



Event-Driven ECG Classification using Functional Approximation and Chebyshev Polynomials

Maryam Saeed, Olev Martens, Benoit Larras, Antoine Frappé, Deepu John, Barry
Cardiff

► To cite this version:

Maryam Saeed, Olev Martens, Benoit Larras, Antoine Frappé, Deepu John, et al.. Event-Driven ECG Classification using Functional Approximation and Chebyshev Polynomials. 2022 IEEE Biomedical Circuits and Systems Conference, BioCAS, Oct 2022, Taipei, Taiwan. pp.595-599, <10.1109/biocas54905.2022.9948612>. <hal-03870169>

HAL Id: hal-03870169

<https://hal.science/hal-03870169v1>

Submitted on 20 Oct 2023

HAL is a multi-disciplinary open access archive for the deposit and dissemination of scientific research documents, whether they are published or not. The documents may come from teaching and research institutions in France or abroad, or from public or private research centers.

L'archive ouverte pluridisciplinaire **HAL**, est destinée au dépôt et à la diffusion de documents scientifiques de niveau recherche, publiés ou non, émanant des établissements d'enseignement et de recherche français ou étrangers, des laboratoires publics ou privés.



HAL Authorization

Event-Driven ECG Classification using Functional Approximation and Chebyshev Polynomials

Maryam Saeed*, Olev Märtens[†], Benoit Larras[‡], Antoine Frappé[‡], Deepu John[§], Barry Cardiff[§]

*[§]University College Dublin, Ireland, [†]Tallinn University of Technology, Estonia,

[‡]Univ. Lille, CNRS, Centrale Lille, Junia, Univ. Polytechnique Hauts-de-France, UMR 8520-IEMN, France

*{maryam.saeed}@ucdconnect.ie, [†]olev.martens@taltech.ee,

[‡]{benoit.larras, antoine.frappe}@junia.com, [§]{deepu.john, barry.cardiff}@ucd.ie

Abstract—Level-crossing ADCs reduce the size of data streams in wearable devices. However, in the context of electrocardiogram (ECG) signals, such an event-driven data source results in a variable length two-dimensional (time-amplitude tuples) data vector for each ECG beat. It is difficult to apply many standard signal processing techniques to this data making classifiers more complex. In this paper we resolve these difficulties by mapping the variable length 2D vectors to a fixed length feature vector comprising the first 80 coefficients of a Chebyshev polynomial expansion of the ECG beat. We show that, by using these 80 coefficients, the average percentage root-mean-square error is only $\approx 3.08\%$. Using this feature set we constructed a simple three-layered ANN binary (Normal / Abnormal) ECG classifier and we demonstrate 98.15% average accuracy and 96.07% average sensitivity. We also constructed a 4-class ANN, using the same ANN structure and we achieved 98.80% average accuracy and 91.5% average sensitivity. Both these networks have only 20k parameters and outperform the state-of-the-art classifiers, enabling low-power edge computing.

Index Terms—level-crossing ADC, event-driven, electrocardiograms, functional approximation, chebyshev polynomials, artificial neural networks, arrhythmia

I. INTRODUCTION

Long-term monitoring of electrocardiogram (ECG) signals effectively identifies individuals with high risks of cardiovascular disease. Morphological changes in ECG beats can indicate abnormalities of the heart and the early detection of these changes is important for preventing life-threatening conditions. A recent study showed the significance of monitoring ECG signals for longer than 14 days, in both cardiovascular disease diagnoses and the study of the efficacy of treatment [1]. Low-power arrhythmia classifiers that prolong battery life in wearable devices [2]–[5] have been proposed for long-term ECG classification tasks. Many such methods use high-dimensional ECG data with computationally expensive deep learning algorithms to classify arrhythmias. Some methods transmit ECG data off-chip to classify on a less power-constrained devices e.g. a mobile phone [6] or cloud-based systems [7].

