ArrhyNet: A High Accuracy Arrhythmia Classification Convolutional Neural Network

Sayli Siddhasanjay Aphale
Department of Electrical and Computer Engineering
University of Texas at San Antonio
San Antonio, TX, USA
sayli.aphale@my.utsa.edu

Eugene John
Department of Electrical and Computer Engineering
University of Texas at San Antonio
San Antonio, TX, USA
eugene.john@utsa.edu

Taposh Banerjee
Department of Electrical and Computer Engineering
University of Texas at San Antonio
San Antonio, TX, USA
taposh.baneerjee@utsa.edu

***Abstract*— Cardiovascular diseases are one of the major causes of all human deaths. Irregular heartbeat or arrhythmia is one among many reasons for cardiovascular diseases. Arrhythmia detection and classification is critical in the treatment of irregular heartbeats. This paper presents a systematic method for high accuracy arrhythmia detection and classification using ArrhyNet, a custom convolutional neural network (CNN) for arrhythmia classification on MIT-BIH Arrythmia Database. High and low frequency noise in the data is eliminated using low pass filter and baseline wander filter respectively, feature extraction is achieved using Daubechies Wavelet Transform and finally Synthetic Minority Over Sampling (SMOTE) technique is utilized to overcome the issue of imbalanced dataset. Using our technique, 16 different types of arrhythmias distributed in Association for Advancement of Medical Instrumentation (AAMI) standard were analyzed. The results indicate that the top-1 accuracy of our five-class classification system for the database used is 92.73%.**

Keywords—Arrhythmia Classification, ECG, Convolutional Neural Network, Daubechies Discrete Wavelet Transform, SMOTE.

I. Introduction

Cardiovascular diseases are one of the major causes of all human deaths. According to the World Health Organization (WHO), 17.9 million people worldwide die annually due to heart diseases accounting for 37% of all deaths globally [1]. Arrhythmia is one among many reasons for cardiovascular diseases. Cardiac arrhythmias are a group of conditions in which the electrical activity of the heart is irregular, manifesting faster or slower rhythm than that under normal conditions. In-order to tackle the problem of irregular heartbeats approximately 200,000 patients are implanted with cardiac devices in the U.S. annually and this number is increasing due to an aging population [2]. Certain types of arrhythmia are a serious threat to the patient's life which can cause sudden cardiac death and early detection of the arrythmia is curial in saving the patient's life.

An Electrocardiogram (ECG) is the most widely used method to measure and monitor the cardiac activity of a patient [3]. A standard ECG device has 24-hour sensing and recording capabilities but a manual analysis of arrythmias for cardiac disease detection becomes a bottleneck and very time consuming. Such traditional methods are not suitable for continuous, long term and real-time monitoring and management of irregular cardiac activities. Thus, automatic detection and classification of arrhythmia is of great importance for the early diagnosis and prevention of cardiovascular diseases. In the past few years there has been a significant growth of interest in the field of automated classification of cardiac arrhythmias [4-15] [17-22]. Feature extraction from the ECG and classification techniques using artificial neural network (ANN) are the basis of current automated classification of arrhythmias. A detailed analysis of the ECG wave form can provide information about the crucial cardiac conditions of the patient as shown in Fig.1 which shows the ECG wave form of premature ventricular contraction and unclassified beat from MIT-BIH Arrythmia Database [16].

The goal of our research is to design a robust method based on deep learning to efficiently and accurately classify cardiac arrhythmias. To this end, a 15-layer convolutional neural network model called *ArrhyNet* is proposed for arrhythmia classification in this research. This model is used to classify data from MIT-BIH arrhythmia database into five classes according to the AAMI standards after pre-processing. In our study Daubechies Wavelet Transform is used for feature extraction.

The rest of the paper is structured as follows: Section 2 gives Literature Review; Section 3 presents the Arrhythmia Classification Methodology followed by Performance and Evaluation in Section 4 and finally, Section 5 gives the conclusion.

