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A NOVEL HYBRID MODEL TO DETECT AND CLASSIFY ARRHYTHMIA USING ECG AND BIO-SIGNALS

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Abstract. In general, arrhythmias, also called cardiac arrhythmia, heart arrhythmia, or dysrhythmias, are abnormal heartbeats which include too fast or too slow. The Cardiovascular Disease (CVD) is a significant cause of death, and the death rate is increasing every year. The Electrocardiogram (ECG) majorly contributes to the CVD diagnosis, providing information about the heartbeat. An automatic detection and classification of arrhythmia performs a significant role in managing and curing cardiovascular diseases. Deep Learning (DL)-based algorithms have emerged as effective solutions in medical applications, particularly in cardiac arrhythmia diagnosis. In this research, a DL-based multi-modal approach is proposed for the classification of cardiac arrhythmia. The MIT-BIH dataset is utilized to evaluate the performance of the proposed method. The proposed method considers physiological signals along with the MIT-BIH dataset to improve accuracy. The Discrete Wavelet Transform (DWT) is used for pre-processing the MIT-BIH dataset. The DL methods of Recurrent Neural Network (RNN) and Long Short-Term Memory (LSTM) are utilized for classifying cardiac arrhythmia. The proposed method is evaluated using various performance metrics such as Accuracy, Specificity, Sensitivity, F1-score, and Cohen's kappa.

Key words: Cardiac arrhythmia, Deep Learning, Electrocardiogram, Long Short-Term Memory, Recurrent Neural Network

1. Introduction. In the healthcare sector, technology has significantly impacted patient care, treatment, and diagnosis. Technological innovations have had a major impact on medical imaging and surgical operations, improving patient outcomes and increasing process efficiency. Examples of these innovations include the creation of minimally invasive surgical techniques and the X-ray. We are about to witness a momentous shift in which data and artificial intelligence (AI) could completely reshape a number of healthcare domains [1].

Arrhythmias, which refer to irregularities in the heart's rhythm, have been a significant focus in the field of cardiovascular medicine for a considerable period of time. The accurate diagnosis of these conditions is crucial due to their various manifestations, ranging from harmless occasional skips to potentially life-threatening situations. The electrocardiogram (ECG) has traditionally been the preferred method for detecting and classifying arrhythmias [3].

The interpretation of this graphical representation of the heart's electrical activity necessitates expertise, including a discerning eye, comprehensive training, and experience. Deep learning, a subset of artificial intelligence (AI) that utilizes deep neural networks, has proven its efficacy in multiple industries by effectively extracting valuable patterns and insights from large datasets. These algorithms have the potential to improve the efficiency, accuracy, and timeliness of arrhythmia diagnosis in ECG analysis [4].

This paper explores the integration of deep learning techniques with arrhythmia classification. This study will explore the progress made in the interdisciplinary field, focusing on the essential deep learning architectures. We will analyze their advantages, drawbacks, and performance metrics. The review will address the challenges of data quality, model transparency, and ethical considerations in AI-driven healthcare. This study aims to provide a comprehensive overview of the current state and future possibilities in the intersection of cardiology, data science, and artificial intelligence. Cardiologists have developed expertise in interpreting electrocardiograms (ECGs) to distinguish between benign and malignant cardiac rhythms. Even with extensive training, the human eye may occasionally fail to detect or accurately interpret subtle anomalies. Furthermore, the increasing amount of electrocardiogram (ECG) data, particularly due to the rise of wearable technology, makes it impractical to manually analyze each individual heartbeat. Smartwatches with miniaturized ECG modules have made health

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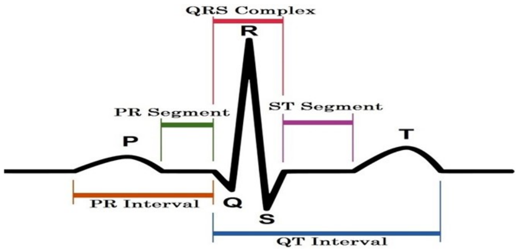

Fig. 1.1: ECG waveform depiction.

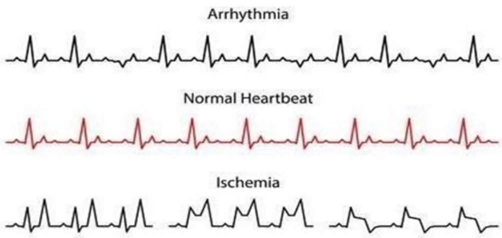

Fig. 1.2: Representation of Arrhythmia waveforms in comparison to Normal Heartbeat.

monitoring more accessible to the general population. However, the main issue remains: how can we effectively and precisely handle this overwhelming amount of data? [6]

Deep-Learning methods plays a significant role in this context. Deep learning, a subfield of artificial intelligence, has experienced significant growth across multiple domains in recent decades. The system's strength lies in its capacity to analyze large volumes of data, acquiring complex patterns, and frequently surpassing human performance in certain tasks. Deep learning has the potential to not only offer computational efficiency but also demonstrate adaptability and scalability [8].

The goal of this work is to document the development of deep learning in arrhythmia classification, from its inception to the most advanced applications today. The several facets of architectures, approaches, accomplishments, and difficulties will all be covered in this study. The goal of this review is to provide a thorough understanding of how technology and healthcare—specifically, cardiac care—intersect. It will examine the field's technological developments, historical background, and clinical applications, emphasizing how it could transform cardiac care in the twenty-first century [12].

Like other technological advancements, the integration of DL into arrhythmia classification faces challenges. Researchers and clinicians encounter various challenges, including data privacy, diverse and representative datasets, model interpretability, and clinical validation.

