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ARRHYTHMIA DETECTION USING MEDICAL IMAGES OF ECG SIGNALS

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Abstract
In the current medical practice, a thorough examination of electrocardiograms (ECGs) by skilled cardiologists is an essential step in diagnosing potentially life-threatening cardiac arrhythmias. Nevertheless, there is growing interest in the automated classification of cardiac arrhythmias using medical image processing techniques. This approach offers several benefits, including providing objective diagnostic test results and saving valuable time for the cardiologists. As a result, there is a significant interest in the utilization of computer aided classification and diagnosis of ECG signals through medical image analysis, both within hospital settings and the wider healthcare community.
The interpretation of the ECG signals images involves the application of several pattern recognition techniques. This means that computer algorithms are trained to recognize patterns and irregularities in ECG waveforms, allowing for the automated detection of cardiac arrhythmias. Importantly, this technology has the potential to significantly alleviate the workload of cardiologists by providing an efficient and accurate means of analyzing readily available ECG data.
As a result, the integration of computerized analysis of ECG waveforms has the dual advantage of enhancing diagnostic accuracy while also streamlining the clinical workflow for healthcare professionals. This combination of objective, time-saving, and precise diagnostic capabilities is driving the growing interest and adoption of computer-aided ECG signal classification and diagnosis in the medical field.

Keywords:Arrhythmia, ECG signals, computer aided.

Introduction
Cardio vascular diseases (CVD) are universally acknowledged as the primary cause of mortality, referred to as a heart-attack. The data from World Health Organization (WHO) shows that cardiovascular disease (CVD) is responsible for causing 17.7 million fatalities globally. Roughly 31% of these deaths are concentrated in low & middle class income countries, 75% of the total occurring in those regions. It represents a subset of CVD characterized by irregular heart rhythms, including both excessively fast and excessively slow heartbeats. Examples of arrhythmias encompass atrial fibrillation (AF), ventricular fibrillation (VF), premature ventricular contractions (PVC) and bradycardia. While individual cardiac arrhythmias may have relatively minor consequences, persistent ones can lead to severe complications, such as prolonged PVCs occasionally progressing to ventricular fibrillation or ventricular tachycardia, which swiftly result in heart failure. Among them, ventricular arrhythmias are notably prevalent and contribute to approximately 80% of cases of sudden cardiac death. Timely detection of arrhythmia conditions by doing the analysis of electrocardiogram (ECG) signals is essential for recognizing cardiac risk factors. ECG serves as a foundational tool for assessing the heart's electrical activity, offering continuous monitoring options and aiding in the diagnosis of various arrhythmias. It facilitates risk stratification, allowing healthcare providers to gauge severity and implement preventive measures promptly. Advancements like remote monitoring and artificial intelligence contribute to more efficient and accurate arrhythmia

identification, ultimately improving patient outcomes. Consequently, it’s reasonable to assert that maintaining a regular regimen of heart rhythm monitoring is crucial for the prevention of cardiovascular diseases. In the realm of cardiovascular diagnostics, healthcare practitioners heavily rely on the electrocardiograph (ECG or EKG) as a pivotal tool for identifying and evaluating a range of cardiovascular diseases, with a particular focus on conditions collectively known as arrhythmias. Arrhythmias entail irregular heart rhythms, carrying significant implications for a patient's overall health. ECGs play a crucial role in comprehending and diagnosing these conditions by recording and interpreting electrical activity within the heart.
In the course of the diagnostic process, an ECG machine is linked to the patient's body using ten electrodes strategically positioned to gather information from 12 unique leads or signals. Each lead offers a distinct viewpoint on the heart's electrical activity, allowing healthcare professionals to gain a comprehensive and nuanced comprehension of its functionality.As per Zubair et al.'s research, the 12 ECG leads can be divided into two sets: precordial leads and
precocious leads. Placed on the patient's chest, the precordial leads, specifically V1, V2, V3, V4, V5, and V6, provide perspectives on the heart's electrical activity from different angles. This strategic placement facilitates the detection of specific abnormalities or irregularities, enhancing the diagnostic capabilities of healthcare professionals. On the other hand, the precocious leads consist of I, II, III, aVL, aVR, and aVF and are placed on the limbs of the patient. These leads help assess the heart's electrical activity in a frontal plane and are crucial for diagnosing arrhythmias and other cardiac conditions.
In the ECG signals generated by these leads, a variety of waves and deflections can be identified, including P , Q , R , S , T and U waves. Each of these waves represents a distinct electrical event occurring within the heart's anatomy and may appear as either positive or negative deviations from the baseline. .In essence, ECGs furnish healthcare professionals with a sophisticated and intricate means to scrutinize electrical behavior of heart. Through the analysis of the signals and a comprehensive understanding of the significance of diverse waves and leads, medical experts can precisely diagnose arrhythmias and various other cardiovascular conditions. This, in turn, guides the formulation of effective treatment strategies, ultimately contributing to enhanced patient outcomes.

