Heart Arrhythmia Detection with Novel Approach H3-SAD

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Abstract— **Research on signals collected from the human heart has been a core subject area as the heart displays a rich set of dynamical information that needs careful analysis for medical diagnosis and treatment. The acquisition of the electrical activity signals is a convenient way to analyze, control, evaluate and understand the heart. Electrocardiography (ECG) measurements are used to categorize the heartbeat behaviors to achieve classification. ECG heartbeat signal classification methods range from classical signal processing to convolutional neural networks. Heterogeneous Harmonization of Heartbeat Signals for Arrhythmia Detection (H3-SAD) method based CNN is proposed in this study. H3-SAD method differs from other methods in the literature with its robust and tempered classification ability against heterogeneous spectrums of ECG Signal by targeting being a part of high mobility lifestyle. Literature studies have reasonable estimation rates for MIT-BIH Dataset but not for the heterogeneous acquisition of data in real-life applications. The key point that tempers our classification algorithm is applied dynamic augmentation details towards different signal sources and input values that adduct data to real-life, and heterogeneous augmentation-based CNN architecture.**

I. Introduction

The increasing industry needs and the fast-paced life marathon in our lives have brought about various changes in our lifestyle like diet, the form of entertainment, stress relief, lack of sports activities that result in unhealthy routines. These routines bring humankind's life lots of disease in its root. Although technological developments and humanity increase its presence in discoveries, investments for the solution of health problems cause very high costs. One of the most important effects of unhealthy routines is based on blood vessels and heart problems that tackle under the Cardiovascular System Diseases. Key symptoms of CVDs are included hypertension, obesity, diabetes, smoking, hyperlipidemia, and lack of physical activities as mentioned in [1]. All of these factors cause lots of deaths. Over 17 million people died from CVDs in 2019 as an estimation that equivalent to 32 percent of all cases in the world and 85% of these mortalities are caused by heart attacks and stroke according to [2]. The way that we can keep track of these abnormalities controlling some of the morphological sides of the human body is arrhythmia monitoring. Apart from correct and accurate real-time monitoring of heartbeat, classification of heartbeat is another crucial for the detection of heart arrhythmia in the early phase. Therefore, arrhythmias are the focus of the study. Heart Arrhythmia means erratic heartbeats. In this work, the electrical disorder and symptom type of the heartbeat are categorized and classified under five types of heartbeats. Arrhythmias under the non-life-threatening category [2] can be classified into N, S, V, F, and Q means respectively non-ectopic, supraventricular ectopic, ventricular ectopic, fusion, and unknown.

One of the most popular data for working on the issue is MIT-BIH Arrhythmia Database [3] consists of Holter recordings that hold over 4000 long-term records obtained in Beth Israel Hospital Arrhythmia Laboratory between 1975 and 1979. Approximately 60% of these recordings were obtained from inpatients between ages 24 and 89. The database contains 48 records, each record consisting of "atr", "dat", "hea", and "xws" files. Each of these files is required to exist in the project directory for complete data processing. Each of the recordings is approximately 30 minutes long and taken by 360 Hz. Dataset has it is own reading methods. PhysioNet – WFDB is the main environment for reading signals, classifying them, and putting their classes/annotations into the neural networks.

Arrhythmias characteristics can be briefly represented with the keywords such as slow, fast, or irregular heartbeat. MIT-BIH Arrhythmia Database has 15 types of annotations for heartbeats. Some of these types are known as sub-types and some of them are ancestors. Our study focuses on five of these classes. N-Type, V-Type, F-Type, S-Type, and Q-Type are the five of general distribution. These heartbeat types denote Non-Ectopic, Supra Ventricular Ectopic, Ventricular Ectopic Beat, Fusion Beat, and Unknown Beat respectively. Each of the ECG heartbeats has 260 signal samples long.

MIT-BIH Arrhythmia Database has many noisy heartbeat signals, an unbalanced set of distribution, and insufficiency of some classes. Unfortunately, these heartbeats classes have an unbalanced amount of distribution. N, V, F, S, and Q types of heartbeats are the classes that are not represented equally in the database. American Hospital Association Annotation Codes are N, V, F, E, P, Q, and O respectively. As seen in Table 1, our dataset has imbalanced distribution. "." Type (N-Type in AHA Codes) has predominance on other heartbeat types. We are unable to collect data for missing class types. This situation affects the accuracy paradox in our Convolutional Neural Network (CNN) if the issue is not addressed with the correct paradigm. These noises, distribution, and insufficiency in the ECG Signals can affect CNN negatively because sensing different spectrums for the same class type can cause an imbalance in the system.

