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Article *in* Applied Intelligence · March 2018

DOI: 10.1007/s10489-018-1179-1

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Deep Convolutional Neural Network for the Automated Diagnosis of Congestive Heart Failure Using ECG Signals

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Abstract

Congestive heart failure (CHF) is a chronic heart condition associated with debilitating symptoms that result in increased mortality, morbidity, healthcare expenditure and decreased quality of life. Electrocardiogram (ECG) is a noninvasive and simple diagnostic method that may demonstrate detectable changes in CHF. However, manual diagnosis of ECG signal is often subject to errors due to the small amplitude and duration of the ECG signals, and in isolation, is neither sensitive nor specific for CHF diagnosis. An automated computer-aided system may enhance the diagnostic objectivity and reliability of ECG signals in CHF. We present an 11-layer deep convolutional neural network (CNN) model for CHF diagnosis herein. This proposed CNN model requires minimum pre-processing of ECG signals, and no engineered features or classification are required. Four different sets of data (A, B, C and D) were used to train and test the proposed CNN model. Out of the four sets, Set B attained the highest accuracy of 98.97%, specificity and sensitivity of 99.01% and 98.87% respectively. The proposed CNN model can be put into practice and serve as a diagnostic aid for cardiologists by providing more objective and faster interpretation of ECG signals.

Keywords – congestive heart failure; convolutional neural network; electrocardiogram signals; PhysioBank.

1. Introduction

Congestive heart failure (CHF) is a pathophysiological syndrome where there is abnormal filling and/or emptying of the left heart chamber [1]. It is caused by structural and/or functional derangements due to - and can also be considered the final stage of - diverse heart diseases. The prevalence and incidence of CHF are increasing, with approximately 26 million adults diagnosed with CHF worldwide in 2014 [2]. It is a major contributor to global mortality and morbidity, as well as an important factor for loss of quality life years and increased healthcare expenditure. This is because of the debilitating symptoms such as breathlessness and fatigue experienced by sufferers of CHF. Consequently, these patients experience a decline in their quality of life as they are increasingly unable to carry out physical and social activities [3]. It is also noted that CHF predominantly affects the elderly (age > 64 years) [4]. Therefore, there is a need for early detection of CHF in the ageing population, which is a problem many countries in the world are facing right now. In addition, CHF contributes to increased care and economic burden on patients' families with around 40% of them having to struggle with their daily routine [3]. An early detection will allow institution of preventative measures and treatment that may alter the course of the disease and impede the progression of CHF among the elderly.

Figure 1 shows the comparison of a healthy and a CHF heart with impaired pump function. In the healthy heart, there is good stroke volume (blood flow volume ejected per heart beat) and oxygen-rich blood is pumped to the body from the left ventricle. However, in a common type of CHF with impaired pump function, stroke volume drops and the heart is unable to efficiently pump oxygen-rich blood to the rest of the body. The heart is remodeled from the underlying disease process, becoming enlarged with stiff muscle walls as it is being stretched to hold more oxygen-rich blood to pump to the body. The weakened pumping capacity results in easy fatiguability. It also causes blood and fluid to back up into the lungs and the body, resulting in breathlessness and generalized swelling, respectively [5].

The diagnosis of CHF is a clinical one, requiring a conglomerate of symptoms and signs, as well as corroborative evidence from investigative tests. The electrocardiogram (ECG) is a noninvasive test commonly used by the healthcare professionals to record the heart activities of patients. Although the ECG signals are altered in CHF, the changes are non-specific and by themselves, are insensitive and not specific for diagnosis of CHF when using standard manual analytic methods. Typically, the recorded ECG signals are visually examined by cardiologists for the detection of any abnormalities present in the signals. However, visual assessment of different ECG readings recorded from various patients is time-consuming. Further, manual interpretation of the ECG signals may be subject to inter-observer variability.

2. Related Work

Many different traditional machine learning techniques have been employed to surmount the inadequacies of manual analysis of ECG signals in CHF (refer to Table 10). Traditional machine learning technique refers to an algorithm which has pre-processing, feature extraction and selection, and classification processes. The selection of distinctive features between normal and CHF signals is difficult and involves a lot of time and effort. Also, the robustness of the features extracted from the signals is dependent upon the quality of data. Pre-processing of the signals such as noise removal and R-peak detection are required in order to extract the most significant features for classification. To avoid the pitfalls of traditional machine learning, we propose deep learning in this work in order to optimize the performance of an automated CHF diagnosis system. Deep learning is a form of machine learning approach where the network learns and picks up distinct characteristics automatically based on the input ECG signals [6].

