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A Comparative Study of ECG Sampling Rates in Predicting Cardiac Arrhythmias Using a Deep Learning Approach

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Abstract— Cardiac arrhythmias are a group of conditions that have caused great concern among healthcare professionals because they have a high incidence and prevalence worldwide, and their early diagnosis and effective treatment are essential to alleviate the negative impacts they can have on people's quality of life. In recent years, many studies have suggested Deep Learning models for diagnosing cardiac arrhythmias by analysing data from electrocardiograms (ECG). The heart's electrical activity can be measured using different ECG sampling rates, and the chosen rate can impact the model's prediction accuracy and associated computational costs. This study presents a comparative analysis of various sampling rates for predicting cardiac arrhythmias using a Deep Learning model and a large public dataset. The findings can serve as a guideline for doctors and researchers to select the most appropriate sampling rates to achieve greater efficiency when using the ECG and better outcomes in predicting cardiac arrhythmias.

Keywords— cardiac arrhythmias, electrocardiogram, sampling rates, deep learning

1. Introduction

Cardiac arrhythmias are a group of conditions significantly harmful to people's quality of life, as they can range from a feeling of discomfort to sudden death in severe cases. In recent years, the medical community has been concerned about these diseases because many factors related to modern lifestyle have contributed to increasing their incidence and prevalence. Li et al. [1] highlight that a global epidemiological study released in 2019 has reported an incidence of 4.71 million cases and a prevalence of 59.7 million cases.

The electrocardiogram (ECG) is the commonly used tool for predicting and diagnosing cardiac arrhythmias. This equipment allows for the recording of the heart's electrical activity using a set of electrodes attached to the skin. According to iMotions [2], the main reason the ECG has become the gold standard for analyzing cardiac diseases is its ability to collect high-resolution data using a non-invasive and cost-effective technique. Bloe [3] highlights that the ECG is a

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versatile equipment as it allows the use of different electrode configurations, and this characteristic makes it possible to utilize it in various scenarios.

In recent years, numerous researchers have proposed Deep Learning-based solutions for detecting and diagnosing cardiac arrhythmias through the analysis of data from ECG exams. Singh et al. [4] state that one of the main objectives of using Deep Learning for data analysis is to automate this process to reduce the time necessary for analysis and help healthcare professionals detect diseases early and achieve greater precision in diagnoses. According to Nagarajan et al. [5], the increased interest in using Artificial Intelligence (AI)-based technologies in cardiologic practice has been promoted by the rise in computational capacity, availability of web-based platforms, and popularization of wearable devices, and new advances in healthcare practices have been glimpsed due to advances in sensor technologies and wireless communications.

The ECG can be configured with different sampling rates to register the heart's electrical activity. Zhou et al. [6] state that choosing an adequate sampling rate is a crucial issue because it can directly impact diagnostic accuracy and associated computational costs. There is usually a trade-off between the accuracy achieved in ECG analysis and the necessary costs to collect and process the data. Mahdiani et al. [7] highlight that selecting a lower rate can result in time savings and reduced computational resources for storing and processing data, but the loss of information may lead to unsatisfactory accuracy; on the other hand, using a high sampling rate can create difficulties or even make it unfeasible to utilize the data in certain scenarios. According to Zhou et al. [6], the availability of guidelines to assist in choosing sampling rates is desirable to help define adequate sampling rates to achieve a balance between costs and performance.

This study presents a comparative analysis of some ECG sampling rates for predicting cardiac arrhythmias using a Convolutional Neural Network (CNN) model. The main objective is to provide empirical data that can assist in selecting ECG configurations and preparing data for processing, aiming to achieve greater efficiency in the use of Deep Learning models in the cardiological field.

2. Background

The cardiac cycle comprises the set of events that occur in the heart's internal chambers in order to eliminate carbon dioxide and oxygenate the blood that will be transported to the rest of the body. These events are the contraction (systole) and relaxation (diastole) of the myocardium's inner walls, and their purpose is to coordinate blood flow through the cardiac system to ensure the necessary supply of oxygen to the muscle cells. According to Kingma et al. [8], the events of the cardiac cycle occur in an orderly and synchronized manner in order to guarantee the proper functioning of the cardiovascular system. Chakrabarti and Stuart [9] state that the proper functioning of the cardiovascular system depends on the actions of a set of specialized cells that

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generate and conduct electrical impulses, as well as on a series of complex interactions between chemical elements occurring inside and outside the myocardial cells.

