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A Comparative Study of ECG Leads in Predicting Cardiac Arrhythmias Using Deep Learning Models

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ABSTRACT

Cardiac arrhythmias are a group of conditions that have a high incidence and prevalence worldwide, and receive considerable attention from the medical community because they are associated with several risk factors and can cause serious impairment of the individual's cardiac function in more critical cases. The electrocardiogram is the main tool for the diagnosis of cardiac arrhythmias because it is considered flexible, non-invasive, and low-cost. The so-called 12-lead system is the most widely used ECG configuration in clinical practice and has been considered for several years as the gold standard for detecting cardiac arrhythmias. Although this configuration is widely popular, there are situations in which it may be more interesting to use simpler ECG configurations to expand the tool to scenarios other than traditional healthcare environments, such as using mobile devices for cardiac monitoring. These scenarios require using simplified ECG configurations, using a single lead or a subset of leads, due to technical restrictions of the devices or limitations of the scenario itself. Knowing the performance of each lead when considered individually is important for defining which leads are most suitable for use in each scenario. This study presents a comparative analysis of the leads of the 12-lead system for predicting cardiac arrhythmias employing a deep learning-based approach and a large dataset containing diagnoses of 32 types of arrhythmias. A large public dataset well-annotated according to international standards for arrhythmia diagnosis was used. Both individual results on the performance of each lead and patterns involving groups of leads that share common characteristics were highlighted. The results presented allow healthcare professionals to be equipped with quantitative data that can provide a robust basis for decision-making and overall improvement of medical processes. The results demonstrate the feasibility of using technologies based on Artificial Intelligence as tools to support cardiology practice and the expansion of cardiac monitoring practices to environments outside clinics and hospitals.

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1. Introduction

Cardiac arrhythmias are a group of conditions that receive considerable attention from the medical community because they are associated with several risk factors and, in more critical cases, can compromise cardiac function and lead to sudden death from fulminant infarction. This condition has a high incidence and prevalence worldwide, affecting a significant portion of the population. According to Li et al. (2022), the concern about this disease can be justified by the results presented by a study that analyzed epidemiological data from 204 countries and reported an incidence of approximately 4.71 million cases and a prevalence of approximately 59.7 million cases in 2019. The scenario presented in that study reinforces the importance of investing in applying strategies and technologies to support the prevention and treatment of arrhythmias.

Among the alternatives proposed to respond to the challenges imposed by this scenario is the use of technologies based on Artificial Intelligence (AI) for the automatic detection and classification of cardiac arrhythmias. According to Nagarajan et al. (2021), the growing interest in using AI-based technologies in cardiology practice can be evidenced by the large amount of research related to the topic published in the last few years. This interest has been motivated by factors such as the evolution of Machine Learning and Deep Learning techniques, the increase in available computing power, and the dissemination of sensor technologies and wearable devices. As highlighted by Singh et al. (2023), several researchers have presented technologies based on Machine Learning and Deep Learning for diagnosing cardiac arrhythmias using data from Electrocardiogram (ECG) exams.

The ECG is a device that records the electrical signals generated by the heart through electrodes attached to the skin. According to iMotions (2024), ECG has become widely used in medical practice because it is a non-invasive and low-cost technique that allows obtaining high-resolution data. This characteristic makes the ECG a more cost-effective option when compared to other advanced imaging exam modalities or invasive procedures. Bloe (2021) states that another characteristic that favors the use of the ECG is the flexibility of allowing different configurations of the number of electrodes, which allows its use in different scenarios.

The most widely used ECG configuration is the so-called 12-lead system. This system uses 10 electrodes positioned to generate 12 leads (or derivations) that correspond to different points of view (or angles) of myocardial activity. According to Jarvis (2021), considering the 12 leads in an ECG exam is the most common practice in clinics and hospitals, and has been considered for several years as the gold standard for detecting cardiac arrhythmias. Meek and Morris (2002) highlight that the 10-electrode configuration provides the advantage of providing a more complete and detailed view of myocardial activity. However, there are situations in which it may be more interesting to use only a subset of the leads to reduce the amount of data processed to optimize diagnostic time and reduce the complexity of the procedure. Cardiac monitoring by wearable devices is an example of a scenario in which only one lead or a subset of leads is used due to the processing and storage capacity limitations of these devices. In addition, emergency or rapid triage situations may also benefit from using a subset of leads, as this can expedite patient care.

