF, 1538 HFmrEF patients	Area under the receiver operating characteristic of DEHF: 0.843
[61], 2019	• CNN model • Traditional classifiers • K-fold (k = 10) validation technique	CHF: 10 801 patients	**SVM:** **AC: 84** **CNN:** **AC for Heart failure severity: 88.30**
[62], 2020	• LSTM model • Pre-processing of signals	N: 10 recordings CHF:	**AC:** 99.86 **SN:** 99.85 **SP:** 99.85

Abbreviations used: AC-Accuracy, SN-Sensitivity, SP-Specificity, Ppv-Positive Predicitive Value.

3. Method

3.1. Information on data

In this work, we have acquired Lead II ECG signals from 92 healthy controls, 7 CAD, 148 MI and 15 CHF patients. The details of four databases used to develop the CNN and GaborCNN models are given in Table 1. Signals obtained from Fantasia and St. Petersburg databases were upsampled to measure up to the sampling frequency (1000 Hz) of all signals and the segmentation of each signal resulted in a window length of 2 s (2000 samples). In all, 150,268 segments were used in the study. The number of segments belonging to each class is shown in Table 3. Fig. 1 shows the sample ECG signal belonging to N, CAD, MI and CHF class (extracted signals may not show the typical patterns).

3.2. GaborCNN architecture

3.2.1. CNN model

In typical CNN models, filters undergo training to extract distinct features from input data and represent their position on the feature map. Deep CNN models then use the feature map as input to the subsequent layers, which use new filters to create another new feature map [64]. This process continues in the successive layers where the extracted features become more complex and competent for making predictions. The output feature map then classifies the signals based on the extracted features [24,64]. The CNN model is trained using backpropagation algorithm [65] where the gradient values for the weight coefficients on various layers are collected repeatedly. Different variants of stochastic gradient descend techniques are then used to update the weights [32]. Fig. 2a depicts the typical architecture CNN model used in this work.

Table 2
Summary of studies that employed machine learning techniques for automated detection of N,CAD,MI, CHF classes using ECG signals.

Authors	Method	Participant data	Findings/ Results (%)
[18], 2020	• CNN-LSTM model • K-fold (k = 10) validation	MI: 148 patients CAD: 7 patients N: 92 subjects CHF: 15 patients	AC: 98.5 SN: 99.30 SP: 97.89 Ppv: 97.33
[63], 2017	• Continuous wavelet transform • Contourlet and Shearlet transforms • Entropies and statistical features • Binary Particle Swarm Optimization	MI: 148 patients CAD: 7 patients N: 92 subjects CHF: 15 patients	**Contourlet transform:** **AC: 99.55%**
This study	• **GaborCNN** • **CNN** • **K-fold (k = 10) validation**	**Databases: PTB Diagnostic ECG + Fantasia Databases, St. Petersburg Institute of Cardiological Technics 12-lead Arrhythmia Database, PTB Diagnostic ECG Database, BIDMC Congestive Heart Failure Databa** **GaborCNN model:** **MI: 148 patients** **CAD: 7 patients** **N: 92 subjects** **CHF: 15 patients** **CNN model:** **MI: 148 patients** **CAD: 7 patients** **N: 92 subjects** **CHF: 15 patients**	**CNN model:** **AC: 99.55** **SN: 99.27** **SP: 99.67** **Ppv: 98.69** **GaborCNN model:** **AC: 98.74** **SN: 98.74** **SP: 99.46** **Ppv: 97.50**

Abbreviations used: AC-Accuracy, SN-Sensitivity, SP-Specificity, Ppv-Positive Predicitve Value.

Table 3
Number of segments in each class.

Type of signal	Segment information
Healthy	4703(PTB) & 80 000(Fantasia)
Myocardial infarction	20 265
Coronary artery disease	15 300
Congestive heart failure	30 000

3.2.2. *Gabor filters*

Gabor filters [66] are defined by a sinusoidal plane wave with specific frequencies and various orientations are used to extract spatial frequency structures from images [67]. 1-dimensional (D) Gabor function is ruled by the following equation [68],

$$\mathbf{G}\ \sigma,\ u\ (r) = \mathbf{g}\ \sigma\ (r)\ .\ \mathbf{exp}\ [\mathrm{j}2^{\pi} ur],\ r = 0,\ 1,\ 2,\ \ldots\ \ldots\ W/2 \tag{1}$$

where.

$$\mathbf{G}\ \sigma\ (r) = \frac{1}{\sqrt{2\pi}}\ .\ \mathbf{exp}\ \left[\ -\frac{1}{2}\left(\frac{r}{\sigma}\right)^2\ \right].$$

The expression $g\ \sigma\ (r)$ denotes the 1D Gaussian function with scale parameter σ. The intricate $\exp$ comprises a spatial frequency u. Hence, 1D Gabor filter parameters are specified by the frequency u and scale σ [68]. These filters are commonly used in computer vision, texture representation and face detection domains [32,69]. Gabor filters can be used to generate Gabor features which can be fed to the CNN model [70]. The first or subsequent layers can be set as a stable Gabor filter bank to reduce the trainable parameters in the network [71]. Also, convolutional layers can be fine-tuned with learnable parameters by non-learnable convolutional Gabor filter bank [72]. Finally, the Gabor layer can be integrated into a CNN model by using it to substitute a convolutional layer in the deep model [32].

3.2.3. *Gabor CNN deep model*

A CNN model was developed, for the automated categorization of N, CAD, MI and CHF classes (Fig. 2a). Inspired by Alekseev et al. [31], we used a Gabor filter with learnable parameters to substitute the first convolutional layer of the developed CNN model. First, an 8-layered (excluding the first layer) CNN model was developed using the following hyper-parameters: batch size 50, 60 epochs, learning rate 0.001 and Adam optimization parameters (betas 0.9, 0.999) [73] (Fig. 2b). The weight map [74] from weighted loss function was used to counter the imbalanced dataset. Weight balancing helps to balance the data by changing the weight of training data, as the loss is computed. Hence weight balancing ensures that all the classes used in this study, contribute equally to the loss. Using weighted loss function is also less computationally intensive and hence used to tackle the imbalance in the dataset. Hence in this study, the weight of each class was computed using the equation n_classes * np.bincount(y) for optimal weights. The acquired signals were used to train the CNN model where the most discriminatory features were extracted and classified. K-fold cross -validation (k = 10) [75] was used to estimate the model's performance wherein 80% of the data was used for training, while 20% was used for validation. Using the same specifications, a GaborCNN model was constructed (Fig. 2b). The only difference was that eight Gabor filters were used to replace the convolutional layer in the CNN model. The signals were fed to GaborCNN model and classified thereafter, similar to the CNN model. Tables 4 and 5 present the parameter details of each layer used to develop the CNN and GaborCNN models, respectively. Fig. 3 shows the Gabor filter that was used for the learning of data in each class. This filter was applied to the input signals of each class. Fig. 4a–d illustrate the output from each class using 8 filters, respectively.