Cardiac arrhythmias are alterations in the rhythm or sequence of events in the cardiac cycle. These alterations are caused by diseases or disorders in the cardiovascular system. Chakrabarti and Stuart [9] state that arrhythmias can result from an abnormality that impairs the generation of electrical impulses by pacemaker cells or from a structural alteration that affects the propagation of electrical impulses between the heart chambers. Patil et al. [10] emphasize that there is significant concern regarding cardiac arrhythmias because these disorders are associated with various risk factors such as smoking, alcohol consumption, hypertension, diabetes, and obesity, and can even lead to myocardial infarction in more severe cases. The arrhythmias can be asymptomatic in some cases, but can also be associated with disorders that include palpitations, dizziness, fainting, chest pain, shortness of breath, fatigue, and anxiety.

Arrhythmias are classified according to the rhythmic alterations caused in the heartbeat (bradycardia or tachycardia) and the site of origin of the disorder (atria, atrioventricular junction, or ventricles). Diagnosis can be challenging because there are several types of arrhythmias, and certain types share common characteristics. According to Mason et al. [11], diagnosis can also be hampered by overlapping or imprecise terminology in the medical literature. The American Heart Association (AHA) has compiled a concise and standardized list of terms for classifying cardiac arrhythmias. This list was released in a statement published by Mason et al. [11] and its aim is to serve as a guideline for medical professionals to improve the interpretation of cardiology tests. The AHA-proposed list contains 117 types of arrhythmias organized into 14 groups.

The medical community has considered the ECG as the gold standard exam for cardiac monitoring and arrhythmia detection for the last decades. This device records the heart's electrical activity through a set of electrodes attached to the skin. The ECG records the electrical signals (in microvolts) and presents the data as a time series in which the vertical axis displays the recorded voltage and the horizontal axis represents the temporal sequence of action potentials generated by pacemaker cells. The result of an ECG exam is visualized as a trace, as shown in Fig. 1. According to Stracina et al. [12], the ECG trace highlights the waves of the cardiac cycle and facilitates the detection of abnormalities by analyzing the frequency and morphology of the waves. Becker [13] emphasizes that the trace of a healthy heart exhibits a sequence of regular and ordered waves, whereas the trace of an arrhythmic heart may present different patterns, including no waves or waves with morphological anomalies.

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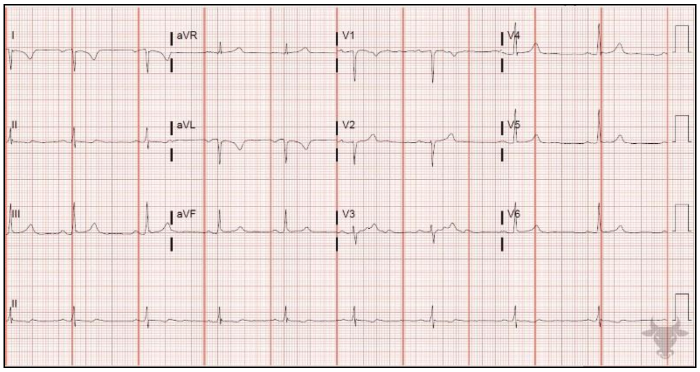

Figure 1: ECG exam.

ECG electrodes are attached to the individual's chest or limbs. The ECG is a versatile device that permits various electrode placement configurations, and the positioning system considered the universal standard is the so-called 12-lead system. This system uses 6 electrodes attached to the chest and 4 electrodes attached to the limbs. According to Becker [13], the combination of the 10 electrodes allows the generation of 12 leads that represent 12 different views of myocardial electrical activity. The precordial leads (or chest leads) are obtained through the electrodes attached to the chest and are designated V1, V2, V3, V4, V5, and V6. The limb leads are obtained using the electrodes attached to the limbs and are designated I, II, III, aVR, aVL, and aVF. Fig. 2 and 3 show a representation of the 12 leads.