Recent development in level-crossing analogue-to-digital converters (ADCs) has shown a promising future for low-power wearable devices. Level-crossing ADCs can implicitly

This work is supported by 1) JEDAI project under the Chist-Era Program; 2) Schlumberger Foundation’s Faculty for the Future Program 3) Irish Research Council under the New Foundations Scheme and 4) Microelectronic Circuit Centre Ireland.

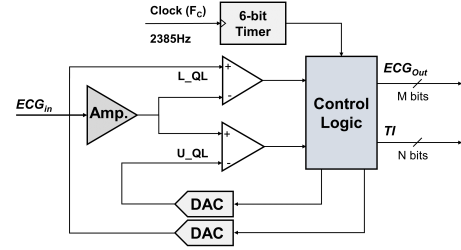


Fig. 1. The 7-bit level-crossing design with a 2385Mz clock frequency and 6-bit clock timer.

compress ECG data by 3x while maintaining signal quality in comparison with SAR ADCs [8], however the complexity of many non-uniform signal processing techniques make the realization of simple classifiers difficult on a low-powered device. For example, each beat in a event-driven ECG system comprises a variable number of (non-uniform) two dimension (2D) time-amplitude samples, making it impossible to feed into conventional deep learning networks.

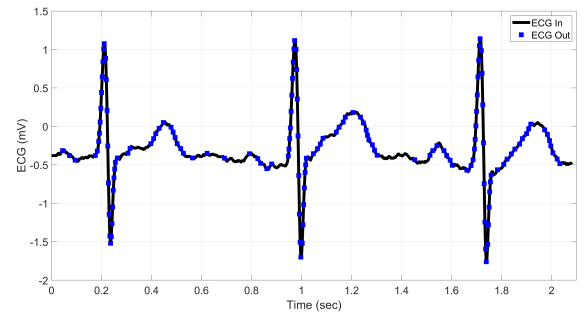


Fig. 2. Level-crossing sampling of ECG from the MIT-BIH dataset.

A recent study [9] explored functional approximation coefficients as features on several time-series datasets. They showed that there is only negligible or no change in classification accuracy using approximation coefficients as features. However, they achieved a large reduction in input dimensions. This study [9] is the motivation for our work. In [10], Chebyshev polynomials were used to classify entire ECG records in a dataset, however the focus of our work is the classification of

individual ECG beats and so direct comparison with [10] is not possible.

In [11] the authors show that it is possible to represent continuous time functions with a weighted sum of Chebyshev polynomials. In our we apply this concept to transform the non-uniformly sampled ECG beats to a fixed number of features (namely the 80 Chebyshev weights/coefficients) and use these to classify arrhythmias within the MIT-BIH dataset. In this context, the major contributions of this paper are as follows: a) This work uses functional approximation to estimate a fixed number of features from non-uniform level-crossing samples, and b) presents a low-power ANN (binary and 4-class) to classify four types of beats in the MIT-BIH dataset with results better than the state-of-the-art. The rest of the article is organized as follows. Section II presents the level-crossing ADC principles, introduces the functional approximation technique, and proposes a three-layered ANN classifier. Section III presents results and a comparison with the state-of-the-art. Finally, in Section IV, conclusions are drawn.

II. METHODOLOGY

A. Level-Crossing Sampling

In contrast to uniform sampling, level-crossing sampling does not sample at every clock cycle of the ADC. A level-crossing ADC produces an output only when the amplitude of the input signal crosses either an upper or a lower threshold at which point the threshold are updated. If there are no level crossings within a clock roll-over period, the ADC will produce an output at that time. Fig. 1 shows the 7-bit level-crossing ADC design used in this study with a 2385 Hz clock frequency and 6-bit clock timer (corresponding to a roll-over time of 26.8 ms). These parameters were chosen based on the analysis in [8].