4. Results

Tables 5a and b show the results of the developed CNN and GaborCNN models, respectively. High accuracy, specificity and sensitivity values of 99.55%, 99.67% and 99.27% were achieved respectively, with the CNN model, for the categorization of normal, CAD, MI and CHF classes. The GaborCNN model attained good performance as well, with high accuracy, specificity and sensitivity values of 98.74%, 99.46% and 98.74% respectively, for the same classification type.

5. Discussion

It can be noted from Table 1 that, CNN models [35,37,40,41,43,46,47,57,59,61] and CNN hybrid models [18,39,42,45,51,53], have been explored for the detection of CAD/MI/CHF classes using ECG signals. In Ref. [58], conventional classifiers and ANN were used for the classification, and random forest classifier achieved an accuracy of 100% using a small dataset. The studies in Refs. [38,43–46,51,58,62] had achieved higher classification results than our study. However, these studies reported on two- class (binary) classification problems, different from our study. Baloglu et al. [46] studied ECG signals from normal subjects and 10 different types of MI. Their CNN-LSTM model obtained the highest accuracy of 99.78%. However, this study is different from ours as the authors did not perform a 4-class classification.

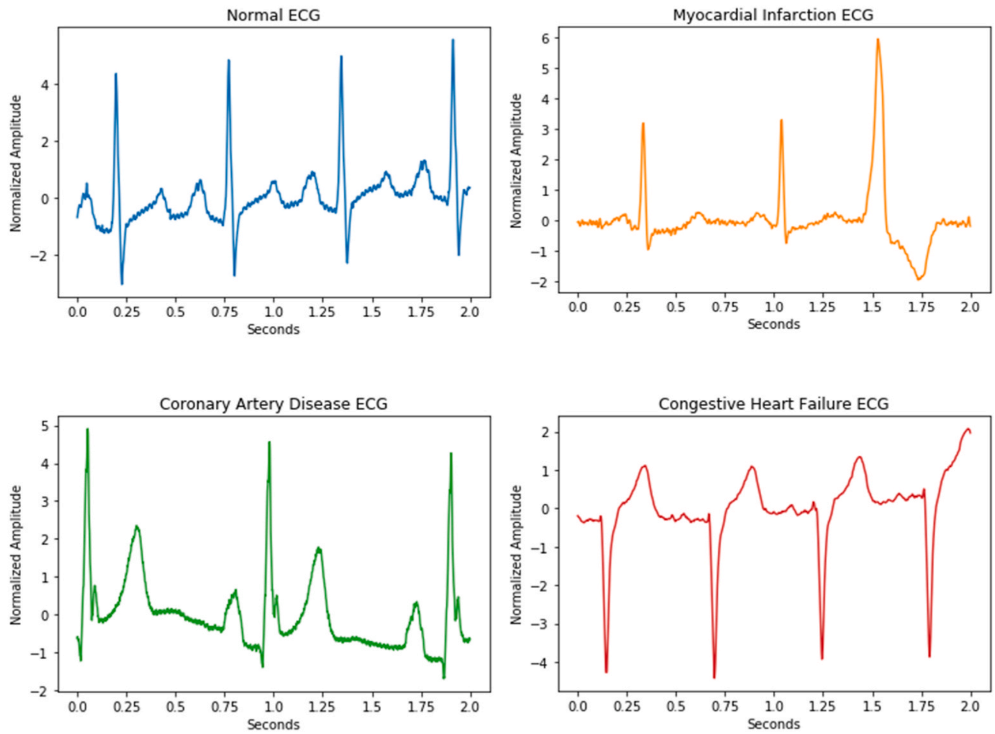

Fig. 1. Typical ECG signals of N, MI, CAD and MI classes.