Identifying which leads provide the best accuracy in classifying certain arrhythmias is essential in scenarios where a subset of leads must be selected for use. Knowing which leads are most relevant for diagnosing each type of arrhythmia can contribute to faster and more accurate diagnoses. This study presents a comparative analysis between the 12 leads for classifying arrhythmias using a Deep Learning model and a large dataset containing diagnoses of 32 types of arrhythmias. This study aims to present insights and patterns to optimize the use of ECG in conjunction with Deep Learning techniques for classifying arrhythmias.

2. Literature Review

The cardiac cycle is made up of the set of events that occur within the heart's valves and chambers between the beginning of one heartbeat and the next. These events pump oxygen-poor blood to the lungs for oxygenation and oxygenated blood to the aorta for distribution throughout the body. The cycle is executed through synchronized myocardial contractions and relaxations, ensuring proper blood flow throughout the cardiovascular system. This process is regulated by specialized cells that generate electrical signals propagated across the myocardium to control these movements.

Disruptions in the regular sequence of these events, known as cardiac arrhythmias, often result from diseases or disorders of the cardiovascular system. According to Kingma et al. (2003), arrhythmias may stem from structural abnormalities in the myocardium or risk factors related to genetic or environmental conditions. Arrhythmias are classified by heart rhythm speed (tachycardia or bradycardia) and origin (upper or lower heart chambers). Chakrabarti and Stuart (2005) highlight that they can result from abnormalities in signal generation or conduction within the myocardium.

The ECG is the primary diagnostic tool for identifying and classifying cardiac arrhythmias. The ECG visualizes myocardial electrical activity as a trace, where the vertical axis represents voltage (in microvolts) and the horizontal axis represents time (in milliseconds). Figure 1 illustrates an ECG trace showing the 12 leads generated by the 10 electrodes of the 12-lead system. According to Becker (2006), the trace exhibits a regular sequence of waves in healthy hearts, while arrhythmic hearts show irregular intervals, extra waves, altered wave morphology, or wave absence.

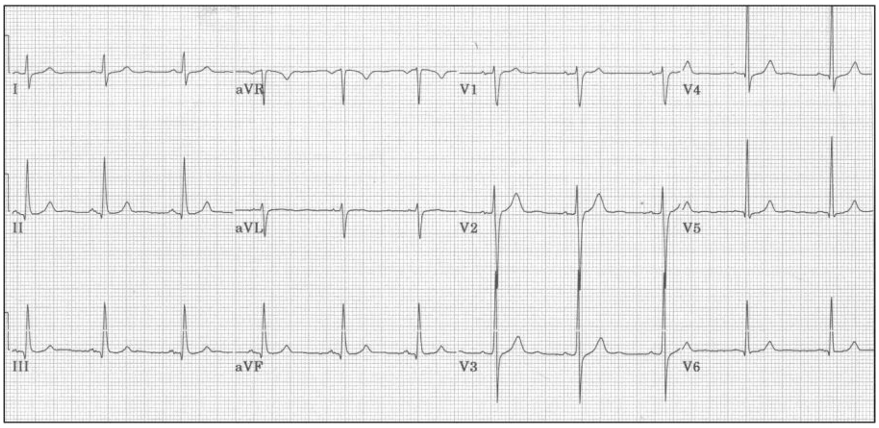

Figure 1. Example of an ECG exam

According to Javis (2021), a lead represents the electrical potential difference between two points measured using body-attached electrodes. The 12-lead system includes precordial leads (V1 to V6), derived from chest electrodes, and limb leads (I, II, III, aVR, aVL, and aVF), derived from limb electrodes. Figure 2 shows the positioning of electrodes for generating precordial leads and figure 3 shows the positioning of electrodes for generating limb leads. Precordial leads provide a transverse perspective of the heart's activity, while limb leads offer a frontal view. Together, they enable a three-dimensional analysis of myocardial function. Meek and Morris (2002) describe four key anatomical perspectives provided by this arrangement: the inferior surface (leads II, III, and aVF), the anterior surface (leads V1 to V4), the lateral surface (leads I, aVL, V5, and V6), and the right atrium and left ventricular cavity (leads V1 and aVR). Figure 4 shows the heart's activity visualized from the vertical plane (frontal perspective) through the limb leads and the horizontal plane (transverse perspective) through the precordial leads.