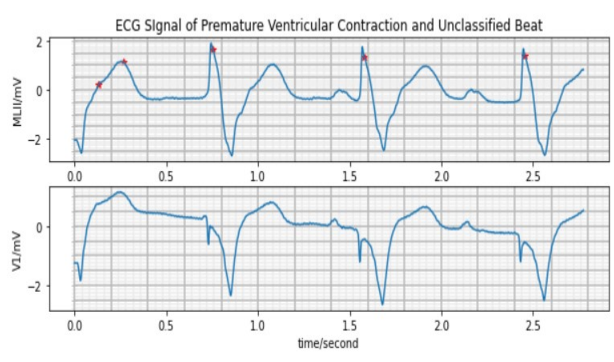

Fig 1. ECG Waveform of Premature Ventricular Contraction and Unclassified Beat from MIT-BIH Database[16].

II. LITERATURE REVIEW

Several research groups have used varied methods for classification of different types of arrythmia [6-15] [17-22]. ANN based classification is one of the main techniques for ECG arrhythmia classification. Ref [11] classifies normal beats and all other arrythmias as abnormal beats by introducing three CNN models. Ref [7] proposed a neural network named novel multi-module neural network system which includes four submodules to classify first four types of classes from AAMI standard trained on 1 dimensional MIT-BIH arrythmia database. Detection of normal sinus rhythm, cardiac arrythmia and congestive heart failure on an ECG dataset of 162 patients is proposed in Ref [9] using an LSTM method having four hidden layers. Dasan et al. [3] proposed a method of combining convolutional denoising autoencoder and a single layer of LSTM for compression and denoising of samples and focuses on the signal to noise ratio of a proposed CNN, LSTM and a combination of both for the varied noise levels. Ref [12] compares two different CNN models one with 8 layers and other with 12 layers to distinguish 5 different arrhythmias, viz. atrial premature contraction, left bundle branch block, paced beat, premature ventricular contraction beat and right bundle block. Ref. [1] emphasizes on automated atrial fibrillation, normal beat, atrial flutter and junctional rhythm detection trained on MIT-BIH arrhythmia database utilizing a hybrid CNN-LSTM network.

III. ARRHYTHMIA CLASSIFICATION METHODOLOGY

The arrythmia recognition and classification system presented in this paper consists of the following stages: pre-processing of the data, viz. denoising and over-sampling followed by feature extraction, and classification according to AAMI standards into five classes using convolutional neural network. The work is performed in Jupyter notebook on the Anaconda platform on Intel Core i5 8^{th} Gen processor with NVIDIA GeForce MX250 Version 417.35, plied with TensorFlow Keras packages.

A. ECG Datasets

In this research we use a total of 27,776 beats from MIT-BIH Arrythmia Database [16] and MIT-BIH Supraventricular Database. MIT-BIH Arrythmia database contains 48 half-hour excerpts of ECG recordings of 47 subjects, studied by Beth Israel Hospital Arrhythmia Laboratory. Every record is 30 minutes long, sampled at a frequency of 360 Hz. MIT-BIH Supraventricular Database includes 78 half-hour ECG recordings chosen to supplement the examples of supraventricular arrhythmias in the MIT-BIH Arrhythmia Database and sampled at a frequency of 250 Hz. The objective of this study is to follow the AAMI standard which categorises each heartbeat into five different types, viz. *Non-Ectopic Beats (N)*, *Supraventricular Ectopic Beats (S)*, *Ventricular Ectopic Beats (V), Fusion Beats (F)* and *Unknown Beats (Q)*, and to achieve a high accuracy five class multi-class classification solution for all the 16 different types of arrythmias in the database.