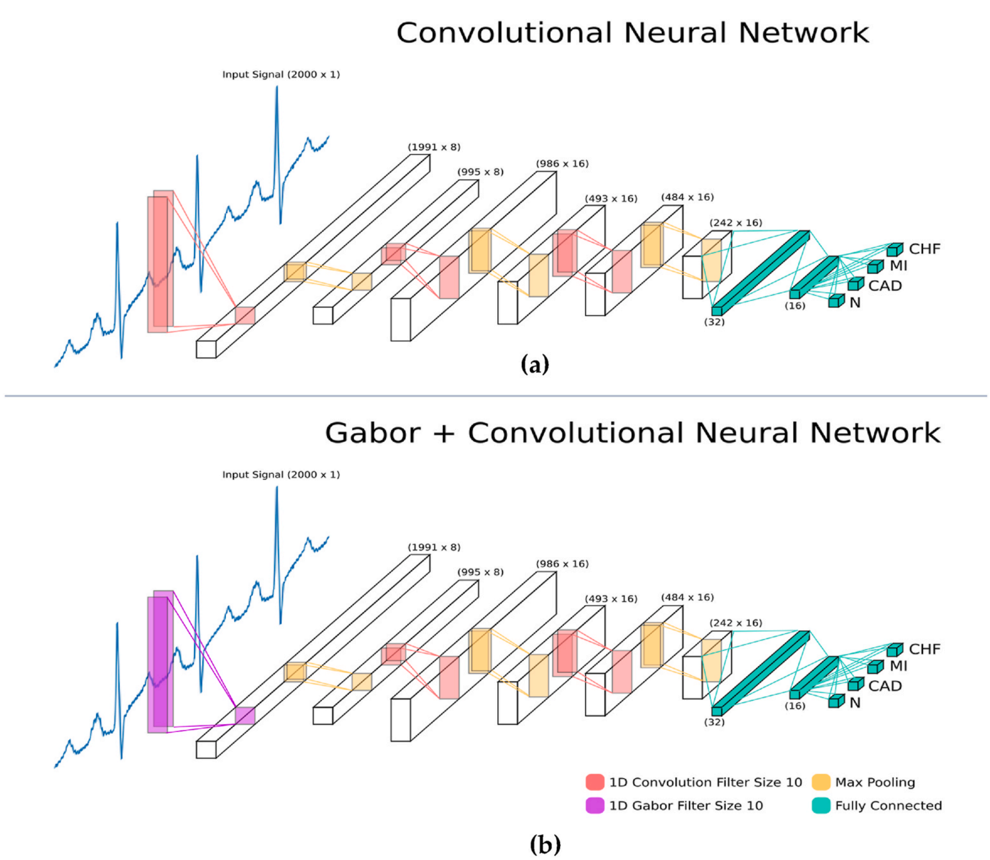

Fig. 2. Proposed model:(a) CNN and (b) GaborCNN.

Table 4
Parameter details in each layer of the develop CNN architecture.

Layers	Layer type	Number of neurons (output layer)	Number of parameters
1	1d-convolution	1991 × 8	88
2	max pooling	995 × 8	0
3	1d-convolution	986 × 16	1296
4	max pooling	693 × 16	0
5	1d-convolution	484 × 16	2576
6	max pooling	242 × 16	0
7	linear	32	123 936
8	dropout	32	0
9	linear	16	528
10	linear	4	68

Acharya et al. [63] had performed a similar 4-class classification and obtained the same accuracy of 99.55% as our study. However, the authors had employed conventional machine learning methods which require features to be extracted and selected manually. This is more time-consuming as compared to features being extracted automatically from the deep models, in our study. Similar to us, Lui et al. [39] and Lih et al. [18] (Table 2) developed hybrid CNN-LSTM models for the detection of normal, MI and other CVDs and for the detection of normal, CAD, MI and CHF classes, respectively. Lui et al. [39] employed the sample shuffling technique but did not report the classification accuracy while Lih et al. [18] obtained an accuracy of 98.5%, which is less than our study. In fact, both our developed CNN and GaborCNN models obtained higher classification accuracies than Lih et al. [18] for the same type of classification. While both models are competent, comparing Table 4 and 5, it is evident that lesser parameters were used for the first

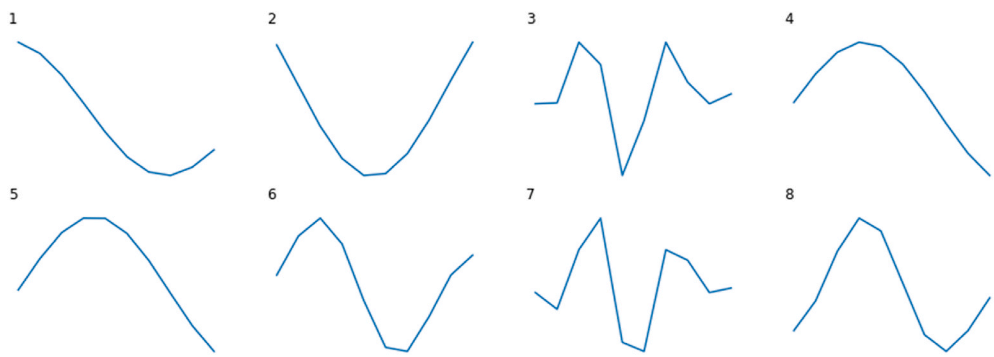

Fig. 3. Learned Gabor filters.

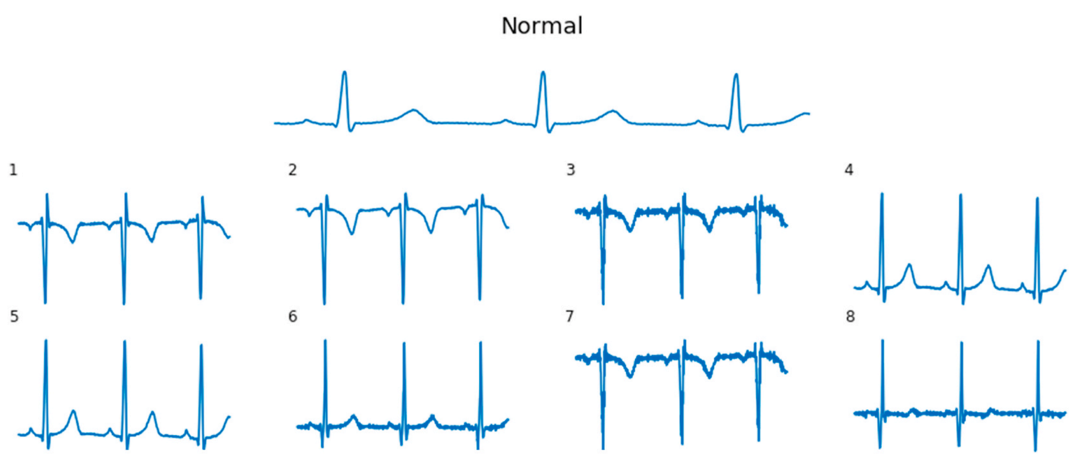

Fig. 4a. Gabor transformed normal signals (output).