Our purpose is to propose a method yielding high accuracy and having capabilities for wearable devices that can detect diseases in a short period. Our approach differentiates from the existing body of literature from the points of robust data augmentation and enhanced background

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noise-canceling capability. The main novelty of our approach is a robust synthetic data generation method for poor classes that will help accurate feature extraction process in real-time and varying data gained from different human sources. Furthermore, the proposed method contributes literature as a new level of training and evaluating of ECG Heartbeat Signal with its lightweight capacity.

This paper is organized as follows: the second section discusses the related works; the third section explains the proposed H3-SAD approach. The results are discussed in the fourth section, and the fifth section is devoted to the concluding remarks. Lastly, we discuss potentially valuable future works.

II. RELATED WORKS

Identified studies and discussions exist in the literature related to ECG Heartbeat Classification in a similar problem domain as heart arrhythmias-based signal preprocessing, machine learning, or neural network solutions. The distinguishing point of this study is applying a novel approach for synthetic data generation that creates a robust feature extraction capability for convolutional neural networks and getting classification to another level that makes detection processes faster and more resilient against unknown data in real-life applications.

It is more difficult to detect some classes such as Supraventricular Ectopic Beats, Fusion Beats, and also Unknown Beats due to the biological topology as well as the deficiencies in the dataset. MIT-BIH, which was taken as a reference for literature research on such an important subject for humanity, was made available between 1989 and 1992. The most crucial point that our algorithm solves is the input factor that misleads CNN. It offers a powerful classification capability independent of the input source for real-life applications. Thus, H3-SAD brings a new quest by changing his understanding of literature research due to the fact that creating a new input space based on robust CNN for a specific type of data that belongs to the root class but can be missed by the traditional systems.

The study proposed in [4] is a deep learning approach to identify five types of ECG Heartbeat automatically which focuses on cardiac arrhythmia. Developed 9 Layers of CNN able to classify N, S, V, F, and Q Types of heartbeats. Each of these operations applied to ECG signals in triplicate to extract feature maps and obtain estimations. Various kernel sizes, regularization rate, learning rate, and momentum are handled with the brute force method in this work, and biases and weights are updated with the chain rule. It covers weight update use x/n multiplication common in both bias and weights and also $x\lambda$/r multiplication for weight only where x, λ, n, and r is learning rate, regularization, the total number of training samples, and unknown parameters respectively. Two sets of data were processed in this work as segmented A and B sets with 93.47% and 94.03% accuracies respectively in 20 epochs. Synthetics Data Generation is performed under Z-Score and Standard Deviation procedures. Furthermore, the Pan-Tompkins algorithm is used for R-Peak detection and Daubechies Wavelet Filter 6 is used for denoising ECG Signals. The Synthetic Data Generation process is too poor for the exact detection of outer sets of data in real life. Also, Daubechies filter does not bring advantages to the process. Moreover, some of the classes like S and F achieve accuracy saturation delayed in this approach because of data distribution and augmentation. Finally, there are open doors like “r” and infinity barrier for coefficients in updating equations for weights updating in this method.

Ziyu et al. proposed an attentional CNN model for the diagnosis of heart arrhythmia in [5]. According to the author’s claims, traditional ML algorithms and models takes time-consuming preprocessing and feature extraction that depends on the area of interest knowledge. The proposed model named by Attention Based Convolutional Neural Networks takes benefits of multi-head attention and convolution operations to obtain an informative classification for raw ECG data. ABCNN automates the process of extraction of special representations taught by raw ECG signals to achieve the exact identification of arrhythmia. Attention mechanism combined with CNN such a manner to prioritize important information in the signal set. The brilliant part of this work is to apply weights by the multi-head attention method. This method is applied by paying more attention to the signature's most important ones. Then, weights are broadcasted to all same shapes and updating samples based multiplication of elements. This is not affirmed but it can be a good solution for study [4]. The designed attention layer is the focal side of this work but the most important ECG signal can be varied according to the patient and it is not a savior for lightweight systems.