Convolutional neural network (CNN) is one of the forms of deep learning which has been widely employed in speech and image recognition [7] and is receiving plenty of attention in the medical field [7]. Recently, researchers are using CNN models to develop computer-aided diagnosis system to diagnose diverse medical conditions [8]–[17]. The authors have employed CNN models in the detection of various heart diseases such as identifying arrhythmias with 2-seconds and 5-seconds ECG segments [13], diagnosing myocardial infarction ECG beats with and without noise removal [14], distinguishing coronary artery disease ECG signals from normal ECG signals with 2-seconds and 5-seconds signals [15], classifying 5 different types of heartbeats with ECG beats [16], and lastly, the detection of shockable and non-shockable 2-seconds ECG ventricular arrhythmias [17]. These published works have demonstrated relatively good performance with minimum pre-processing and no feature extraction or selection. Lately, Tan et al. [18] designed a long-short term memory (LSTM) with CNN to diagnose coronary artery disease. Their network achieved a high diagnostic accuracy of 99.85%. But, as compared to the LSTM network, CNN has faster computational time and is less complex. Hence, this paper uses a deep CNN model (11-layers) to study the automatic classification of ECG signals into normal and CHF classes.

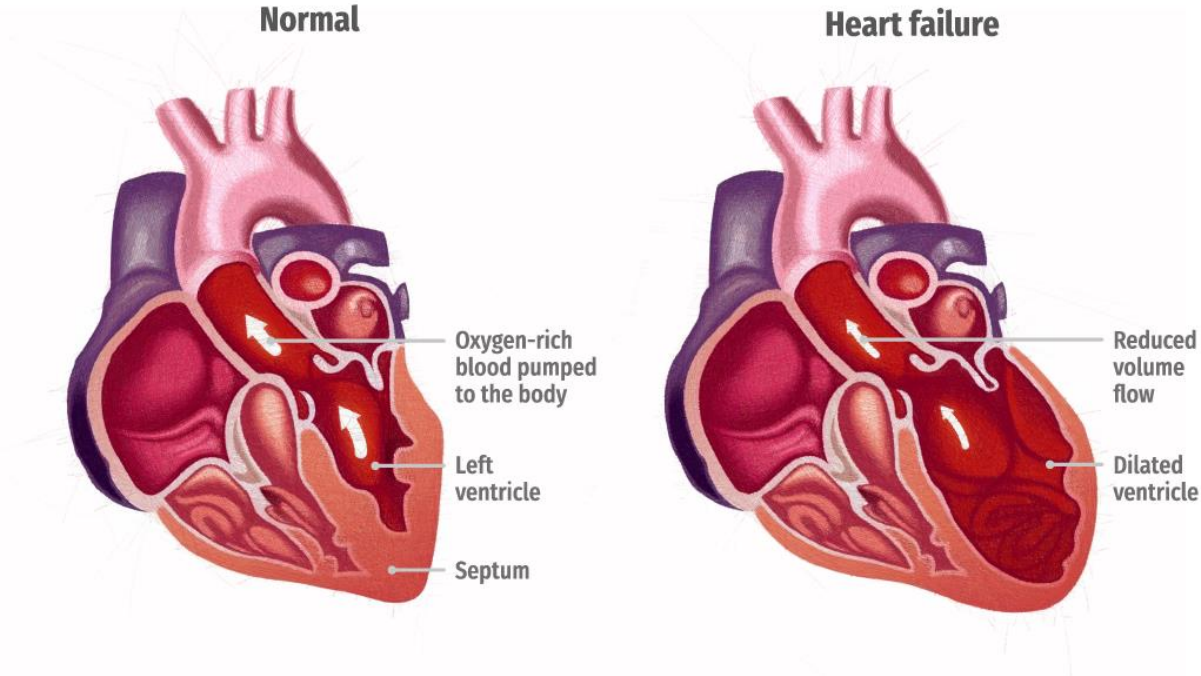

Figure 1: Illustration of a healthy heart and one with heart failure.

3. Materials Used

The ECG signals used in this work were obtained from public databases (PhysioBank) namely the Beth Israel Deaconess Medical Centre (BIDMC) Congestive Heart Failure Database, Fantasia Database, and MIT-BIH Normal Sinus Rhythm Database (NSRDB) [19]. Table 1 summarizes the details of the ECG data collected from each database.

The severity of CHF symptoms is graded based on the New York Heart Association (NYHA) scale [20]:

Class 1: mild with no limitation of physical activity;

Class 2: mild with slight limitation of physical activity;

Class 3: moderate with marked limitation of physical activity; and

Class 4: severe with total limitation of physical activity.

The CHF ECG data used in this work are in *Class 3* and *Class 4* categories.

A total of four datasets (Set A, Set B, Set C, and Set D) are used in this work. Both Sets A and B consist of full ECG data (unbalanced), while Sets C and D have balanced number of ECG data (see Table 2). 30,000 normal ECG data are randomly selected from the full set for Sets C and D.

Figure 2 shows typical normal and CHF ECG segments obtained from the public databases.

