Lecture Notes in Networks and Systems 619

Miguel Botto-Tobar · Omar S. Gómez · Raul Rosero Miranda · Angela Díaz Cadena · Washington Luna-Encalada *Editors*

Trends in Artificial Intelligence and Computer Engineering

Proceedings of ICAETT 2022

Springer

Lecture Notes in Networks and Systems 619

The series "Lecture Notes in Networks and Systems" publishes the latest developments in Networks and Systems—quickly, informally and with high quality. Original research reported in proceedings and post-proceedings represents the core of LNNS.

Volumes published in LNNS embrace all aspects and subfields of, as well as new challenges in, Networks and Systems.

The series contains proceedings and edited volumes in systems and networks, spanning the areas of Cyber-Physical Systems, Autonomous Systems, Sensor Networks, Control Systems, Energy Systems, Automotive Systems, Biological Systems, Vehicular Networking and Connected Vehicles, Aerospace Systems, Automation, Manufacturing, Smart Grids, Nonlinear Systems, Power Systems, Robotics, Social Systems, Economic Systems and other. Of particular value to both the contributors and the readership are the short publication timeframe and the world-wide distribution and exposure which enable both a wide and rapid dissemination of research output.

The series covers the theory, applications, and perspectives on the state of the art and future developments relevant to systems and networks, decision making, control, complex processes and related areas, as embedded in the fields of interdisciplinary and applied sciences, engineering, computer science, physics, economics, social, and life sciences, as well as the paradigms and methodologies behind them.

Indexed by SCOPUS, INSPEC, WTI Frankfurt eG, zbMATH, SCImago.

All books published in the series are submitted for consideration in Web of Science.

For proposals from Asia please contact Aninda Bose (aninda.bose@springer.com).

More information about this series at https://link.springer.com/bookseries/15179

Miguel Botto-Tobar · Omar S. Gómez ·
Raul Rosero Miranda · Angela Díaz Cadena ·
Washington Luna-Encalada
Editors

Trends in Artificial Intelligence and Computer Engineering

Proceedings of ICAETT 2022

Springer

Editors
Miguel Botto-Tobar
Eindhoven University of Technology
Eindhoven, The Netherlands

Omar S. Gómez
Escuela Superior Politécnica de Chimborazo
Riobamba, Ecuador

Raul Rosero Miranda
Escuela Superior Politécnica de Chimborazo
Riobamba, Ecuador

Angela Díaz Cadena
Universitat de Valencia
Valencia, Valencia, Spain

Washington Luna-Encalada
Escuela Superior Politécnica del Chimborazo
Riobamba, Ecuador

ISSN 2367-3370 ISSN 2367-3389 (electronic)
Lecture Notes in Networks and Systems
ISBN 978-3-031-25941-8 ISBN 978-3-031-25942-5 (eBook)
https://doi.org/10.1007/978-3-031-25942-5

This Springer imprint is published by the registered company Springer Nature Switzerland AG
The registered company address is: Gewerbestrasse 11, 6330 Cham, Switzerland

Preface

The 4th International Conference on Advances in Emerging Trends and Technologies (ICAETT) was held on the main campus of the Escuela Superior Politécnica de Chimborazo, in Riobamba–Ecuador, from October 26 to 28, 2028, and it was proudly organized by Facultad de Informática y Electrónica (FIE) at Escuela Superior Politécnica de Chimborazo and supported by GDEON. The ICAETT series aims to bring together top researchers and practitioners working in different domains in the field of computer science to exchange their expertise and to discuss the perspectives of development and collaboration [1, 2]. The content of this volume is related to the following subjects:

- Artificial Intelligence
- Communications
- e-Learning
- AT for Engineering Applications
- Security
- Technology Trends.

ICAETT 2022 received 234 submissions written in English by 940 authors coming from 15 different countries. All these papers were peer-reviewed by the ICAETT 2022 Program Committee consisting of 162 high-quality researchers. To assure a high-quality and thoughtful review process, we assigned each paper at least three reviewers. Based on the peer reviews, 54 full papers were accepted, resulting in a 23% acceptance rate, which was within our goal of less than 40%.

We would like to express our sincere gratitude to the invited speakers for their inspirational talks, to the authors for submitting their work to this conference and the reviewers for sharing their experience during the selection process.

