Deep Learning of Arrhythmia Analysis Based on Convolutional Neural Network

Anake Pomprapa[a], Waqar Ahmed[a], André Stollenwerk[b],
Stefan Kowalewski[b], and Steffen Leonhardt[a]
[a]Medical Information Technology, RWTH Aachen University, Germany
[b]Informatik 11 Embedded Software, RWTH Aachen University, Germany

Correspondence: Anake Pomprapa, Medical Information Technology, RWTH Aachen University,
Pauwelsstrasse 20, 52074 Aachen, Germany
E-mail: *pomprapa@hia.rwth-aachen.de* Website: *www.medit.hia.rwth-aachen.de* Phone: +49 241 80-23145

Abstract. Currently, novel approaches of deep learning are being investigated with respect to their potential for self-improvement in clinical applications. This article presents a deep learning algorithm to handle big data acquired from an electrocardiogram system. Based on this measurement modality, electrical activity of the heart can be monitored over a period of time in various sitting scenarios, such as in the hospital, at home, or during travel. The automatic classification of arrhythmia is carried out based on a biorthogonal wavelet filter bank and a convolutional neural network in order to categorize the ECG signals into normal, left and right bundle branch block, and premature ventricular contraction on a beat-by-beat basis, based on supervised machine learning using the standard MIT-BIH database. An averaged sensitivity of 99.2% was achieved. With the proposed system architecture of deep structured learning, the potential of learning mechanisms can be implemented in batch processing. The benefits of the proposed technique are to save the diagnostic time, to reduce the overall cost in healthcare, and to promote individual cardiac monitoring.

Keywords: Arrhythmia, deep learning, convolutional neural network (CNN), feature extraction, biorthogonal wavelet filter bank, arrhythmia classification system.

1. Introduction

Cardiac arrhythmia is a heart disorder manifesting with irregular patterns of a heartbeat. It is caused by an abnormal contraction sequence of the heart, leading to reduced efficiency of blood pumping and, eventually, to other life-threatening conditions such as sudden cardiac arrest, stroke (brain attack), and heart failure. Arrhythmias can be diagnosed with several techniques, including the traditional electrocardiogram (ECG), the Holter monitor (Hanke et al., 2009), or an echocardiogram (Rychik et al., 2004). For the present study, non-contact ECG monitoring was used to detect abnormal electrical activity in the heart. In principle, analysis of the P wave, QRS complex, T wave, and/or R-R interval is important to identify an abnormality in the ECG signal. For instance, an increasing amplitude of the P wave (> 0.25 mV) indicates right atrial enlargement (Reeves et al., 1981) and variation in the R-R interval of > 120 ms correlates with sinus bradycardia (slow heartbeat of ≤ 60 bpm).

To process large amounts of ECG signals (ECG big data), various algorithms have been implemented for automatic diagnosis and classification of arrhythmia, to optimize individual medical decisions and to reduce long-term costs of healthcare. Classical classification techniques have been implemented by performing feature extraction and processing further decisions based on autocorrelation function (Guillén et al., 1989), time-frequency analysis (Afonso and Tompkins, 1995), Fourier-transform neural network (Minami et al., 1999), and wavelet transform (Khadra et al., 1997). Additionally, a statistical modeling technique has been applied based on the Hidden Markov Models (HMM) (Coast et al., 1990). A modern technique based on learning algorithms is also applied, such as a genetic algorithm (Guvenir et al., 1997), principal component analysis, or least-squares support vector machine (LS-SVM) (Polat and Günes, 2007).

A deep learning technique was applied to imitate the activity of virtual neuron layers in the neocortex inspired by the Nobel Prize-winning studies of the visual system (Hubel and Wiesel, 1979) and to

formulate complex mathematical models with the aid of convolutional operators for image recognition and natural language understanding in real time. A recent medical application for arrhythmia classification based on deep learning was proposed for recognition of premature ventricular contraction (PVC) (Jun et al., 2016). Six hidden layers of a deep neural network were used based on the TensorFlow library, to categorize normal ECG signals and PVC, yielding a sensitivity of 99.4%. Another challenge was to classify normal ECG signals with paroxysmal atrial fibrillation (Pourbabee et al., 2016). The proposed convolutional neural network (CNN) model was able to classify ECG signals with a sensitivity of 85.3%. Another complex classification task (Isin and Ozdalili, 2017) was carried out targeting normal (N), right bundle branch block (RBBB) and paced beats using the transferred deep CNN cascaded with a conventional back propagation neural network; this yielded a sensitivity of 92%.

In this article, a combination of feature extraction and a supervised learning algorithm using CNN is proposed for the classification of arrhythmia based on the standard MIT-BIH database developed by the Association for the Advancement of Medical Instrumentation (AAMI) (Moody and Mark, 2001; Goldberger et al., 2000). The prototype of the deep learning system is capable of classifying every single heartbeat into four different categories i.e., N, left bundle branch block (LBBB), RBBB and PVC, and transferring the ECG data to cloud storage for further batch processing, as well as for monitoring the real-time stream data on a tablet. In the present work, ECG signals were used to predict cardiac arrhythmias based on a deep learning algorithm. The proposed system should ultimately support Medicine 4.0 (De Micheli, 2017), which promotes the movement to establish a smart digitalized healthcare framework by blending state-of-the-art technologies, i.e., mathematical modeling of individual patients, cloud computing, big data analysis, deep learning and control engineering, for decision support and treatment in medical applications.