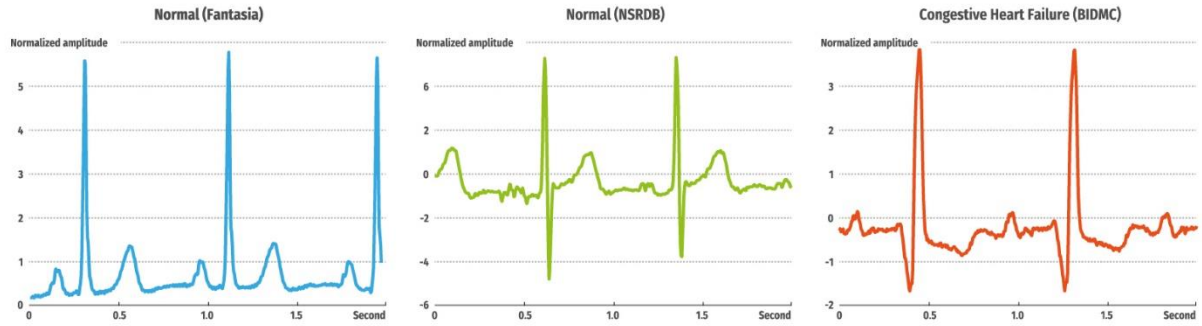

Figure 2: A typical normal (Fantasia and NSRDB) and CHF ECG segments.

Table 1: The details of ECG signals obtained from various databases.

Database	Diagnosis	Number of ECG Records	Subject(s) (age)
BIDMC Congestive Heart Failure	CHF	15	• 11 men (22 to 71) • 4 women (54 to 63) (NYHA class 3–4)
MIT-BIH Normal Sinus Rhythm	Normal	18	• 5 men (26 to 45) • 13 women (20 to 50)
Fantasia	Normal	40	• 20 young (21 to 34) • 20 elderly (68 to 85)

Table 2: The total ECG segments used in each data set.

Type (Database)	Number of 2 seconds ECG segments			
	Unbalanced/Full Set		Balanced Set	
	A	B	C	D
Normal (NSRDB)	70,308	-	30,000	-
Normal (Fantasia)	-	110,000	-	30,000
CHF (BIDMC)	30,000	30,000	30,000	30,000

4. Methodology

4.1 Pre-processing

The Fantasia and BIDMC ECG databases are sampled at 250 Hz frequency whereas the MIT-BIH Normal Sinus database (NSRDB) is sampled at 128 Hz frequency. Therefore, the signals obtained from NSRDB are up sampled to 250 Hz. This ensures that the frequency of ECG signals is standardized. Then, the ECG records were segmented into 2 seconds ECGs (without performing R-peak detection). Each ECG signal (2 seconds) is 500 samples in length.

Also, each ECG signal is regularized with Z score normalization, standard deviation of 1, and zero mean before inputting into the network.

4.2 CNN Architecture

The details of the proposed CNN model are tabulated in Table 3 and the graphical representation of the architecture can be seen in Figure 3. The number of layers and the tuning parameters are varied by brute force method until the optimum diagnostic performance is achieved. Hence, the proposed model consists of 4 convolutions, 4 max-pooling, and 3 fully-connected layers. The stride (the amount by which the filter shifts) is set at 1 and 2 for convolution and max-pooling respectively in this work. These layers make up the fundamental structure of CNN whereby convolution picks up distinctive features from the input ECG signal. The max-pooling operation reduces the dimensions of feature maps and at the same time retain important and significant features of the input ECG signal. The max-pooling is performed after every convolution operation in this work. Lastly, the fully-connected layer is intended to connect the neurons in the previous layers into a two-class (normal or CHF) probability distribution.

Layer 0 (input layer) is convolved with a size 5 kernel (filter) to produce the first layer. Then, a max-pooling operation (kernel 2) is administered on layer 1 (496 x 5) to form layer 2 (248 x 5). After which, in layer 2, a convolution is performed with a filter (size 5) to construct layer 3. Then, a max-pooling is once again applied to decrease the number of output neurons. Again, a convolution is performed in layer 4 (122 x 5) with a kernel size 3 to form layer 5. Then, a max-pooling is performed to decrease the number of neurons from 120 x 10 to 60 x 10 (layer 6). Another round of convolution with kernel size 3 is applied followed by one last max-pooling operation to form layer 8 with 29 x 10 neurons. Layer 8 is fully-connected to 40 output neurons in layer 9 and fully-connected to 20 neurons in layer 10. Lastly, layer 10 is fully-connected to the final layer (layer 11) with 2 outputs which represent the two classification classes (normal and CHF).