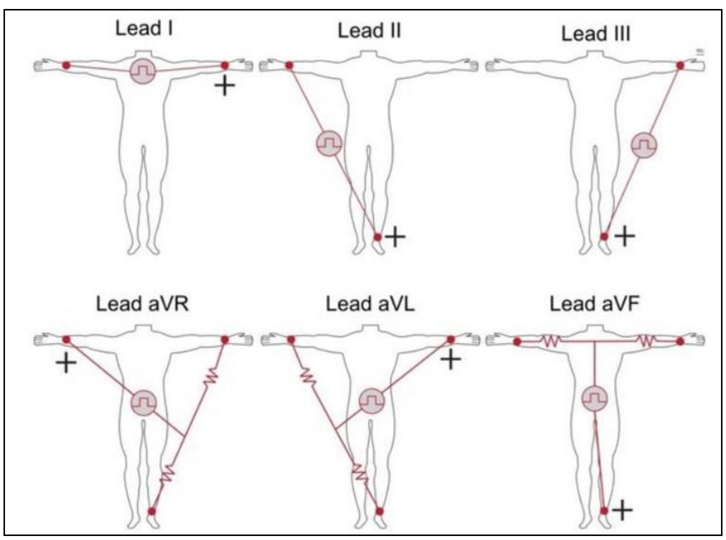

Figure 2: Limb leads representation.

Different sampling rates can be used to record electrical activity on an ECG. The rate is measured in Hertz (Hz) and represents the quantity of events recorded during 1 second. The values typically utilized for ECGs are 50 Hz, 100 Hz, 125 Hz, 250 Hz, 500 Hz, and 1000 Hz. According to Zhou et al. [6], although the use of high sampling rates allows for high resolution

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and detailed information about cardiac function, the consumption of computational resources for data storage and processing may make their use unfeasible in certain scenarios. Kwon et al. [14] state that there are situations in which it is necessary to apply downsampling techniques to reduce the sampling rate of the original data to make their use viable, and it is important to know the minimum acceptable rate that allows for the desired accuracy in ECG signal analysis. Mahdiani et al. [7] highlight that the growing use of wearable devices for cardiac monitoring is one of the motivators for studies related to ECG sampling rates due to the storage capacity and energy consumption restrictions of these devices.

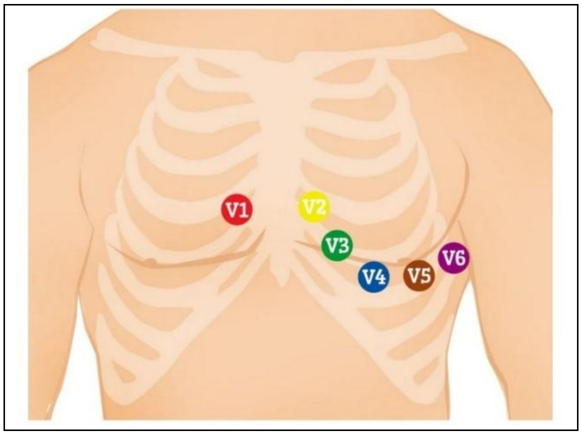

Figure 3: Precordial leads localization.

Stracina et al. [12] state that a motivation for the growing enthusiasm in applying AI-based tools for interpreting ECG exams is the possibility of analysing large volumes of data in a short time and detecting complex patterns associated with cardiac pathologies. CNN models have stood out among Deep Learning techniques due to their ability to automatically extract relevant features from raw data and reduce the time and effort required for feature engineering. According to Wibawa et al. [15], CNN models have demonstrated excellent performance in data processing tasks organized as time series. This capability makes the CNNs an excellent tool to learn complex patterns behind the ECG data.

Deep Learning models are typically trained using huge datasets to achieve better generalization and high prediction accuracy. Training with large datasets can demand high computational costs and extensive training time, and it can hinder the training or make it even impractical in certain cases. Mahdiani et al. [7] emphasize that the reduction in computational costs generated by resampling sampling rates can facilitate and expand the use of cardiac monitoring technologies and create new opportunities for improving healthcare services.

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3. Methods

3.1. Dataset Description

The dataset generated by Liu et al. [16] was utilized in this study. This dataset consists of 25,770 ECG exams obtained from 24,666 individuals who underwent examinations between 2019 and 2020 at Shandong Provincial Hospital (Jinan, China). The researchers created a large dataset of ECG exams annotated according to AHA standards to make it publicly available to support the development and assessment of tools for diagnosing cardiac arrhythmias.