B. Pre-Processing

The ECG signal databases are adulterated by different types of low and high frequency noises. This step is used to eliminate the noise and obtain the pure signal without any significant loss of information. The low-frequency noise is due to baseline wander, which is a low frequency artefact in the ECG that arises from breathing, electrically charged electrodes, or subject movement. Using a baseline removal filter, filtered at 360 Hz for MIT-BIH arrythmia dataset and 250 Hz for MIT-BIH supraventricular dataset respectively the baseline wander noise can be eliminated. An order 12 low pass filter with a cut-off frequency of 60 Hz sampled at their respective frequencies of 360 Hz and 250 Hz is utilized for both the databases to remove the high- frequency noise and power line interference.

After the ECG signal is filtered, it is segmented equally into a length of 200 points on either end. R-peak is considered as fiducial point. The segmented digital signal is 1-D data in which each beat is represented by the chosen first 200 points. Subsequently, the data is normalized using the standard process. Discrete Wavelet Transform (DWT) is one of the best methods for feature extraction, and this research utilizes Daubechies Wavelet Transform for temporal feature extraction.

As mentioned earlier the AAMI standard categorises each heartbeat into top five main classes, which include a total of 16 subclasses represented by the specific type or either a *Normal Beat* or an *Abnormal Beat*. Table I represents the detailed segregation of the different forms of arrythmia types into their required classification of classes and the number of heartbeats taken into consideration for our experimental setup per main class. Both the databases have unequal number of samples per arrythmia type resulting in the issue of imbalanced dataset. Significant disproportion in the total number of beats is apparent from Table I. However, it is essential that we use a minimum number of data set for appropriate training of the CNN model for obtaining a better performance.

C. Oversampling Technique

In the original database the number of *Normal Beats* is more than twice when compared to all other beats combined. And not all classes of arrhythmia have enough representation of its type in the database. In order to overcome the problem of imbalance of classes we used oversampling techniques. In this paper we used the method of data augmentation known as *Synthetic Minority Oversampling* (SMOTE). SMOTE [1,3] is the method used in supervised learning in which the minority class data is oversampled not by simple replication but by synthesis of new data from the existing ones. SMOTE works by selecting samples close in feature space and is applied to *Nodal Escape Beats, Atrial Escape Beat, Fusion of Ventricular and Normal Beat* and other classes, and used to create the synthetic samples. Table II gives the individual subclass beats utilized for training of the CNN model after SMOTE is applied.

D. ArrhyNet Architecture

In this paper we introduce *ArrhyNet*, a high accuracy CNN for arrhythmia classification. This 15-layer CNN model is used to classify the 16 different types of arrhythmias in the MIT database distributed in 5 classes according to the AAMI standard. The proposed CNN model consists of a total of six *1-D convolution layers*, four *max pooling layers*, one *global max pooling layer*, a *flatten layer* and three *dense layers*.

TABLE I: *ECG class description using AAMI standard and the number of beats for each class used in this research.*

AAMI Standard Classes	Sub Classes	Total Number of Beats
Non-Ectopic Beats: (N)	Normal Beats	6572
	Left Bundle Branch Block Beat	
	Right Bundle Branch Block Beat	
	Nodal Junction Escape Beat	
	Atrial Escape Beat	
Supraventricular Ectopic Beats: (S)	Aberrated Atrial Premature Beat	6471
	Premature/ Ectopic Super ventricular Beat	
	Nodal Junction Premature Beat	
	Atrial Premature Beat	
Ventricular Ectopic Beat: (V)	Ventricular Flutter Wave	5673
	Ventricular Escape Beat	
	Premature Ventricular Contraction	
Fusion Beats: (F)	Fusion of Ventricular and Normal Beat	3242
Unknown Beats: (Q)	Paced Beat	7318
	Unclassifiable Beat	
	Fusion and Paced and Normal Beat	

The training and testing split of data are 24,003 and 5,272 respectively with input shape (200,1). Reshaping of input data from (24003,200) to (24003,200,1) for loading it in the Conv1D layer is required as data is 1-D and the input for Conv1D is 2-D. Table III gives the detailed description of the *ArrhyNet* convolutional neural network model implemented for this study.