The remainder of this article is organized as follow. The background of arrhythmias and their classification criteria are presented in Section 2. A brief description of the hardware configuration and software implementation, including feature extraction of the ECG signals and the deep learning algorithm, are presented in Section 3. Section 4 presents the results. Finally, the discussion and conclusions are presented in Sections 5 and 6, respectively.

2. Medical Background of Arrhythmias

The basic background of the heart in terms of physiology, conduction mechanism, and the concept of cardiac rhythm can be found in, for example, (Malmivuo and Plonsey, 1995). Therefore, this section focuses on the background of arrhythmias based on ECG signals, providing a simple and cost-effective solution for the diagnostics of patients with cardiac problems.

2.1 Normal ECG Signal

The normal cardiac cycle starts with impulse depolarization of the sinus atrial (SA) node, located at the upper part of the right atrium. A wave of electrical depolarization spreads through the right atrium and across the inter-atrial septum into the left atrium, subsequently routing through the atrioventricular (AV) node, the bundle of His, and the right and left bundle branches. In normal conduction, the two ventricles contract simultaneously, yielding maximal cardiac efficiency. After that, repolarization must take place before the next cardiac cycle; this conduction mechanism corresponds to the generation of the ECG signal (Figure 1).
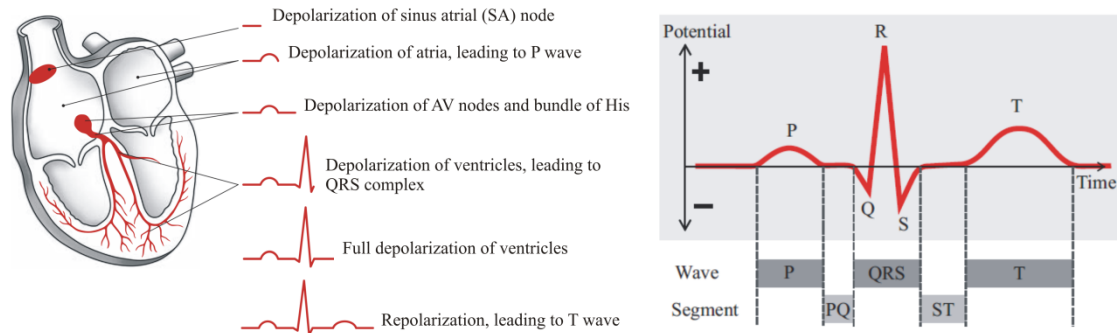

Figure 1. Conduction mechanism of a normal ECG signal.

The quantitative and qualitative characteristics of a normal ECG signal are shown in terms of the heart rate and the normal duration time (Table 1) (Jacobson et al., 2014).

Table 1. *Normal characteristics of an ECG signal.*

Component	Characteristics
Heart rate	60-100 bpm
PR interval	120-200 ms
QRS interval	40-100 ms
ST interval	80 ms

Irregularities of the ECG signal include, for example, irregular RR rhythms indicating either sinus tachycardia (heart rate > 100 bpm) or sinus bradycardia (heart rate < 60 bpm), atrial fibrillation exhibiting chaotic electrical activity in the atria, and asystole representing the total loss of ventricular electrical activity. The present work focuses on only two specific types of arrhythmia, i.e., bundle branch block and PVC.

2.2 Bundle Branch Block

The concept of bundle branch block, based on electrophysiology, was introduced over 100 years ago (Eppinger and Bothberger, 1909). This occurs when there is an obstruction in one of the branches and can be classified into two types of conduction disturbance: right bundle branch block (RBBB) and left bundle branch block (LBBB). For RBBB, electrical impulses cannot be transmitted through the right ventricle via the right bundle branch, whereas the left ventricle is still activated as normal. Delayed activation of the right ventricle gives a persistent rise in ST depression. RBBB can be caused by the Brugada syndrome (Brugada and Brugada, 1992), pulmonary embolism, or myocarditis. Similarly, for LBBB, delayed activation of the left ventricle causes a slower contraction of the left ventricle compared with the right ventricle, resulting in the absence of a Q wave and a tall R wave. Causes of LBBB include, for example, acute myocardial infarction (Sgarbossa et al., 1996) and Lyme disease (McAlister et al., 1989). In both RBBB and LBBB, a QRS complex ≥120 ms and loss of ventricular synchrony is observed during diagnosis. Since LBBB is associated with greater disease severity and mortality (Baldasseroni et al., 2002), early detection is important for successful treatment.