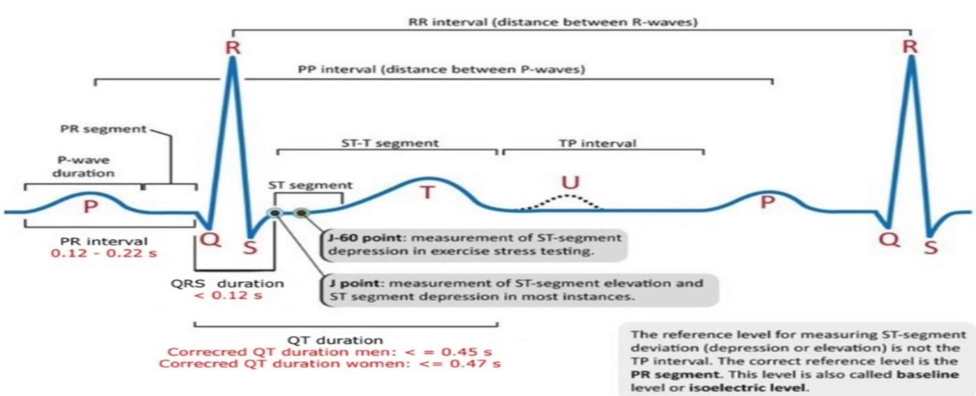

Figure 1. Representation of complete electrical activity of the heart.

1.1 State of Art
Various methods have been proposed to develop an automated model for arrhythmia classification. Valuable data within the electrocardiogram (ECG) is located within the durations and heights of the distinctive waves.. Any abnormality in the wave shape and duration of the wave feature is considered an arrhythmia. The classifier employs Logistic
Model Trees (LMT) to categorize 11 distinct types of arrhythmias. Anwar et al. proposed a

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multiclass arrhythmia classification in their study, utilizing SVM based approaches such as One Against One (OAO), One Against All (OAA), and Codes Error Correction (ECC) with feature selection enhancements. In a separate work by Babak et al., a SVM based classification is presented, utilizing reduced features from the Heart rate variable (HRV) signal. The algorithm suggested in this study is founded on the feature reduction scheme of Generalized Discriminant Analysis (GDA).
Nasiri introduced a novel classification approach that integrates both SVM & genetic algorithm methodologies. The genetic algorithm is employed to enhance the generalization performance of the SVM classifier, thereby improving the classification accuracy of ECG signals.
In another study, Parul Madan presented "A Hybrid Deep Learning Approach for ECG-Based Arrhythmia Classification," where a deep learning framework was utilized to identify arrhythmias based on ECG signal images.
his portion present the comparative study of the introduced approach with the earlier researches done in this field. From the above section and state-of-art comparison it is clear that all existing studies have only focus on textual or image posts for two or three topics of harassment and no earlier work have satisfied purpose of this research using merging DL and big data technologies and attain satisfactory results for future advancements.

1.2 Project Objective

The objective of the project is to develop an automated system for the detection and classification of arrhythmias using medical images of ECG signals. The primary goals are as follows:
Automation of Arrhythmia Classification: Implement machine learning and deep learning algorithms to automate the classification of cardiac arrhythmias from ECG signal images.
Diagnostic Support for Cardiologists: Create a computer-aided diagnostic system that supports expert cardiologists by providing intelligent, time-efficient, and cost-effective arrhythmia diagnostics.
Reduction of Discrepancies: Address the disparities between manual classifications by cardiologists and the automated system, aiming to enhance accuracy and reliability.
Utilization of Diverse Algorithms: Explore various algorithms, such as K-Nearest Neighbors, Logistic Regression, Decision Tree, Random Forest, Support Vector Machine, and Principal Component Analysis, for robust arrhythmia classification.
Integration of Image Processing Techniques: Utilize image processing techniques, such as Continuous Wavelet Transformation (CWT), to convert ECG signals into coloredscalogram images for improved feature extraction.
Comprehensive Data Modeling: Model the ECG data from normal and life-threatening rhythms, leveraging datasets like MIT-BIH arrhythmia database, and categorize arrhythmias into specific groups.
Enhancement of Diagnostic Precision: Employ feature selection techniques, such as Chi-square testing and Particle Swarm Optimization (PSO), to refine the feature set and improve the precision of the diagnostic model.
Evaluation and Validation: Assess the performance of the automated system using a 10fold cross-validation technique, considering sensitivity, specificity, positive predictivity, and accuracy as evaluation metrics.
Investigation of Deep Learning Structures: Explore the effectiveness of deep learning structures, including Convolutional Neural Networks (CNNs) and Principal Component Analysis (PCA), for enhanced accuracy in arrhythmia classification.
Future Scope Consideration: Provide insights into the potential future enhancements and developments in the field of automated arrhythmia detection and classification.