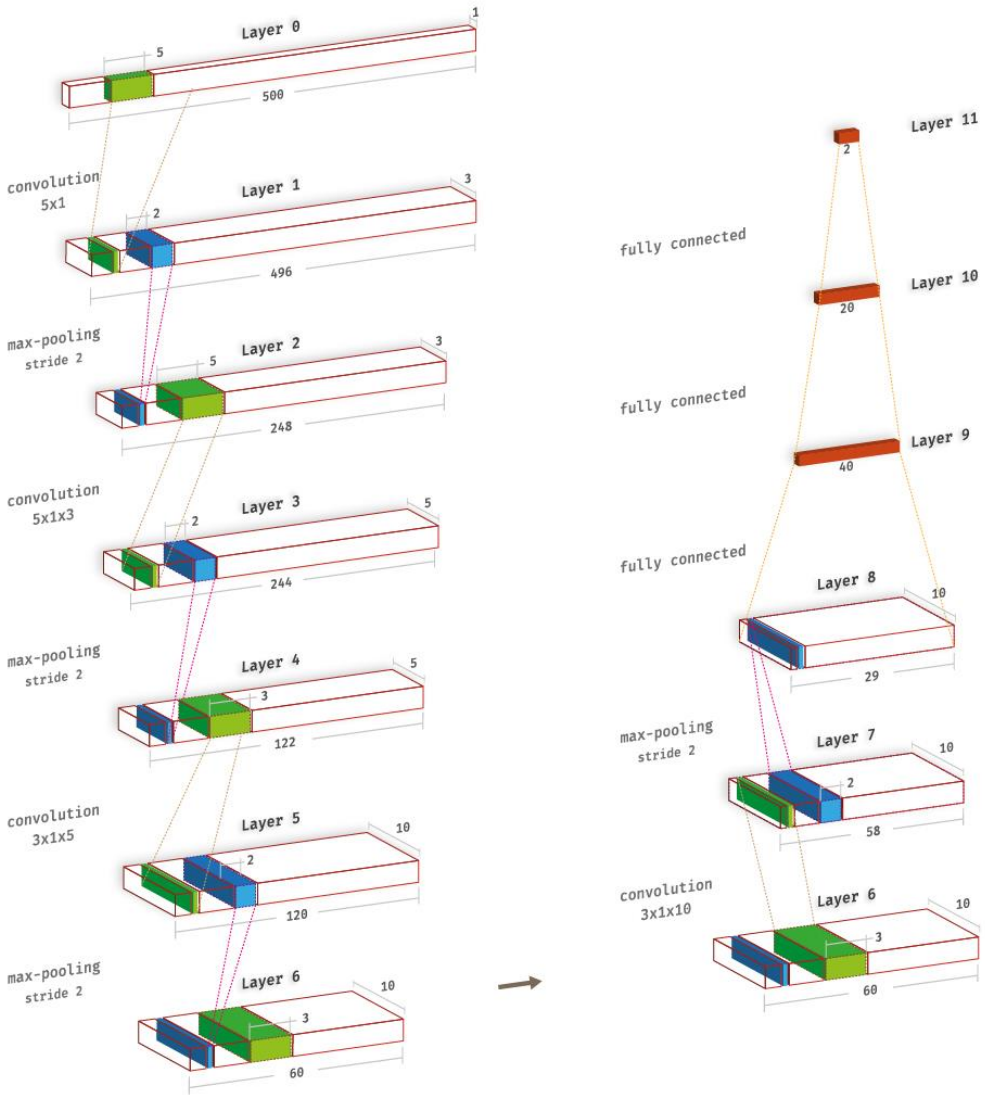

Figure 3: The architecture of the proposed CNN model.

Table 3: The structure of the CNN model for Sets A to D.

Layers	Type	No. of output neurons	Filter size for each output feature map	Stride
0-1	convolution	496 x 5	5	1
1-2	max-pooling	248x 5	2	2
2-3	convolution	244 x 5	5	1
3-4	max-pooling	122 x 5	2	2
4-5	convolution	120 x 10	3	1
5-6	max-pooling	60 x 10	2	2
6-7	convolution	58 x 10	3	1
7-8	max-pooling	29 x 10	2	2
8-9	fully connected	40	-	-
9-10	fully connected	20	-	-
10-11	fully connected	2	-	-

4.3 Training and Testing of CNN model

Xavier initialization is used to initialize the model weights [21]. A backpropagation [22] with a batch size of 10 is used to update the CNN model in this study. The network loss is evaluated using the cross-entropy function. The parameters used to train the proposed CNN structure in order to yield the maximum diagnostic performance are lambda (L1 regularization) = 0.2, learning rate = $3x10^{-4}$ and momentum = 0.3. These parameters help to impede overfitting of the data (regularization), assist in data convergent (learning rate), and adjust the speed of the learning (momentum) [23].

Furthermore, leaky rectifier linear unit (LeakyRelu) [24] shown in Equation (1) is employed as activation function for layers 1, 3, 5, 7, 9, and 10 whereas layer 11 implemented the SoftMax function as seen in Equation (2).

$$f(x)\begin{cases} x & \text{for } x > 0 \\ 0.01x & \text{for } x =< 0 \end{cases} \tag{1}$$

$$P_i = \frac{e^{x_i}}{\sum_1^j e^{x_j}} \quad \text{for } i = 1, \dots j \tag{2}$$

Where $f(x)$ represents the function, P_i is the probability distribution over the total possible classes, and j denotes the total number of classes.

Stratified ten-fold cross-validation strategy [25] is performed in this work. The ECG segments of *four* sets are divided into *ten* parts. Nine parts are used to train the model whilst the remaining part is used to test the model. Each divided part contains approximately the same target class percentage as the entire dataset. Ten iterations are conducted in this work. The average of the ten iterations for the four sets are tabulated in Table 9.