The goal of this work is to document the development of deep learning in arrhythmia classification, from its inception to the most advanced applications today. The several facets of architectures, approaches, accomplishments, and difficulties will all be covered in this study. The goal of this review is to provide a thorough understanding of how technology and healthcare—specifically, cardiac care—intersect. It will examine the field's technological developments, historical background, and clinical applications, emphasizing how it could transform cardiac care in the twenty-first century [15].

1.1. Motivation. If left undiagnosed and untreated, arrhythmias can cause serious health issues, even potentially fatal situations. Only ECG data is used in the diagnosis process and technologies used today. As such, it ignores a number of additional physiological cues, such as heart rate and blood pressure. The combination of various physiological cues, artificial intelligence, and ECG data allows for the early identification and categorization of arrhythmias. Artificial intelligence can be used to create adaptive algorithms and real-time monitoring due to the dynamic nature of arrhythmias. Therefore, the goal of this research is to use modern technologies for the early identification and categorization of arrhythmias. Convolution neural networks can be used to detect arrhythmias in an efficient manner because of its capacity to identify patterns and spatial hierarchies in the input data. CNN also provides the best result when the model containing diverse data set of arrhythmias are trained [16].

1.2. Major Contributions. As per the reports of the World Health Organization (WHO), the number one cause of death today is cardiovascular diseases (CVDs). As per their statistics, the number of deaths caused by CVDs are roughly 30 percent. Cardiac Arrhythmia is a condition in which the electrical activity of the heart is abnormal. The electrical activity is very irregular leading to the disruption in the cardiac rhythm. ECG data is very complex owing to different waveforms and their interpretation. With the advent of different computational paradigms, researchers have been very curious to explore the possibilities of leveraging different techniques like Machine Learning (ML), deep learning (DL) etc. to interpret the ECG like a cardiologist. It is very important to note that the accuracy if diagnosis is very critical as any deviation could be fatal [18].

Most of the conventional researchers so far have been focused around exploring the optimal computational paradigms for predicting and classifying the cardiac arrhythmia using a variety of different hardware and programming languages. Many research works range from leveraging techniques like SVM, PCA to feed-forward based neural networks and apply wavelet transform for feature extraction [20].

However, some of the downsides are a) achieving better performance without cross-validation, b) losing the beats due to filtering and feature extraction c) less number of arrhythmia type classification d) low accuracy and performance.

In our work, we novel deep learning-based framework to analyze the complex ECG data and develop a transferable representation of ECG signals. It is important to know that to realize such a framework it is very important to describe an architecture that offers scope for learning the signal representation. Once we build a model and train that model on a huge training data set, the model will be able to learn from the pattern and allow to use those representation to transfer the knowledge. We have further experimented the CNN by adding the batch normalization layer between subsequent layers thereby inhibiting the hidden / convolution layers from normalizing the values which facilitate in improving the efficiency. Also, the proposed algorithm employs a 2-D CNN with monochrome images of the ECG. One of the advantages of our approach is that conventional data pre-processing steps like feature extraction and noise removal and filtering are not required as the algorithm converts the 1-D Signal data to a 2-D image. Additionally, to improve the accuracy of the model we can augment the 2-D images and increase the size of the training data. Since our algorithm transforms a 1D signal to a 2D image, the model will automatically ignore the noise and extract the feature map. This allows the proposed model to be employed on heterogeneous signals and devices with different feature sets like sampling rate, amplitude etc. unlike the conventional models. Nonetheless, our approach can be implemented in an end-to-end clinical set up and that adds to the novelty of our work.

2. Background.

2.1. Arrhythmias: An Undeniable Obstacle. Derived from the Greek word "arrhythmias," which means "without rhythm," arrhythmias refer to a broad spectrum of illnesses marked by an irregular heartbeat. These disorders can manifest as a variety of heart rhythms, including bradycardias (slow heartbeats), atrial fibrillations (chaotic rhythm), and tachycardias (rapid heartbeats). These abnormalities might have a variety of causes, including extrinsic influences like stress or drug usage, congenital problems, and cardiomyopathies [21].

Early detection and management of arrhythmias are crucial due to the potential for severe complications, as some arrhythmias are benign while others are not. The electrocardiogram (ECG) is the primary tool used in this field. It is a non-invasive test that visually displays the heart's electrical activity [23].

2.2. Electrocardiograms (ECGs): The Diagnostic Mainstay. The introduction of the ECG in the early 20th century brought about a significant transformation in cardiac diagnostics. Clinicians can visualize the heart's electrical impulses by applying electrodes to the skin, which are then represented as waveforms on a graph. The various components of this waveform, including the P wave, QRS complex, and T wave, provide valuable information about different stages of the cardiac cycle. Variations in these waveforms and complexes

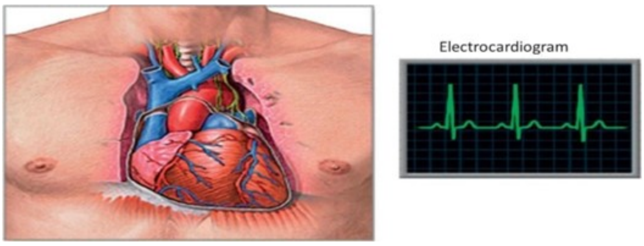

Fig. 2.1: Human Heart and ECG.

may suggest the presence of underlying arrhythmias or other cardiac pathologies. However, the analysis of electrocardiograms (ECGs) is not a simple process. Detecting subtle anomalies, such as distinguishing between a normal rhythm and a potentially dangerous arrhythmia, necessitates significant training, experience, and a discerning eye.