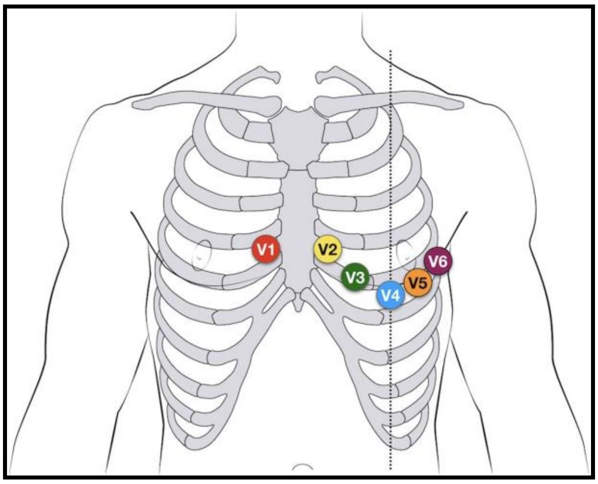

Figure 2. Precordial leads placement

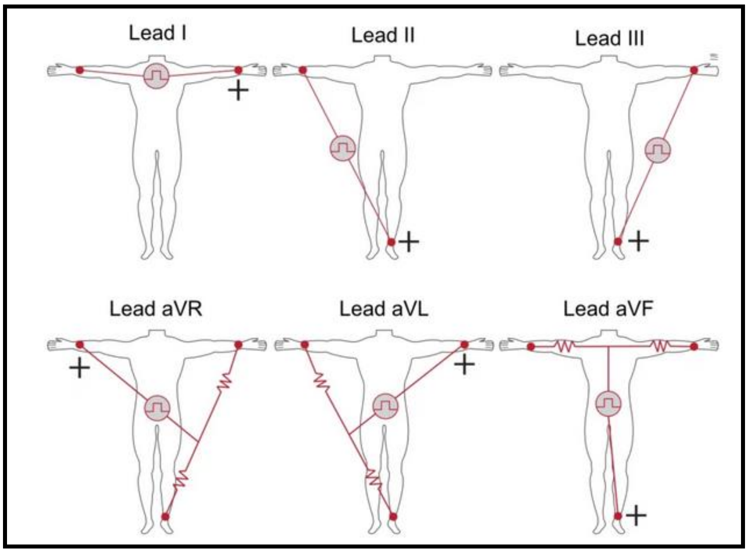

Figure 3. Limb leads placement

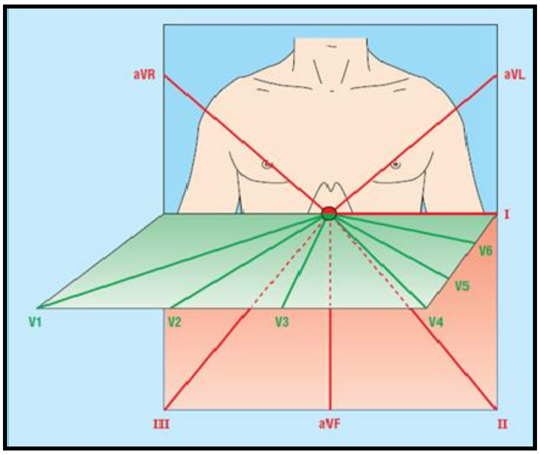

Figure 4. The perspective of the leads

According to Hibbitt (2024), the 12-lead system has the advantage of being highly informative because it allows multiple views of cardiac activity, but is typically confined to clinical settings due to the complexity of the operation and the number of electrodes required. Wearable ECG devices have emerged as a promising alternative, extending cardiac monitoring beyond healthcare environments and enabling early diagnosis. However, these devices often rely on a single lead or a reduced set due to technical constraints. Choi et al. (2024) and Funston et al. (2022) highlight that studies evaluating the accuracy of a single lead for cardiac diagnoses have been carried out to verify the potential of using wearable devices as tools to aid in the practice of cardiological monitoring and diagnosis.