October 2022

Miguel Botto-Tobar
Omar S. Gómez
Raúl Rosero Miranda
Angela Díaz Cadena
Washington Luna-Encalada

Organization

General Chairs

Miguel Botto-Tobar — Eindhoven University of Technology, The Netherlands

Omar S. Gómez — Escuela Superior Politécnica de Chimborazo, Ecuador

Organizing Committee

Miguel Botto-Tobar — Eindhoven University of Technology, The Netherlands

Omar S. Gómez — Escuela Superior Politécnica de Chimborazo, Ecuador

Raúl Rosero Miranda — Escuela Superior Politécnica de Chimborazo, Ecuador

Ángela Díaz Cadena — Universitat de Valencia, Spain

Sergio Montes León — Universidad Rey Juan Carlos Madrid, Spain

Washington Luna-Encalada — Escuela Superior Politécnica de Chimborazo, Ecuador

Steering Committee

Miguel Botto-Tobar — Eindhoven University of Technology, The Netherlands

Ángela Díaz Cadena — Universitat de Valencia, Spain

Publication Chair

Miguel Botto-Tobar — Eindhoven University of Technology, The Netherlands

Program Chairs

Technology Trends

Miguel Botto-Tobar	Eindhoven University of Technology, The Netherlands
Sergio Montes León	Universidad Rey Juan Carlos Madrid, Spain
Hernán Montes León	Universidad Rey Juan Carlos, Spain

Electronics

Ana Zambrano Vizuete	Escuela Politécnica Nacional, Ecuador
David Rivas	Universidad de las Fuerzas Armadas (ESPE), Ecuador
Edgar Maya-Olalla	Universidad Técnica del Norte, Ecuador
Hernán Domínguez-Limaico	Universidad Técnica del Norte, Ecuador

Intelligent Systems

Guillermo Pizarro Vásquez	Universidad Politécnica Salesiana, Ecuador
Janeth Chicaiza	Universidad Técnica Particular de Loja, Ecuador
Gustavo Andrade Miranda	Universidad de Guayaquil, Ecuador

Machine Vision

Julian Galindo	LIG-IIHM, France
Erick Cuenca	Université de Montpellier, France
Pablo Torres-Carrión	Universidad Técnica Particular de Loja, Ecuador

Communication

Óscar Zambrano Vizuete	Universidad Técnica del Norte, Ecuador
Pablo Palacios Jativa	Universidad de Chile, Chile

Security

Luis Urquiza-Aguiar	Escuela Politécnica Nacional, Ecuador
Joffre León-Acurio	Universidad Técnica de Babahoyo, Ecuador

e-Learning

Miguel Zúñiga-Prieto	Universidad de Cuenca, Ecuador
Doris Macias	Universitat Politécnica de Valencia, Spain

e-Business

Angela Díaz Cadena	Universitat de Valencia, Spain

e-Goverment and e-Participation

Alex Santamaría Philco	Universidad Laica Eloy Alfaro de Manabí, Ecuador

Program Committee

Abdón Carrera Rivera	University of Melbourne, Australia
Adrián Cevallos Navarrete	Griffith University, Australia
Alba Morales Tirado	University of Greenwich, UK
Alejandro Ramos Nolazco	Instituto Tecnológico y de Estudios Superiores Monterrey, Mexico
Alex Santamaría Philco	Universitat Politècnica de València, Spain/Universidad Laica Eloy Alfaro de Manabí, Ecuador
Alex Cazañas Gordon	The University of Queensland, Australia
Alexandra Velasco Arévalo	Universität Stuttgart, Germany
Alexandra Elizabeth Bermeo Arpi	Universidad de Cuenca, Ecuador
Alfonso Guijarro Rodríguez	Universidad de Guayaquil, Ecuador
Alfredo Núñez	New York University, USA
Allan Avendaño Sudario	Università degli Studi di Roma "La Sapienza", Italy
Almílcar Puris Cáceres	Universidad Técnica Estatal de Quevedo, Ecuador
Ana Guerrero Alemán	University of Adelaide, Australia
Ana Santos Delgado	Universidade Federal de Santa Catarina (UFSC), Brazil
Ana Núñez Ávila	Universitat Politècnica de València, Spain
Andrea Mory Alvarado	Universidad Católica de Cuenca, Ecuador
Andrés Calle Bustos	Universitat Politècnica de València, Spain
Andrés Jadan Montero	Universidad de Buenos Aires, Argentina
Andrés Molina Ortega	Universidad de Chile, Chile
Andrés Robles Durazno	Edinburgh Napier University, UK