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The overarching goal is to contribute to the advancement of cardiovascular diagnostics by providing a reliable and efficient automated system for arrhythmia detection, aiding healthcare professionals in timely and accurate diagnoses.

Literature

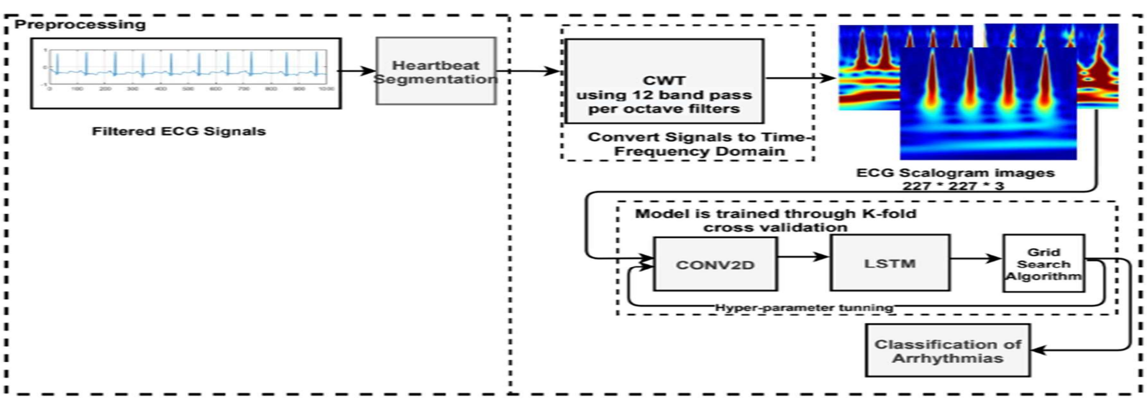
Irregularities in the heartbeat can pose a significant threat to one's life. Consequently, it is imperative to accurately identify and categorize arrhythmias. Numerous factors can be extracted from ECG waveform images, and when coupled with supplementary patient information like age and medical history, they aid in identifying arrhythmias. Despite this, healthcare professionals may face difficulty in identifying subtle abnormalities in extensive ECG recordings. Therefore, the application of deep learning provides significant support in automating the detection of arrhythmias. This project aims to utilize various machine learning and deep learning algorithms to predict and categorize arrhythmias into specific groups.

2.1 Aims & Objective

The objective of the paper is that it helps to create a computer aided diagnostic system designed to support the expert cardiologists by offering intelligent, time-efficient and cost effective ECG arrhythmia diagnostics. This system leverages medical images for a comprehensive and streamlined diagnostic process. In our research, we aim to differentiate between the existence and non-existence of cardiac arrhythmia and categorize it into one of the 16 groups. Currently, there is a computer program in place that performs this classification. Nevertheless, distinctions exist between the cardiologist's classification and that of the program. Our objective is to reduce this disparity through the utilization of machine learning and deep learning tools.

2.2 Proposed Work

This study utilizes ECG data from both normal heart rhythms and life threatening rhythms too, sourced from the MIT-BIH arrhythmia database. The database contains various folders containing 100-200 images of different conditions of the patients, having images of different types of ECG Signals. It makes it easier for the algorithm to classify the type of problem and categorize them within different classes.