2.3. The Advent of Artificial Intelligence in Healthcare. The integration of technology into healthcare has significantly increased during the 21st century. The evolution of healthcare is evident through the digitization of medical records, utilization of advanced imaging modalities, and the increasing prevalence of telemedicine. Data has played a central role in this technological wave. The growing accessibility of extensive datasets has paved the way for the emergence of artificial intelligence (AI) in the field of medicine. AI, which refers to the simulation of human intelligence processes by machines, has been increasingly utilized in various medical fields. Machine learning, a subset of computer science, involves the use of statistical techniques by computers to learn from data. This has subsequently facilitated the development of more sophisticated techniques. Deep learning, a subfield of machine learning, has shown great promise as it utilizes neural networks algorithms. One of its notable strengths is its capacity to acquire knowledge and make informed choices based on data, frequently outperforming human abilities in certain tasks [26].

2.4. The Confluence of Deep Learning and ECG Analysis. Researchers started examining the combination of the two because of the difficulties involved in manually interpreting ECG data and the potential of deep learning in handling enormous volumes of data. Is it possible to train deep learning algorithms to identify arrhythmias as accurately as expert cardiologists, if not more so? Numerous studies,inventions, and discussions have resulted from the pursuit of an answer to this topic, which has set the stage for the information contained in this article.

3. Deep Learning Techniques for Arrhythmia Classification.

3.1. Convolutional Neural Networks (CNNs). Originally designed for image processing, convolutional neural networks (CNNs) have had a profound impact on fields involving the recognition of patterns in geographical data. These networks automatically identify hierarchical patterns in the data by using convolutional layers. By transforming ECG segments into time-frequency representations like spectrograms and treating them like image-like structures, CNNs can be utilized to identify arrhythmic patterns. Convolutional layers are very good at capturing the subtle fluctuations and anomalies that point to different kinds of arrhythmias because they are skilled at identifying spatial patterns in converted ECG data [29].

Multiple studies have shown that CNNs have proven to be effective in achieving high levels of accuracy in detecting arrhythmia. In some cases, CNNs have even demonstrated comparable performance to that of expert cardiologists [30].

3.2. Recurrent Neural Networks (RNNs) and Long Short-Term Memory (LSTM) Networks. Because they are made expressly to handle sequential data, recurrent neural networks or RNNs are ideal for evaluating time-series data like ECG sequences. Artificial neural networks have the ability to store data from previous calculations, which allows them to identify patterns and trends over time. LSTMs are a kind of RNN that effectively preserve patterns over lengthy sequences, hence resolving the vanishing gradient problem commonly observed in traditional RNNs [32].

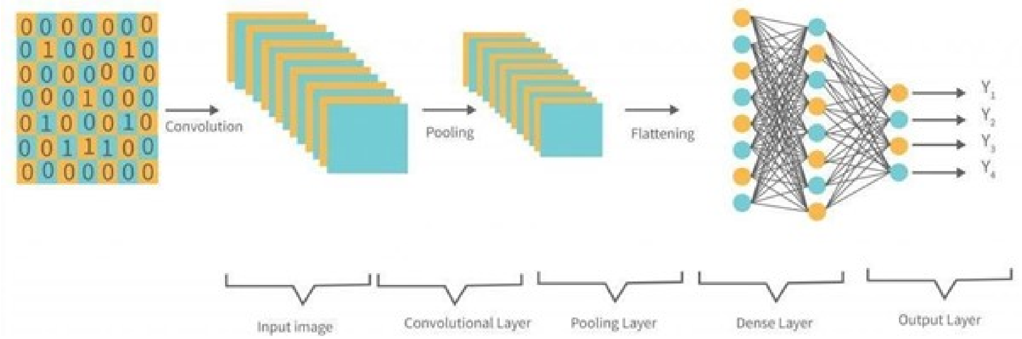

Fig. 3.1: Representation of Deep Learning CNN method.

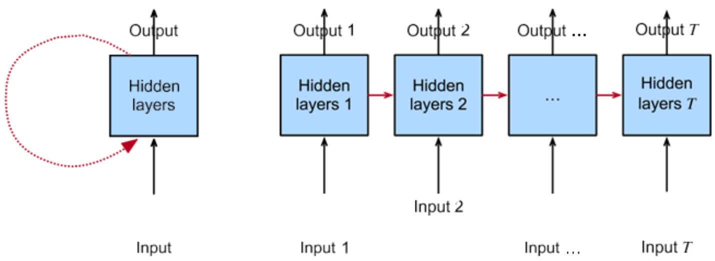

Fig. 3.2: Representation of Deep Learning CNN method.

RNNs and LSTMs are effective in analyzing raw ECG sequences due to their ability to capture temporal patterns which can serve as indicators of arrhythmias. Their capacity to identify long-term dependencies in the ECG sequence renders them highly valuable, particularly in instances where the arrhythmia's distinctive pattern is distributed over an extended period.

3.3. Attention Mechanisms and Transformers. Attention mechanisms, derived from the domain of natural language processing, enable models to selectively concentrate on particular segments of the input data. Transformers, which rely solely on attention mechanisms, have demonstrated considerable potential across diverse domains. In the context of ECG data, attention mechanisms enable models to prioritize segments of the data that may be more indicative of an arrhythmia. By assigning weights to different components of an ECG sequence, these models have the potential to enhance accuracy by prioritizing the most pertinent signals [35].

3.4. Autoencoders. Autoencoders are a type of unsupervised neural network that aim to learn compact representations of input data. These models operate by compressing the input data into a condensed form and subsequently reconstructing the original input using this condensed representation. Autoencoders are a viable method for detecting anomalies in electrocardiogram (ECG) signals. Deviation or anomaly in the input signal, such as arrhythmic events, can lead to a high reconstruction error when trained on normal ECG data. This characteristic can be utilized to identify possible arrhythmias.Data, resulting in enhanced rates of arrhythmia detection.