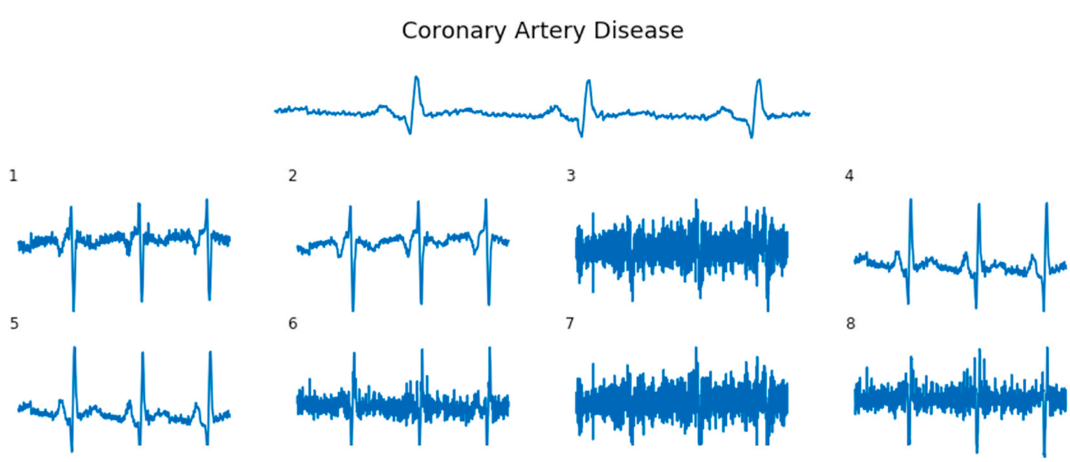

Fig. 4b. Gabor transformed CAD signals (output).

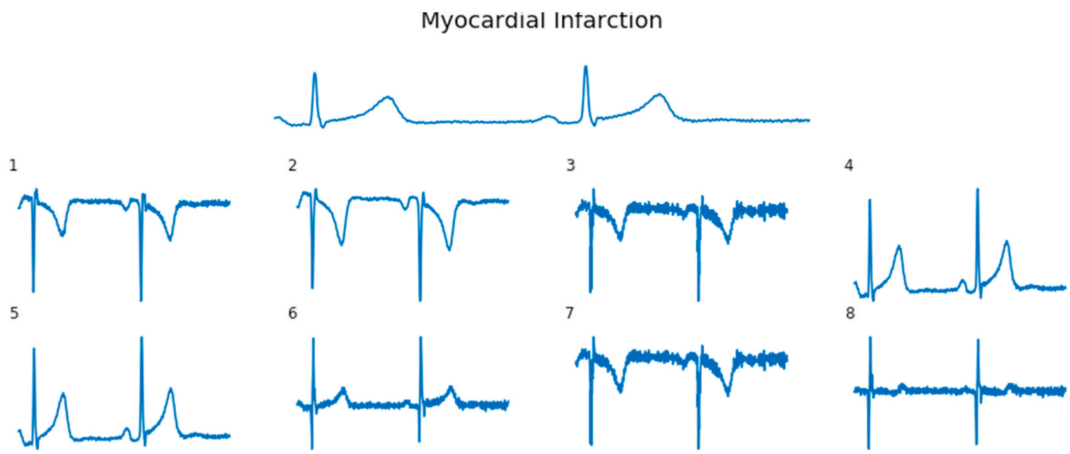

Fig. 4c. Gabor transformed MI signals (output).

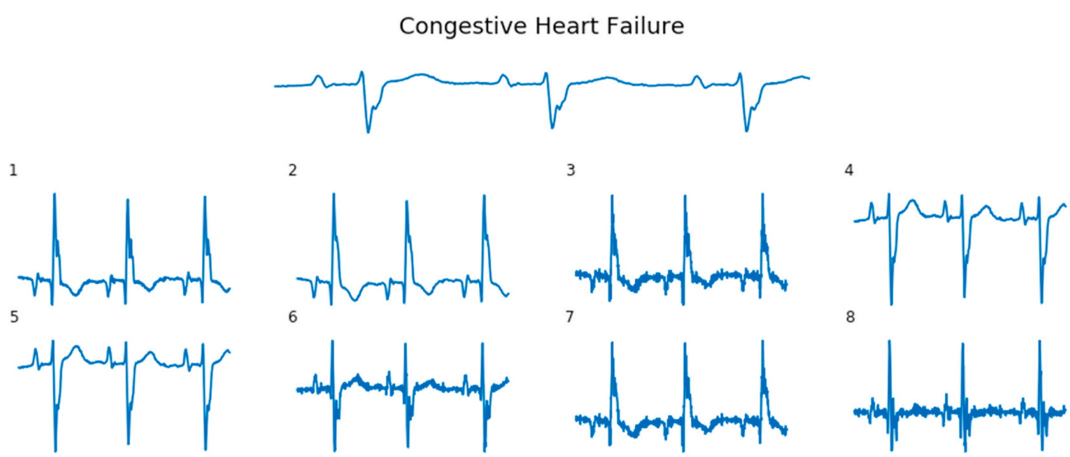

Fig. 4d. Gabor transformed CHF signals (output).

layer in the GaborCNN model as compared to the CNN model, hence the GaborCNN model is less computationally intensive than the CNN model. Thus, compared with the aforementioned, it is apparent that both our models exhibit good performance and our GaborCNN is a preferred model for the 4-class classification due to its reduced computational complexity. Additionally, to the best of our knowledge this is the **first study** to use GaborCNN model for the classification of normal, CAD, MI and CHF classes using ECG signals.

Figs. 5 and 6 depict the confusion matrices obtained for CNN and GaborCNN models, respectively. Confusion matrices are used to describe the performance of the model wherein the average number of correct and incorrect predictions of a model are provided for each class. It can be seen that the CNN model has obtained high accuracy due to smaller

Table 5a
Parameter details in each layer used of the develop GaborCNN architecture.

Layers	Layer type	Number of neurons (output layer)	Number of parameters
1	Gabor 1d-convolution	1991 × 8	24
2	max pooling	995 × 8	0
3	1d-convolution	986 × 16	1296
4	max pooling	493 × 16	0
5	1d-convolution	484 × 16	2576
6	max pooling	242 × 16	0
7	linear	32	123 936
8	dropout	32	0
9	linear	16	528
10	linear	4	68

Table 5b
Classification results of model: (a) CNN and (b)GaborCNN.