The proposed study in [6] unveils a novel approach by using recurrent neural networks for classifying arrhythmias. The author's proposal encompasses a machine-learning approach for a more challenging setting. They focus on harnessing the native beat-wise separation of ECG signals to facilitate learning of subjection on the temporal format. Moreover, the study used stacked denoising autoencoders to observe differences in morphologic context. Finally, the proposed RNN is empowered by a soft attention mechanism that activates sensing which segments are prioritized for decision-making of themselves.

Jing et al. proposed Adversarial Convolutional Neural Network for interpatient heartbeat classification in [7]. The main goal of this study is to create a generalized model to unknown patients’ heartbeats identified by their deep learning-based framework. The study tackles the generalizable features by introducing adversary loss into the convolutional neural networks. Model assisted to master by an inadequate amount of subject owing to the adversary game. The proposed framework comprises classifier, encoder, and adversary sub-networks. The adversary is the inventive side of this work but robustness requires more spatio-temporal diversity in the data side among interpatient variability.

Novel approaches both CNN-based and traditional solutions like signal processing and transforming signal in the pre-classification phase are proposed also in [8-13] for detecting cardiac arrhythmia. Authors process ECG signal through denoising, signal processing and transforming, QRS peak detection both based R-Peak and also a combination of P, Q, R, S and T Peaks together, segmentation of heartbeat, and data augmentation before classification step. Each of the studies has better overall accuracy among its related studies, but this is also not sufficient for real-life application. Because the main reference for the dataset is MIT-BIH Arrhythmia similar to other works with poor data augmentation techniques. Proposed studies do not rely on heterogeneous data topology.

All studies have high accuracy and typical CNN models or good estimations for the classification of heartbeat arrhythmia. There are more studies not mentioned here that also exist for arrhythmia classification too, but these applications are not enough on one major side called resistant ubiquity against real-life data spectrum. None of these models are ready to operate against challenging real-life patient data under the variety of signal acquisition methods. So, our proposed work will be a step further than other approaches. It brings a novel application for ECG Arrhythmias in its base ubiquity resistance against real-life needs. Our framework has robust classification capability that can tolerate different spectrums of data segments against variable conditions for ECG Arrhythmias.

III. PROPOSED STUDY

The most challenging part of the detection and classification of arrhythmia classes is identifying heartbeat data among heterogeneous ECG signals correctly. Our theory is about normal neural network classification algorithms by use standard augmentation methods are incompetent because of poor reaction capabilities to detect arrhythmia. H3-SAD covers Substitution, Upscaling, Downscaling, Wave-Segment Shifting, QRS Geneticization, Magnitudization, Time-Chopping/Expansion, Extra-Noising, and Mirroring operation separately as well as light-weight convolutional neural network operations. It generates synthetically enhanced real-life focused heartbeat signals in the augmentation phase.

The first phase is LPCEH (Low Probability Coefficient Extraction for Heartbeats) which means achieving data builder coefficients for the augmentation phase. Synthetic data generation rate for each data type determined by (1) means scaling factor multiplied by synthetic data count divided by actual data count in MIT-BIH.

$$G = S \times (\rho / N) \quad (1)$$

Annotation processing covers the acquisition of heart signals towards Two-Tailed Z-Score around built-in R-Peaks presented by WFDB outputs and classification into separate structures that allow us independent data processing for each augmentation phase. S and Z-Score Threshold were obtained by brute force. Augmentation results achieved by applied methods can be seen in Fig. 1 with a detailed description.

A. *Augmentation and Novel Dataset*

Substitution application covers both pure shuffle operation and mirror-based shuffle operations in the augmentation phase. α, β, and γ are start and end mirroring indexes and signal length respectively. Shuffle operation does not affect the QRS-Complex to avoid topological change in the signal.

$$ECG_{1\text{ to }\alpha} = [h_1, h_2, \ldots\ldots, h_\alpha] \quad (2)$$

$$ECG_{\alpha\text{ to }\beta} = [h_\alpha, h_{\alpha+1}, \ldots\ldots, h_\beta] \quad (3)$$

$$ECG_{\beta\text{ to }\gamma} = [h_\beta, h_{\beta+1}, \ldots\ldots, h_\gamma] \quad (4)$$