5. Results

Two Intel Xeon 2.40 GHz (E5620) processor and a 24 GB RAM are used to train the proposed network without the implementation of graphics processing unit (GPU). Table 4 shows the average time needed to train an epoch for each dataset. 60 epochs are run in this study to develop the model.

The confusion matrix for sets A to D are shown in Tables 5 to 8 respectively. Table 9 shows the overall average performance to classify normal and CHF classes with our proposed CNN model. The proposed CNN model achieved the highest accuracy of 98.97%, sensitivity of 98.87%, and specificity of 99.01% for Set B.

In Set A, 95.75% of the normal ECG segments are correctly classified in the normal class and 96.52% of CHF signals are correctly classified in the CHF class. Only 4.25% and 3.48% of the ECG signals are incorrectly categorized as CHF and normal class respectively. Also, in Set B, a very small percentage of approximately 0.99% normal ECG signals are incorrectly grouped as CHF class, and 1.13% of CHF ECG signals are misclassified into the normal class.

Likewise, 5.88% of normal ECG signals are wrongly classified to CHF class in Set C. Also, the misclassification rate of CHF ECG signals is about 5.32%. Set D attained better classification results than Set C with 1.84% of CHF ECG signals and 1.50% of normal ECG signals wrongly classified into normal and CHF classes, respectively.

Table 4: Training time to complete an epoch.

Dataset	Average training time per epoch (seconds)
A	2736.537
B	3285.140
C	954.842
D	951.944

Table 5: Confusion matrix for the unbalanced data set - NSRDB/BIDMC (Set A).

		Predicted					
		Normal	CHF	Accuracy (%)	PPV (%)	Sensitivity (%)	Specificity (%)
Original	Normal	67,323	2,985	95.98	98.47	95.75	96.52
	CHF	1,045	28,955	95.98	90.65	96.52	95.75

*PPV – Positive Predictive Value

Table 6: Confusion matrix for the unbalanced data set - Fantasia/BIDMC (Set B).

		Predicted					
		Normal	CHF	Accuracy (%)	PPV (%)	Sensitivity (%)	Specificity (%)
Original	Normal	79,206	794	98.97	99.57	99.01	98.87
	CHF	340	29,660	98.97	97.39	98.87	99.01

Table 7: Confusion matrix for the balanced data set - NSRDB/BIDMC (Set C).

		Predicted					
		Normal	CHF	Accuracy (%)	PPV (%)	Sensitivity (%)	Specificity (%)
Original	Normal	28,235	1,765	94.40	94.65	94.12	94.68
	CHF	1,597	28,403	94.40	94.15	94.68	94.12

Table 8: Confusion matrix for the balanced data set - Fantasia/BIDMC (Set D).

		Predicted					
		Normal	CHF	Accuracy (%)	PPV (%)	Sensitivity (%)	Specificity (%)
Original	Normal	29,447	553	98.33	98.49	98.16	98.50
	CHF	451	29,549	98.33	98.16	98.50	98.16

Table 9: Summary of classification results for different datasets.

	Dataset	TP	TN	FP	FN	Accuracy (%)	PPV (%)	Sensitivity (%)	Specificity (%)
Full	A	28,955	67,323	2,985	1,045	95.98	90.65	96.52	95.75
	B	29,660	79,206	794	340	98.97	97.39	98.87	99.01
Balanced	C	28,403	28,235	1,765	1,597	94.40	94.15	94.68	94.12
	D	29,549	29,447	553	451	98.33	98.16	98.50	98.16

*TP – True Positive, TN – True Negative, FP – False Positive, FN – False Negative, PPV – Positive Predictive Value

6. Discussion

Based on Table 9, it can be noted that Set B and Set D achieved better performance as compared to Set A and Set C. In addition, it can also be observed that the full set (Set A and Set B) yielded better performance as compared to the balanced set (Set C and Set D). This might be because more variations in the large number of ECG signals (see Table 2) in the full set ensure more diversity learning during training and hence helped to achieve better results than in the balanced set. Also, the quality of the ECG signals may affect the overall diagnostic performance. Out of the four sets, Set B is reported to achieve the highest diagnostic accuracy of 98.97%.

Table 10 discusses the different algorithms developed for the automated detection of CHF with ECG signals obtained from PhysioBank. The different techniques recorded in Table 10 yielded high diagnostic performance. Most of the works listed in Table 10 performed denoising and R-peak detection in the pre-processing step. But, our proposed CNN model does not require any processing of the ECG data. Further, the majority of the ECG signals are either segmented into an ECG beat or into different segments of ECG signals. However, in this work, the ECG signals used are shorter in duration.

Although the proposed CNN model did not obtain 100.00% accuracy in the classification of normal and CHF ECG signals, this study is the first to implement a CNN model to classify ECG signals into normal and CHF classes. Unlike our proposed algorithm, the works in Table 10 adopted the conventional machine learning techniques. Hence, the novelty of this work is the development of an 11-layer deep CNN model for the detection of CHF ECG signals.