At every level-crossing the output is a tuple comprising an ECG amplitude ECG_{out} , and corresponding timing information TI_n , where n is an index indicating the n^{th} sample. TI_n is an N bit word (in our case 6-bit) and indicates the time between two consecutive samples w.r.t the clock frequency of 2385 Hz. Fig. 2 shows an example of the level-crossing sampling of an ECG beat from the MIT-BIH dataset.

B. Functional Approximation Features

Functional approximation is a method for estimating an underlying unknown function from a set of observations. Functional approximation can also be used where samples exist at irregular intervals in time [9] assuming these samples are from a continuous signal [12].

We define the variable length vector $\vec{t}_{j,i}$ as the vector of time values (in seconds) where a variable number of level crossing events associated with the j^{th} beat occurred. These time vectors are formed by only selecting those level crossing events that lie with a specific window about the R-peak of the j^{th} beat, denoted here as occurring at time t_j^R , as follows:

$$-260 \text{ ms} < t_{j,i} - t_j^R < 400 \text{ ms}$$

For the purpose of Chebyshev polynomial approximation we need to normalize these time values to the range $[-1, +1]$ so we perform the following mapping:

$$\vec{x}_{j,i} = 2 \frac{\vec{t}_{j,i} - t_j^R + 260 \text{ ms}}{260 \text{ ms} + 400 \text{ ms}} - 1$$

Let $f_j(x)$ denote the continuous function representing the j^{th} beat. Then, the amplitudes of the level-crossings at the times $t_{j,i}$ can be represented as $f_j(x_{j,i})$.

Given a suitable set of finite basis functions, $f_j(x)$ can be represented as a weighted sum of basis functions defined on the interval $[-1, 1]$ as:

$$f_j(x) = \sum_{k=0}^n c_{j,k} g_k(x)$$

where, $c_{j,k}$ are the functional approximation coefficients of the j^{th} beat and they represent the amount of the respective basis function present in the signal $f_j(x)$. Motivated by [9], we choose Chebyshev polynomials of the first kind as the set of basis functions in this study. They can be represented by the following recurrence relations:

$$\begin{aligned} T_0(x) &= 1 \\ T_1(x) &= x \\ T_{n+1}(x) &= 2xT_n(x) - T_{n-1}(x) \end{aligned}$$

Then, we compute the $c_{j,k}$ by a dot product of the points corresponding to the roots of the $(n+1)^{\text{th}}$ polynomial [9]:

$$c_{j,k} = \frac{2}{n+1} \sum_{l=0}^n f_j(x_l) T_k(x_l) \quad (1)$$

where, x_l time points are defined by:

$$\text{where, } x_l = \cos \left(\left(l + \frac{1}{2} \right) \frac{\pi}{n+1} \right) \quad (2)$$

However, we do not know exactly the points $f_j(x_l)$, therefore we use linear interpolation to approximate the $f_j(x_l)$ from the set of points $f_j(x_{j,i})$ throughout this study.

1) *Raised Cosine Windowing and Rotation*: Fig. 3a shows the distribution of x_l points on an ECG beat using (2). It can be seen that the distribution of these points is mostly concentrated towards the edges of the ECG beat, whereas, the highest activity of the QRS complex lies around the R peak. We observed that using these x_l time points resulted in high error when the ECG beat was reconstructed using the coefficients. To address this issue, we introduce a preprocessing step, which applies raised cosine windowing to the ECG beat followed by a rotation around the R peak.

The raised cosine window is used to taper of the edges of the ECG beat as follows:

$$w(t) = \begin{cases} 1 & |t| < (1 - \beta) \\ 0 & |t| > 1 \\ 1/2 \left(1 + \cos \left(\pi \frac{|t| - (1 - \beta)}{\beta} \right) \right) & \text{elsewhere} \end{cases}$$