Table 4.1: Overview of Arrhythmia Detection Studies

No	Paper Title	Authors	Year	Key Findings
1	Arrhythmia detection using deep convolutional neural network with long duration ECG signals	Ozal Yıldırım, Paweł Pławiak	2018	This study proposes deep convolutional neural network (DCNN) to detect arrhythmia in long-duration ECG signals. The investigation of the model's ability to detect less common or subtle arrhythmias which is crucial for clinical applications is currently limited.
2	Automated diagnosis of arrhythmia using combination of CNN and LSTM techniques with variable length heart beats	Shu Lih Oh, Eddie Y.K. Ng	2018	In this study, the authors employed the model's ability to accommodate heartbeats of varying lengths has not been thoroughly examined by means of the challenges or potential data misalignments it may pose. based on convolutional neural networks.
3	Multiclass Classification of Cardiac Arrhythmia Using Improved Feature Selection and SVM Invariants	Anam Mustaqeem, Syed Muhammad	2018	In this paper, the authors propose a novel approach for classifying cardiac arrhythmia. Although improved feature selection is suggested, it is possible that other advanced feature extraction or transformation techniques could provide a more effective representation and consequently improve classification outcomes.
4	Automated arrhythmia detection using novel hexadecimal local pattern and multilevel wavelet transform with ECG signals	Turker Tuncer, Sengul Dogan	2019	This paper reports the novel hexadecimal local pattern (HxLP) has been introduced but further research is needed to assess its robustness in the presence of noisy or artifact-laden ECG signals.
5	A Fast Machine Learning Model for ECG-Based Heartbeat Classification and Arrhythmia Detection	Miquel Alfaras, Silvia Ortín, Miguel Cornelles Soriano	2019	The research presents a machine learning model specifically designed for ECG signals with a primary focus on classifying heartbeats and detecting arrhythmias. Understanding the decision-making process of the model is crucial due to the critical nature of arrhythmia detection. The paper lacks in-depth analysis of model interpretability and the significance of the selected features.
6	Automated arrhythmia classification based on a combination network of CNN and LSTM	Chen Chen, Zhengchun Hua, Ruiqi Zhang	2020	This work presents arrhythmia classification through the use of hybrid model i.e CNN and LSTM. The model is more accurate and robust than the traditional model in terms of accuracy and robustness. The limitations of this study are that QRS detection is necessary which leads to additional computational cost. The second issue is that the data set used in this work is imbalanced.
7	Multirate Processing with Selective Sub bands and Machine Learning for Efficient Arrhythmia Classification	Saeed Mian Qaisar	2021	This study proposes a Multi-rate processing chain for the arrhythmia classification. Multi-rate processing feature selection were employed to decrease the information amount procedure thus reducing the complexity of the computational system. The performance results of model were varied by chosen various number of features.
8	Arrhythmia and Disease Classification Based on Deep Learning Techniques	Ramya G. Franklin, B. Muthukumar	2021	This work predicts converting raw ECG data to 2D pictures may cause information loss. Using straight 1D convolution on raw signals or different transformation methods may improve or accelerate results.
9	An Ensemble of Deep Learning-Based Multi-Model for ECG Heartbeats Arrhythmia Classification	Ehab Eesa, Xianghua Xie	2021	This research proposes multi-model system that was presented for the arrhythmia classification. It focusses on two models: CNN-LSTM to capture dynamics in temporal as well as local features for data ECG; RRHOS-LSTM that concatenated some features for classical i.e. RR intervals. This approach does not perform the feature extraction process.
10	ECG Heartbeat Classification Using Multimodal Fusion	Zeeshan Ahmad	2021	This work introduced two computationally effective multimodal feature fusion framework classification for ECG heart beat named Multimodal Image Fusion (MIF) and Multimodal feature fusion (MFF). This framework consumed much time for training and inference.

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Table 4.1 – continued from previous page

No	Paper Title	Authors	Year	Key Findings
11	Interpreting Arrhythmia Classification Using Deep Neural Network and CAM-Based Approach	Niken Prasasti Martono	2021	The work proposes an extension of CNN-based learning in detecting arrhythmia using recurrence plots from ECG signal and then the authors then conduct visualization using the Grad-CAM approach on the recurrence plot data to have a better interpretation of the classification process. In this work in the data preprocessing stage the appearance of R wave with irregular timing has been noted.
12	Arrhythmia Classification Techniques Using Deep Neural Network	Ali Haider Khan	2021	The research is focused on the latest trends in arrhythmia classification techniques and the system is constructed using deep neural networks. The study focused on understanding arrhythmia classification techniques to overcome their limitations. Time-series data was used by the authors to create the proposed automated system which is not applicable to different systems. For classification a balanced dataset is necessary.
13	Classification of Arrhythmia in Heartbeat Detection Using Deep Learning	Wusat Ullah	2021	The research developed a CNN model to classify ECG signals into eight categories. MIT-BIH arrhythmia database and PTB Diagnostic ECG database are used in this work. The study should concentrate on the development of denoising and data augmentation techniques.
14	Interpretation and Classification of Arrhythmia Using Deep Convolutional Network	Prateek Singh, and Ambalika Sharma	2021	The authors of this research trained a deep learning model and evaluated its classification performance Post-hoc explanation methods like SHapley Additive explanations (SHAP), local interpretable model- agnostic explanations (LIME), and Grad-CAM were used to interpret the decision rationale after interpreting the classification findings. This works lags in Interpretability.
15	Automatic cardiac arrhythmia classification based on hybrid 1-d CNN and bi-LSTM model	Jagdeep Rahul A , Lakhan Dev Sharma	2021	This work reports automatic classification system of ECG beats based on the multi-domain features derived from the ECG signals. This work reports overfitting where large dataset was used to remove.
16	Electrocardiogram based arrhythmia classification using wavelet transform with deep learning model	Shadhon Chandra Mohonta	2022	The study proposes a Deep Learning approach for the ECG based classification of the arrhythmia disease. The scalogram was acquired through the Continuous Wavelet Transform (CWT) was classified by the network based on signature according to arrhythmia. This approach was only suitable for the smaller segments of the signal
17	Inter-patient arrhythmia classification with improved deep residual convolutional neural network	Yuanlu Li	2022	The research paper presents enhanced Deep Residual Convolutional Neural Network (DRCNN) for automatic classification of arrhythmias. This approach was ability to effectively classified the arrhythmias without heartbeats extraction. This method had poor directionality as well as lack of phase information
18	A Hybrid Deep Learning Approach for ECG-Based Arrhythmia Classification	Parul Madan, Vijay Singh	2022	This work reports a hybrid model 2D-CNN-LSTM for the automation of the detection and process of classification. The dimension of the data was insufficient in classification, and the attributes has irrelevant data. This caused leads to inaccurate classification results in cardiac analysis.
19	Local-Global Temporal Fusion Network with an Attention Mechanism for Multiple and Multiclass Arrhythmia Classification	Yun Kwan Kim	2022	This research developed a new framework for an automatic classification that combined the residual network with squeeze-and-excitation (SE) block and bi- directional LSTM. This method designed to extract the features from original ECG data to acquire a unique intersubject attributes. The augmentation effect could be reduced due to baseline wander as well as noise couldbe extended to rhythm data.
20	An End-to-End Cardiac Arrhythmia Recognition Method with an Effective DenseNet Model on Imbalanced Datasets Using ECG Signal	Hadaate Ullah ,Md Belal Bin Heyat , Faijan Akhtar	2022	This research proposed a 2D CNN Method to recognize arrhythmia from ECG automatically. This approachuses two datasets. The proposed model lags with real- time monitoring and end-to end clinical study.