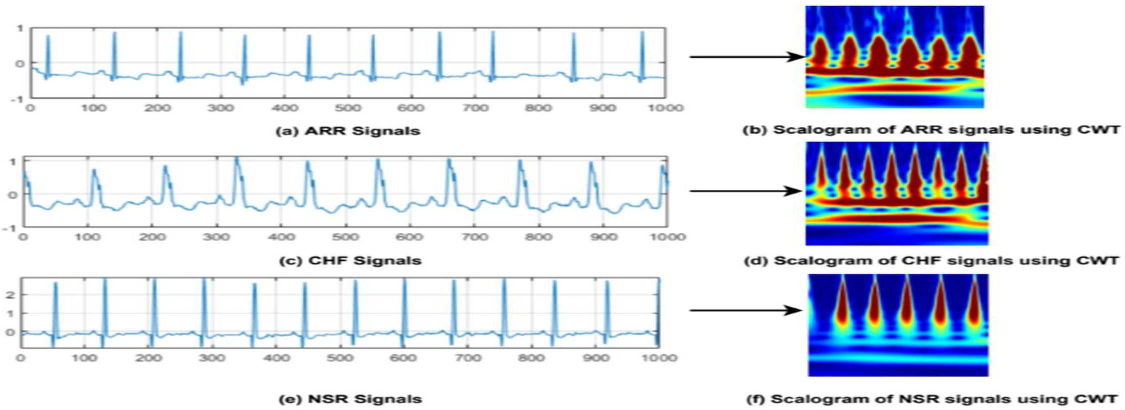


2.3Architecture of our System

2.3.1.Data Pre-processing

This phase is employed to preprocess the data for both training and testing purposes. Initially, this data undergoes segmentation through the utilization of a modified data repository.Furthermore, the function for assisting in resizing data is employed. Additionally, the utilization of Continuous

Wavelet Transformation (CWT) is implemented to convert unidimensional ECG signals into colored scalogram images with two dimensions.



2.3.2 Exploratory Data Analysis

Dynamic models like Convolutional Neural Networks (CNNs) are employed for feature extraction in Deep Learning. They demand a substantial amount of data for effective training of the procedural model. If exceedingly long signals are fed into CNN network, the expected performance might deteriorate. To address this concern, it is necessary to fragment the ECG signals and their associated label masks. This can be achieved by employing a tailored data store and the resizing data assistance function. In our study, we employed a dataset sourced from databases containing medical images of ECG recordings from patients. Recording of each patient comprised sequence segments.

2.3.3 Data Modelling

a) Mount Google Drive to access the dataset.
b) Define paths to the train and test folders containing subdirectories for each class.
c) Create data generators for training and validation datasets, specifying image resizing and batch size.
d) Define a convolutional neural network (CNN) model for image classification.
e) Compile the model with the RMSprop optimizer and binary cross-entropy loss for multi-class classification.
f) Train the model using the fit method with the training data generator, specifying the number of steps per epoch and epochs.
g) For each class folder in the test dataset, predict the class of each image using the trained model.
h) Print the predicted class for each image along with its file name.
i) Repeat steps 7-8 for all class folders in the test dataset.

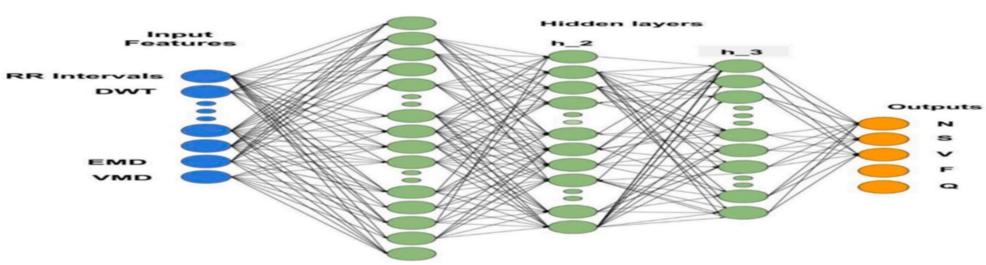


Fig. 3. Proposed DNN architecture used for arrhythmia detection.

2.4 Predictive analytics in agriculture

Kiran M. Sabu et al [55] used the time-series data and machine learning algorithms, to forecast the arecanut prices that are charged on a monthly basis in Kerala. On the arecanut price dataset with