Upscaling and downscaling are applied in the augmentation phase to adjust and strengthen signal spectrum hits in a specific range that can be differentiated in real-life sensor measurement capability differences. Scaling factors for up and down operations were determined as 0.047 during the determination of adjustment coefficient by brute-force as $\daleth$ in minimal ranges.

$$ECG_{1\text{ to }\gamma} = [h_1+\daleth, h_2+\daleth, \ldots\ldots, h_\gamma+\daleth] \quad (5)$$

$$ECG_{1\text{ to }\gamma} = [h_1-\daleth, h_2-\daleth, \ldots\ldots, h_\gamma-\daleth] \quad (6)$$

Wave-Segment Shifting is another method to achieve a better data perspective in the augmentation phase. It is a normal shift operation except by taking under consideration the QRS-Complex of the signal. τ is determined by brute-force and augmentation output protected against any negative effect to CNN results.

$$ECG_{1\text{ to }\gamma} = [h_\tau, h_{\tau+1}, \ldots\ldots, h_{\tau+\gamma}] \quad (7)$$

QRS Geneticization is a novel approach to achieve strictly the same but a little mutation in the genealogy of signal. Robust classification requires the detection of the different spectrums of data. Acquisition of fresh data from scratch is a costly case due to human, material, and environmental factors. Especially if the data will be obtained from sources of different quality and categories, this situation is much more difficult. QRS-Complex is the first affected point in this augmentation phase. QRS-Complex's min and max hit difference is ϕ and randomly generated hit between min and max is ζ.

$$ECG_{QRS\text{-}\alpha\text{ to }QRS\text{-}\beta} = [(h_\phi+\zeta)_\alpha, (h_\phi+\zeta)_{\alpha+1}, \ldots\ldots, (h_\phi+\zeta)_\beta] \quad (8)$$

Magnitudization means adjusting specific points by enlargement operation. This method is also affects QRS-Complex in minimal ranges. Moreover, magnitudization affects P and T Waves also with enlargement factor.

$$ECG_{1\text{ to }\alpha\,|\,\ldots\,|\,\Omega\text{ to }\psi} = [h_1+\vartheta_1, h_2+\vartheta_2, \ldots, h_\Omega+\vartheta_\nu, h_\Omega+\vartheta_{\nu+1}, \ldots, h_\psi] \quad (9)$$

Time-Chopping/Expansion is using mirroring and permutation with some product-based enlargement operations. The crucial operation point of this method is adding smooth vector transition to signal by protecting signal topology.

$$ECG_{1\text{ to }\alpha} = [h_\eta, h_{\eta+1}, \ldots\ldots, h_\alpha] \quad (10)$$

$$ECG_{\alpha\text{ to }\beta} = [h_1, h_2, \ldots\ldots, h_\eta] \quad (11)$$

$$ECG_{\beta\text{ to }\gamma} = [h_{\eta+CL}, h_{\eta+CL+1}, \ldots\ldots, h_\gamma] \quad (12)$$

The Wave-Segment Extra-Noising method is adding extra noise to the signal. Denoising operations are decent for the classification phase but achieving robust results requires extra impairments in the signal. White Gaussian Noise is used in this phase. Signal Extra Noise Power is acquired by brute-force as 26.

$$ECG_{1\text{ to }\gamma} = \text{WGN}[h_1, h_2, \ldots\ldots, h_\gamma] \quad (13)$$

The Wave-Segment Mirroring method is extracting specific parts of the signal that is similar to the right or left flip side of it and alters that part with the reflection portion. Detection of similar twins is based on brute force.

B. *Segmentation*

Thereafter applied synthetic data generation process three sets of data prepared. The first one is raw data that consists of 0.2 test and 0.8 train data of root pool. The second one is augmented data 0.2 test and 0.8 data of obtained result from Section A. Third one is a mixture of the first two sets to execute robust training backbone. Heterogeneous harmony between different data spectrums brings a strong capability to the classification phase. Each set of data was evaluated through our CNN model. There are more details available in the section CNN Architecture and Results.