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Table 4.1 – continued from previous page

No	Paper Title	Authors	Year	Key Findings
21	Detection of heart arrhythmia based on UCMFB and deep learning technique	B MOHAN RAO and AMAN KUMAR	2022	This research presents Resnet50 model that classifies healthy people and patients with 4 types of cardiovascular diseases (CVD) based on ECG abnormalities. The study was done based on short and long segments of ECG databases. This has not deployed for Specific ECG multiclass classification
22	Arrhythmic Heartbeat Classification Using 2D Convolutional Neural Networks	M.Degirmenci, M.A.Ozdem ir	2022	This study presents deep learning approach CNN to identify arrhythmias in ECG signals trained by two- dimensional (2D) ECG beat images. This work lags with real time monitoring.
23	Lightweight Shufflenet Based CNN for Arrhythmia Classification	HURUY TESFAI	2022	This research work proposes a lightweight Convolution Neural Network (CNN) model based on the ShuffleNet architecture targeting arrhythmia classification with a 9x reduction factor in the number of trainable parameters. In this work feature extraction capabilities on convolution block should be improved.
24	A novel automated CNN arrhythmia classifier with memory-enhanced artificial hummingbird algorithm.	Evren Kıymaç, Yasin Kaya	2023	This work presents a novel method for the hyperparameter optimization (HPO)of a convolutional neural network (CNN) arrhythmia classifier using a metaheuristic (MH) algorithm. The proposed approach has not applied in different datasets for arrhythmia classification.
25	Classifying Cardiac Arrhythmia from ECG Signal Using 1DCNN Deep Learning Model	AdelA, Ahmed Waleed Ali	2023	The study proposes a deep learning model, specially convolutional neural network (1D-CNN), for the classification of arrhythmias. Limitations in this approach are dataset is imbalanced and it requires large dataset to train the model.
26	Electrocardiogram Heartbeat Classification for Arrhythmias and Myocardial Infarction	Bach-Tung Pham	2023	The research presents novel approach for ECG heartbeat classification.it uses MIT-BH and PTB datasets. the limitations of this approach is effectiveness of the model needs to be checked for additional datasets.
27	Cardiac arrhythmia detection using deep learning approach and time frequency representation of ECG signals	Yared Daniel Daydulo, Bheema Lingaiah D	2023	This research proposed an automated deep learning model capable of accurately classifying ECG signals into three categories The model was trained on ECG data from the MIT-BIH and BIDMC database. Authors of this research concentrated on classifying ECG signals into three classes. Its better to collect more data for this work.
28	A novel deep learning approach for arrhythmia prediction on ECG classification using recurrent CNN with GWO	Prem Narayan Singh, Rajendra Prasad Mahapatra	2023	This research proposes a method called recurrent convolutional neural network (RCNN) and Grey Wolf Optimization (GWO) for predicting arrhythmia. The proposed method is evaluated by using two publicly available datasets PTB diagnostic ECG and Grey Wolf Optimization (GWO). The proposed method has been compared with other ML techniques. Improvement is need in terms of adapting metamodel approach and identifying different arrhythmia types.
29	A novel deep neural network heartbeats classifier for heart health monitoring	Velagapudi, Swapna Sindhu, Kavuri Jaya Lakshmi	2023	This presents one dimensional convolutional neural network (1D CNN) for the classification of heart arrhythmia. Hyperparameter tuning was not adapted in order to improve accuracy of the model.
30	Automated inter-patient arrhythmia classification with dual attention neural network	He Lyua,, Xiangkui Li b, Jian Zhang b	2023	This work presents a dual attention mechanism with hybrid network (DA-net) for arrhythmia classification. DA-net is based on modified convolutional networks with channel attention (MCC-Net) and sequence-to- sequence network with global attention (Seq2Seq). Improvement is needed in terms of adapting data augmentation techniques.

4. Comparative Study.

5. Proposed Methodology.

1. Obtain ECG datasets from various sources in order to guarantee a wide range of cardiac conditions.
2. Prepare the ECG signals for analysis by means of normalization, filtering, and segmentation.
3. Incorporate deep learning alongside conventional signal processing methods to autonomously extract pertinent features from electrocardiogram (ECG) data.