From the model description, the filter sizes of the consecutive Conv1D layers are formatted in ascending order and their kernel size in descending order as it gives better performance for our model. The activation function incorporated to increase the non-linearity is *ReLu* (Rectified Linear Activation) function (Eq. 1).

$$R(z) = \max\,(0, z) \ \ldots \qquad \text{Eq (1)}$$

In Eq.1, R(z) is the output which is the maximum of two values. It is best suited for the convolutional layer activations for the application of image classification. For Conv1D the assigned padding type is "*same*", with this type of padding the layers output will have the same spatial dimensions as its input when the stride = 1. Using *"same*" padding type ensures that the filter is applied to all the elements of the input. This results in the output size being mathematically convenient for further computations.

TABLE II: *Individual Number of Beats*

Sub Classes	Training Beats
Normal Beats	1000
Left Bundle Branch Block Beat	1000
Right Bundle Branch Block Beat	1000
Nodal Junction Escape Beat	1000
Atrial Escape Beat	1000
Aberrated Atrial Premature Beat	1500
Premature/ Ectopic Super ventricular Beat	1250
Nodal Junction Premature Beat	1250
Atrial Premature Beat	1503
Ventricular Flutter Wave	1500
Ventricular Escape Beat	1750
Premature Ventricular Contraction	1750
Fusion of Ventricular and Normal Beat	3000
Paced Beat	2000
Unclassifiable Beat	1500
Fusion and Paced and Normal Beat	2000

Table III: *ArrhyNet Architecture*

Model Layers	Specifications of Layers
Conv1D	filter size = 16, kernel size = 30, strides =1, activation = 'relu', padding = "same", input shape = (200,1)
MaxPooling1D	pool size =2
Conv1D	filter size =32, kernel size=21, strides=1, activation="relu", padding="same"
MaxPooling1D	pool size =2
Conv1D	filter size =64, kernel size=15, strides=1, activation="relu", padding="same"
Conv1D	filter size =128, kernel size=7, strides=1, activation="relu", padding="same"
MaxPooling1D	pool size =2
Conv1D	filter size =256, kernel size=3, strides=1, activation="relu", padding="same"
Conv1D	filter size =512, kernel size=3, strides=1, activation="relu", padding="same"
MaxPooling1D	pool size =2
GlobalMaxPooling1D	data format="channels_last"
Flatten	Flattens the layers
Dense	units = 256, activation="relu"
Dense	units = 64, activation="relu"
Dense	units = 5, activation="softmax"

For the CNN model the utilized *MaxPooling1D Layer* has the default pool size = 2 and *GlobalMaxPooling1D Layer* has the default parameters set for the optimum results. The *Flatten Layer* is used before the *Dense Layer* in-order to flatten out the data before it is given as an input to the *Dense Layer* which ensures smooth transition of information to the single dimension. Units defined in the dense layers establishes the number of neurons in that layer under operation. Since it is a five class multi class classification the output dense layer has five neurons. *"Softmax"* activation function is utilized as the activation function for the final layer of CNN model. Softmax activation function is incorporated since it normalizes the output of the network to a probability distribution over predicted output class. It scales inputs into probabilities making it an ideal application in our model.

$$\sigma(\vec{z})_i = \frac{e^{z_i}}{\sum_{j=1}^{K} e^{z_j}} \ldots \qquad \text{Eq (2)}$$

Eq (2) defines the Softmax function where $\vec{z}$ is the input vector, σ is the Softmax function, e^{z_i} is the standard exponential function for input vector, K is the number of classes in the multi-class classifier. In this case K=5, e^{z_j} is the standard exponential function for output vector.

IV. Results and Performance Analysis

The *ArrhyNet* CNN model is compiled with a total number of epochs = 20 as an increase in the number of epochs may result in overfitting of the model. The *adam* optimizer is used for compilation and it performs weights upgradation iteratively based on training data. *SparseCategorialCrossentropy* is the implemented CNN loss function since the classes are mutually exclusive. It is used to optimize the classification model. The following section presents the performance metrics for our model.