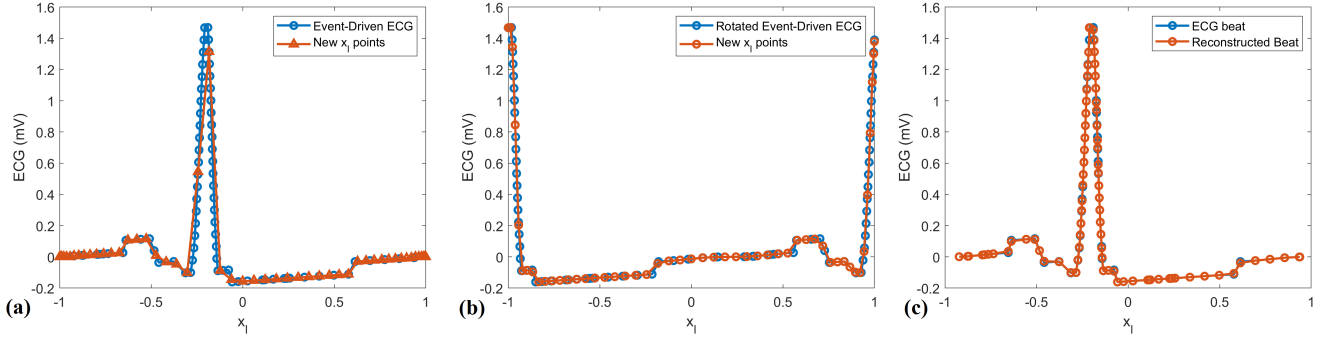


Fig. 3. (a) An example of the x_l time points using linear interpolation on an ECG beat for $n=50$, (b) after linear interpolation, windowing and a rotation for $n=50$, and (c) Reconstructed ECG beat using 50 approximation coefficients (PRD of 2.034%).

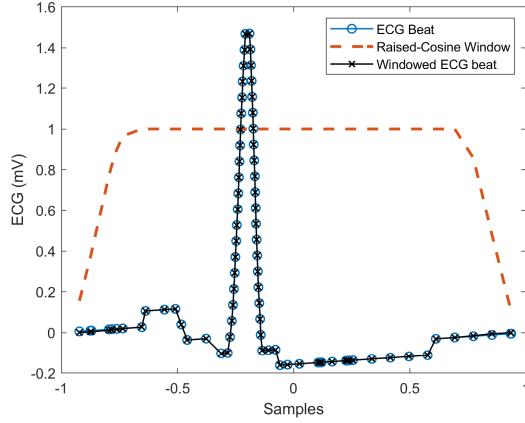


Fig. 4. The effect of the windowing function $w(t)$ on an ECG beat with a roll-off factor of 0.3.

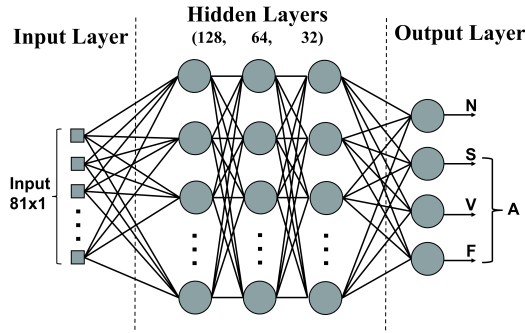


Fig. 5. The three-layered artificial neural network used to classify the ECG beats in the MIT-BIH dataset.

where, β is the roll-off factor and signifies the percentage of the signal being tapered off. Fig. 4 shows the effect of windowing the ECG beat with a roll-off factor of 0.3.

Next, the beat is rotated around the R-peak such that the R-peak is now concentrated around the edges as shown in Fig. 3b and the new time points x_l capture the R peak more uniformly. Fig. 3c shows a reconstructed ECG beat using windowing and rotation method and 50 approximation coefficients. The

percentage root-mean-square difference (PRD) between the original ECG beat and the reconstructed beat is 2.034%, which is well under the signal quality limit of 10% [13].