The exams were performed using equipment configured according to the 12-lead system with a sampling rate of 500 Hz, and each exam lasted between 10 and 60 seconds. Certain exams received more than one diagnosis due to exhibiting symptoms of multiple diseases. For this study, only the first diagnosis assigned to each exam was considered, resulting in a total of 40 classifications, as 4 classifications used solely as secondary diagnoses were eliminated from the study. Table 1 shows the number of diagnoses for each type of arrhythmia.

Table 1: Quantity of diagnoses by type of arrhythmia.

AHA Code	Quantity	%	AHA Code	Quantity	%
1	13905	53.96	165	64	0.25
22	2659	10.32	104	62	0.24
147	1334	5.18	36	44	0.17
23	1123	4.36	160	35	0.14
145	1045	4.06	155	28	0.11
105	917	3.56	108	22	0.09
60	786	3.05	88	20	0.08
21	723	2.81	54	12	0.05
50	663	2.57	80	9	0.03
146	540	2.10	83	8	0.03
106	473	1.84	140	7	0.03
30	384	1.49	166	7	0.03
125	201	0.78	102	5	0.02
120	122	0.47	31	4	0.02
121	111	0.43	148	4	0.02
82	98	0.38	87	3	0.01
142	96	0.37	152	3	0.01
51	94	0.36	37	2	0.01
101	77	0.30	84	2	0.01
161	77	0.30	143	1	0.00

The dataset contains 12 features corresponding to the 12 leads whose voltage (in microvolts) was recorded at a specific instant of time. Each sample in the dataset corresponds to the recording of 12 viewpoints of myocardial activity at a specific instant. Although the duration of each exam varied from 10 to 60 seconds, for this study, only the first 10 seconds of each exam were considered for standardization purposes. Therefore, each exam contains 5,000 samples, as a

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sampling rate of 500 Hz was utilized. The dataset considered for this study contains 128,850,000 samples, each with 12 features.

3.2. Preprocessing

In this study, only data obtained from the aVR lead were utilized. The aVR lead was chosen because the study presented by Dos Santos [17] highlighted it as one of the leads that provides the highest accuracy for predicting cardiac arrhythmias with the dataset being investigated.

The records were restructured so that the data were organized in a "time window" format. Every 5,000 samples (corresponding to an ECG exam) were converted to a single sample with 5,000 features, in which each feature represents the voltage recorded by the aVR lead at a specific moment in time. The main motivation for organizing the data in a "time window" is that cardiac arrhythmia analysis involves verifying changes in cardiac activity patterns over time.

The dataset was stratified into 90% of samples for training and 10% for testing. As the dataset was considerably imbalanced, it was necessaire to apply techniques to address this issue. The Synthetic Minority Over-sampling Technique (SMOTE) was applied to the training set. The generation of synthetic instances helped to improve the model generalization and reduce the risk of overfitting. The SMOTE requires a minimum number of samples of each class because it utilizes a K-Nearest Neighbors algorithm to generate new samples. For this reason, classes with fewer than 6 samples (AHA codes 31, 37, 84, 87, 102, 143, 148, and 152) were removed from the set, thus reducing the number of classes used to 32. After combining the SMOTE and undersampling techniques, the training set now contains 200,000 samples. The test dataset remained with 2,577 samples (10%).

Data in the original sampling rate (500 Hz) was downsampled to rates of 10 Hz, 25 Hz, 50 Hz, 100 Hz, 125 Hz, and 250 Hz. The downsampling was conducted using a Butterworth 4th-order low-pass filter to avoid signal distortion. The model was trained with each of the selected rates.

3.1. Model Training

The model used in this study is a Convolutional Neural Network (CNN), and its architecture is represented in Figure 4. This architecture achieved better performance compared to other alternatives analysed. The architecture is formed by 4 convolutional layers, 2 max pooling layers, 1 flatten layer, 1 fully connected layer, and 1 output layer.