2.3 Premature Ventricular Contraction

In the case of PVC arrhythmia, ventricular contraction occurs earlier than in a normal cardiac cycle due to an abnormal contraction signal, or to depolarization originating from somewhere in the ventricles rather than from the SA node. Causes of PVC include the effects of drugs (e.g., cocaine, methamphetamine), electrolyte imbalance, heart attack, or even anxiety. Indications in the ECG signal can range from an abnormal T wave due to abnormal timing and direction of repolarization, to the QRS complex (the direction of the T wave is generally opposite to that of the QRS complex), or the P wave may be buried in (or may immediately precede) the QRS complex. The premature beat causes an irregular R-R interval (Sims and Miracle, 1997). Repeated PVCs can lead to heart muscle weakening and, possibly, sudden cardiac death.

3. Material and Methods

3.1 MIT-BIH Arrhythmia Database

This database consists of 48 half-hour portions (24 hours duration) of two-channel ambulatory ECG recordings, obtained from 47 subjects, conducted by the BIH Arrhythmia Laboratory between 1975 and 1979 (Moody and Mark, 2001; Goldberger et al., 2000). There were 25 men with the age of 32 to 89 years and 22 women with the age of 23 to 89 years. In most records, the principal lead was a modified limb lead II (ML II) with the electrode placed on the chest. The other lead was typically Lead V1 (occasionally V2, V4, or V5 in some cases). The analog ECG signals were digitized at 360 Hz per channel with 11-bit resolution. The anti-aliasing was implemented by using a pass-band filter of 0.1 to 100 Hz. Two or more cardiologists independently annotated each record. The disagreements were eventually resolved to obtain the annotations for each beat. This database was a standard test for arrhythmias, developed by the Association for the Advancement of Medical Instrumentation (AAMI).

3.2 Software Architecture

Python (Python Software Foundation, Delaware, USA) was used for encoding the whole software programming. This is an interpreted high-level multi-paradigm programming language that supports object-oriented, functional and procedural programming paradigms. The core software architecture consists of three layers.

- A data layer, including data source from the data acquisition system, database access in persistent storage, and data representation
- A processing layer, including pre-processing of the ECG signals, wave detection in the ECG, and feature extraction
- A diagnostic layer, representing the deep learning algorithm as a brain model to classify arrhythmias in real time

Figure 2 is a graphical representation of the system architecture. The aim of this software architecture is to classify arrhythmias into four types, i) normal (N), ii) RBBB, iii) LBBB and iv) PVC, on a beat-by-beat basis in real time. Cloud storage is also proposed based on the InfluxDB database platform in the data layer, to allow global access with an authorized password. InfluxDB (developed by InfluxData) is an open source and extensible database platform for metrics and user-defined time series data that is suitable for Internet of Thing (IoT) application and real-time analytics. In this work, a tablet-based application is used for data retrieval from cloud storage in order to simulate possible global access to the data in real time. The ECG signals can be monitored with the real-time predefined classification of arrhythmias.
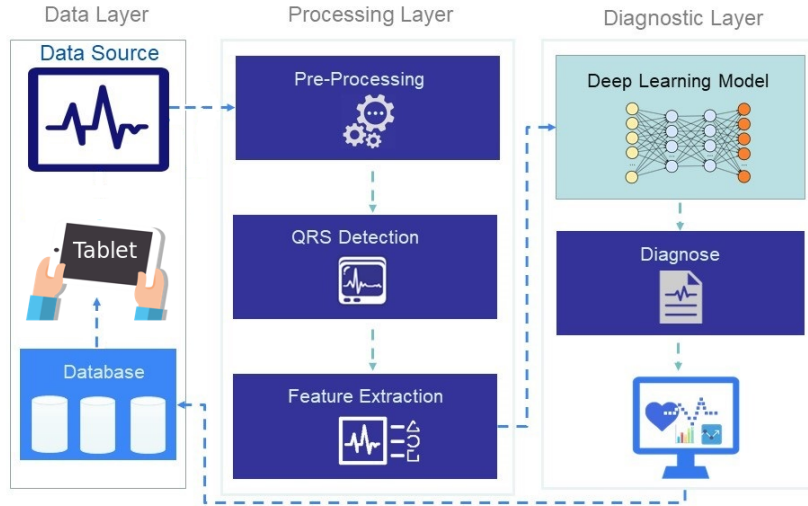

***Figure 2.** Software layers for real-time processing in arrhythmia analysis (Ahmed, 2018).*

When the ECG signal in the data layer has been acquired from the ECG measurement system, it is transmitted to the next processing layer where preprocessing and feature extraction are implemented. In this data layer, an Android application is also programmed for monitoring of the ECG signals and labeling of arrhythmias in real time based on a beat-to-beat basis. The processing layer is a crucial step for successful classification of arrhythmias and includes various processes, e.g., denoising, filtering, normalizing, detecting the P wave, QRS complex or T wave, and extracting essential features (i.e., the amplitude of the P wave or the R-R interval). A biorthogonal wavelet filter was also employed in this layer to specify the position of all related waves in the ECG signal so that further feature extraction can be efficiently implemented. In the diagnostic layer, a deep learning model based on CNN was designed and trained based on Keras. This is an open source library written with Python and run on top of TensorFlow, which allows fast implementation of a deep neural network for the diagnosis of arrhythmias.