Andrés Vargas González	Syracuse University, USA
Andrés Barnuevo Loaiza	Universidad de Santiago de Chile, Chile
Andrés Chango Macas	Universidad Politécnica de Madrid, Spain
Andrés Cueva Costales	University of Melbourne, Australia
Andrés Parra Sánchez	University of Melbourne, Australia
Ángel Plaza Vargas	Universidad de Guayaquil, Ecuador
Angel Vazquez Pazmiño	Université Catholique de Louvain, Belgium
Ángela Díaz Cadena	Universitat de València, Spain
Angelo Vera Rivera	George Mason University, USA
Antonio Villavicencio Garzón	Universitat Politècnica de Catalunya, Spain
Audrey Romero Pelaez	Universidad Politécnica de Madrid, Spain
Bolívar Chiriboga Ramón	University of Melbourne, Australia
Byron Acuna Acurio	Flinders University, Australia
Carla Melaños Salazar	Universidad Politécnica de Madrid, Spain
Carlos Barriga Abril	University of Nottingham, UK
Carlos Valarezo Loiza	Manchester University, UK
Cesar Mayorga Abril	Universidad Técnica de Ambato, Ecuador
César Ayabaca Sarria	Escuela Politécnica Nacional (EPN), Ecuador
Christian Báez Jácome	Wageningen University & Research, The Netherlands
Cintya Aguirre Brito	University of Portsmouth, UK
Cristian Montero Mariño	University of Melbourne, Australia
Daniel Magües Martínez	Universidad Autónoma de Madrid, Spain
Daniel Silva Palacios	Universitat Politècnica de València, Spain
Daniel Armijos Conde	Queensland University of Technology, Australia
Danilo Jaramillo Hurtado	Universidad Politécnica de Madrid, Spain
David Rivera Espín	University of Melbourne, Australia
David Benavides Cuevas	Universidad de Sevilla, Spain
Diana Morillo Fueltala	Brunel University London, UK
Diego Vallejo Huanga	Universitat Politècnica de València, Spain
Edwin Guamán Quinche	Universidad del País Vasco, Spain
Efrén Reinoso Mendoza	Universitat Politècnica de València, Spain
Eric Moyano Luna	University of Southampton, UK
Erick Cuenca Pauta	Université de Montpellier, France
Ernesto Serrano Guevara	Université de Neuchâtel, Switzerland
Estefania Yánez Cardoso	University of Southampton, UK
Esther Parra Mora	University of Queensland, Australia
Fabián Corral Carrera	Universidad Carlos III de Madrid, Spain
Felipe Ebert	Universidade Federal de Pernambuco (UFPE), Brazil
Fernando Borja Moretta	University of Edinburgh, UK
Franklin Parrales Bravo	Universidad Complutense de Madrid, Spain

Gabriel López Fonseca	Sheffield Hallam University, UK
Gema Rodriguez-Perez	LibreSoft/Universidad Rey Juan Carlos, Spain
Georges Flament Jordán	University of York, UK
Germania Rodríguez Morales	Universidad Politécnica de Madrid, Spain
Ginger Saltos Bernal	University of Portsmouth, UK
Gissela Uribe Nogales	Australian National University, Australia
Glenda Vera Mora	Universidad Técnica de Babahoyo, Ecuador
Guilherme Avelino	Universidade Federal do Piauí (UFP), Brazil
Héctor Dulcey Pérez	Swinburne University of Technology, Australia
Henry Morocho Minchala	Moscow Automobile And Road Construction State Technical University (Madi), Russia
Holger Ortega Martínez	University College London, UK
Iván Valarezo Lozano	University of Melbourne, Australia
Jacqueline Mejia Luna	Universidad de Granada, Spain
Jaime Jarrin Valencia	Universidad Politécnica de Madrid, Spain
Janneth Chicaiza Espinosa	Universidad Politécnica de Madrid, Spain
Jefferson Ribadeneira Ramírez	Escuela Superior Politécnica de Chimborazo, Ecuador
Jeffrey Naranjo Cedeño	Universidad de Valencia, Spain
Jofre León Acurio	Universidad Técnica de Babahoyo, Ecuador
Jorge Quimí Espinosa	Universitat Politècnica de Catalunya, Spain
Jorge Cárdenas Monar	Australian National University, Australia
Jorge Illescas Pena	Edinburgh Napier University, UK
Jorge Lascano	University of Utah, USA
Jorge Rivadeneira Muñoz	University of Southampton, UK
Jorge Charco Aguirre	Universitat Politècnica de València, Spain
José Carrera Villacres	Université de Neuchâtel, Switzerland
José Quevedo Guerrero	Universidad Politécnica de Madrid, Spain
Josue Flores de Valgas	Universitat Politécnica de València, Spain
Juan Barros Gavilanes	INP Toulouse, France
Juan Jiménez Lozano	Universidad de Palermo, Argentina
Juan Romero Arguello	University of Manchester, UK
Juan Zaldumbide Proaño	University of Melbourne, Australia
Juan Balarezo Serrano	Monash University, Australia
Juan Lasso Encalada	Universitat Politècnica de Catalunya, Spain
Juan Maestre Ávila	Iowa State University, USA
Juan Miguel Espinoza Soto	Universitat de València, Spain
Juliana Cotto Pulecio	Universidad de Palermo, Argentina
Julio Albuja Sánchez	James Cook University, Australia
Julio Proaño Orellana	Universidad de Castilla La Mancha, Spain
Julio Balarezo	Universidad Técnica de Ambato, Ecuador
Karla Abad Sacoto	Universidad Autónoma de Barcelona, Spain