Classes	Average SN (%)	Average SP (%)	Average PPV (%)	Average AC (%)	Average success rate (%)
(a)					
N	98.85	99.49	99.60	99.13	99.55
MI	**99.95**	**99.95**	**99.58**	**99.95**	
CAD	98.67	99.35	95.96	99.26	
CHF	99.64	99.90	99.62	99.85	
(b)					
N	97.95	99.39	99.52	98.58	98.74
MI	99.13	99.75	97.82	99.68	
CAD	98.56	98.92	93.47	98.87	
CHF	**99.30**	**99.79**	**99.19**	**99.69**	

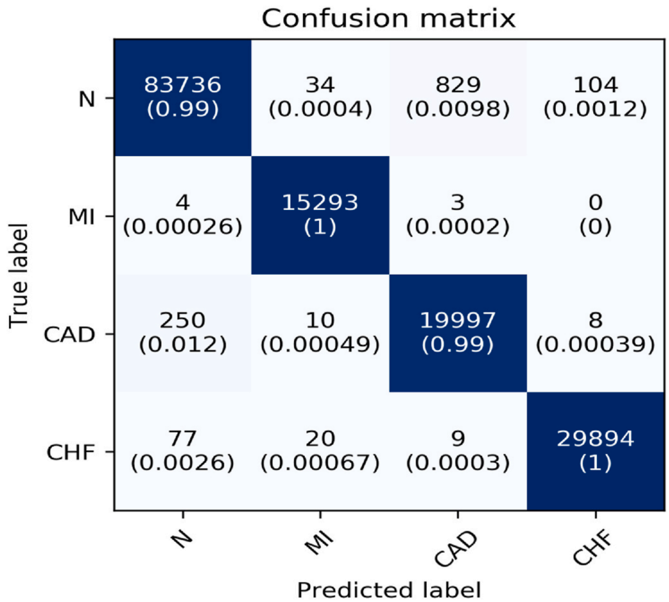

Fig. 5. Confusion matrix of CNN model.

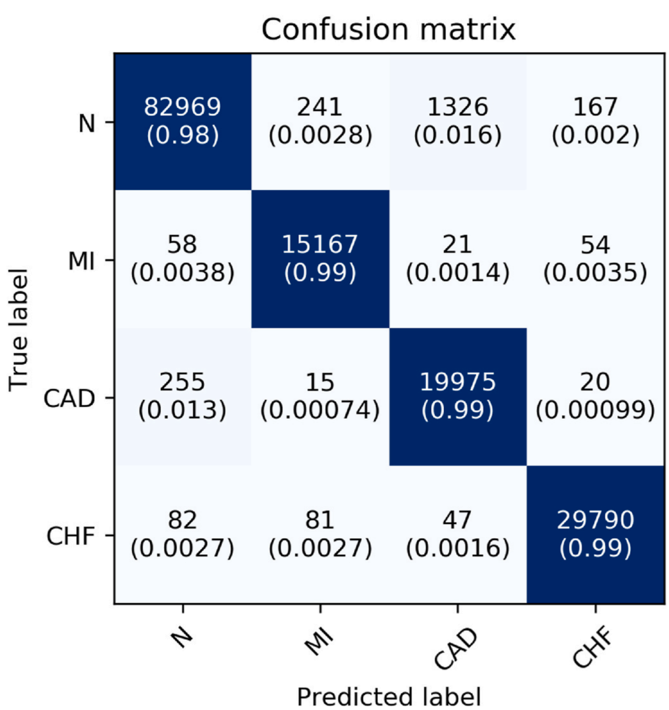

Fig. 6. Confusion matrix of GaborCNN model.

misclassification values of 0.01%, 0%, 0.01% and 0% for normal, CAD, MI and CHF groups, respectively. Similarly, smaller misclassification values of 0.02%, 0.01%, 0.01% and 0.01%, are obtained for normal, CAD, MI and CHF groups, respectively contributing to the high classification accuracy using Gabor CNN model. Figs. 7 and 8 show the plots of accuracy versus number of epochs obtained for CNN and GaborCNN models, respectively. Both models learned the data well over the epochs during training and validation, attesting the robustness of both models. However, the GaborCNN model diverges less (less gap between training and validation accuracy curves) compared to the CNN model, implying less overfitting and better performance. Additionally, the GaborCNN model used lesser training weights and is computationally less intensive compared to the CNN model. This indicates that our proposed GaborCNN model is fast and accurate for the classification of ECG classes.

Advantages and limitations of this study are listed below:

5.1. Advantages

1. This is the **first study** to have integrated Gabor filter in the CNN model to automatically classify normal, CAD, MI and CHF classes using ECG signals.
2. Obtained high classification accuracies of 99.55% and 98.74% by CNN and GaborCNN models respectively for the detection of normal, CAD, MI and CHF classes.
3. Employed ten-fold validation and the model is robust.
4. Generated GaborCNN model used less weights and hence can be trained faster.
5. GaborCNN model has the potential to classify other ECG classes with highest classification performance.

5.2. Limitations

1. Used few subjects for CAD and CHF groups in our proposed study.
2. Larger dataset is necessary to train and test the GaborCNN model.

In our future work, we hope to gather more data to train the GaborCNN model and improve the classification accuracy of CAD ECG signals, so that the onset of CAD could be detected early to prevent it from progressing to MI or CHF.

6. Conclusion

CVDs are the primary cause of death globally, costing about 17.9 million lives yearly. Thus, early diagnosis of CAD is crucial to provide timely treatment and avert the progression of CAD to MI or CHF. This study aims to compare the performance of two deep models for the automated categorization of normal, CAD, MI and CHF classes using ECG signals. The ECG data used in this work data used were imbalanced. Hence, weight balancing was used to balance the dataset. Both the CNN and GaborCNN models yielded high classification accuracies of more than 98.5%, for the 4-class classification of normal, coronary artery disease, myocardial infarction and congestive heart failure classes. This is the **first study** to use Gabor filter in the CNN model to develop a GaborCNN model for the detection of normal, CAD, MI and CHF classes. Furthermore, our proposed GaborCNN model is more effective than the CNN model for the diagnosis of four classes, as it can be trained faster with lesser weights and achieving high accuracy performance. Hence, the developed model is preferred for the classification and can be potentially used as an assistive tool for clinical experts to confirm their diagnostic decisions quickly.