Several studies have proposed adopting AI-based technologies in medical practice in recent years. Alowais et al. (2023) highlight several possible applications of AI in tasks such as disease diagnosis, selection of treatments, laboratory tests, drug discovery, recommendation systems through virtual assistants and chatbots, and mental health support. As stated by the authors, AI-based tools have the potential to provide improved accuracy and efficiency in medical processes, as well as the optimization of the use of resources, cost reduction, and time savings.

According to Bajwa et al. (2021), despite the advances made in this field, there are still several challenges to the widespread adoption of AI-based tools in clinical practice. The authors state that there is a need to address issues related to the availability and quality of data, aspects associated with ethics and regulations, and difficulty in ensuring security and data privacy. Alowais et al. (2023) stated the need to address issues related to bias and lack of user expertise to increase users' confidence in the outcomes obtained using these tools.

3. Methods

3.1. Dataset Description

The dataset generated by the work developed by Liu et al. (2022) was used in this study. The data were collected in an experiment carried out at Shandong Provincial Hospital (Jinan, China) between 2019 and 2020. A total of 25,770 ECG records were generated from 24,666 individuals who underwent the exams. Liu et al. (2022) highlight that the lack of large-scale public ECG datasets and the standardization problems found in existing datasets motivated the development of this work. The dataset was made publicly available for use in research related to the classification of cardiac arrhythmias.

An equipment configured according to the 12-lead system with a sampling frequency of 500 Hz was used to perform the exams. Each individual was monitored for a time interval that varied from 10 to 60 seconds. A cardiologist assigned the diagnosis to each exam following the standard recommended by the American Heart Association (AHA). Mason et al. (2007) highlight that the statement proposed by the AHA suggests a classification with 117 types of arrhythmias and has as its main objective the improvement of the accuracy of diagnoses through the use of a concise list of standardized terms. The cardiologist considered 44 classifications among the 117 suggested by the AHA and certain exams received more than one diagnosis. Table 1 presents the 44 classifications considered in this experiment.

Table 1. Classification of arrhythmias as suggested by the AHA statement.

Code	Description	Code	Description
1	Normal ECG	102	Left posterior fascicular block
21	Sinus tachycardia	104	Left bundle-branch block
22	Sinus bradycardia	105	Incomplete right bundle-branch block
23	Sinus arrhythmia	106	Right bundle-branch block
30	Atrial premature complex(es)	108	Ventricular preexcitation
31	Atrial premature complexes, nonconduct	120	Right-axis deviation
36	Junctional premature complex(es)	121	Left-axis deviation
37	Junctional escape complex(es)	125	Low voltage
50	Atrial fibrillation	140	Left atrial enlargement
51	Atrial flutter	142	Left ventricular
54	Junctional tachycardia	143	Right ventricular hypertrophy
60	Ventricular premature complex(es)	145	ST deviation
80	Short PR interval	146	ST deviation with T-wave change
81	AV conduction ratio N:D	147	T-wave abnormality
82	Prolonged PR interval	148	Prolonged QT interval
83	Second-degree AV block, Mobitz type I	152	TU fusion
84	Second-degree AV block, Mobitz type II	153	ST-T change due to ventricular hypertrophy
85	2:1 AV block	155	Early repolarization
86	AV block, varying conduction	160	Anterior MI
87	AV block, advanced (high-grade)	161	Inferior MI
88	AV block, complete (third-degree)	165	Anteroseptal MI
101	Left anterior fascicular block	166	Extensive anterior MI

The dataset has 12 features that represent the 12 leads obtained by the ECG at a given time. Each feature stores the voltage in microvolts (μV) recorded by the set of electrodes that generate a given lead. The dataset target stores the code of the type of arrhythmia attributed to the diagnosis. Each instance of the dataset represents the 12 views of cardiac activity at a given time. The number of samples generated in each exam varied between 5,000 and 30,000 records, taking into account the sampling frequency used and the duration of each exam.

3.2. Preprocessing

For this study, it was chosen to use only the first 10 seconds of each exam for standardization reasons. The records were resampled to a sampling frequency of 125 Hz to reduce the data processed and the computational resources required to train the model. Thus, each ECG record now contains 1,250 samples. Only the first diagnosis attributed to each ECG was considered for cases in which the exam received more than one classification.