Leopoldo Pauta Ayabaca	Universidad Católica de Cuenca, Ecuador
Lorena Guachi Guachi	Università della Calabria, Italy
Lorenzo Cevallos Torres	Universidad de Guayaquil, Ecuador
Lucia Rivadeneira Barreiro	Nanyang Technological University, Singapur
Luis Carranco Medina	Kansas State University, USA
Luis Pérez Iturralde	Universidad de Sevilla, Spain
Luis Torres Gallegos	Universitat Politècnica de València, Spain
Luis Benavides	Universidad de Especialidades Espíritu Santo, Ecuador
Luis Urquiza Aguiar	Universitat Politècnica de Catalunya, Spain
Manuel Beltrán Prado	University of Queensland, Australia
Manuel Sucunuta España	Universidad Politécnica de Madrid, Spain
Marcia Bayas Sampedro	Vinnitsa National University, Ukraine
Marco Falconi Noriega	Universidad de Sevilla, Spain
Marco Tello Guerrero	Rijksuniversiteit Groningen, The Netherlands
Marco Molina Bustamante	Universidad Politécnica de Madrid, Spain
Marco Santórum Gaibor	Escuela Politécnica Nacional, Ecuador/Université Catholique de Louvain, Belgium
María Escalante Guevara	University of Michigan, USA
María Molina Miranda	Universidad Politécnica de Madrid, Spain
María Montoya Freire	Aalto University, Finland
María Ormaza Castro	University of Southampton, UK
María Miranda Garcés	University of Leeds, UK
Maria Dueñas Romero	RMIT University, Australia
Mariela Barzallo León	University of Edinburgh, UK
Mauricio Verano Merino	Eindhoven University of Technology, The Netherlands
Maykel Leiva Vázquez	Universidad de Guayaquil, Ecuador.
Miguel Botto-Tobar	Eindhoven University of Technology, The Netherlands
Miguel Arcos Argudo	Universidad Politécnica de Madrid, Spain
Mónica Baquerizo Anastacio	Universidad Complutense de Madrid, Spain
Mónica Villavicencio Cabezas	Université du Quebec À Montréal, Canada
Omar S. Gómez	Escuela Superior Politécnica del Chimborazo (ESPOCH), Ecuador
Orlando Erazo Moreta	Universidad de Chile, Chile/Universidad Técnica Estatal de Quevedo, Ecuador
Pablo León Paliz	Université de Neuchâtel, Switzerland
Pablo Ordoñez Ordoñez	Universidad Politécnica de Madrid, Spain
Pablo Palacios Jativa	Universidad de Chile, Chile
Pablo Saá Portilla	University of Melbourne, Australia
Patricia Ludeña González	Politecnico di Milano, Italy

Paulina Morillo Alcívar	Universitat Politècnica de València, Spain
Rafael Campuzano Ayala	Grenoble Institute of Technology, France
Rafael Jiménez	Escuela Politécnica del Litoral (ESPOL), Ecuador
Ramiro Santacruz Ochoa	Universidad Nacional de La Plata, Argentina
Richard Ramírez Anormaliza	Universidad Estatal de Milagro, Ecuador/Universitat Politècnica de Catalunya, Spain
Roberto Larrea Luzuriaga	Universitat Politècnica de València, Spain
Roberto Sánchez Albán	Université de Lausanne, Switzerland
Rodrigo Saraguro Bravo	Escuela Superior Politécnica del Litoral (ESPOL), Ecuador
Rodrigo Cueva Rueda	Universitat Politècnica de Catalunya, Spain
Rodrigo Tufiño Cárdenas	Universidad Politécnica Salesiana, Ecuador/Universidad Politécnica de Madrid, Spain
Samanta Cueva Carrión	Universidad Politécnica de Madrid, Spain
Sergio Montes León	Universidad Rey Juan Carlos Madrid, Spain
Tania Palacios Crespo	University College London, UK
Tony Flores Pulgar	Université de Lyon, France
Vanessa Echeverría Barzola	Université Catholique de Louvain, Belgium
Vanessa Jurado Vite	Universidad Politécnica Salesiana, Ecuador
Verónica Yépez Reyes	South Danish University, Denmark
Victor Hugo Rea Sánchez	Universidad Estatal de Milagro, Ecuador
Voltaire Bazurto Blacio	University of Victoria, Canada
Washington Velásquez Vargas	Universidad Politécnica de Madrid, Spain
Wayner Bustamante Granda	Universidad de Palermo, Argentina
Wellington Cabrera Arévalo	University of Houston, USA
Xavier Merino Miño	Instituto Tecnológico y de Estudios Superiores Monterrey, Mexico
Yan Pacheco Mafla	Royal Institute of Technology, Sweden
Yessenia Cabrera Maldonado	Pontificia Universidad Católica de Chile, Chile
Yuliana Jiménez Gaona	Università di Bologna, Italy