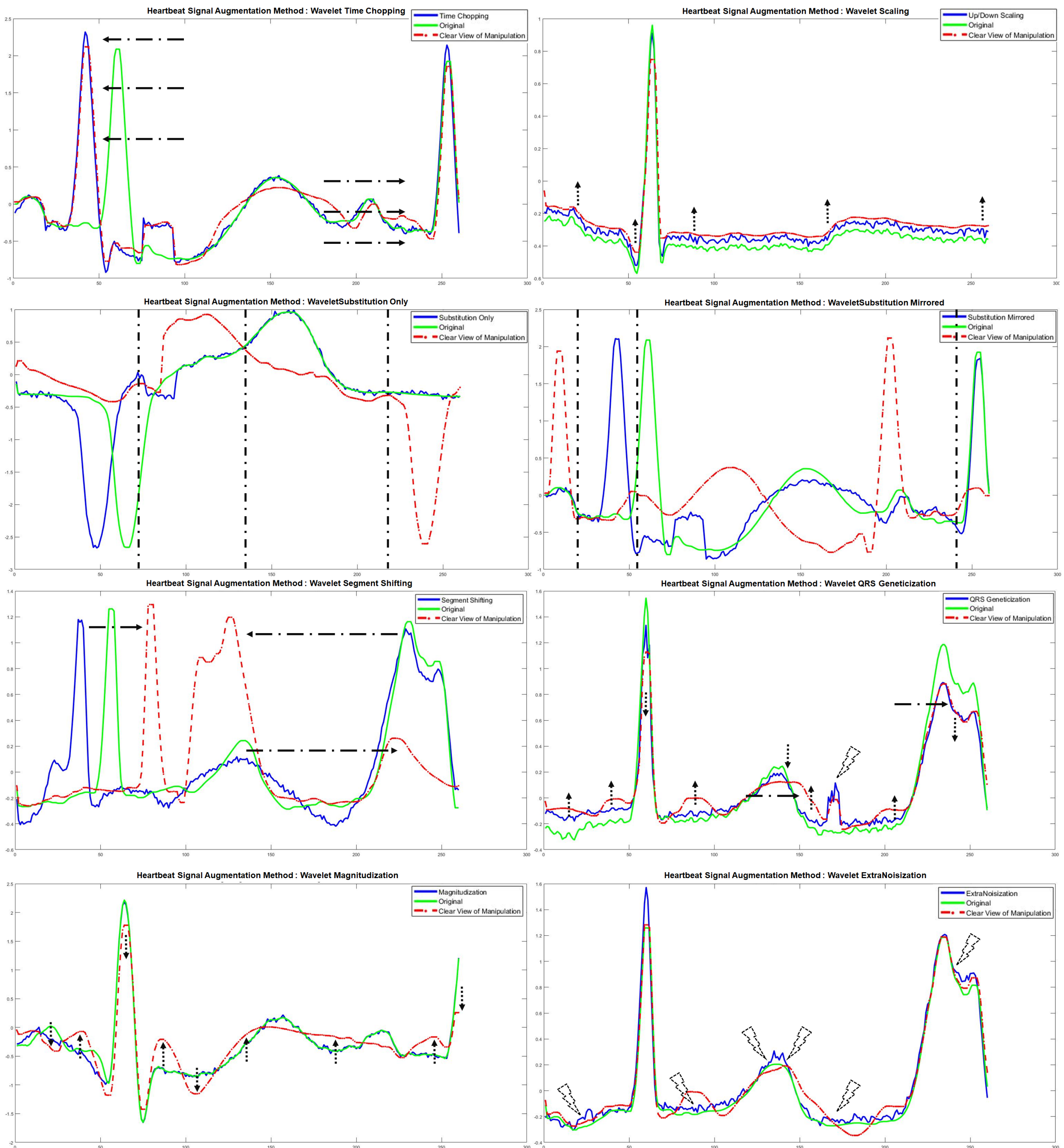

Fig. 1. Synthetic Data Generation Results. It consist Time Chopping/Expansion, Up-Down Scaling, Substitution, Shifting QRS Geneticization, Magnitudization and Extra-Noising operations.

C. CNN Architecture

Convolution, Max-Pooling, Fully-Connected and Flatten Layers are used in the proposed architecture as seen in Table 1. Only convolution and connected layers have an activation function. The activation function is used as Sigmoid. It is a lightweight CNN architecture with robust classification capabilities. The input size varies across the CNN Layers determined by the window positions of the P, Q, R, S, and T Wave in the signal. Weights and Biases updated by (14) and (15).

$$\Delta \omega_\iota (t+1) = \Delta \omega_\iota (t) - r \frac{\partial C}{\partial \omega_\iota} \quad (14)$$

$$\Delta \beta_\iota (t+1) = \Delta \beta_\iota (t) - \frac{r}{s} \frac{\partial C}{\partial \beta_\iota} \quad (15)$$

$$ECG_{out(1\rightarrow\lambda)} = \sum_{\alpha=1}^{T-1} ECG_{in(\alpha)} f_{\lambda-\alpha} \quad (16)$$

The weight equation has chain rule and regularization rate used as 0.2 and bias update rule has a number of training samples in the process as well regularization rate too.