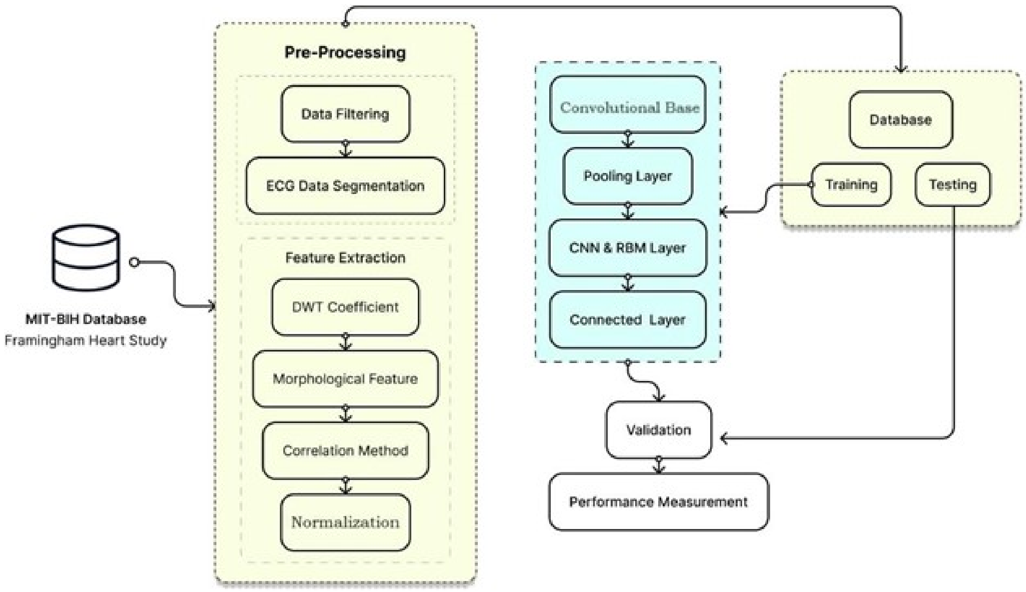

Fig. 5.1: Proposed work flow diagram for arrhythmia detection and classification.

4. Construct and evaluate a deep learning architecture that incorporates the gathered attributes to identify arrhythmias.
5. Performance can be enhanced and overfitting prevented by implementing regularization techniques and fine-tuning hyperparameters.
6. Evaluate the accuracy and robustness of the model using data obtained from multiple ECG devices.
7. Incorporate explainable AI methodologies in order to comprehend and represent the decision-making process of the model.
8. Evaluate the model on a test dataset utilizing metrics such as accuracy, sensitivity, specificity, and F1 score.
9. Develop a prototype system to demonstrate the arrhythmia detection capabilities.
10. Continuously refine the model using feedback and additional data for ongoing improvement.

6. Results and Discussion. In our work, we novel deep learning-based framework to analyze the complex ECG data and develop a transferable representation of ECG signals. It is important to know that to realize such a framework it is very important to describe an architecture that offers scope for learning the signal representation. Once we build a model and train that model on a huge training data set, the model will be able to learn from the pattern and allow to use those representation to transfer the knowledge. We have further experimented the CNN by adding the batch normalization layer between subsequent layers thereby inhibiting the hidden / convolution layers from normalizing the values which facilitate in improving the efficiency.

Also, the proposed algorithm employs a 2-D CNN with monochrome images of the ECG. One of the advantages of our approach is that conventional data pre-processing steps like feature extraction and noise removal and filtering are not required as the algorithm converts the 1-D Signal data to a 2-D image. Additionally, to improve the accuracy of the model we can augment the 2-D images and increase the size of the training data. Since our algorithm transforms a 1D signal to a 2D image, the model will automatically ignore the noise and extract the feature map. This allows the proposed model to be employed on heterogeneous signals and devices with different feature sets like sampling rate, amplitude etc. unlike the conventional models. Nonetheless, our approach can be implemented in an end-to-end clinical set up and that adds to the novelty of our work.

As shown in Figure 6.1, Individual cardiologist performance is indicated by the red crosses and averaged cardiologist performance is indicated by the green dot. The line represents the ROC curve of model performance.