No problems with missing or inconsistent data were found in the exploratory data analysis, thus eliminating the need to perform specific procedures to deal with these types of problems. However, it was necessary to use robust normalization techniques to adjust the data due to the presence of outliers and an asymmetry in the data distribution that could affect the training performance.

The dataset was restructured into a "time window" format. The 1,250 samples corresponding to each ECG exam were converted to a single record composed of 1,250 features, in which each feature stores the voltage captured by a specific lead at a given instant in time. This data structuring aligns with the concepts of Cardiology since doctors analyze the existence of patterns in electrical waves over time. The dataset now contains 25,770 samples (quantity of ECG exams performed).

Table 2 shows the distribution of classes in the dataset. The data were considerably unbalanced, as 53% of the samples belonged to the AHA code 1, while there were certain classes with less than 1% of the samples. The training set was balanced using upsampling and downsampling techniques. The Synthetic Minority Over-sampling (SMOTE) technique was used to upsample the data. This technique consists of generating synthetic samples from the samples existing in the minority class to balance the dataset. It was necessary to remove the classifications that had less than 6 samples (AHA codes 31, 37, 84, 87, 102, 143, 148, and 152) because the SMOTE technique requires a minimum number of samples in each class to generate synthetic samples. The training set now contains 200,000 samples distributed among 32 classes. The test set remained with 2,577 samples (10%).

Table 2. Dataset balance analysis

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

3.3. Model Training

This study is based on the work presented by Dos Santos (2024). That study proposed the use of a Convolutional Neural Network (CNN) to detect cardiac arrhythmias using the same dataset, however, using only data from the feature corresponding to Lead II. Lead II was selected for that work because it is considered the most used lead due to its location being close to the cardiac axis and providing better alignment with the direction of transmission of electrical signals through the myocardium. The choice to use a CNN model stems from its recent success in time series analysis by outperforming other types of Deep Learning models. The proposed CNN model proved to be a high-precision tool for detecting cardiac arrhythmias by achieving a high accuracy in its predictions. A similar CNN model was used in this study.

Figure 5 shows a representation of the CNN model architecture. The feature extraction block is composed of 4 convolutional layers and 2 Max Pooling layers, while the pattern detection block is composed of 1 Flatten layer, 1 Fully Connected layer, and 1 output layer. The convolutional layers and Fully Connected layers are followed by Batch Normalization layers.

The use of 4 convolutional layers provided better performance than other configurations with 3 layers that were also tested. Batch Normalization layers were used to avoid the gradient vanishing problem and make training more stable.

Table 3 shows the configuration of the model's hyperparameters. The Rectified Linear Activation Unit (ReLU) activation function was used because it presents simplicity of execution and computational efficiency when compared to other popular activation functions. The "he_normal" initializer was used because it gives better results in layers that use the ReLU function due to its adaptation to the characteristics of ReLU to improve the efficiency of gradient flow through the network.

The CNN model was developed with the Tensorflow/Keras library. The training was run 12 times and each run only used data from one of the 12 leads. The training was performed in 300 epochs and used the Adam optimizer configured with a learning rate of 0.001. The standard batch size of 32 was used to strike a balance between performance and consumption of computational resources. The training was performed using the cross-validation technique (10 folds).

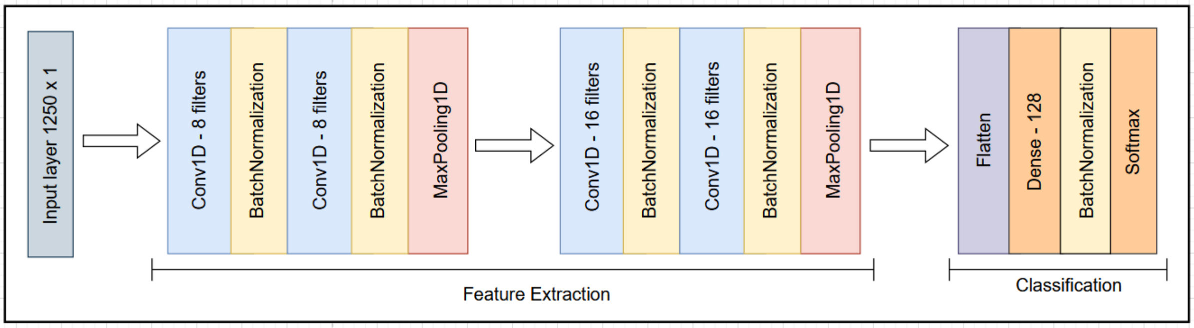

Figure 5. Representation of CNN architecture.