TABLE I. LIGHTWEIGHT CNN ARCHITECTURE

Layer No	Layer Type	Layer Size	Layer Depth	Kernel Size
0	Input	1 x 260	N/A	N/A
1	Convolutional	1 x 260	3	5
2	Activation	1 x 196	3	5
3	Max-pooling	1 x 196	3	5
4	Flatten	1 x 153	1	5
5	Connected	1 x 765	1	1
6	Activation	1 x 5	1	N/A

In addition to the weight and bias procedures, convolution operations executed through (16) where λ, α, T, and f are ECG Signal Current Index, ECG Signal Boundary Index, ECG Signal Length, and CNN Filter respectively. Fig. 2. shows the flow diagram of the proposed H3-SAD in detail.

IV. RESULTS

Proposed H3-SAD based lightweight convolutional neural network training process for ECG Heartbeat classification completed with different sets of Test/Train Signals around 20% and 80% rule. The proposed algorithm was implemented without a framework in MATLAB with an Intel Core i5 4200H 2.8 GHz Processor and 8GB of RAM. The time consumption to obtain the data augmentation results took 348.43s. In addition, each training epoch took 5947.29s, 2731.91s, and 5817.32s, respectively for Table II-IV.

The standard distribution of data segments in the literature is obtaining test data directly from pre-processed data that has denoising operations. The proposed study has preprocessed-preprocessed, preprocessed-augmented, and preprocessed-mixed data segmentations. Preprocessed keyword means that dataset contains original data after denoise operations. Augmented keyword means that obtained dataset after synthetic data generation operations. Mixed keyword means the dataset that contains both augmented and preprocessed together.

The proposed CNN architectures or other classification methods achieve high accuracies above 90%. However, these results are not effective for heterogeneous data. It means that accuracy decreases in the case of existing different data spectrums despite their characteristics being the same. Total accuracy after the preprocessed-augmented phase is between 50% and 60% despite it having 97.1% accuracy as seen in Table II for only preprocessing approach.

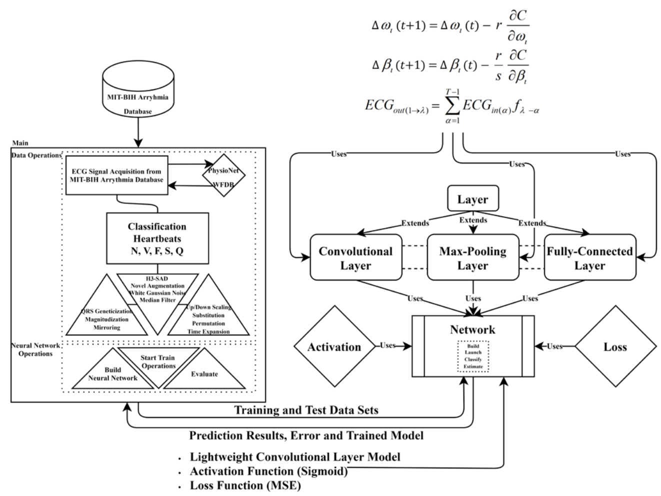

Fig. 2. H3-SAD Flow Diagram

TABLE II. PREPROCESSED TRAIN SET & PREPROCESSED TEST SET

N Type	S Type	V Type	F Type	Q Type	Conf. Matrix
6146 22.5%	0 0.0%	24 0.1%	49 0.2%	324 1.2%	93.9% 6.1%
0 0.0%	5562 20.4%	0 0.0%	1 0.0%	0 0.0%	100.0% 0.0%
1 0.0%	0 0.0%	5107 18.7%	123 0.5%	263 1.0%	93.0% 7.0%
0 0.0%	0 0.0%	1 0.0%	568 2.1%	0 0.0%	99.8% 0.2%
0 0.0%	0 0.0%	1 0.0%	7 0.0%	9153 33.5%	99.9% 0.1%
100% 0.0%	100% 0.0%	99.5% 0.5%	75.9% 24.1%	94.0% 6.0%	97.1% 2.9%

H3-SAD method increases ECG Heartbeat Classification accuracy from 56.8% to 93.5% with its robust heterogeneous augmentation methods. The detailed dataset signal amounts during the CNN operations for preprocessed train, preprocessed test, preprocessed & mixed test, and preprocessed & augmented test are respectively 75722, 27330, 79421, 26595, 41560, and 12920. Thus, we achieve better results in case considering the lack of literature and real-life needs for ECG Heartbeat Classification.