prices ranging from 2007 to 2017, the models SARIMA, Holt-Seasonal Winter's approach, and the LSTM neural network were used, and the performance of these models was assessed based on the RMSE value. It was discovered that the LSTM neural network model is the one that provides the greatest match to the data.
MininathBendre et al [56] used large amounts of data from weather stations, to make predictions about future conditions. These predictions are made by employing predictive methods that are based on time series and neural networks using the MapReduce programming paradigm. Techniques to predictive analytics have been suggested by us, and these approaches include the modules of analysis and decomposition, classification, and prediction. Decomposing the data and identifying its trend, regular, and sophisticated components is the goal of the time series-based decomposition technique, which has been offered. The time series MapReduce based Autoregressive Integrated Moving Average (M-ARIMA) model is responsible for handling the linear components, while the M-K-Nearest Neighbors (M-KNN) model is responsible for handling the nonlinear components. In addition, the MapReduce-based Hybrid Model (M-HM) was presented. This model would make use of the benefits that time series and neural networks provide in order to improve the accuracy of its predictions. The research shows that the suggested model is more accurate than the regular and random components of the data.
Divas Karimanzira et al [57] Discussed the ways in which SCADA, ERP, and MES may be improved with the use of IoT in aquaponics, as well as how IoT-based predictive analytics might assist in obtaining more from the system. To illustrate the advantages of Internet of Things on example Predictive Analytics services, the authors will give a use case illustration of an aquaponics project that includes five demonstration sites located in various parts of the world. Collecting data from all five demonstration sites using IoT is an innovative approach that is being used to strengthen the mathematical models of fish, tomatoes, and other technical components like filters that are used for remote monitoring, predictive remote maintenance, and economical optimization of individual plants. Monte Carlo Simulations were used to assess the robustness of a variety of models, including models for the development of fish and crops as well as models for econometric optimization. The results revealed, as was to be predicted, that IoT-based models were better.
Ummesalma M et al [58] provided any and all information pertaining to the uses of IoT in the agricultural sector. This contains the specifics of the data collecting, the kinds of sensors that were used, the deployment particulars, and the data availability through cloud. Additionally, it delves into the specifics of a variety of communication technologies that are used in the Internet of Things, including Bluetooth, LoRaWAN, LTE, 6LowPAN, NFC, RFID, and others. In addition, the importance of the Internet of Things (IoT) to the fields of agronomics, agricultural engineering, crop production, and animal production is the primary emphasis of this chapter. The research presented in this chapter is the result of an investigation of the impact that the Internet of Things has had in the realm of agriculture. The years 2008–2018 are covered by this collection of around 40 research articles taken from conferences and publications that have undergone peer assessment.
Rohit Sharma et al [59] presented a systematic literature review (SLR), covering 120 research publications on the many uses of large GIS analytics (BGA) in agriculture. The articles that were chosen for further consideration have been organised into two major categories: the level of analytics, and GIS applications in agricultural settings. In this research, the following GIS applications are taken into consideration: land suitability; site search and selection; resource allocation; impact assessment; land allocation; and knowledge-based systems.
Sachin S. Kamble et al [60] collected and analysed data from 84 scholarly articles published between the years 2000 and 2017. The primary objective of the review was to gain an understanding of the level of analytics that was being utilised (descriptive, predictive, and prescriptive), the sustainable agriculture supply chain objectives that were achieved (social, environmental, and economic), the

supply chain processes from which the data is collected, and the supply chain resources that were being deployed for the same. On the basis of the findings of the review, the authors propose an application framework for the practitioners who are involved in the agri-food supply chain. This framework identifies supply chain visibility and supply chain resources as the primary driving force for developing data analytics capability and achieving sustainable performance. This framework is intended for use by those who are actively engaged in the agri-food supply chain. The practitioners will use the framework as a guide when planning their investments in order to construct a strong data-driven agri-food supply chain.

Design & Implementation

The following design and implementation utilize deep learning techniques to detect arrhythmia from electrocardiogram (ECG) images. The code employs convolutional neural networks (CNNs) to classify ECG images into different categories: ECG images of myocardial infarction patients, ECG images of patients with a history of myocardial infarction, ECG images of patients with abnormal heartbeats, and normal person ECG images.

3.1. Data Preparation

ECG images are stored in directories based on their categories: myocardial infarction, history of myocardial infarction, abnormal heartbeat, and normal.
ImageDataGenerator is used to preprocess the data by rescaling pixel values to the range [0,1].

3.2. Model Building

A sequential CNN model is constructed consisting of convolutional layers, max-pooling layers, and dense layers.
The model is compiled with binary cross-entropy loss function and RMSprop optimizer.
Training is performed on the training dataset with specified parameters such as batch size, target size, and class mode.

3.3. Training

The model is trained for a specified number of epochs with the training dataset.
Validation is performed on a separate validation dataset to monitor model performance and prevent overfitting.

3.4. Testing

ECG images from test directories are loaded one by one.
Each image is resized to match the input shape of the model.
The model predicts the category of each image.
Based on the predicted category, the corresponding label is printed.

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