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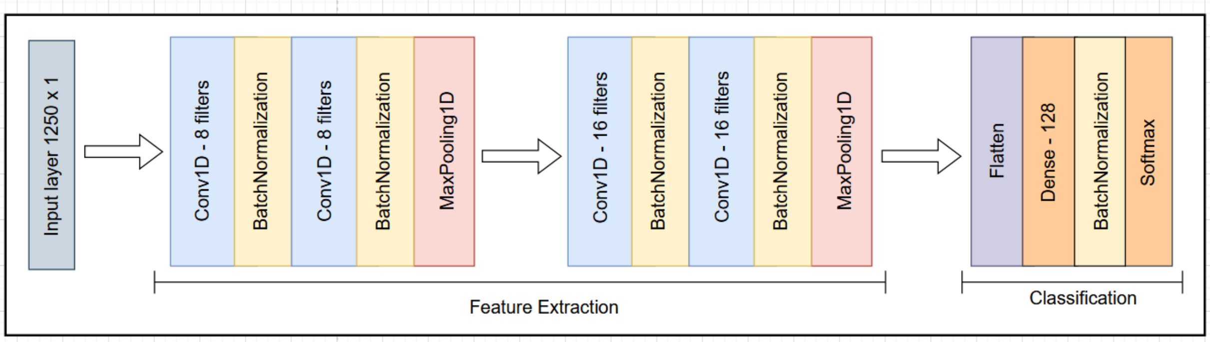

Figure 4: CNN model architecture.

Table 2 presents the model's hyperparameter configuration. The use of 4 convolutional layers provided better generalization capabilities compared to other configurations that use fewer layers. The activation function used in all layers was ReLU due to its simplicity and computational efficiency, as well as for its capacity to handle the vanishing gradient problem. Kernel sizes of 3x3 and 5x5 were employed in the convolutional layers to strike a better balance between computational costs and model representation capability.

Table 2: Hyperparameters setup.

Layer type	Filters	Kernel size	Activation	Units
Conv1D	8	3	ReLU	-
BachNormalization	-	-	-	-
Conv1D	8	3	ReLU	-
BachNormalization	-	-	-	-
MaxPooling1D	-	-	-	-
Conv1D	16	5	ReLU	-
BachNormalization	-	-	-	-
Conv1D	16	5	ReLU	-
BachNormalization	-	-	-	-
MaxPooling1D	-	-	-	-
Flatten	-	-	-	-
Dense	-	-	ReLU	128
BachNormalization	-	-	-	-
Dense	-	-	Softmax	32

The model was implemented using the Tensorflow/Keras library. The training was carried out with a limit of 300 epochs. It was employed Adam optimizer, learning rate of 0.001 and batch size of 32. This combination of learning rate and batch size values provided greater stability and faster convergence during training. It was used the cross-validation technique (10-fold).

4. Results and Discussion

Table 3 shows the training accuracies achieved with each sampling rate and the number of training parameters used in each configuration. The findings exemplify the trade-off between the

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training costs and the accuracy achieved in model predictions. The use of higher sampling rates resulted in increased accuracy; on the other hand, it also increased the model complexity and computational costs required for training. The findings support the notion that the choice of sampling rate to be used in each situation should consider not only the desired accuracy or minimum acceptable accuracy, but also the amount of computational resources available for training.

Table 3: Training metrics.

Rate (Hz)	% Accuracy	Nr. of parameters
10	57.56	48,104
25	82.88	123,880
50	87.23	252,904
100	91.73	508,904
125	92.24	635,880
250	92.32	1,276,904

A better balance between performance and computational costs was achieved when using the 100 Hz and 125 Hz rates, enabling accuracies above 90% with models of smaller complexity. The 250 Hz rate provided an inconsiderable improvement in accuracy compared to the 100 Hz and 125 Hz rates, however resulted in a significant increase in model complexity, making training more time-consuming and costly. The 25 Hz and 50 Hz rates yielded moderate accuracies (between 80% and 90%) and would be more suitable alternatives for scenarios where computational resources are limited and accuracy is not highly demanding. The accuracy achieved with the 10 Hz rate was considerably low and would likely not meet the requirements or expectations in situations in which robust performance and higher prediction accuracy are essential.

Table 4 shows detailed metrics achieved by the model. These metrics make it possible to verify the model's performance in predicting each type of arrhythmia to assess its robustness. The 250 Hz rate provided better performance when predicting 20 arrhythmia types, while the 100 Hz and 125 Hz rates achieved the highest F1-score when predicting 10 arrhythmia types each. The model's performance with the 100 Hz and 125 Hz rates positions them as an alternative with an excellent balance between accuracy and computational cost. The model achieved an F1-score exceeding 80% in predicting 28 of the 32 arrhythmia types with the 100 Hz and 125 Hz rates.