A. Performance Evaluation

Accuracy is one of the metrics of performance evaluation, it is equal to the fraction of number of correct predictions divided by total number of predictions. Eq (3) gives the accuracy for binary classification. *TP, TN, FP*, and *FN* represent *True Positive, True Negative, False Positive* and *False Negative* values respectively of the classified data. Multiclass classification is calculated using the *scikit-learn* package in python as seen in the classification report in Table IV. Considering all the factors the results indicate that the overall top-1 accuracy achieved is 92.73 %.

Precision, Recall and *F_1 score* (Eq (4) – Eq (5)) are the other performance metrics for the multi-class classification model evaluated in this paper. Precision is defined as the ratio of correct positive predictions out of all positive and negative predictions. Recall is described as the number of correct positive predictions made from all positive predictions. Recall provides the indication of missed positive prediction and F_1 score is the harmonic mean of precision and recall. The macro-average i.e., the mean average of precision/recall/F_1 score for all classes are 91 %, 92 % and 91 % respectively. The weighted average of all classes is 93 % for all data sets. Table IV gives the detailed Classification Report of Five Class Classification. The report gives the class wise precision, recall and F1-Score for the count of testing beats per class. Out of 1572 test beats 1539 are classified as True positives for class 0 indicating a very good performance.

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \ldots \qquad \text{Eq (3)}$$

$$Precision = \frac{TP}{TP + FP} \ldots \qquad \text{Eq (4)}$$

$$Recall = \frac{TP}{TP + FN} \ldots \qquad \text{Eq (5)}$$

$$F_1\ Score = \frac{2 * Precision * Recall}{Precision + Recall} \ldots \qquad \text{Eq (6)}$$

Table V gives the Confusion Matrix (CM) which gives the visualization of the performance of the algorithm.

Table IV*: Classification Report*

	Precision	**Recall**	**F1-Score**	**Support**
0	0.98	0.98	0.98	1572
1	0.79	0.95	0.86	968
2	0.94	0.90	0.92	673
3	0.87	0.88	0.88	242
4	0.98	0.89	0.93	1818
accuracy			0.93	5273
macro avg	0.91	0.92	0.91	5273
weighted avg	0.93	0.93	0.93	5273

Figure.2 gives the Receiver Operating Characteristic (ROC) Curve and Area Under Curve (AUC) for individual classes from the CNN model. All five classes have AUC above 90%.

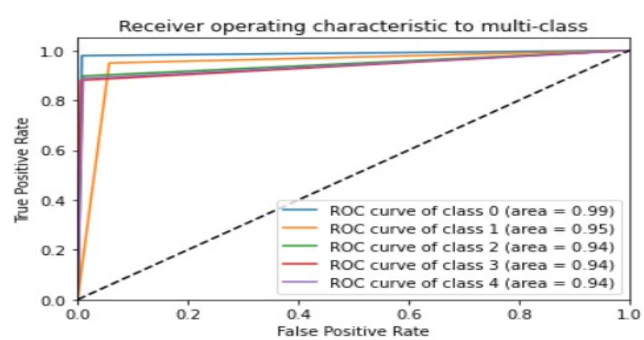

Fig.2 ROC Curve and AUC for all Classes

V. Conclusion

Detection and classification of arrhythmia is critical in the treatment of irregular heart rhythms. This paper presents a systematic methodology to achieve high accuracy arrhythmia classification using a custom CNN called *ArrhyNet* for classification of arrhythmia pertaining to AAMI standards into five classes. After pre-processing the data for denoising and over sampling to address data imbalance we used Daubechies Wavelet transform for feature extraction. The study achieved an overall top-1 accuracy of 92.73 %. The classification report and confusion matrix give a clear picture of the high-performance evaluation on *Precision, Recall* and *F1 score* of the proposed multi-class classification model.