According to our study, special approaches in the literature are not satisfactory enough and not ready to apply for real-life based on traditional processing techniques. CNN classification accuracy is falling down seriously as seen in Table II-IV when the system inputs are diversified as some conceptual conditions in terms of heterogeneity. H3-SAD brings a robust classification backbone for ECG Heartbeat Classification by increasing accuracy by almost 40%.

TABLE III. PREPROCESSED TRAIN SET & AUGMENTED TEST SET

N Type	S Type	V Type	F Type	Q Type	Conf. Matrix
1807 14.0%	346 2.7%	416 3.2%	390 3.0%	407 3.2%	53.7% 46.3%
21 0.2%	1236 9.6%	0 0.0%	0 0.0%	0 0.0%	98.3% 1.7%
634 4.9%	871 6.7%	2135 16.5%	1040 8.0%	982 7.6%	37.7% 62.3%
0 0.0%	0 0.0%	2 0.0%	1103 8.5%	139 1.1%	88.7% 11.3%
122 0.9%	131 1.0%	31 0.2%	51 0.4%	1056 8.2%	75.9% 24.1%
69.9% 30.1%	47.8% 52.2%	82.6% 17.4%	42.7% 57.3%	40.9% 59.1%	56.8% 43.2%

TABLE IV. PROPOSED TRAIN SET & TEST SET

N Type	S Type	V Type	F Type	Q Type	Conf. Matrix
4820 18.1%	0 0.0%	4 0.0%	5 0.0%	0 0.0%	99.8% 0.2%
22 0.1%	8146 30.6%	0 0.0%	0 0.0%	0 0.0%	99.7% 0.3%
181 0.7%	0 0.0%	5006 18.8%	12 0.0%	0 0.0%	96.5% 3.5%
448 1.7%	0 0.0%	732 2.8%	3320 12.5%	0 0.0%	73.6% 26.2%
3 0.0%	0 0.0%	337 1.3%	1 0.0%	3558 13.4%	91.3% 8.7%
88.1% 11.9%	100.0% 0.0%	82.3% 17.7%	99.8% 0.2%	100.0% 0.0%	93.5% 6.5%

V. CONCLUSION

The proposed H3-SAD study covers the methods to ensure robust classification for ECG Heartbeat Signals with Convolutional Neural Networks. Our method improves the classification capability on non-life threatening heartbeats for real-life application with its powerful augmentation procedures based on achieving heterogeneous harmonization of heartbeat signals. The pre-augmentation phase of our study is LPCEH means prioritization of poor data contents to response classification needs in challenging data acquisition systems in real-life. The applied dynamic augmentation details that decompose and adduct data to real-life is the state-of-art approach that reinforces our classification algorithm towards different signal sources and input values. We achieved 93.5% accuracy where the normal system responses around 56.8%. Thus, the proposed H3-SAD moves the ECG Heartbeat Classification issue forward to a more robust level in literature by increasing the accuracy by almost 40% in the case of heterogeneous acquisition inputs. The study can be extended by combining life-threatening heartbeats into the existing work.

VI. FUTURE WORKS

Proposed method more ready to challenge against heterogeneous ECG data topologies among different studies in literature under the variety of signal acquisition methods and conditions. However, determination of real-time arrhythmia status of human body is not sufficient without classification of results by ensuring identification of life-threatening arrhythmias. So, a possible future study will be cover building a robust model that serves co-predicting to detection of life-threatening and non-life-threatening arrhythmias together to unveil alert identification-based stimulant wearable devices. Key focal point for this future study is composition of malignant ventricular fibrillation and normal arrhythmia database. At the end of this study, external wearable devices will be wielding their potential power to detect continual monitoring of humankind's lifestyle via heartbeats.

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