In this work, we have developed the deep learning model using short durations (2-seconds) of ECG signals to diagnose the CHF. Such deep learning model can also be implemented using HRV signals and echocardiographic images to identify CHF automatically. The authors have developed automated diagnostic system using heart rate variability (HRV) signals [26], [27] and

echocardiographic images [28] to detect CHF. Hence, the authors intend to design a CNN model to automatically diagnose CHF using HRV signals or echocardiogram images.

Also, this two-class (normal and CHF) diagnostic stratification can potentially be extended to four classes. Acharya et al. [29] and Fujita et al. [30] developed an algorithm to diagnose normal, CHF, myocardial infarction (MI), and coronary artery disease (CAD). Both works demonstrated high diagnostic performance (see Table 10). Moreover, our group has already performed automated diagnosis of CAD [15] and MI [14] with an 11-layer deep CNN model respectively. We have also detected automatically non-ectopic, supraventricular ectopic, ventricular ectopic, fusion, and unknown ECG beats using CNN [16]. In future, the authors intend to develop a CNN model to detect the MI, CHF, CAD, and normal (four-class) ECG signals.

The advantages of the proposed CNN model are:

- 11-layer deep CNN model is proposed.
- Denoising is not required.
- R-peak detection is not required.
- Hand-crafted features are not required.

The limitations of the proposed CNN model are:

- Requires big data to achieve the optimum performance.
- Requires extensive computational power for training the model.

Nevertheless, running the proposed model with a graphics processing unit (GPU) will accelerate the time taken to train the model and reduces the processing power needed for training. In addition, the performance will increase if there are more diverse ECG signals used to train the CNN model. Hence, the advantages outweigh the drawbacks of this proposed deep CNN model.

Table 10: Selected studies of an automated CHF detection system using ECG data obtained from PhysioBank.

Author	Year	Number of ECG data	Techniques	Performance
		Normal and CHF classes		
Kamath [31]	2012	Set A and Set B CHF + Normal: 6,912 (BIDMC, NSRDB, Fantasia)	(14-seconds ECG segment) • Filtered high-frequency noise • Sequential spectrum • Approximate entropy	Set A and Set B Acc – 100.00% Sen – 100.00% Spec – 100.00%
Orhan [32]	2013	CHF: 3,000 Normal: 3,600 (BIDMC, NSRDB)	(ECG beat) • Denoising • Equal frequency in amplitude and equal width in time discretization • Linear regression	Acc – 99.33% Sen – 99.36% Spec – 99.30%
Mašetić et al.	2013	CHF: 1,500	(ECG beat)	Acc – 99.86%

[33]		Normal: 1,300 (BIDMC, MIT-BIH Arrhythmia database)	• Autoregressive burg • C4.5 decision tree	Sen – 99.77% Spec – 99.93%
Kamath [34]	2015	Set A CHF: 3,510 Normal: 3,510 (BIDMC, NSRDB) Set B CHF: 3,510 Normal: 3,510 (BIDMC, Fantasia)	(20-seconds ECG segment) • Detrended fluctuation analysis	Set A Acc – 98.20% Sen – 98.40% Spec – 98.00% Set B Acc – 79.20% Sen – 71.50% Spec – 87.80%
Mašetić et al. [35]	2016	Set A CHF: 1,500 Normal: 1,300 (BIDMC, MIT-BIH Arrhythmia database) Set B: CHF: 171 Normal: 1,300 (PTB diagnostic database, MIT-BIH Arrhythmia database)	(2.5-seconds ECG segment) • Pre-processed ECG segments • Autoregressive burg • Random forest classifier	Set A and Set B Acc – 100.00%
Sudarshan et al. [36]	2017	Set A CHF: 25,328 Normal: 59,624 (BIDMC, NSRDB) Set B CHF: 25,328 Normal: 57,099 (BIDMC, Fantasia) Set C CHF: 25,328 Normal: 25,328 (BIDMC, NSRDB) Set D CHF: 25,328 Normal: 25328 (BIDMC, Fantasia)	(2-seconds ECG segment) • Denoising and baseline removal • Dual tree complex wavelet transform • KNN classifier	Set A Acc – 98.42% Sen – 97.04% Spec – 99.01% Set B Acc – 99.87% Sen – 99.69% Spec – 99.95% Set C Acc – 97.94% Sen – 98.19% Spec – 97.69% Set D Acc – 99.86% Sen – 99.78% Spec – 99.94%
Normal, MI, CHF, and CAD classes				
Acharya et al. [29]	2017	CAD: 41,545 CHF: 89,237 MI: 40,182 Normal: 10,546 (St. Petersburg Institute of Cardiology Technics 12-lead Arrhythmia database, PTB diagnostic	(ECG beat) • Denoising and baseline removal • Contourlet transform • Particle swarm optimization • KNN classifier	Acc – 99.55% Sen – 99.93% Spec – 99.24%