Table V: *Confusion Matrix*

	Actual Class					
Predicted Class	**Class**	**0**	**1**	**2**	**3**	**4**
	0	1539	32	1	0	0
	1	17	919	10	9	13
	2	0	43	604	6	20
	3	1	22	4	213	2
	4	11	150	26	16	1615

Acknowledgements

Research reported in this paper was supported in part by National Institute of General Medical Sciences of the National Institutes of Health under award number 1SC3GM096937-01A1. The content is solely the responsibility of the authors and does not necessarily represent the official views of NIH.

References

[1] Georgios Petmezas, Kostas Haris, Leandros Stefanopoulos, Vassilis Kilintzis, Andreas Tzavelis, John A Rogers, Aggelos K Katsaggelos, Nicos Maglaveras, “Automated Atrial Fibrillation Detection using a Hybrid CNN-LSTM Network on Imbalanced ECG Datasets,”*Biomedical Signal Processing and Control*, vol. 63, 102194, Jan. 2021.

[2] C. Hao, S. Wibowo and K. S. Rajput, "Compressive Sampling Based Multi-Spectrum Deep Learning for Sub-Nyquist Pacemaker ECG Analysis," *2020 42nd Annual International Conference of the IEEE Engineering in Medicine & Biology Society (EMBC)*, Montreal, QC, Canada, 2020, pp. 357-360, doi: 10.1109/EMBC44109.2020.9175625.

[3] Evangelin Dasan, Ithayarani Panneerselvam,“A novel dimensionality reduction approach for ECG signal via convolution denoising autoencoder with LSTM,” in *Biomedical Signal Processing and Control*, vol. 63, 102225, Jan. 2021.

[4] Suyash Ghuge, Nishant Kumar, Tilak Shenoy, Sowmya Kamath S, “Deep Neural Network Models for Detection of Arrhythmia based on Electrocardiogram Report”. *2020 11th International Conference on Computing, Communication and Networking Technologies (ICCCNT)*, Kharagpur, India, pp. 1-7, doi: 10.1109/ICCCNT49239.2020.9225534, 1-3 Jul. 2020.

[5] Fei-yan Zhou, Lin-peng Jin, Jun Dong, “Premature ventricular contraction detection combining deep neural networks and rules inference,” *Artificial Intelligence in Medicine*, vol.79, pp. 42–51, Jun. 2017.

[6] Abdul Qayyum, Fabrice Meriaudeau, Geneviev C Y Chan,“Classification of Atrial Fibrillation with Pre-Trained Convolutional Neural Network Models,” *2018 IEEE-EMBS Conference on Biomedical Engineering and Sciences (IECBES)*, Sarawak, Malaysia, pp. 594-599, doi: 10.1109/IECBES.2018.8626624, 3-6 Dec. 2018.

[7] Jing Jiang, Huaifeng Zhang, Dechang Pi, Chenglong, “A novel multi-module neural network system for imbalanced heartbeat classification,” *Expert Systems with Applications: X*,Volume 1,100003, Apr. 2019

[8] Saumendra Kumar Mohapatra, Geetika Srivastava, Mihir Narayan Mohanty, “Arrhythmia Classification using Deep Neural Network,” in *2019 International Conference on Applied Machiene Learning (ICAML)*,vol.1, no.63,pp. 296-300, 25-26 May. 2019.

[9] Sachin Singh, Animesh,Thomas Penzel, “Classification and Detection of Heart Rhythm Irregularities using Machine Learning,” *2020 First International Conference on Power, Control and Computing Technologies (ICPC2T)*, Raipur, India, 2020, pp. 438-442, doi: 10.1109/ICPC2T48082.2020.9071495.

[10] H. Yang and Z. Wei, "Arrhythmia Recognition and Classification Using Combined Parametric and Visual Pattern Features of ECG Morphology," in IEEE Access, vol. 8, pp. 47103-47117, 2020, doi: 10.1109/ACCESS.2020.2979256.