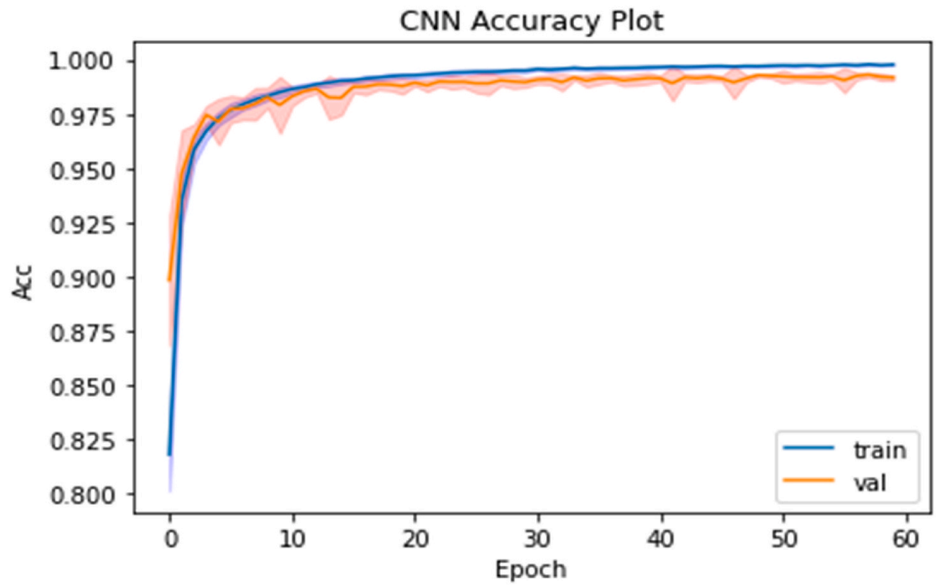

Fig. 7. Accuracy plot of CNN model.

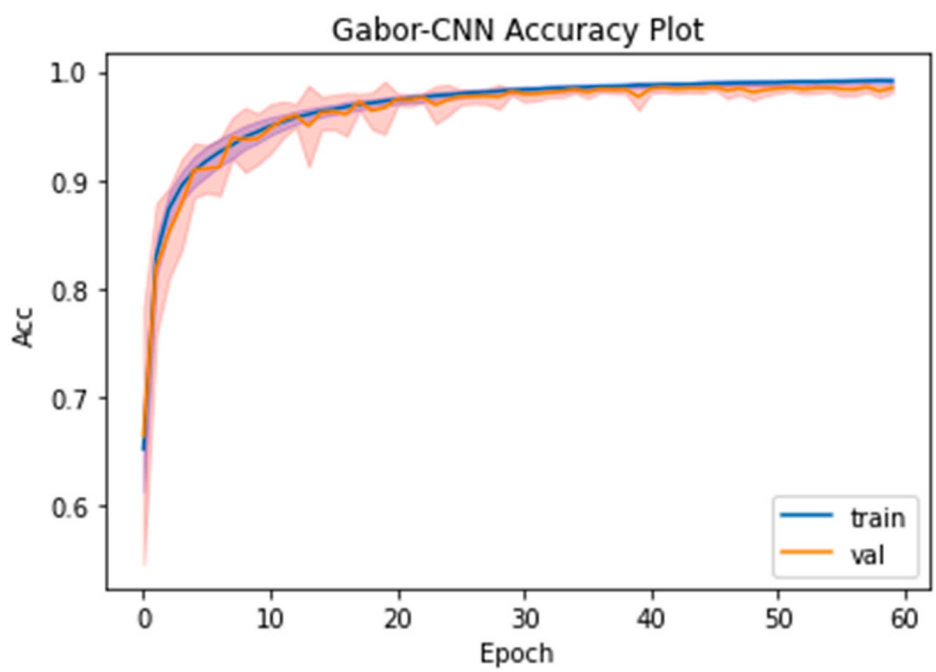

Fig. 8. Accuracy plot of GaborCNN model.

References

[1] H. Antoni, in: R.F. Schmidt, G. Thews (Eds.), Function of the Heart BT - Human Physiology, Springer Berlin Heidelberg, Berlin, Heidelberg, 1989, pp. 439–479.

[2] D. Mozaffarian, et al., Heart Disease and Stroke Statistics-2015 Update : A Report from the American Heart Association, *Circulation*, 2015.

[3] World Health Organisation. https://www.who.int/health-topics/cardiovascular-diseases/#tab=tab_1.

[4] I. Tabas, Nonoxidative modifications of lipoproteins in atherogenesis, Annu. Rev. Nutr. 19 (1999) 123–139.

[5] P. Libby, P. Theroux, Pathophysiology of coronary artery disease, Circulation 111 (25) (2005) 3481–3488.

[6] L. Maximilian Buja, J.T. Willerson, The role of coronary artery lesions in ischemic heart disease: insights from recent clinicopathologic, coronary arteriographic, and experimental studies, Hum. Pathol. 18 (5) (1987) 451–461.

[7] B. Liu, et al., A novel electrocardiogram parameterization algorithm and its application in myocardial infarction detection, Comput. Biol. Med. 61 (2015) 178–184.

[8] Z. Masetic, A. Subasi, Congestive heart failure detection using random forest classifier, Comput. Methods Progr. Biomed. 130 (2016) 54–64.

[9] J.A. Akoh, World J. Transplant. 1 (1) (2011) 4–12.

[10] F.S. Kıraç, Noninvasive Cardiac Imaging for the Diagnosis of Coronary Artery Disease in Women, vol. 15, 2015, p. 5.

[11] T.H. Marwick, S. Neubauer, S.E. Petersen, Use of cardiac magnetic resonance and echocardiography in population-based studies: why, where, and when? Circ. Cardiovasc. Imaging 6 (4) (2013) 590–596.

[12] R. Alizadehsani, et al., Machine learning-based coronary artery disease diagnosis: a comprehensive review, Comput. Biol. Med. 111 (2019) 103346.

[13] U.R. Acharya, et al., Entropies for automated detection of coronary artery disease using ECG signals: a review, Biocybern. Biomed. Eng. 38 (2) (2018) 373–384.

[14] R. Alizadehsani, A. Khosravi, M. Abdar, N. Sarrafzadegan, Coronary artery disease detection using artificial intelligence techniques: a survey of trends, geographical differences and diagnostic features 1991-2020 running title: a mapping review of ML application for CAD detection, Artic. Comput. Biol. Med. (October) (2020).