References

1. Botto-Tobar, M., León-Acurio, J., A. D. Cadena, and P. M. Díaz, *Preface*, vol. 1067 (2020)
2. Botto-Tobar, M., Gómez, O. S., Miranda, R. R., Cadena, Á. D.: *Preface*, vol. 1302 (2021)

Organizing Institutions

Contents

Communications

e-Learning

Artificial Intelligence

Recognition and Classification of Cardiac Arrhythmias Using Discrete Wavelet Transform (DWT) and Machine Learning Techniques

Hermes Andrés Ayala-Cucas[1], Edison Alexander Mora-Piscal[1], Dagoberto Mayorca-Torres[1,2(✉)], Alejandro José León-Salas[2], and Diego Hernán Peluffo-Ordoñez[3]

[1] Grupo de investigación de Ingeniería Mecatrónica, Universidad Mariana, Pasto, Colombia
{hayala,dmayorca}@umariana.edu.co

[2] Departamento de Lenguajes y Sistemas Informáticos, Universidad de Granada, C/Periodista Daniel Saucedo Aranda s/n, 18071 Granada, Spain

[3] Modeling, Simulation and Data Analysis (MSDA) Research Program, Mohammed VI Polytechnic University, Ben Guerir, Morocco

Abstract. Cardiac arrhythmias are heart rhythm problems that usually occur when the electrical impulses coordinated with the heartbeat do not work correctly. For this reason, detecting abnormalities in an electrocardiogram (ECG) plays a vital role in patient follow-up. Due to the presence of noise, the irregularity of the heartbeat, and the nonstationary nature of ECG signals, their interpretation can be difficult, requiring the use of advanced computer systems to support the diagnosis of cardiac disorders. Therefore, the development of assisted ECG analysis systems is a current topic of study, and the main challenge is to achieve adequate accuracy for application in the clinical setting. Therefore, this article describes a software tool for classifying ECG samples into the main classes of cardiac arrhythmias by removing noise from the ECG signal at the preprocessing stage using conventional digital filters; the location of the QRS complex is essential for the identification of the ECG signal. Therefore, the position and amplitude of the R peaks are determined in the segmentation stage. Then the selection of the most relevant features of the ECG signal is performed using the discrete wavelet transform (DWT). The ability of the extracted features to differentiate between different classes of data is tested using machine learning techniques such as k-Nearest Neighbors, Neural Networks, and Decision Trees with 10-fold cross-validation. These methods are evaluated and tested with the MIT-BIH arrhythmia database, achieving the best accuracy of 98.54% using the k-Nearest Neighbors classifier.

Keywords: Electrocardiogram (ECG) · Cardiac arrhythmia · Feature extraction · Machine learning · Performance measures

M. Botto-Tobar et al. (Eds.): ICAETT 2022, LNNS 619, pp. 3–15, 2023.
https://doi.org/10.1007/978-3-031-25942-5_1

1 Introduction

Cardiovascular diseases are the leading cause of death in the world; around 17.5 million people die from these heart disorders, which represents 31% of deaths worldwide [2]. In general, the increase in the mortality rate from cardiovascular disease is related to unhealthy lifestyles, such as lack of physical activity, poor diet, and smoking. The main factors in these cardiovascular conditions are cardiac arrhythmias, which are disturbances or disorders that alter the normal functioning of the heart's electrical activity [10]. Electrical activity monitoring is performed through the electrocardiogram (ECG), a non-invasive method in which the propagation of the electromagnetic wave propagating in the heart can be recorded through a series of electrodes placed on the body's surface. From these recordings, it is possible to study, analyze and identify irregular patterns in the ECG signal. Because the recorded data is so extensive, it is necessary to classify or categorize the different types of signal beats using advanced computer diagnostic tools. Hence, in recent years, the development of computational systems and the adoption of artificial intelligence techniques to support the detection and diagnosis of cardiovascular diseases have increased. Not to mention that, at times, cardiologists must perform analyses on extensive records of different patients, which can lead to erroneous diagnoses.

Some researchers have proposed different studies with efficient methods for classifying cardiac arrhythmias in the scientific literature. Briefly, Malik *et al.* [12] proposes an optimized classification model for automated cardiac arrhythmia recognition. First, it uses the discrete wavelet transform (DWT) to extract the most significant features from the ECG signal. It then evaluates the multidomain features using machine learning techniques such as support vector machine (SVM) and the Grasshopper optimization algorithm to identify five classes of cardiac arrhythmias. Similarly, Madan *et al.* [11] uses a hybrid approach based on deep learning for cardiovascular disease detection and classification, using various configurations; in a first step, they use 2D Scalogram images to reduce signal noise and extract features. The second step uses a combination of deep learning models, such as convolutional neural networks (CNN) and short-term memory networks (LSTM), to identify abnormal heartbeats. On the other hand, statistical analysis techniques and hybrid feature-based techniques are used for feature selection and extraction. These features can be classified using machine learning techniques, such as Decision Trees [19], k-Nearest Neighbor (KNN) classification techniques [7], Support Vector Machines (SVM) [20], and Neural Networks (NN) [4], among others.