[11] Xin-Cheng Cao, Bin Yao, Bin-Qiang Chen, “Atrial Fibrillation Detection Using an Improved Multi-Scale Decompotion Enhanced Residual Convolution Neural Network” in *IEEE Access Special Section On Data-Enabled Intelligence for Digital Healt. Digital Object Identifier*, vol. 7, pp. 89152 – 89161, 04 Jul. 2019.

[12] U. Rajendra Acharya, Hamido Fujita, Oh Shu Lih, Yuhi Hagiwara, Jen Hong Tan, Muhammad Adam, “Automated detectionof arrhythmia using different intervals of tachycardia ECG segments with convolution neural network,”*Information Sciences*,vol. 405, pp. 81-90, Sep. 2017

[13] Rizqi Hadi Prawira, Adi Wibowo, Ajif Yunizar Pratama Yusuf, “Best Paramneters Selection of Arrhythmia Classification Using Convolution Neural Network,” *2019 3rd International Conference on Information and Compuatation Sciences (ICICoS)*, Semarang, Indonesia, pp. 1-6, doi: 10.1109/ICICoS48119.2019.8982418, 29-30 Oct. 2019.

[14] Runnan He, Yang Liu, Kuanquan Wang, Na Zhao, Yongfeng Yuan, Qince Li, Henggui Zhang, “Automatic Cardiac Arrhythmia ClassificationUsing Combination of Deep Residual Netwok and Bidrectional LSTM,” in *IEEE Access*, vol. 7, pp. 102119-102135, 2019, doi: 10.1109/ACCESS.2019.2931500.

[15] Suyash Ghuge, Nishant Kumar, Tilak Shenoy, Sowmya Kamath S, “Deep Neural Network Models for Detection of Arrhythmia based on Electrocardiogram Report”. *2020 11th International Conference on Computing, Communication and Networking Technologies (ICCCNT)*, Kharagpur, India, pp. 1-7, doi: 10.1109/ICCCNT49239.2020.9225534, 1-3 Jul. 2020.

[16] Goldberger, A., et al. "PhysioBank, PhysioToolkit, and PhysioNet: Components of a new research resource for complex physiologic signals. Circulation [Online]. 101 (23), pp. e215–e220." (2000).

[17] Elif IZCI, Mehmet Akif OZDEMIR, Murside DEGIRMENCI and Aydin AKAN, “Cardiac Arrhythmia Detection from 2D ECG Images by Using Deep Learning Technique,” in *2019 Medical Technologies Congress(TIPTEKNO)*, Izmir, Turkey, pp. 1-4, doi:10.1109/TIPTEKNO.2019.8895011, 3-5 Oct. 2019.

[18] Mohamed Hammad, Abdullah M Iliyasu, Abdullamit Subasi, Edmond S. L. Ho and Ahmed A. Abd El-Latif, “A Multi-tier Deep Learning Model for Arrythmia Detection,” in *IEEE Transactions on Instrumentation and Measurement*, vol. 70, pp. 1-9, 2021, Art no. 2502809, doi: 10.1109/TIM.2020.3033072, Oct.2020.

[19] D. Wang et al. “Automatic Detection of Arrhythmia Based on Multi-Resolution Representation of ECG Signal” Sensors (Basel) 2020 Mar; 20(6): 1579. Published online 2020 Mar 12. doi: 10.3390/s20061579

[20] Ye C., Kumar B.V., Coimbra M.T. “Heartbeat classification using morphological and dynamic features of ECG signals”, IEEE Trans. Biomed. Eng. 2012; 59: pp. 2930–2941.

[21] Acharya et al. “Automated Characterization of Arrhythmias Using Nonlinear Features from Tachycardia ECG Beats”; Proceedings of the 2016 IEEE International Conference on Systems, Man, and Cybernetics (SMC); Budapest, Hungary. 9–12 October 2016; pp. 000533–000538.

[22] A.Y. Hannun et al. “Cardiologist-level arrhythmia detection and classification in ambulatory electrocardiograms using a deep neural network” Nat Med 25, 65–69 (2019). https://doi.org/10.1038/s41591-018-0268-3.