2) *Choosing the right number of coefficients:* To understand the effect of windowing and rotation on the ECG beat, we ran simulations on the entire MIT-BIH dataset with and without the technique described in Section II-B1. We observed that without the windowing and rotation technique, 200 more x_l time points and approximation coefficients were required for the PRD to converge. Similarly, we observed that when using windowing and rotation, the PRD converged to $\approx 3.08\%$ at $n = 200$ interpolation time points, x_l , and for $k = 80$ approximation coefficients. Therefore, for the rest of this article, we use $n = 200$ and $k = 80$ for estimating the approximation coefficients. Due to the page limits of this article, this comparative study is not presented in detail here.

C. Classification

For every beat in the MIT-BIH dataset, we generate a feature vector of 81 values using functional approximation with $n = 200$ and $k = 80$. This feature vector is fed into a three-layered ANN as shown in Fig. 5. There are 128, 64 and 32 neurons in the three hidden layers. Finally, each output is classified into one of the following four classes: normal (N), supraventricular (S), ventricular (V), and fusion (F) beats. The number of hidden layers and the respective number of neurons were chosen from several simulations of one to five hidden layers and 8-256 neurons per layer. Here, the dataset is split into 62%, 13%, and 25% of training, validation and test set. Synthetic minority over-sampling [14] is used to handle the class-imbalance. Adam optimizer, sparse categorical cross entropy loss and a batch size of 64 is used to train the model. We also tested the same classifier for binary classification performance, where each beat was classified into two classes: normal (N) and abnormal(A). Accuracy (ACC), sensitivity (SEN), positive predictivity (+PV or precision), and false positive rate (FPR) are used to assess the classifier performance as defined in [8].

TABLE I
ARRHYTHMIA CLASSIFICATION USING ARTIFICIAL NEURAL NETWORK
AND APPROXIMATION COEFFICIENTS

Model	Class	ACC(%)	SE(%)	+PV(%)	FPR(%)
4-class ANN	N	97.83	98.22	99.34	5.4
	S	98.38	87.91	65.5	1.31
	V	99.39	95.15	96.33	0.28
	F	99.61	84.73	71.97	0.27
2-class ANN	N	98.15	98.72	99.2	6.5
	A	98.15	93.43	89.76	1.27

TABLE II
COMPARISON WITH PREVIOUS WORKS (EVENT-DRIVEN)

Study	Model	#Params	Class	ACC(%)	SEN(%)	+PV(%)
This work*	ANN	20,964	N	97.83	98.22	99.34
			S	98.38	87.91	65.5
			V	99.39	95.15	96.33
			F	99.61	84.73	71.97
[15]	ANN	3,717	N	99.32	99.45	99.76
			S	99.70	97.75	94.39
			V	99.68	98.67	98.07
			F	98.87	49.03	87.80
[8]	1D-CNN	132,676	N	98.57	99.55	98.86
			S	99.13	76.98	90.01
			V	99.49	95.19	97.45
			F	99.74	80.48	87.56

III. RESULTS AND DISCUSSION

We also tested the classification performance using SVM with Gaussian and Cubic kernels as well as an ensemble of bagged trees. However, the ANN showed consistently superior performance for lower computational complexity. Table I shows the results for the four-class and two-class ANN. The 4-class ANN has an average 98.80% accuracy, 91.5% sensitivity, 83.28% precision, and 1.81% false positive rate. The 2-class ANN has an average 98.15% accuracy, 96.07% sensitivity, 94.48% precision, and 3.88% false positive rate.

Table II shows a comparison with previous arrhythmia classifiers in literature using level-crossing ADCs. This study and [8] use a class-oriented evaluation scheme whereas, [15] uses a patient-specific scheme. The performance in [8] is comparable to this work but requires 6x more computational resources. The classifier in [15] outperforms this work for the S class, specifically in precision and requires much less computations. However, the classifier performs poorly for the minority F class with 49.03% sensitivity. Additionally, as it is a patient-specific design it requires labeled data from each patient to train the classifier before analyzing real-time data. This is generally not possible in real-time analysis. In [18], a patient-specific 2-class ANN was presented using event-driven ECG using 296 parameters. They reported an average accuracy of 98.4% and an average sensitivity of 98.4% using selected records from the database.