In arrhythmia classification techniques using machine learning approaches, achieving acceptable accuracy with efficient features is desirable. In this regard, this paper presents a novel technique that uses discrete wavelet transform (DWT) based ECG beat features and efficiently classifies five classes of abnormal ECG beats using machine learning techniques such as K-Nearest Neighbors, neural networks, and decision trees. These techniques are fundamental in this field as they are becoming an essential method for reliable decision-making by analyzing large data sets and events. Likewise, it is used to study and analyze the cardiac rhythm problems that the heart presents, identify the type of arrhythmia that the person may manifest, as well as to implement prevention strategies adopted by different types of processing and characterization of ECG signals.

This paper is structured as follows: Sect. 2 specifies the methodological design and the stages of database selection, data processing, segmentation, feature extraction, and classification. Section 3 describes the results and discussions and Sect. 4 concludes future work. One of the significant contributions of this study is the development of a methodology based on conventional methods.

2 Methodology

The methodological scheme of the proposed method for detecting and classifying cardiac arrhythmias is presented in Fig. 1. The following subsections specify the database to be used, the stages of preprocessing, segmentation, feature extraction, and classification.

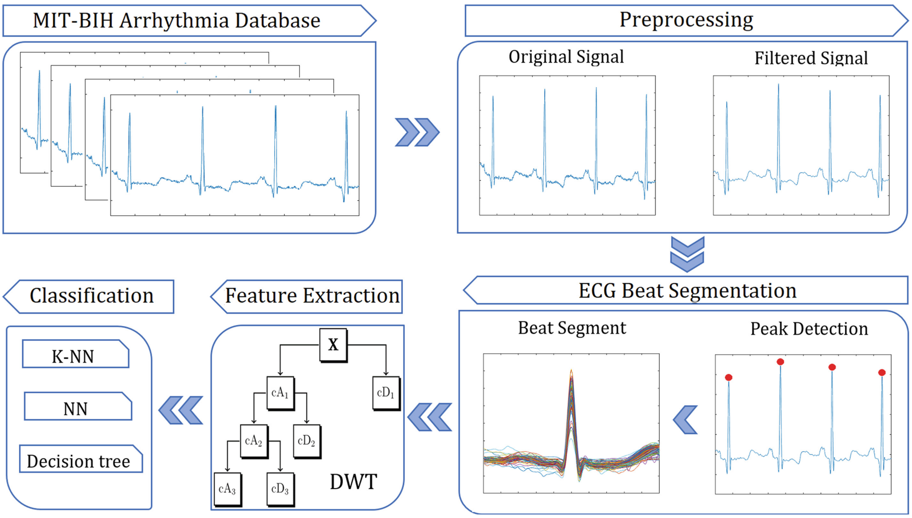

Fig. 1. Methodological scheme for the detection of cardiac arrhythmias.

2.1 MIT-BIH Arrhythmia Database

The dataset selected for this study corresponds to the MIT-BIH cardiac arrhythmia database [6]. The database contains two-channel ambulatory ECG records from 47 individuals analyzed by the BIH Arrhythmia Laboratory between 1975 and 1979. Forty-eight half-hour recordings were collected using analog Holter equipment with a sampling rate of 360 Hz and 11-bit resolution over a range of 10 mV. The database includes about 110.000 records, with five classes of arrhythmias: Nonectopic beats (N), Fusion beats (F), Supraventricular ectopic beats (S), Ventricular ectopic beats (V), and Unknown beats (U). Cardiologists performed the classification and annotation of the recordings of each heartbeat. Table 1 shows the specifications of the different beats from the MIT-BIH database and summarizes the five types of ECG beat samples used in this study.

Table 1. MIT-BIH arrhythmia beat classification according to the ANSI/AAMI EC57:1998 standard database.