3.3 Biorthogonal Wavelet Filter Bank

The discrete wavelet transform was applied to decompose the ECG signals; the main objective of this is to identify the position of each particular wave, starting from the detection of the R wave, or the highest amplitude in an ECG beat to the other waves. Therefore, a biorthogonal wavelet filter bank is proposed to handle the non-stationary ECG signals and to analyze the signals in multiresolution scales. Figure 3 presents the basic structure of the filter bank, which consists of two filters:
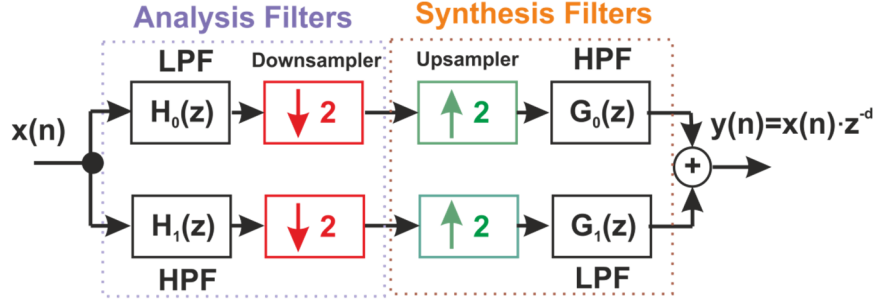
Figure 3. One stage biorthogonal filter (Pomprapa et al., 2018).

• Analysis filters: these are used to split the input signal into mutually orthogonal subbands (low-pass filter and high-pass filter), and the filtered signals are directly downsampled by a factor of two.

• Synthesis filters: these upsample the input signals and reconstruct the original input signals x(n) based on the orthogonal subbands. Both signals from the subbands are subsequently combined.

Also, several mother wavelet families contain energy spectrum concentrated at the low-frequency band, similar to the ECG signals. In the present work, the biorthogonal spline wavelet is used based on pyramid decomposition proposed by Mallet. These filters are $H_0(z)$ and $H_1(z)$ in the analysis phase, and $G_0(z)$ and $G_1(z)$ in the synthesis phase; they are defined by the following equations in Z-transform.

$$H_0(z) = \frac{1}{4} + \frac{3}{4}z^{-1} + \frac{3}{4}z^{-2} + \frac{1}{4}z^{-3} \tag{1}$$

$$H_1(z) = -\frac{1}{4} - \frac{3}{4}z^{-1} + \frac{3}{4}z^{-2} + \frac{1}{4}z^{-3} \tag{2}$$

$$G_0(z) = H_1(-z) = -\frac{1}{4} + \frac{3}{4}z^{-1} + \frac{3}{4}z^{-2} - \frac{1}{4}z^{-3} \tag{3}$$

$$G_1(z) = -H_0(-z) = -\frac{1}{4} + \frac{3}{4}z^{-1} - \frac{3}{4}z^{-2} + \frac{1}{4}z^{-3} \tag{4}$$

These kernels (Wang et al., 2001) have the structure of a symmetric half-band polynomial and an important property of regularity in terms of smooth scaling. To detect the best position of the R peak, further decomposition levels must be chosen by iteration of higher stages of biorthogonal wavelet filter after analysis filter at the low-pass filter (LPF) or the approximation subband, resulting in a tree-like structure or a multi-stage biorthogonal wavelet filter bank (Figure 4). The multi-stage filter can be used to extract the signal in a higher order of wavelet scales.
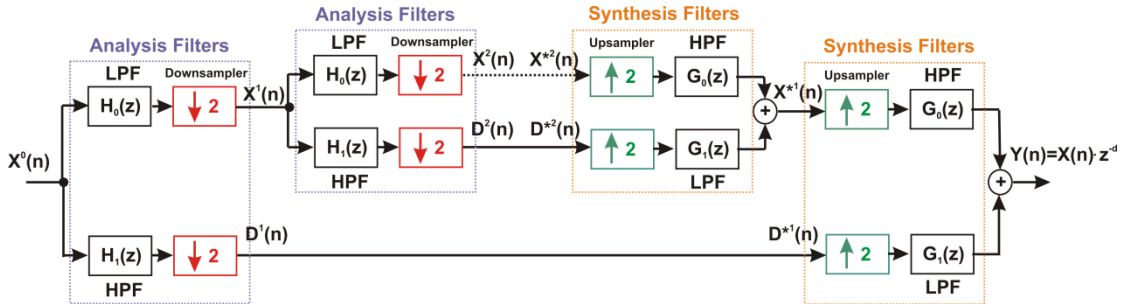

Figure 4. Example of a multi-stage biorthogonal filter bank up to the second order.