[15] V. Jahmunah, et al., "Computer-aided diagnosis of congestive heart failure using ECG signals – a review, Phys. Med. 62 (March) (2019) 95–104.

[16] O. Yildirim, M. Talo, E.J. Ciaccio, R.S. Tan, U.R. Acharya, Accurate deep neural network model to detect cardiac arrhythmia on more than 10,000 individual subject ECG records, Comput. Methods Progr. Biomed. 197 (August) (2020).

[17] Y. Birnbaum, J.M. Wilson, M. Fiol, A.B. De Luna, M. Eskola, K. Nikus, "ECG diagnosis and classification of acute coronary syndromes," *Ann*, Noninvasive Electrocardiol 19 (1) (2014) 4–14.

[18] O.S. Lih, et al., Comprehensive electrocardiographic diagnosis based on deep learning, Artif. Intell. Med. 103 (January) (2020).

[19] Q. Mastoi, T.Y. Wah, R. Gopal Raj, U. Iqbal, Automated diagnosis of coronary artery disease: a review and workflow, Cardiol. Res. Pract. (2018) 2016282, 2018.

[20] R.Y. Choi, A.S. Coyner, J. Kalpathy-Cramer, M.F. Chiang, J. Peter Campbell, Introduction to machine learning, neural networks, and deep learning, Transl. Vis. Sci. Technol. 9 (2) (2020) 1–12.

[21] T.M. Mitchell, Mach. Learn, McGraw-Hill, Inc., New York, 1997.

[22] Trevor Hastie Robert Tibshirani Jerome Friedman Stanford, The Elements of Statistical Learning Data. Data Mining, Inference, and Prediction, 2001.

[23] S. Uddin, A. Khan, M.E. Hossain, M.A. Moni, Comparing different supervised machine learning algorithms for disease prediction, BMC Med. Inf. Decis. Making 19 (2019) 1–16, 1.

[24] Y. Lecun, Y. Bengio, G. Hinton, Deep learning, Nature 521 (7553) (2015) 436–444.

[25] D.C.K. Soh, E.Y.K. Ng, V. Jahmunah, S.L. Oh, R.S. Tan, U.R. Acharya, Automated diagnostic tool for hypertension using convolutional neural network, Comput. Biol. Med. 126 (2020) 103999.

[26] Z. Sherkatghanad, et al., Automated detection of autism spectrum disorder using a convolutional neural network, Front. Neurosci. 13 (2019).

[27] O. Faust, R. Barika, A. Shenfield, E.J. Ciaccio, U.R. Acharya, Accurate detection of sleep apnea with long short-term memory network based on RR interval signals, Knowl. Base Syst. 212 (2021) 106591.

[28] S. Xu, et al., "Using a deep recurrent neural network with EEG signal to detect Parkinson's disease, Ann. Transl. Med. 8 (14) (2020) (July 2020) Ann. Transl. Med.

[29] S. Nurmaini, A. Darmawahyuni, A.N.S. Mukti, M.N. Rachmatullah, F. Firdaus, B. Tutuko, Deep learning-based stacked denoising and autoencoder for ECG heartbeat classification, Electron 9 (1) (2020).

[30] A. Darmawahyuni, et al., Deep learning with a recurrent network structure in the sequence modeling of imbalanced data for ECG-rhythm classifier, Algorithms 12 (6) (2019) 1–12.

[31] S.S. Sarwar, P. Panda, K. Roy, Gabor filter assisted energy efficient fast learning Convolutional Neural Networks, in: 2017 IEEE/ACM Int. Symp. Low Power Electron. Des., 2017, pp. 1–6.

[32] A. Alekseev, A. Bobe, GaborNet: Gabor Filters with Learnable Parameters in Deep Convolutional Neural Networks, *arXiv*, 2019.

[33] N. Safdarian, N.J. Dabanloo, G. Attarodi, A new pattern recognition method for detection and localization of myocardial infarction using T-wave integral and total integral as extracted features from one cycle of ECG signal, J. Biomed. Sci. Eng. (10) (2014) 818–824, 07.

[34] P. Kora, S.R. Kalva, Improved Bat algorithm for the detection of myocardial infarction, SpringerPlus 4 (1) (2015) 1–18.

[35] U.R. Acharya, H. Fujita, S.L. Oh, Y. Hagiwara, J.H. Tan, M. Adam, Application of deep convolutional neural network for automated detection of myocardial infarction using ECG signals, Inf. Sci. 415 (416) (2017) 190–198.

[36] A. Diker, Z. Cömert, E. Avci, A diagnostic model for identification of myocardial infarction from electrocardiography signals, Bitlis Eren Univ. J. Sci. Technol. 7 (2) (2017) 132–139.

[37] T. Reasat, C. Shahnaz, Detection of inferior myocardial infarction using shallow convolutional neural networks, R10-HTC 2017, in: 5th IEEE Reg. 10 Humanit. Technol. Conf. 2017, vol. 2018, 2018, pp. 718–721. Janua, no. Imi.

[38] M. Sharma, R. San Tan, U.R. Acharya, A novel automated diagnostic system for classification of myocardial infarction ECG signals using an optimal biorthogonal filter bank, Comput. Biol. Med. 102 (2018) 341–356.

[39] H.W. Lui, K.L. Chow, Multiclass classification of myocardial infarction with convolutional and recurrent neural networks for portable ECG devices, Informatics Med. Unlocked 13 (June) (2018) 26–33.

[40] W. Liu, et al., Real-time multilead convolutional neural network for myocardial infarction detection, IEEE J. Biomed. Heal. Informatics 22 (5) (2018) 1434–1444.

[41] N. Strodthoff, C. Strodthoff, Detecting and interpreting myocardial infarction using fully convolutional neural networks, Physiol. Meas. 40 (1) (2019) 1–11.

[42] K. Feng, X. Pi, H. Liu, K. Sun, Myocardial infarction classification based on convolutional neural network and recurrent neural network, Appl. Sci. 9 (9) (2019) 1–12.

[43] R.J. Martis, U.R. Acharya, H. Adeli, Current methods in electrocardiogram characterization, Comput. Biol. Med. 48 (1) (2014) 133–149.