Table III shows a comparison of this work with previous arrhythmia classifiers using uniform-sampling. In [16], the authors used a patient-specific approach to classify S and V classes only. Their ANN model required a smaller amount of computational resources, however, the accuracy and sensitivity

TABLE III
COMPARISON WITH PREVIOUS WORKS (UNIFORMLY-SAMPLED)

Study	Model	#Params	Class	ACC(%)	SEN(%)	+PV(%)
This work*	ANN	20,964	N	97.83	98.22	99.34
			S	98.38	87.91	65.5
			V	99.39	95.15	96.33
			F	99.61	84.73	71.97
[16]	ANN	8,415	N	-	-	-
			S	88.6	86.4	-
			V	92.5	83.7	-
			F	-	-	-
[17]*	SVM	32M+32A	N	-	-	-
			S	97.9	78.6	68.9
			V	98.0	91.1	81.3
			F	-	-	-

performance was much lower than this work. Similarly, in [17], a patient specific approach was used to classify S and V type beats using a very low power linear SVM that only requires 32 multiplications and 32 additions. However, the performance was much lower compared to this work.

A. Complexity considerations

As a measure of complexity of the pre-processing step, i.e. the conversion from the 2D variable length vectors to fixed length Chebyshev coefficients, we count the number of multiplications (or equivalently divisions) required. According to the linear interpolation process to generate the 200 interpolated values, $f_j(x_i)$, requires approximately 400 multiplication operations. The subsequent windowing function requires an additional 200 multiplications and the rotation in time can be implemented for free by careful pre-rotation of the stored Chebyshev basis functions¹. Each of the 80 coefficients is computed by a length 200 dot product each requiring 200 multiplications as per (1). In total the pre-processing steps require $400+200+80*200 \approx 17k$ multiplications per ECG beat. Similarly, we can take the number of multiplications in the ANN itself as being approximately equal to the number of trained parameters as enumerated in Tables II and III.

IV. CONCLUSION

In this study, a low-power feature extraction technique using functional approximation and Chebyshev polynomials is presented. Using 200 Chebyshev time points and 80 approximation coefficients, event-driven ECG beats can be accurately reconstructed with only an average $\approx 3.08\%$ PRD. A low-computation artificial neural network with three-hidden layers was also presented. The 2-class ANN classifies the dataset with 98.15% average accuracy, 96.07% average sensitivity. The 4-class ANN classifies the dataset with 98.80% average accuracy and 91.5% average sensitivity. Both these networks take only 20k parameters and outperforms the state-of-the-art classifiers. The combination of event driven ADCs and our presented algorithms represent a power efficient solution for ECG recording and classification at the edge.

¹The windowing can be absorbed into the stored Chebyshev basis functions.