With the implementation of this filter, an effective method to detect the sharp edges can be retrieved at the zero crossing points in the transformation at different scales, corresponding to the local extrema of the given signals. The searching algorithm for the sharp edges is carried out starting from localizing the R peak, the QRS complex, and the P wave and T wave.

3.4 The Architecture of Deep Learning

A deep learning (or a special class of machine learning) technique comprises numerous information levels of nonlinear modules in hierarchical architecture that transforms the raw input into a representation at a higher level with slightly more complicated abstraction (Lecun et al., 2015). For the adequate composition of such transformations, the underlying functions have to be learned or identified. Therefore, the essence of deep learning is to process features or representations of the observational data from lower-level features to higher-level features. Many industrial applications (e.g., AlphaGo, self-driving cars, or

Google Translate) have progressively applied this technological advancement in their products. In the present work, deep learning is proposed for use in medical applications.
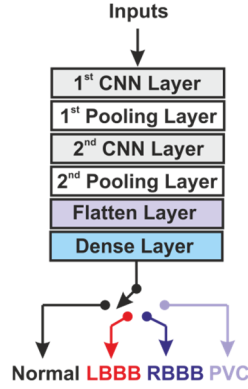

Figure 5. *A deep learning model for the classification of cardiac arrhythmias (Pomprapa et al., 2018).*

For the classification of arrhythmias, the well-known MIT-BIH Arrhythmia dataset (Moody and Mark, 2001; Goldberger et al., 2000) is applied for model training. A supervised learning approach is then used with a huge data set to train the model. The aim of this simplified deep learning model based on CNN is to classify cardiac arrhythmias based on six structural layers (Figure 5).

In this particular scenario, a one-dimensional (1-D) convolution layer is applied for beat-by-beat classification in order to extract higher-order invariant features in the ECG data via convolutions. The convolutional layers are the basic blocks of this deep learning architecture, which computes a mathematical operation between inputs and the kernel filters, yielding a convoluted feature as an output. The kernel filters are applied across the inputs in a sliding manner. To identify or train the parameters of the neurons in a CNN layer, a gradient descent algorithm is used. The activation function in the CNN layer is defined by rectified linear units (ReLU). The input-output relationship of ReLU is computed based on the following equation:

$$y = f(x) = \max(0, x), \tag{5}$$

where x represents the input to the ReLU and y is the corresponding output value.

Details of all layers are presented in Table 2, based on the number of filters and the number of parameters in each specific layer.

Table 2. *Defined parameters in the deep learning model.*

Type	Number of Filters	Number of Parameters
1st CNN Layer	64	256
1st Pooling Layer	64	0
2nd CNN Layer	32	6,176
2nd Pooling Layer	32	0
Flatten Layer	-	0
Dense Layer	-	9,640

CNN layers compute the output of neurons, and each individual CNN layer is directly followed by a pooling layer, which performs a downsampling operation to reduce the size of the data representation on the one hand and to optimize overfitting on the other. This can be carried out using a max operation, which is called the 'max pooling layer'. In general, practical implementation, a structural combination of the CNN layer and a pooling layer can be repeated many times to extract higher feature information. A flattened layer converts the output of the max pooling layer into a 1-D feature vector, and the final classification is carried out in a dense layer. Both the flattened and dense layers use a softmax activation

function that calculates the probability distribution ($P(y = i)$) for the output vector between 0 and 1. The summation of all output entries is 1.

$$P(y = i) = \frac{e^{y_i}}{\sum_{j=1}^{K} e^{y_j}},$$ (6)

where K represents the input dimensional space, y denotes the output, and i symbolizes one of all possible target classes. The output of the softmax function can be applied to present a categorical distribution to the target class.

With the proposed model of six layers, the batch size of 1,000 samples is used to train the model. This deep learning model requires optimization of all 16,036 parameters: specifically, 256 in the first CNN layer, 6,176 in the second CNN layer, and 9,640 in the dense layer. In summary, deep learning performs a nonlinear mapping of inputs to outputs similar to the brain model, and the action is performed for the classification of arrhythmias in real time.

4. Results

4.1 Detection of R-peaks and Other Waves

Based on the Physiobank, the MIT-BIT Arrhythmia Database (Moody and Mark, 2001; Goldberger et al., 2000) was used to build a model of arrhythmia classification for normal, RBBB, LBBB, and PVC. The biorthogonal wavelet filter bank was applied up to the fourth scale, and the first derivative was carried out for each scale. The extremal values in the first derivative at different scales can be used to localize R-peaks, where they are defined at the zero crossing points between the maximum and minimum points of the first derivative curve at the third or fourth scales. Using this approach, the onset of R-peaks can be identified. Using a similar procedure, by defining an appropriate window size, the onset of other waves (i.e., Q waves, S waves, P waves, and T waves) can be detected, and further feature extraction can be implemented, such as the amplitude of P waves, R-R intervals, or the heart rate.