Table 3. Hyperparameters setup.

Layer	Layer type	Filters	Kernel size	Activation	Kernel initializer	Units
1	Conv1D	8	3	ReLU	he_uniform	-
2	BachNormalization	-	-	-	-	-
3	Conv1D	8	3	ReLU	he_uniform	-
4	BachNormalization	-	-	-	-	-
5	MaxPooling1D	-	-	-	-	-
6	Conv1D	16	5	ReLU	he_uniform	-
7	BachNormalization	-	-	-	-	-
8	Conv1D	16	5	ReLU	he_uniform	-
9	BachNormalization	-	-	-	-	-
10	MaxPooling1D	-	-	-	-	-
11	Flatten	-	-	-	-	-
12	Dense	-	-	ReLU	he_uniform	128
13	BachNormalization	-	-	-	-	-
14	Dense	-	-	Softmax	-	32

4. Results and Discussion

This section presents the results obtained from the training of the CNN model using the 12 ECG leads and discusses their implications for arrhythmia detection and clinical practice.

Table 4 presents the accuracies obtained across the 12 training runs, highlighting the superior performance of aVR. The best accuracies were obtained using leads aVR and II, respectively. These results suggest that the anatomical positioning of these two leads in relation to myocardial electrical currents favors their sensitivity for identifying cardiac cycle waves and enables the detection of different types of arrhythmias. The accuracy obtained using the lead

V6 was lower than that obtained using the other leads. This result suggests that the extreme lateral positioning of this lead limits its sensitivity for capturing cardiac cycle waves and makes it difficult to detect types of arrhythmias originating in locations distant from the left chambers of the myocardium.

Table 4. Model accuracy

Lead	**%**
aVR	92.09
Lead II	91.91
Lead I	90.43
V1	90.23
V3	90.03
V4	89.98
aVF	89.19
V5	88.38
Lead III	87.40
aVL	85.80
V2	85.70
V6	84.49

Table 5 presents detailed training metrics. The best F1-Score rate obtained for each type of arrhythmia among the 12 training runs is presented and which were the leads with which it was possible to achieve the best rate. The F1-Score metric was used because it is a robust metric and provides a more balanced view of model performance.

Table 5. Detailed metrics

Condition	**F1-Score**	**Leads**
Normal ECG	0.95	Lead II, aVR
Sinus tachycardia	0.96	aVR
Sinus bradycardia	0.96	Lead I, Lead II, aVR, V1, V3
Sinus arrhythmia	0.84	Lead II
Atrial premature complex(es)	0.85	Lead II, V1, V3
Junctional premature complex(es)	0.90	V3
Atrial fibrillation	0.91	Lead II, V1
Atrial flutter	0.92	Lead II, V3
Junctional tachycardia	0.87	Lead I, Lead II, V1, V5
Ventricular premature complex(es)	0.89	aVR
Short PR interval	0.94	V3
Prolonged PR interval	0.88	Lead II, aVR
Second-degree AV block, Mobitz type I	0.88	V5
AV block, complete (third-degree)	0.95	V3
Left anterior fascicular block	0.91	Lead II
Left bundle-branch block	0.93	Lead I
Incomplete right bundle-branch block	0.84	Lead I, aVR, V1
Right bundle-branch block	0.96	V1
Ventricular preexcitation	0.91	V4
Right-axis deviation	0.90	V3
Left-axis deviation	0.88	Lead II, aVF
Low voltage	0.87	V3
Left atrial enlargement	1.00	Lead II
Left ventricular	0.87	Lead II, aVR
ST deviation	0.85	aVR
ST deviation with T-wave change	0.86	Lead II
T-wave abnormality	0.86	Lead II
Early repolarization	0.94	Lead II
Anterior MI	0.97	V3

Inferior MI	0.90	V4
Anteroseptal MI	0.93	V3
Extensive anterior MI	0.92	aVR, V3

Considering individual results; leads II, V3, and aVR were the best leads for identifying most types of arrhythmia, which suggests that these leads provide a comprehensive view of the heart's electrical activity and enable the detection of arrhythmias originating from different locations in the myocardium. Leads III, aVL, V2, and V6 were not the best for any type of arrhythmia, suggesting that these leads have limitations in their sensitivity and are more indicated for identifying specific types of arrhythmias.