Table 4: F1-Score metrics.

Condition	10 Hz	25 Hz	50 Hz	100 Hz	125 Hz	250 Hz
Normal ECG	0.64	0.88	0.91	0.94	**0.95**	**0.95**
Sinus tachycardia	0.85	0.93	0.94	**0.96**	0.93	0.93
Sinus bradycardia	0.87	0.93	0.94	**0.96**	**0.96**	**0.96**
Sinus arrhythmia	0.30	0.59	0.70	0.82	**0.83**	**0.83**
Atrial premature complex(es)	0.42	0.67	0.72	0.84	0.85	**0.87**
Junctional premature complex(es)	0.33	0.69	0.77	**0.87**	0.86	**0.87**

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Atrial fibrillation	0.64	0.88	0.91	**0.92**	0.90	0.89
Atrial flutter	0.50	0.83	0.85	0.91	0.89	**0.93**
Junctional tachycardia	0.19	0.73	0.67	0.65	0.74	**0.92**
Ventricular premature complex(es)	0.64	0.80	0.83	0.87	**0.88**	**0.88**
Short PR interval	0.21	0.67	0.63	0.73	0.73	**0.84**
Prolonged PR interval	0.39	0.76	0.83	0.85	0.86	**0.89**
Second-degree AV block, Mobitz type I	0.60	0.67	0.67	0.82	0.75	**0.93**
AV block, complete (third-degree)	0.40	0.76	0.80	0.90	0.92	**0.95**
Left anterior fascicular block	0.39	0.69	0.76	0.90	0.86	**0.91**
Left bundle-branch block	0.49	0.93	0.89	**0.93**	**0.93**	0.92
Incomplete right bundle-branch block	0.26	0.60	0.71	0.82	**0.85**	0.84
Right bundle-branch block	0.49	0.84	0.91	0.92	**0.93**	0.92
Ventricular preexcitation	0.30	0.74	0.84	0.89	**0.93**	**0.93**
Right-axis deviation	0.33	0.71	0.77	0.88	0.84	**0.90**
Left-axis deviation	0.38	0.73	0.76	**0.89**	0.85	0.88
Low voltage	0.44	0.74	0.81	0.89	0.87	**0.90**
Left atrial enlargement	0.35	0.43	0.60	**0.93**	0.88	0.70
Left ventricular	0.33	0.66	0.71	0.85	0.85	**0.86**
ST deviation	0.43	0.71	0.75	0.83	0.84	**0.86**
ST deviation with T-wave change	0.52	0.77	0.78	**0.88**	0.87	0.87
T-wave abnormality	0.47	0.75	0.78	0.85	**0.87**	0.86
Early repolarization	0.23	0.56	0.69	**0.90**	0.86	0.84
Anterior MI	0.48	0.78	0.76	0.90	0.89	**0.96**
Inferior MI	0.34	0.64	0.71	0.86	**0.92**	0.90
Anteroseptal MI	0.31	0.68	0.72	0.86	0.87	**0.89**
Extensive anterior MI	0.27	0.57	0.59	**0.77**	0.75	0.71

5. Conclusion

Deep Learning models can meet the expectations and needs of healthcare professionals in predicting cardiac arrhythmias even using lower ECG sampling rates, and this can be a viable alternative for many scenarios. The findings of this study show the possibilities of using AI-based solutions in scenarios in which computational resources are limited and leverage the use of these technologies in environments outside of clinics and hospitals.

It can be verified that the use of higher sampling rates can provide better accuracy, but it is important to evaluate whether the improvements achieved outweigh the computational costs. Health professionals can benefit from empirical data provided by comparative studies to assist in decision-making, improving the medical process.