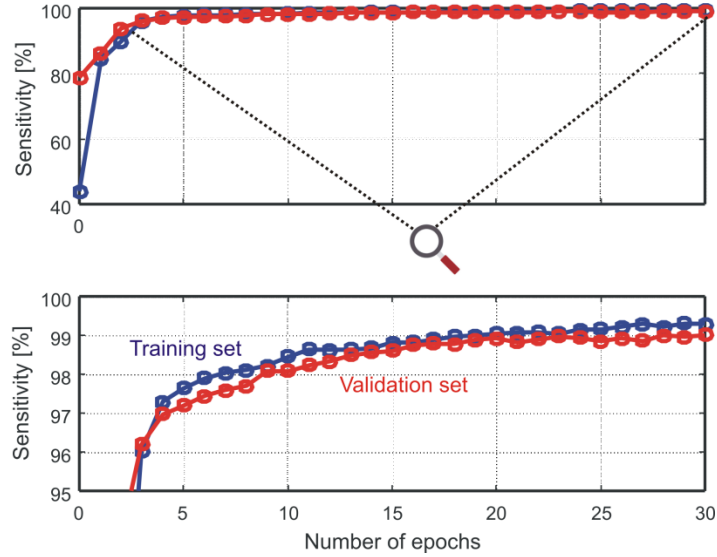### 4.2 Training of the Deep Learning Model

Figure 6. Performance of deep learning for arrhythmia classification.

The ECG data of 16,415 records were divided into 67% for training in deep learning, and the remaining 33% was used for model validation. The training performance gradually improved after each iteration and remained stable (Figure 6). After 30 iterations or epochs, an averaged sensitivity of 99.2% was achieved in the validation set for arrhythmia classification.

4.3 Model Prediction

A total of 16,415 ECG records were extracted from the MIT-BIH dataset. In the present work, 10,998 records were used for training the deep learning, and the remaining 5,417 records were used for model validation. The validation data consisted of the following dataset: 1,648 normal records, 1,308 LBBB

records, 1,285 RBBB records, and 1,176 PVC records. The classification performance is summarized in Table 3, including details on the number of training data and validation data.

Table 3. *Classification performance based on the learning.*

	Normal	LBBB	RBBB	PVC	Total
Number of training data	**3,352**	**2,641**	**2,498**	**2,507**	**10,998**
Number of validation data	1,648	1,308	1,285	1,176	5,417
Number of correct prediction	1,643	1,302	1,277	1,153	5,375
Sensitivity [%]	**99.7**	**99.5**	**99.4**	**98.0**	**99.2**

In the validation process, of the total 5,417 records, 42 ECG signals were incorrectly classified. Details on fault classifications are summarized in the confusion matrix (Table 4). In the validation set with 1,648 records of normal ECG data, 1,643 were correctly predicted as a normal ECG signal. One normal ECG record was predicted as LBBB, and another was predicted as RBBB. In addition, three normal ECG records were erroneously predicted as PVC. A similar interpretation can be made for the true labels of LBBB, RBBB, and PVC in the confusion matrix.

Table 4. *Confusion matrix for arrhythmia classification.*

		Predicted Label			
		Normal	LBBB	RBBB	PVC
True Label	Normal	1,643	1	1	3
	LBBB	0	1,302	0	6
	RBBB	5	0	1,277	3
	PVC	9	12	2	1,153

5. Discussion

Based on the validation data, the cases of incorrect classification have been thoroughly examined, and the main findings are summarized as follow:

- Deep learning incorrectly classified the signal which was (e.g.) normal but predicted it as RBBB. However, since RBBB requires a QRS complex ≥ 120 ms and a depressed ST segment, both these criteria need to be fulfilled for justification of RBBB. In that case, only a depressed ST segment can be observed, but the QRS complex is comparable to that in a normal ECG signal; therefore, it should be predicted as normal rather than as RBBB.
- Some noise or motion artifacts induced the abnormal ECG shape to resemble LBBB. In that particular shape, it should be predicted as LBBB, but the signal is from a healthy person; therefore, the classification was wrong.
- For wrong PVC classification, it appeared that the QRS complex was ≥ 120 ms with a deep S wave and an inverted ST segment. Therefore, the prediction of PVC may be acceptable. However, in one case, the RR intervals were equal, or no irregular RR interval was observed meaning that it was an incorrect PVC classification.

Recurrent neural network architecture, based on long short-term memory (LSTM), is suitable for learning from sequences of values in time series; it has a feedback structure to encode past information as a vector in order to make the prediction. However, its performance decreases significantly with an increase in the length of an input sequence (Cho et al., 2014). In contrast, CNN has no feedback structure

and allows parallel computation, which speeds its performance for a long input sequence compared to LSTM. With the time series dataset based on the ECG signal, 1-D CNN can thereby be used to classify a series of data in real time.

To extract features in an ECG dataset, a biorthogonal filter bank (up to the scale of 4) was implemented to specify the positions of the P, Q, R, S, and T wave on a beat-by-beat basis. This information serves as an additional feature for the model. In other words, the original ECG data combined with these processed features are used as input to the deep learning model, so that further classification can be performed. Alternatively, feature extraction of the ECG dataset based on the biorthogonal filter can be omitted, and the deep learning model can be left to classify the arrhythmias. In doing so, the additional complexity in terms of the number of CNN layers should be given in the model, and these features will simply be treated as unknown parameters hidden in the model.