[44] C. Han, L. Shi, Computer Methods and Programs in Biomedicine ML – ResNet : a novel network to detect and locate myocardial infarction using 12 leads ECG, 185, 2019.

[45] W. Liu, F. Wang, Q. Huang, S. Chang, H. Wang, J. He, MFB-CBRNN: a hybrid network for MI detection using 12-lead ECGs, IEEE J. Biomed. Heal. Informatics 1 (2019).

[46] U.B. Baloglu, M. Talo, O. Yildirim, R.S. Tan, U.R. Acharya, Classification of myocardial infarction with multi-lead ECG signals and deep CNN, Pattern Recogn. Lett. 122 (2019) 23–30.

[47] U.R. Acharya, H. Fujita, O.S. Lih, M. Adam, J.H. Tan, C.K. Chua, Automated detection of coronary artery disease using different durations of ECG segments with convolutional neural network, Knowl. Base Syst. 132 (September) (2017) 62–71.

[48] G. Altan, N. Allahverdi, Y. Kutlu, Diagnosis of coronary artery disease using deep belief networks, Eur. J. Eng. Nat. Sci. 2 (1) (2017) 29–36.

[49] A. Caliskan, M.E. Yuksel, Classification of coronary artery disease data sets by using a deep neural network, EuroBiotech J. 1 (4) (2017) 271–277.

[50] U.R. Acharya, et al., Application of higher-order spectra for the characterization of Coronary artery disease using electrocardiogram signals, Biomed. Signal Process Contr. 31 (2017) 31–43.

[51] J.H. Tan, et al., Application of stacked convolutional and long short-term memory network for accurate identification of CAD ECG signals, Comput. Biol. Med. 94 (December 2017) (2018) 19–26.

[52] K.H. Miao, J.H. Miao, Coronary heart disease diagnosis using deep neural networks, Int. J. Adv. Comput. Sci. Appl. 9 (10) (2018) 1–8.

[53] S.L. Oh, E.Y.K. Ng, R.S. Tan, U.R. Acharya, Automated diagnosis of arrhythmia using combination of CNN and LSTM techniques with variable length heart beats, Comput. Biol. Med. 102 (June) (2018) 278–287.

[54] J. Gao, H. Zhang, P. Lu, Z. Wang, An Effective LSTM Recurrent Network to Detect Arrhythmia on Imbalanced ECG Dataset, 2019, 2019.

[55] O. Yildirim, U.B. Baloglu, R.S. Tan, E.J. Ciaccio, U.R. Acharya, A new approach for arrhythmia classification using deep coded features and LSTM networks, Comput. Methods Progr. Biomed. 176 (2019) 121–133.

[56] P. Pławiak, U.R. Acharya, Novel deep genetic ensemble of classifiers for arrhythmia detection using ECG signals, Neural Comput. Appl. 2 (2019).

[57] F.B. Roberta Avanzato, Automatic ECG Diagnosis Using Convolutional Neural Network, *Electronics*, 2020.

[58] Z. Masetic, A. Subasi, Congestive heart failure detection using random forest classifier, Comput. Methods Progr. Biomed. 130 (2016) 54–64.

[59] U.R. Acharya, et al., Deep convolutional neural network for the automated diagnosis of congestive heart failure using ECG signals, Appl. Intell. 49 (1) (2019) 16–27.

[60] J. Kwon, et al., Development and validation of deep-learning algorithm for electrocardiography-based heart failure identification, Korean Circ. J. 49 (7) (2019) 629.

[61] S. Khade, A. Subhedar, K. Choudhary, T. Deshpande, U. Kulkarni, A system to detect heart failure using deep learning techniques, Int. Res. J. Eng. Technol. 6 (June) (2019) 384–387.

[62] A. Darmawahyuni, S. Nurmaini, M. Yuwandini, Muhammad Naufal Rachmatullah, F. Firdaus, B. Tutuko, Congestive heart failure waveform classification based on short time-step analysis with recurrent network, Informatics Med. Unlocked 21 (2020) 100441.

[63] U.R. Acharya, et al., Automated characterization of coronary artery disease, myocardial infarction, and congestive heart failure using contourlet and shearlet transforms of electrocardiogram signal, Knowl. Base Syst. 132 (2017) 156–166.

[64] G.E. Hinton, R.R. Salakhutdinov, Reducing the dimensionality of data with neural networks, Science 313 (5786) (2006) 504.

[65] J.L. Rumelhart, D.E. McClelland, Learning internal representations by error propagation - MIT press books, in: Parallel Distributed Processing: Explorations in the Microstructure of Cognition: Foundations, *MIT Press*, 1987, pp. 318–362.

[66] D. Gabor, Theory of communication, J. Inst. Eng. Electron. Part I Gen. 93 (3) (1947) 429–457.

[67] A.K. Jain, N.K. Ratha, S. Lakshmanan, Object Detection Using Gabor Filters, *Pattern Recognit.*, 1997.

[68] D.M. Tsai, C.P. Lin, Fast defect detection in textured surfaces using 1D Gabor filters, Int. J. Adv. Manuf. Technol. 20 (9) (2002) 664–675.

[69] L.L. Huang, A. Shimizu, H. Kobatake, Classification-based face detection using Gabor filter features, in: In Proceedings - Sixth IEEE International Conference on Automatic Face and Gesture Recognition, 2004.

[70] B. Kwolek, Face detection using convolutional neural networks and gabor filters, in: In Lecture Notes in Computer Science (Including Subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics), 2005.

[71] A. Calderón, S. Roa, J. Victorino, Handwritten Digit Recognition Using Convolutional Neural Networks and Gabor Filters, *Topology*, 2003.

[72] S. Luan, C. Chen, B. Zhang, J. Han, J. Liu, Gabor convolutional networks, IEEE Trans. Image Process. 27 (9) (2018) 4357–4366.

[73] D.P. Kingma, J. Ba, Adam: A Method for Stochastic Optimization, 2014, pp. 1–15.

[74] M. Jafari, et al., FU-Net: Multi-class image segmentation using feedback weighted U-net, in: In Lecture Notes in Computer Science (Including Subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics), 2019.

[75] D. Berrar, Cross-validation 1 (2018) 542–545.