		ECG database, BIDMC)		
Fujita et al. [30]	2017	CAD: 41,545 CHF: 89,237 MI: 40,182 Normal: 10,546 (St. Petersburg Institute of Cardiology Technics 12-lead Arrhythmia database, PTB diagnostic ECG database, BIDMC)	(ECG beat) • Denoising and baseline removal • Wavelet packet decomposition • ReliefF • KNN classifier	Acc – 97.98% Sen – 99.61% Spec – 94.84%
Present work	**2017**	**Set A** **CHF: 30,000** **Normal: 70,308** **(NSRDB, BIDMC)** **Set B** **CHF: 30,000** **Normal: 110,000** **(Fantasia, BIDMC)** **Set C** **CHF: 30,000** **Normal: 30,000** **(NSRDB, BIDMC)** **Set D** **CHF: 30,000** **Normal: 30,000** **(Fantasia, BIDMC)**	**(2-seconds ECG segment)** • **11-layer deep CNN**	**Set A** **Acc – 95.98%** **Sen – 96.52%** **Spec – 95.75%** **Set B** **Acc – 98.97%** **Sen – 98.87%** **Spec – 99.01%** **Set C** **Acc – 94.40%** **Sen – 94.68%** **Spec – 94.12%** **Set D** **Acc – 98.33%** **Sen – 98.50%** **Spec – 98.16%**

Acc – Accuracy, Sen – Sensitivity, Spec – Specificity

7. Conclusion

Unlike the conventional machine learning techniques, this study implemented an 11-layer deep CNN model to automatically diagnose CHF using ECG signals. The proposed model is fully-automatic and R-peak detection is not required. Also, four different sets of data obtained from PhysioBank were used to train and test the CNN model. Set B obtained the highest performance using our proposed model with an accuracy, specificity and sensitivity of 98.97%, 99.01% and 98.87% respectively. Nevertheless, the diagnostic ability of the suggested model can be enhanced using huge ECG database belonging to different stages of CHF. It is anticipated such CNN models can also be developed to detect different cardiac diseases like dilated, ischemic, and hypertrophic cardiomyopathy. Once the CNN model is well-trained, it can be introduced in the healthcare industries as an adjunct tool to assist cardiologists in providing quick and reliable second opinions on the diagnosis.

8. References

[1] C. W. Yancy *et al.*, "2013 ACCF/AHA guideline for the management of heart failure: Executive summary: A report of the American college of cardiology foundation/american heart association task force on practice guidelines," *J. Am. Coll. Cardiol.*, vol. 62, no. 16, pp. 1495–1539, 2013.

[2] P. Ponikowski, S. D. Anker, and K. F. Alhabib, "Heart failure: Preventing disease and death worldwide," *Eur. Soc. Cardiol.*, vol. 373, no. 9667, pp. 941–955, 2014.

[3] M. J. Calvert, N. Freemantle, and J. G. F. Cleland, "The impact of chronic heart failure on health-related quality of life data acquired in the baseline phase of the CARE-HF study," *Eur. J. Heart Fail.*, vol. 7, pp. 243–251, 2005.

[4] F. A. Masoudi, E. P. Havranek, and H. M. Krumholz, "The burden of chronic congestive heart failure in older persons: Magnitude and implications for policy and research," *Heart Failure Reviews*, vol. 7, no. 1. pp. 9–16, 2002.

[5] V. N. Singh, B. D. Coombs, E. C. Lin, and J. A. Miller, "Congestive heart failure imaging," 2015. [Online]. Available: http://emedicine.medscape.com/article/354666-overview?pa=S%2Fi%2FabtjtTqty6G%2BOeFPLhjWwCFEjmFXths9jrP0e6aaQbfL10Dp5dORPrNJ48llxqoopjEGq13BmWLQMLXc2%2FFDqoONiUtlOtdX6maZcRI%3D.

[6] L. Yann, B. Yoshua, and G. Hinton, "Deep learning," *Nature*, vol. 521, pp. 436–444, 2015.

[7] J.-G. Lee *et al.*, "Deep learning in medical imaging: General overview," *Korean J. Radiol.*, vol. 18, no. 4, p. 570, 2017.

[8] J. H. Tan, U. R. Acharya, S. V. Bhandary, K. C. Chua, and S. Sivaprasad, "Segmentation of optic disc, fovea and retinal vasculature using a single convolutional neural network," *J. Comput. Sci.*, vol. 20, pp. 70–79, 2017.

[9] N. Tajbakhsh *et al.*, "Convolutional Neural Networks for Medical Image Analysis: Full Training or Fine Tuning?," *IEEE Trans. Med. Imaging*, vol. 35, no. 5, pp. 1299–1312, 2016.

[10] A. Arindra *et al.*, "Pulmonary Nodule Detection in CT Images: False Positive Reduction Using Multi-View Convolutional Networks," *IEEE Trans. Med. Imaging*, vol. 35, no. 5, pp. 1160–1169, 2016.