With reference to the MIT-BIH database, many algorithms have been used for arrhythmia classification. Table 5 presents a (selected) list of algorithms, their performance, and their classification targets. It can be seen that our proposed deep learning approach should provide a promising solution for classification, with better performance compared to the others in the list. However, an extension of the target classes needs to be implemented in the future to cover all wider classes of arrhythmia.

Table 5. *Different algorithmic performances for arrhythmia classification.*

Authors	Algorithm	Averaged Sensitivity [%]	Target Class Description
Soria and Matinez (2009)	Floating feature selection	90	Normal beat, supraventricular beat, and ventricular beat
Rai and Trivedi (2012)	Discrete Wavelet Transform and Back Propagation	97.8	normal beat and abnormal beat
Das and Ari (2014)	Mixture of features	68.4	normal beat, ventricular ectopic beat, supraventricular ectopic beat, fusion beat, and unknown beat
Nikan et al. (2017)	Adaptive segmentation	98.9	normal beat, ventricular ectopic beat, supraventricular ectopic beat, fusion beat, and unknown beat

6. Conclusions

A deep learning model of six layers was applied for arrhythmia classification in four categories, i.e., normal (N), left bundle branch block (LBBB), right bundle branch block (RBBB), and premature ventricle contraction (PVC). The averaged sensitivity of 99.2% can be achieved in real time on a beat-by-beat basis. The arrhythmia classification can be realized using the proposed deep learning architecture. Since the real-time data were stored on a cloud storage system, it can be used to evaluate additional (historical) records of an individual patient. With the aid of artificial intelligence, big data analysis, this should revolutionize the way we diagnose arrhythmias for patients and offer economic benefits in the challenging era of Medicine 4.0.

References

Ahmed, W. (2018). Deep learning of cardiac-related conditions using a non-contact multisensor system. Master thesis, RWTH Aachen University.

Afonso, V.X., & Tompkins, W.J. (1995). Detecting ventricular fibrillation, selecting the appropriate time-frequency analysis tool for the application. *IEEE Eng. Med. Biol. Mag.*, page 152–159.

Baldasseroni, S., Opasich, C., Gorini, M., Lucci, D., Marchionni, N., Marini, M., Campana, C., Perini, G., Deorsola, A., Masotti, G., Tavazzi, L., & Maggioni, A.P. (2002). Left bundle-branch block is associated with increased 1-year sudden and total mortality rate in 5517 outpatients with congestive heart failure: A report from the Italian network on congestive heart failure. *American Heart Journal*. 143(3):398-405.

Brugada, P., & Brugada, J. (1992). Right bundle branch block, persistent ST segment elevation and sudden cardiac death: a distinct clinical and electrocardiographic syndrome. *JACC*, 20(6):1391-1396.

Cho, K., Van Merrienboer, B., Gulcehre, C., Bahdanau, D., Bougares, F., Schwenk, H., and Bengio, Y. (2014). Learning phrase representations using RNN encoder-decoder for statistical machine translation. *arXiv:1406.1078*.

Coast, D.A., Stern, R.M., Cano, C.G., & Briller, S.A. (1990). An approach to cardiac arrhythmia analysis using hidden Markov models. *IEEE Trans Biomed Eng.*, 37(9):826–836.

Das, M.K., & Ari, S. (2014). ECG beats classification using mixture of features. *Int Sch Res Notices*, 2014:178436.

De Micheli, G. (2017). Cyber-medical systems: requirements, components and design examples. *IEEE Transactions on Circuits and Systems*, 64(9):2226–2236.

Eppinger, H., & Bothberger, C.J. (1909). Zur Analzse des Elektrokardiogramms. *Wien Klin Wehnschr*. 22:1091.

Goldberger, A.L., Amaral, L.A.N., Glass, L., Hausdorff, J.M., Ivanov, P.Ch., Mark, R.G., Mietus, J.E., Moody, G.B., Peng, C-K., & Stanley, H.E. (2000). PhysioBank, PhysioToolkit, and PhysioNet: Components of a New Research Resource for Complex Physiologic Signals. *Circulation*, 101(23):e215-e220.

Guillén, S.G., Arredondo, M.T., Martin, G., & Corral, J.M.F. (1989). Ventricular fibrillation detection by autocorrelation function peak analysis. *J Electrocardiol*, 22 Suppl:253–262.

Guvenir, H.A., Acar, B., Demiroz, G., & Cekin, A. (1997). Supervised machine learning algorithm for arrhythmia analysis. In *Proceedings of the 24th Annual Meeting on Computers in Cardiology*, pages 433–436.

Isin, A., & Ozdalili, S. (2017). Cardiac arrhythmia detection using deep learning. *Procedia Computer Science*, 120:268-275.

Jacobson, C., Marzlin, K., & Webner, C. (2014). Cardiac arrhythmias & 12 lead ECG interpretation module. Cardiovascular Nursing Education Associates, Burien, WA, USA, page 5.