AAMI classes	MIT-BIH annotation	Type	No. of beats
Non-ectopic beat (N)	N	Normal beat	90.604
	L	Left bundle branch block	
	R	Right bundle branch block	
	j	Nodal (junctional) escape	
	e	Atrial escape beat	
Supra-ventricular ectopic beat (S)	A	Aberrated atrial premature	2.781
	a	Atrial premature	
	S	Supraventricular premature	
	J	Nodal (junctional) premature	
Ventricular ectopic beat (V)	V	Ventricular escape	7.235
	E	Premature ventricular contraction	
Fusion beat (F)	F	Fusion of ventricular and normal	802
Unknown beat (U)	U	Unclassifiable	8.041
	p	Paced	
	f	Fusion of paced and normal	
Total number of beats			109.463

2.2 Preprocessing

ECG signals obtained from the MIT-BIH arrhythmia database are affected by different types of noise classified as network disturbances (60 Hz), deviation from baseline, muscle artifacts, and disturbances generated by various electrical equipment. In a stage of identification and selection of the most relevant parameters found in the signal, the elimination of these types of noise is fundamental. If the ECG signal being analyzed contains a high noise level, the identification task becomes even more difficult.

According to these criteria, the ECG signal preprocessing stage has the initial phase, eliminating the baseline noise and filtering the ECG signal. For these purposes, a digital Butterworth filter configured as a third-order high-pass filter with a cutoff frequency of 1 Hz has been implemented to remove low-frequency noise from baseline deviation. In the next phase, the ECG signal is filtered using the Savitzky-Golay (SG) polynomial order digital filter with a window dimension between 5 and 21 according to [9] to reduce the low and high-frequency interferences present in the whole signal. Figure 2 shows the original ECG signal in the presence of noise and the result of the filtered signal.

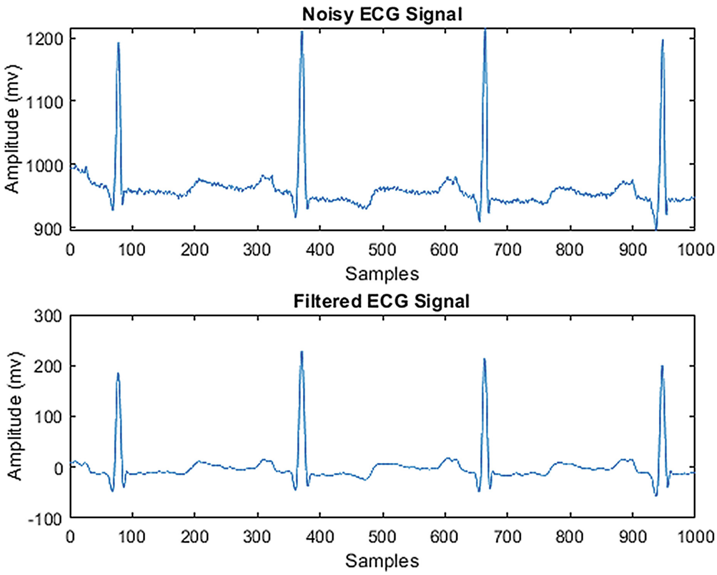

Fig. 2. Removal of noise from ECG signal (Non-ectopic beat).

2.3 ECG Beat Segmentation

In this stage, the location of the QRS complex and landmarks are essential to perform beat segmentation of the ECG signal. Specifically, the QRS complex describes the depolarization originating from the ventricles' contraction [10]. One aspect to consider is that the QRS complex is a fundamental part of the ECG signal that must be analyzed and evaluated.

In this regard, the annotations provided by the MIT-BIH dataset are used for QRS complex localization. The developed algorithm detects the positions of each R peak of the ECG signal (called the midpoint of the QRS complex), whereby a fixed-width window of 200 data is generated with 99 data from the left side and 100 from the right side. The aim is to divide the ECG signal into beat-like fragments with a regular width. The segmentation step results are shown in Fig. 3.

2.4 Feature Extraction

At this stage, the most crucial step is appropriately selecting the most relevant features of the beat segments created in the previous stage to obtain an acceptable classification performance [15,18]. Based on the above, the discrete wavelet transform (DWT) is used for feature extraction. This technique usually decomposes a signal using approximate versions of several families of wavelets,

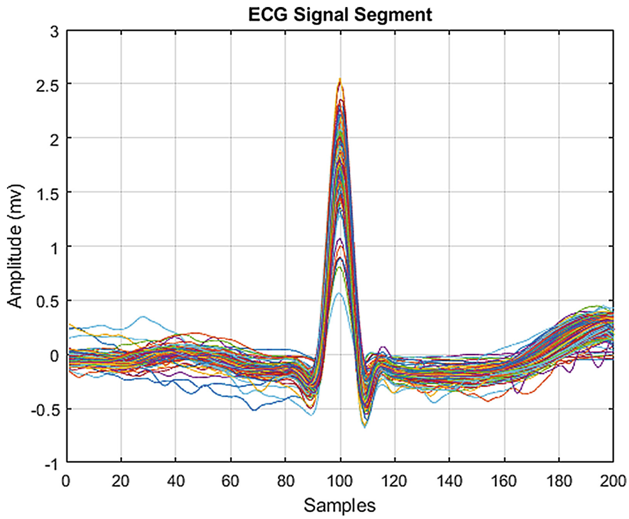

Fig. 3. 200-sample segment of the ECG signal (Non-ectopic beat).