The superiority presented by lead II in the experiment is aligned with the belief highlighted by Meek and Morris (2002) that the characteristics of lead II make it very accurate and reliable for identifying different types of arrhythmias, and this factor makes it the most used lead in clinical practice. However, the good performance achieved by other leads demonstrates that there are alternatives for different ECG configurations with the possibility of obtaining high precision in arrhythmia detection.

The aVR lead achieved the best performance for identifying the normal condition (without arrhythmia). This result reinforces the thesis that the anatomical positioning of this lead facilitates the capture of subtle deviations in the electrical axis that would indicate abnormal conditions and this characteristic can simplify the detection of normal conditions. The performance of this lead, which is often undervalued in clinical practice, demonstrated that it can play an important role in detecting normal conditions and different types of arrhythmias.

The results also suggest patterns related to groups of disorders that share electrocardiographic characteristics or location of origin. Changes in sinus rhythm were better identified by limb leads. Supraventricular changes originating in the atrioventricular node were better detected by most leads, as well as conduction disturbances resulting from blockages and anatomical changes, such as deviations in the cardiac axis or enlargement of the chambers. Leads II and aVR showed the highest precision for detecting changes in the ST segment and T wave. The myocardial infarctions were better detected by precordial leads. Finally, atrial fibrillation, one of the most prevalent cardiac arrhythmias, was most accurately identified by leads II and V1.

The identified patterns could be useful for developing ECG applications in wearable devices, in which subsets of the 12-lead system must be used due to the limitations of these devices. Quantitative data on the performance of each lead is useful to support decisions about which leads to use in a given context. These alternatives contribute to the expansion of healthcare services by helping to reduce limitations associated with cardiac monitoring processes.

Wearable devices equipped with ECGs and highly accurate AI-based systems for diagnosing arrhythmias enable patients to be monitored at different times of the day. This characteristic is desirable because the symptoms of this disease can manifest themselves intermittently and doctors may be unable to make a diagnosis when the patient is outside clinics or hospitals. In this way, possible abnormalities detected by the system can be recorded for later analysis or transmitted in real-time to the responsible doctor. Such systems can also send alerts if a specific patient is affected by some arrhythmia considered more critical, which can be useful for patients who need the help of other people because they have some limitation or disability that prevents them from taking the necessary actions on their own.

5. Limitations and Future Direction

The dataset used in the study is comprehensive and well annotated, however, it was derived from an experiment carried out under specific conditions such as geographic location, population studied, and ECG equipment used. These factors could introduce biases or limitations in generalizing the results for different populations or scenarios. As a future study, it is suggested to replicate this work using other datasets collected in distinct scenarios to verify that the results obtained are robust and generalizable. It is recommended to use datasets collected in experiments involving patients with different profiles and using distinct data acquisition protocols.

Using AI-based systems in environments outside clinics and hospitals presents significant challenges due to the possibility of having a wide variety of data different from those used in training and the quality of the data being affected by noise. There may also be restrictions related to regulatory issues, as in uncontrolled environments there could be difficulties in ensuring that data is being collected following the protocols required for the exams. Future studies addressing these issues and proposing alternatives to mitigate such problems could contribute significantly to the field.

6. Conclusion

The results obtained demonstrate the feasibility of using individual leads or subsets of the 12-lead system for the detection of arrhythmias with the possibility of obtaining high accuracy in predictions generated by Deep Learning models. These findings suggest significant opportunities for optimizing ECG use, which can also reduce costs associated with the cardiac monitoring process. The results may also reinforce confidence in AI-based technologies as tools to support cardiology practice and encourage the development of ECG applications for use in environments outside of clinics and laboratories.

The patterns identified in the analysis of detailed metrics can provide useful information for healthcare professionals. This knowledge can improve the efficiency of exams, reduce the time required for diagnosis, and enhance the overall quality of medical processes. The quantitative data provided prevent decisions from being based solely on hypotheses, offering a robust foundation for clinical practice.

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