References

[1] H. Li, X. Song, Y. Liang, X. Bai, W. Liu-Huo, C. Tang, W. Chen, and L. Zhao, "Global, regional, and national burden of disease study of atrial fibrillation/flutter, 1990–2019: results from a global burden of disease study," BMC Public Health, vol. 22, no. 1, 2015, 2022. doi: 10.1186/s12889-022-14403-2

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[2] iMotions, "Electrocardiography (ECG): the complete pocket guide," [Online]. Available: https://imotions.com/support/document-library/

[3] C. Bloe, "The role of single-use ECG leads in reducing healthcare-associated infections," British Journal of Nursing, vol. 30, no. 11, 2021. doi: 10.12968/bjon.2021.30.11.628

[4] G. Singh, C. Agarwal, I. Kaur, and P. Gupta, "Machine Learning for cardiac arrhythmia detection: a systematic survey," Journal of Physics: Conference Series, vol. 2570, no. 1, 012028, 2023. doi:10.1088/1742-6596/2570/1/012028

[5] V. D. Nagarajan, S. Lee, J. Robertus, C. A. Nienaber, N. A. Trayanova, and S. Ernst, "Artificial intelligence in the diagnosis and management of arrhythmias," European Heart Journal, vol. 42, no. 38, pp. 3904–3914, 2021. doi:10.1093/eurheartj/ehab544

[6] Y. Zhou et al., "Sampling rate requirement for accurate calculation of heart rate and its variability based on the electrocardiogram," Physiological Measurement, vol. 45, no. 2, 025007, 2024. doi:10.1088/1361-6579/ad252d

[7] S. Mahdiani, V. Jeyhani, M. Peltokangas, and A. Vehkaoja, "Is 50 Hz High Enough ECG Sampling Frequency for Accurate HRV Analysis?," in Proc. 37th Annu. Int. Conf. IEEE Eng. Med. Biol. Soc., Milan, Italy, 2015, pp. 5948–5951. doi:10.1109/EMBC.2015.7319746

[8] J. Kingma, C. Simard, and B. Drolet, "Overview of cardiac arrhythmias and treatment strategies," Pharmaceuticals, vol. 16, no. 6, 844, 2023. doi:10.3390/ph16060844

[9] S. Chakrabarti and A. G. Stuart, "Understanding cardiac arrhythmias," Archives of Disease in Childhood, vol. 90, no. 10, pp. 1086–1090, 2005. doi:10.1136/adc.2005.076984

[10] P. R. Patil, A. Sait, and D. R. Patil, "A study of the risk factors of various arrhythmias in patients with coronary heart disease," International Journal of Advances in Medicine, vol. 4, no. 5, pp. 1369–1373, 2017. doi:10.18203/2349-3933.ijam20174285

[11] J. W. Mason, E. W. Hancock, and L. S. Gettes, "Recommendations for the standardization and interpretation of the electrocardiogram," Circulation, vol. 115, no. 10, pp. 1325–1332, 2007. doi:10.1161/circulationaha.106.180201

[12] T. Stracina, M. Ronzhina, R. Redina, and M. Novakova, "Golden standard or obsolete method? Review of ECG applications in clinical and experimental context," Frontiers in Physiology, vol. 13, no. 1, 867033, 2022. doi:10.3389/fphys.2022.867033

[13] D. E. Becker, “Fundamentals of electrocardiography interpretation,” Anesthesia Progress, vol. 53, no. 2, pp. 53–64, 2006. doi:10.2344/0003-3006(2006)53[53:FOEI]2.0.CO;2

[14] O. Kwon et al., "Electrocardiogram sampling frequency range acceptable for heart rate variability analysis," Healthcare Informatics Research, vol. 24, no. 3, pp. 198–206, 2018. doi:10.4258/hir.2018.24.3.198

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[15] A. P. Wibawa, A. B. P. Utama, H. Elmunsyah, U. Pujianto, F. A. Dwiyanto, and L. Hernandez, "Time-series analysis with smoothed Convolutional Neural Network," Journal of Big Data, vol. 9, no. 1, 44, 2022. doi:10.1186/s40537-022-00599-y

[16] H. Liu et al., "A large-scale multi-label 12-lead electrocardiogram database with standardized diagnostic statements," Scientific Data, vol. 9, no. 1, 272, 2022. doi:10.1038/s41597-022-01403-5

[17] R. A. Dos Santos, "A comparative study of ECG leads in predicting cardiac arrhythmias using Deep Learning models," European Journal of Engineering Science and Technology, vol. 8, no. 1, pp. 1–12, 2025. doi:10.33422/ejest.v8i1.1472