[11] A. Pinto, V. Alves, and C. A. Silva, "Brain Tumor Segmentation using Convolutional Neural Networks in MRI Images," *IEEE Trans. Med. Imaging*, vol. 35, no. 5, pp. 1240–1251, 2016.

[12] N. Hatipoglu and G. Bilgin, "Cell segmentation in histopathological images with deep learning algorithms by utilizing spatial relationships," *Medical and Biological Engineering and Computing*, pp. 1–20, 2017.

[13] U. R. Acharya, H. Fujita, S. L. Oh, Y. Hagiwara, J. H. Tan, and M. Adam, "Automated detection of arrhythmias using different intervals of tachycardia ECG segments with convolutional neural network," *Inf. Sci. (Ny).*, vol. 405, pp. 81–90, 2017.

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

[15] U. R. Acharya, H. Fujita, S. L. Oh, M. Adam, J. H. Tan, and K. C. Chua, "Automated detection of coronary artery disease using different durations of ECG segments with convolutional neural network," *Knowledge-Based Syst.*, vol. 946, pp. 1–10, 2017.

[16] U. R. . Acharya *et al.*, "A deep convolutional neural network model to classify heartbeats," *Comput. Biol. Med.*, vol. 89, pp. 389–396, 2017.

[17] U. R. Acharya *et al.*, "Automated identification of shockable and non-shockable life-threatening ventricular arrhythmias using convolutional neural network," *Futur. Gener. Comput. Syst.*, 2017.

[18] 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.*, vol. 94, no. December 2017, pp. 19–26, 2018.

[19] A. L. Goldberger *et al.*, "PhysioBank, PhysioToolkit, and PhysioNet," *Circulation*, vol. 101, no. 23, pp. E215-20, 2000.

[20] The Criteria Committee of the New York Heart Association, *New York Heart Association functional class predicts exercise parameters in the current era*, 9th ed. Little, Brown & Co., Boston, 1994.

[21] X. Glorot and Y. Bengio, "Understanding the difficulty of training deep feedforward neural networks," *Pmlr*, vol. 9, pp. 249–256, 2010.

[22] J. Bouvrie, "Notes on convolutional neural networks," *In Pract.*, pp. 47–60, 2006.

[23] A. Krizhevsky, I. Sutskever, and G. E. Hinton, "ImageNet classification with deep convolutional neural networks," *Adv. Neural Inf. Process. Syst.*, pp. 1–9, 2012.

[24] K. He, X. Zhang, S. Ren, and J. Sun, "Delving deep into rectifiers: Surpassing human-level performance on imagenet classification," in *Proceedings of the IEEE International Conference on Computer Vision*, 2016, vol. 11–18–Dece, pp. 1026–1034.

[25] R. O. Duda, P. E. Hart, and D. G. Stork, *Pattern classification. 2nd*. 2001.

[26] M. Kumar, R. B. Pachori, and U. R. Acharya, "Use of accumulated entropies for automated detection of congestive heart failure in flexible analytic wavelet transform framework based on short-term HRV signals," *Entropy*, vol. 19, no. 3, 2017.

[27] U. R. Acharya *et al.*, "Application of empirical mode decomposition (EMD) for automated identification of congestive heart failure using heart rate signals," *Neural Comput. Appl.*, pp. 1–22, 2016.

[28] U. Raghavendra *et al.*, "Automated screening of congestive heart failure using variational mode decomposition and texture features extracted from ultrasound images," *Neural*

Comput. Appl., pp. 1–10, 2017.

[29] 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," *Knowledge-Based Syst.*, vol. 132, pp. 156–166, 2017.

[30] H. Fujita *et al.*, *Characterization of cardiovascular diseases using wavelet packet decomposition and nonlinear measures of electrocardiogram signal*, vol. 10350 LNCS. 2017.

[31] C. Kamath, "A new approach to detect congestive heart failure using sequential spectrum of electrocardiogram signals," *Med. Eng. Phys.*, vol. 34, no. 10, pp. 1503–1509, 2012.

[32] U. Orhan, "Real-time CHF detection from ECG signals using a novel discretization method," *Comput. Biol. Med.*, vol. 43, no. 10, pp. 1556–1562, 2013.

[33] Z. Mastic and A. Subasi, "Detection of congestive heart failures using C4.5 Decision Tree," *Southeast Eur. J. Soft Comput.*, vol. 5, no. 12, pp. 996–1000, 2013.

[34] C. Kamath, "A new approach to detect congestive heart failure using detrended fluctuation analysis of electrocardiogram signals," *J. Eng. Sci. Technol.*, vol. 10, no. 2, pp. 145–159, 2015.

[35] Z. Masetic and A. Subasi, "Congestive heart failure detection using random forest classifier," *Comput. Methods Programs Biomed.*, vol. 130, pp. 54–64, 2016.

[36] V. K. Sudarshan *et al.*, "Automated diagnosis of congestive heart failure using dual tree complex wavelet transform and statistical features extracted from 2 s of ECG signals," *Comput. Biol. Med.*, vol. 83, no. January, pp. 48–58, 2017.