REFERENCES

- [1] R. Mahajan, A. Gambhir, and S. Adumala, "Efficacy of long-term monitoring on detecting critical cardiac arrhythmias," *Circulation*, vol. 142, no. Suppl_3, pp. A17 461–A17 461, 2020.
- [2] P. H. W. Leong and M. A. Jabri, "A low-power vlsi arrhythmia classifier," *IEEE transactions on neural networks*, vol. 6, no. 6, pp. 1435–1445, 1995.
- [3] N. Bayasi, T. Tekeste, H. Saleh, B. Mohammad, A. Khandoker, and M. Ismail, "Low-power ecg-based processor for predicting ventricular arrhythmia," *IEEE Transactions on Very Large Scale Integration (VLSI) Systems*, vol. 24, no. 5, pp. 1962–1974, 2015.
- [4] A. Faraone and R. Delgado-Gonzalo, "Convolutional-recurrent neural networks on low-power wearable platforms for cardiac arrhythmia detection," in *2020 2nd IEEE International Conference on Artificial Intelligence Circuits and Systems (AICAS)*. IEEE, 2020, pp. 153–157.
- [5] G. Sivapalan, K. K. Nundy, S. Dev, B. Cardiff, and D. John, "Annet: a lightweight neural network for ecg anomaly detection in iot edge sensors," *IEEE Transactions on Biomedical Circuits and Systems*, vol. 16, no. 1, pp. 24–35, 2022.
- [6] S. Gradl, P. Kugler, C. Lohmüller, and B. Eskofier, "Real-time ecg monitoring and arrhythmia detection using android-based mobile devices," in *2012 annual international conference of the IEEE engineering in medicine and biology society*. IEEE, 2012, pp. 2452–2455.
- [7] N. Huda, S. Khan, R. Abid, S. B. Shuvo, M. M. Labib, and T. Hasan, "A low-cost, low-energy wearable ecg system with cloud-based arrhythmia detection," in *2020 IEEE Region 10 Symposium (TENSYP)*. IEEE, 2020, pp. 1840–1843.
- [8] M. Saeed, Q. Wang, O. Mörtens, B. Larras, A. Frappé, B. Cardiff, and D. John, "Evaluation of level-crossing adcs for event-driven ecg classification," *IEEE Transactions on Biomedical Circuits and Systems*, vol. 15, no. 6, pp. 1129–1139, 2021.
- [9] F. Melchert, U. Seiffert, M. Biehl, B. Hammer, T. Martinetz, and T. Villmann, "Functional approximation for the classification of smooth time series," in *GCPR workshop on new challenges in neural computation*. Citeseer, 2016, p. 04.
- [10] M. Bhanu Prakash, K. Sanjana, B. Ganga Gowri, V. Sowmya, E. Gopalakrishnan, and K. Soman, "Detection of cardiac disease with less number of electrocardiogram sensor samples using chebyshev," in *Intelligent Vision in Healthcare*. Springer, 2022, pp. 75–86.
- [11] G. B. Moody and R. G. Mark, "The impact of the mit-bih arrhythmia database," *IEEE Engineering in Medicine and Biology Magazine*, vol. 20, no. 3, pp. 45–50, 2001.
- [12] J. O. Ramsay and B. W. Silverman, "Functional data analysis," *Internet Adress: http*, 2008.
- [13] M. Saeed, Q. Wang, O. Mörtens, B. Larras, A. Frappé, B. Cardiff, and D. John, "Event-driven ecg classification using an open-source, lc-adc based non-uniformly sampled dataset," in *2021 IEEE International Symposium on Circuits and Systems (ISCAS)*. IEEE, 2021, pp. 1–5.
- [14] J. Brownlee, "Smote for imbalanced classification with python," *Machine Learning Mastery*, vol. 16, 2020.
- [15] Y. Zhao, Z. Shang, and Y. Lian, "A 13.34 μ w event-driven patient-specific ann cardiac arrhythmia classifier for wearable ecg sensors," *IEEE transactions on biomedical circuits and systems*, vol. 14, no. 2, pp. 186–197, 2019.
- [16] M. Janveja, R. Parmar, M. Tantuway, and G. Trivedi, "A dnn-based low power ecg co-processor architecture to classify cardiac arrhythmia for wearable devices," *IEEE Transactions on Circuits and Systems II: Express Briefs*, vol. 69, no. 4, pp. 2281–2285, 2022.
- [17] X. Tang, Z. Ma, Q. Hu, and W. Tang, "A real-time arrhythmia heartbeats classification algorithm using parallel delta modulations and rotated linear-kernel support vector machines," *IEEE Transactions on Biomedical Engineering*, vol. 67, no. 4, pp. 978–986, 2019.
- [18] J. Duforest, B. Larras, D. John, O. Martens, and A. Frappé, "Slope-based event-driven feature extraction for cardiac arrhythmia classification," in *2021 IEEE Biomedical Circuits and Systems Conference (BioCAS)*. IEEE, 2021, pp. 01–04.