such as Haar, Daubechies, and Symlet [3]. One aspect to consider is that the selection of a wavelet type is made according to the kind of signal to be studied and the information to be obtained from it. For this purpose, signal features are extracted using the Daubechies wavelet family of order 6 (db6) because it has a morphological structure similar to the signal of an electrocardiogram [17]. The signal decomposition is performed up to eight levels obtaining a series of coefficients from which a feature space of the different types of families is generated. The decomposed signal is made up of a series of detail coefficients (D1 to D8) and an approximation coefficient (A8). From each subband of the detail coefficients, three statistical characteristics are calculated: Maximum, Minimum, and variance, collecting a total of 24 features extracted from each beat and will be fed into the supervised machine learning classifiers.

2.5 Classification

The features extracted in the previous step are evaluated by supervised machine learning algorithms to check which classifier is the most suitable for the task at hand. For comparative purposes, three different classification algorithms were tested:

K-Nearest Neighbor Classifier (KNN). It is considered one of the nonparametric instance-based classification algorithms due to its simplicity and versatility. Classification is performed based on the information provided at the training time to determine that an element x belongs to a class C [22]. The algorithm selects the closest data in the learning dataset to perform classification: its "nearest neighbors". The nearest neighbors are those that show several similarities to the new case. The value of the nearest neighbors to be analyzed is specified by k.

Neural Network Classifier (NN). Neural networks are widely used in various applications, such as parameter identification and classification tasks. In the structure of a neural network model, each neuron performs the balanced sum of its inputs and superimposes the result of the sum on a nonlinear activation function [5]. Similarly, the performance of this type of classifier depends on the parameters set on the number of input neurons, the number of hidden layers, the number of output neurons, and the activation function.

Decision Tree Classifier. Decision trees are the most widely used methods for techniques such as classification and regression. In general, they consist of tracing all possible paths taking into account the importance of each attribute using recursive partitioning to classify the data [14]. When constructing a decision tree, it is crucial to determine which attribute is the best or most predictive for splitting the data based on the feature. Decision trees are constructed by dividing the training set into different nodes, where a node contains most of a data category.

In this study, a search for the best parameters for each of the classifiers was performed using the hyperparameter optimization method. Table 2 shows the parameters that gave the best results for the evaluation metrics used, which are presented later in the experimental design.

Table 2. Parameters used in each classifier.

Classifier	Parameters
K-nearest neighbor	Number of neighbors = 4
	Distance metric = Mahalanobis
	Distance weight = 'Squared inverse'
	Standardize data = No
Neural network	Number of fully connected layers = 1
	First layer size = 80
	Activation = 'Relu'
	Iteration limit = 1000
	Regularization strength = 0
	Standardize data = Yes
Decision tree	SplitCriterion = 'deviance'
	MaxNumSplits = 794
	Surrogate = off

2.6 Experimental Design

This section describes the design of experiments and metrics to evaluate the performance of the developed algorithms. The MIT-BIH database contains a total of 110.000 records with 5 types of arrhythmias (N, S, V, F, U). A total of 3 experiments, including a filtering technique (SG), a feature extraction technique (DWT), and three machine learning algorithms (KNN, NN, TREE), were applied for irregular beat recognition.

The evaluation of the classification models is performed using 10-fold random cross-validation and performance metrics such as Accuracy, Precision, Sensitivity, and F1 Score of four parameters as shown in Eqs. (1), (2), (3) and (4).

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{1}$$

$$Precision = \frac{TP}{TP + FP} \tag{2}$$

$$Sensitivity = \frac{TP}{TP + FN} \tag{3}$$

$$F1 - Score = \frac{TP}{TP + 0.5(FP + FN)} \tag{4}$$

where TP corresponds to correctly classified beats, FN to unclassified beats, TN to correctly unclassified beats, and FP to incorrectly classified beats.

3 Results

Table 3 shows the results of the 3 experiments, considering the stages of filtering, feature extraction, and classification techniques.

Table 3. Classification results with three different classifiers.

Diagnostic system			Performance metrics			
Filtering	Features	Classifier	Accuracy	Precision	Sensitivity	F1-Score
SG	DWT	KNN	98.54%	98.64%	99.59%	99.12%
		NN	98.34%	98.72%	99.30%	99.01%
		TREE	97.09%	97.52%	98.96%	98.23%

To contrast the classification results obtained in Table 3, Fig. 4 shows the box plots of the accuracies of the three classifiers used in this study with 10-fold cross-validation.

As seen in Fig. 4, the KNN classifier is the best performer in terms of the accuracy metric represented with an average of 98.54%, a precision of 98.64%, a