Jun, T.J., Park, H.J., Minh, N.H., Kim, D., & Kim, Y.H. (2016). Premature ventricular contraction beat detection with deep neural network. In *15th IEEE International Conference on Machine Learning and Applications (ICMLA)*, pages 859-864.

Hanke, T., Charitos, E.I., Stierle, U., Karluss, A., Kraatz, E., Graf, B., Hagemann, A., Misfeld, M., & Sievers, H.H. (2009). Twenty-four-hour Holter monitor follow-up does not provide accurate hearth rhythm status after surgical atrial fibrillation ablation therapy. *Circulation*, 120 (11 Suppl):177-184.

Hubel, D.H. & Wiesel, T.N. (1979). Brain mechanisms of vision. *Scientific American*. Vol. 241, pages 150-162.

Khadra, L., Al-Fahoum, A.S., & Al-Nashash, H. (1997). Detection of life-threatening cardiac arrhythmias using the wavelet transformation. *Med. Biol. Eng. Comput.*, 35:626–632.

Leicht, L., Skobel, E., Knackstedt, C., Mathissen, M., Sitter, A., Wartzek, T., Möhler, W., Reith, S., Leonhardt, S., & Teichmann, D. (2018). Capacitive ECG monitoring in cardiac patients during simulated driving. *IEEE Transaction on Biomedical Engineering*, [Epub ahead of print].

Lecun, Y., Bengio, Y. & Hinton, G. (2015). Deep learning. *Nature*, 512:426–444.

Malmivuo, J. & Plonsey, R. (1995). Bioelectromagnetism: Principles and application of bioelectric and biomagnetic fields. Oxford University Press, New York.

McAlister, H.F., Klementowicz, P.T., Andrews, C., Fisher, J.D., & Feld, M. (1989). Lyme carditis: an important cause of reversible heart block. *Ann Intern Med*. 110(5):339-345.

Minami, K., Nakajima, H., & Toyoshima T. (1999). Real-time discrimination of ventricular tachyarrhythmia with Fourier transform neural network. *IEEE Trans. Biomed. Eng.*, 46:179–185.

Moody, G.B., and Mark, R.G. (2001). The impact of the MIT-BIH arrhythmia database. *IEEE Eng in Med and Biol*, 20(3):45–50.

Nikan, S., Gwadry-Sridhar, F., & Bauer, M. (2017). Pattern recognition application in ECG arrhythmia classification. In Proceedings of the 10th International Joint Conference on Biomedical Engineering Systems and Technologies (BIOSTEC), pages 48-56.

Polat, K., & Günes, S. (2007). Detection of ECG arrhythmia using a differential expert system approach based on principal component analysis and least square support vector machine. *Applied Mathematics and Computation*. 186(1):898-906.

Pomprapa, A., Ahmed, W., Stollenwerk, A., Kowalewski, S., Uguz, D.U., & Leonhardt, S. (2018). Arrhythmia analysis in a non-contact ECG chair using convolutional neural network. In: *11th International Conference on Bioelectromagnetism*, ICBEM, Aachen, Germany.

Pourbabaee, B., Roshtkhari, M.J., & Khorasani, K. (2016) Feature learning with deep convolutional neural networks for screening patients with paroxysmal atrial fibrillation. In *International Joint Conference on Neural Networks (IJCNN)*. Pages 5057-5064.

Rai, H.M. & Trivedi, A. (2012). Classification of ECG waveforms for abnormalities detection using DWT and back propagation algorithm. *International Journal of Advanced Research in Computer Engineering & Technology*. 1(4):517:520.
Reeves, W.C., Hallahan, W., Schwiter, E.J., Ciotola, T.J., Buonocore, E., and Davidson, W. (1981). Two-dimensional echocardiographic assessment of electrocardiographic criteria for right atrial enlargement. *Circulation*, 64:387–391.

Rychik, J., Ayres, N., Cuneo, B., Gotteiner, N., Hornberger, L., Spevak, P.J., & Van Der Veld, M. (2004). American society of echocardiography guidelines and standards for performance of the fetal echocardiogram. *J Am Soc Echocardiogr.*, 17:803-10.

Sims, J.M. & Mircle, V. (1997). Premature ventricular contractions. *Nursing*, 27(8):43.

Sgarbossa, E.B., Pinski, S.L., Barbagelata, A., Underwood, D.A., Gates, K.B., Topol, E.J., Califf, R.M., & Wagner, G.S. (1996). Electrocardiographic diagnosis of evolving acute myocardial infarction in the presence of left bundle branch block, *N Engl J Med.*, 334:481-487.

Soria, M.L. & Martinez, J.P. (2009). Analysis of multidomain features for ECG classification. In *Computer in Cardiology*. 36:561:564.

Wang, C., Lu, Y., & Huang, Y. (2001). Using biorthogonal wavelet filter bank for ECG detection and reconstruction. *Beijing Biomedical Engineering*, (1):25–28.