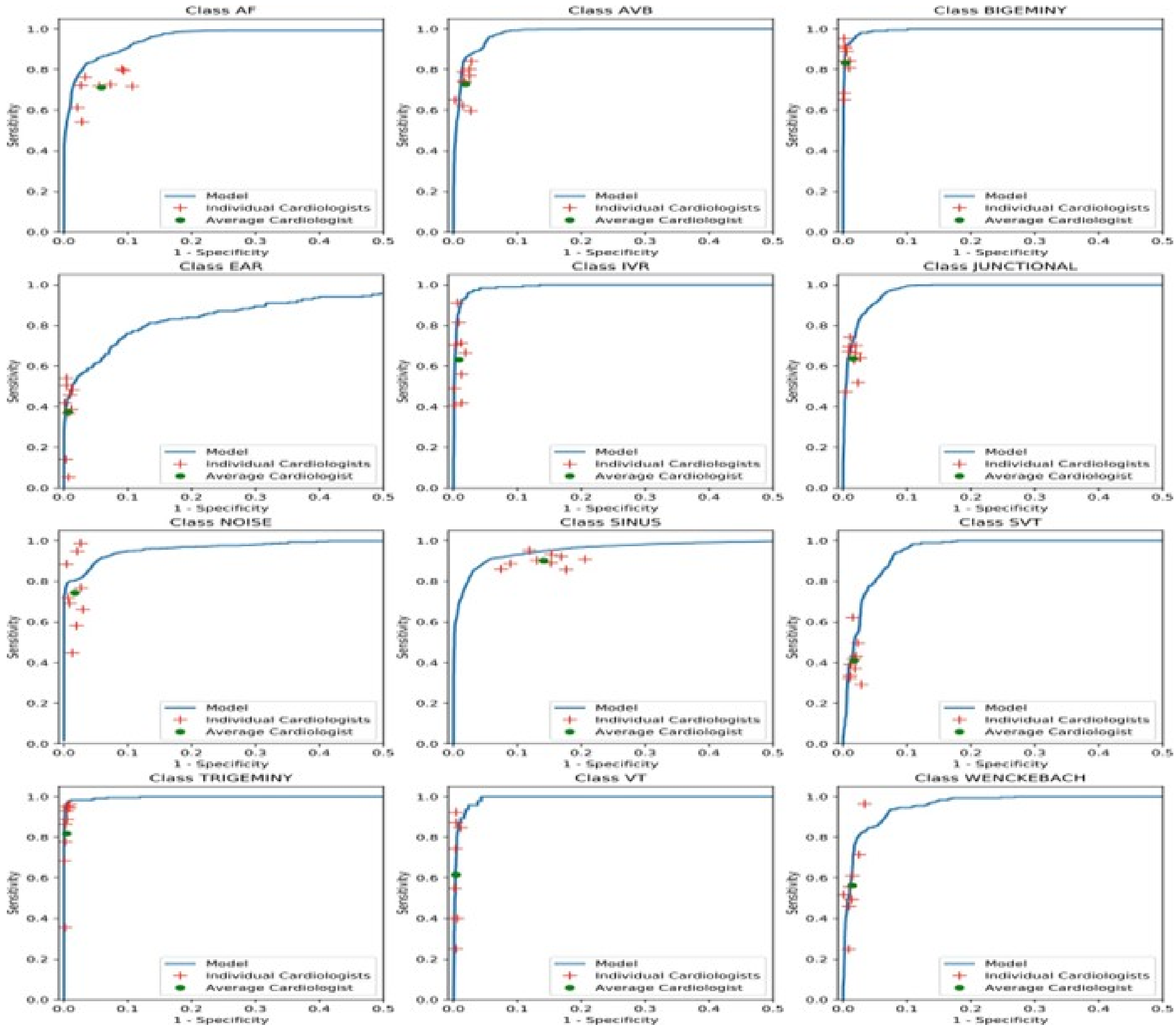

Fig. 6.1: Specificity and Sensitivity of Different classes of Arrhythmia.

AF-atrial fibrillation/atrial flutter; AVB- atrioventricular block; EAR-ectopic atrial rhythm; IVR-idioventricular rhythm; SVT supraventricular tachycardia; VT-ventricular tachycardia. n = 7,544 where each of the 328 30-second ECGs received 23 sequence-level predictions.

Fixing the specificity at the average specificity level achieved by cardiologists, the sensitivity of the DNN exceeded the average cardiologist sensitivity for all rhythm classes. Fixing the specificity at the average specificity level achieved by cardiologists, the sensitivity of the DNN exceeded the average cardiologist sensitivity for all rhythm classes as shown in Table 6.1. And the overall accuracy of the model (AUC) is around 0.97 as shown in Figure 6.2.

Our work demonstrates that the accuracy of the model is around 0.97. Our study demonstrates how employing Deep Learning Methods can improve the accuracy and open new avenues for research. Figure 6.2 shows the AUC of the rhythm classes and we can note that the accuracy is elevated compared to the annotations

When we started experimenting with the dataset, we realized that the data was quite imbalanced as shown

Table 6.1: Sensitivity comparison of our model vs. avg cardiologist

Condition	**Specificity**	**Avg Cardiologist Sensitivity**	**Our Model's Sensitivity**
Atrial fibrillation and flutter	0.941	0.71	0.861
AVB	0.981	0.731	0.858
Bigeminy	0.996	0.829	0.921
EAR	0.993	0.380	0.445
IVR	0.991	0.611	0.867
Junctional Rhythm	0.984	0.634	0.729
Noise	0.983	0.749	0.803
Sinus rhythm	0.859	0.901	0.950
SVT	0.983	0.408	0.487
Ventricular Tachycardia	0.996	0.652	0.702
Wenckebach	0.986	0.541	0.651

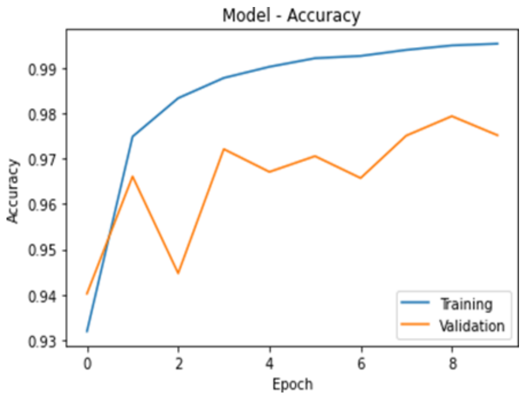

Fig. 6.2: Model Performance.

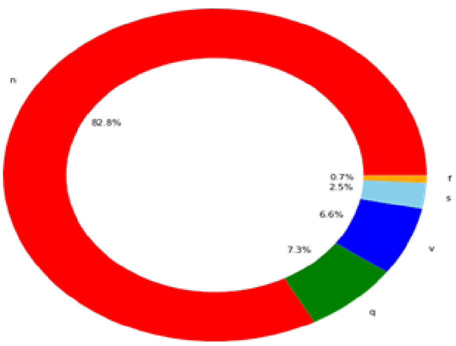

Fig. 6.3: Imbalanced Data.

in Figure 6.3 and after employing the resampling techniques we got a perfectly distributed data as shown in Figure 6.5.

Figure 6.6 as shown below, helps to visualize 1 ECG beat per category in the Time vs Amplitude format. This shows how different arrhythmic beats have different waveforms and how much do they vary from the normal beats shown in blue colour.

Figure 6.5 shows the results derived using the transformation method, where the 1-D signal data was transformed into 2-D 128 x 128 greyscale image. We have tested the classifier on 4,000 beats that we not a

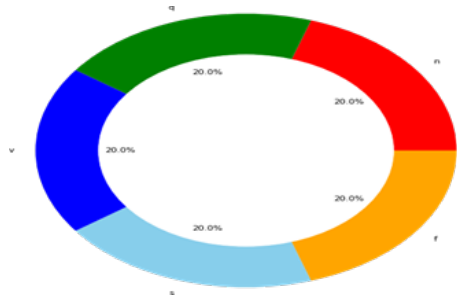

Fig. 6.4: Balanced Data after sampling.

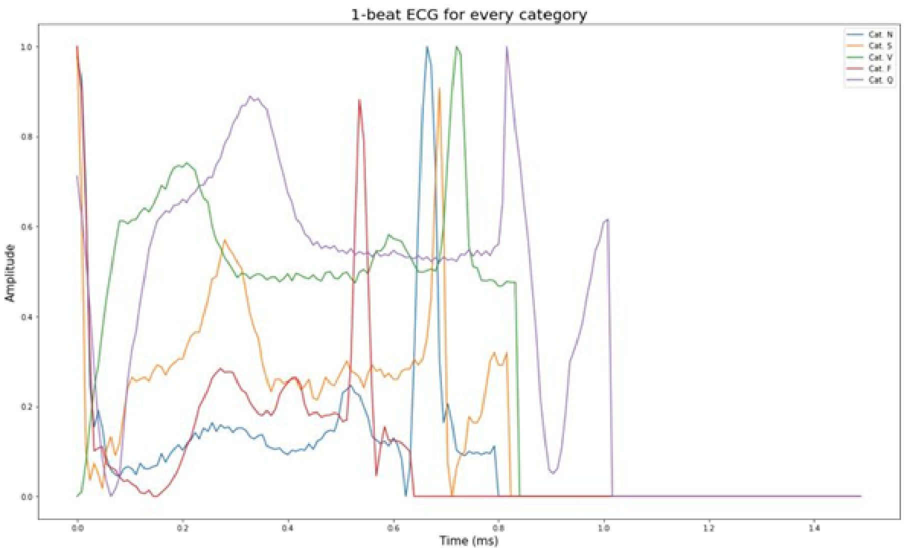

Fig. 6.5: ECG beats visualization.

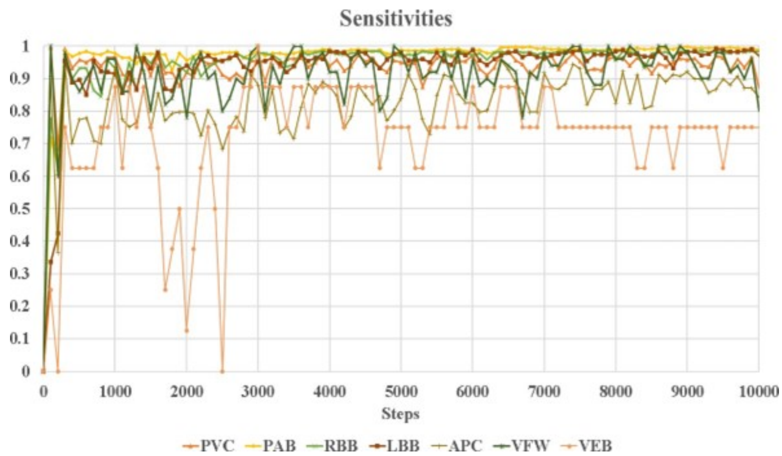

Fig. 6.6: Sensitivity of each type of arrhythmia class using transformation method.

part of training data. Figure 6.6 shows the confusion matrix of the classifier on the test set and we can infer that the model is making accurate predictions and also distinguish various arrhythmia classes.

Table 6.1 shows the avg accuracy of the proposed method. From the results we can infer that the proposed model has a very high accuracy and this has been characterized by the residual connections in the network which allows better learning in the networks compared to conventional methods.

7. Conclusion. This work develops a hybrid model for the automatic feature extraction and classification of various arrhythmias. Nevertheless, there are obstacles that need to be addressed, particularly regarding the accuracy of data, the establishment of standards, and the comprehensibility of these models. Future research should prioritize creation of models that combine features of machine learning and deep learning. These models have the potential to enhance robustness and improve generalization capabilities. Furthermore, it is crucial to develop a unified framework that can effectively integrate with current healthcare systems. In conclusion, although the use of ML and DL for arrhythmia classification is still in its early stages, it holds significant potential for improving patient care. The adoption of these technologies has the potential to significantly transform cardiac care, establishing early and precise diagnosis as the prevailing standard.

8. Future Scope. Our proposed model focusses on detecting and classifying arrhythmia using ECG and bio signals which is a game changer.in Future more focus will be on real time monitoring of patients using the required dataset, where we can achieve more accuracy.

Credit authorship contribution statement. Manjesh B N: Methodology, Software, Data curation, Writing – original draft, Writing – review and editing. Dr.Raja Praveen N-Investigation, Writing – review and editing.

Declaration of Competing Interest. Declaration statement by co-authors for the manuscript, " A Comprehensive Review on Detection of Arrhythmia using Deep Learning Methods with Deep Learning Model". We declare the following:

1. Data: The public database from MIT-BIH has been used in this study.
2. Ethics: The research protocol was approved by Jain University, Bangalore.
3. Conflict of Interest: Nothing to declare.
4. Financial support: Nothing to declare.

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