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A HYBRID MODEL FOR CLASSIFICATION OF CARDIAC ARRHYTHMIAS USING CNN AND LSTM

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Abstract— **Electrocardiograms (ECGs) are vital tools for monitoring heart activity and diagnosing a wide range of heart conditions, including arrhythmias, which are characterized by irregular heartbeats. Arrhythmias, if not properly diagnosed and treated, can result in serious complications such as stroke, heart failure, or even sudden cardiac arrest. Given these risks, the accurate detection and classification of arrhythmias is critical for ensuring timely and effective medical interventions. This project aims to tackle this challenge by using the MIT-BIH Arrhythmia Database, a well-established resource for arrhythmia classification, which contains data for five types of arrhythmias: Normal beat (N), Supraventricular ectopic beat (S), Ventricular ectopic beat (V), Fusion beat (F), and Unknown beat (Q). These different types of heartbeats present varying levels of difficulty in classification, and one of the key challenges is the imbalance in the dataset, where some arrhythmia types are significantly underrepresented. The project uses a hybrid deep learning model that blends Long Short-Term Memory (LSTM) networks with Convolutional Neural Networks (CNNs) to overcome these obstacles. CNNs are well-suited to capture the minute changes in heartbeats that are indicative of various arrhythmia types because they are very good at spotting spatial characteristics and patterns within the ECG signal. On the other hand, LSTMs are designed to handle the temporal relationships in sequential data, which is critical when dealing with ECG signals and other time-series data. The hybrid model can handle the ECG data more efficiently and increase classification accuracy by fusing the advantages of both CNNs and LSTMs. Furthermore, to improve the quality of the input signals and lessen the consequences of dataset imbalance, sophisticated signal processing techniques are applied to the raw ECG data. This all-encompassing strategy not only enhances the model's overall performance but also strengthens its ability to detect uncommon arrhythmias that conventional techniques frequently miss. Ultimately, this project demonstrates the potential of using large, annotated medical databases and cutting-edge computational methods to improve automated arrhythmia diagnosis's precision and dependability, paving the way for better management of cardiovascular health.**

Keywords— **ECG Signals, Arrhythmias, CNN, LSTM**

I. INTRODUCTION

Controlling cardiovascular diseases are of great importance in the contemporary societies where life quality is of greater importance and equal importance is given to life prise. Cardiac dysrhythmias are seen as a condition whereby the electricity that pumps the heart is irregular, leading to fast, slow or irregular heart rates. Such arrhythmias may be normal variants or simple premature contractions and may progress to acquire serious consequences like mass or atrial fibrillation or ventricular fibrillation. Among them, atrial fibrillation – widespread among the elderly – raises the threat of stroke and heart failure; ventricular – may lead to sudden cardiac arrest. Since cardiovascular diseases are common in most countries today, finding signs of arrhythmias early can help prevent adverse health effects or loss of life for millions of people. However, the constant threat of arrhythmias, which can be described as irregular heartbeats is a major factor in heart conditions around the globe. In the past, the diagnosis of arrhythmias was mainly based on ECG, which is an ambulatory diagnostic procedure that analyzes the electrical events of the heart over time. Using ECGs is a great asset in straining the rhythm of the heart and in recognizing that something is amiss, which may indicate that the patient has arrhythmia. However, the substantial amount of data produced when continuous ECG monitoring is performed over large populations as part of health campaigns, tele monitoring, or home monitoring imposes difficulties with manual analysis. The constantly fluctuating and unpredictable nature of the arrhythmia does not help in the diagnosis and can take a considerable amount of time for an irregular episode to be picked up. Furthermore, the traditional analysis of an ECG can be qualitative and approach errors or misinterpretation by a human being, especially in the pattern discrimination of the different types of arrhythmias. This issue becomes more severe in large-scale health monitoring systems where a large number of ECG data is generated further complicating the analysis. With over 17.9 million deaths each year due to cardiovascular conditions, effective arrhythmia management is essential to reduce the global health burden. To these challenges, there has been innovation in AI particularly deep learning as transformative solutions for classification of arrhythmia. Deep learning technologies depending on neural networks proved themselves effectively in the examination of ECG signals with minimal error, identifying intricate patterns that are challenging to detect with the bare human eye. Such automated devices can handle large amount of ECG data within a short time thus improving the detection of the arrhythmias in comparison to manual methods.

This paper focuses on the fact that disease classification of Arrhythmia is critical in a wide range of healthcare domains, including early detection and treatment. In wearable health monitoring devices like smart watches, arrhythmia detection allows checking the heart rhythms in real-time and let the user know when he/she needs medical attention. In clinical situations there is help of automated classification systems that assist in identifying such conditions as atrial fibrillation or ventricular tachycardia and allow for required actions. Also, these systems help with telemedicine by allowing patients' monitoring in-between appointments, which may not require physical meetings. They also improve the performance of vital pieces of equipment in managing life threatening conditions for which precise identification of the problem is critical in formulating the response. In general, the type of arrhythmia diagnosis is significant to enhance the quality of patient's cardiac treatment, providing the most effective treatment strategy. As the healthcare demand increases and new technologies in processing ECG are available, the incentives for creating accurate and efficient arrhythmia classification algorithms are lifesaving, early diagnosis, and helpful advice for clinicians when they face a life threatening situation.

The rest of the paper is organized as follows. Proposed embedding and extraction algorithms are explained in section II. Experimental results are presented in section III. Concluding remarks are given in section IV.

II. LITERATURE SURVEY

A. Machine Learning Based Approaches

[7] presents a novel approach for arrhythmia classification named heartbeat dynamics, which captures the morphological evolution of the heart beats. This feature increases responsiveness to low-frequency oscillations and captures

deeper dynamics of changes at the electrophysiological level during the entire cardiac cycle. The paper contributes towards enhancing the interpretability and general performance to beat the deep learning methods of the arrhythmia. To compare the performance of heartbeat dynamics, they employ classical classifiers, including k-nearest neighbor (KNN), random forest (RF), and support vector machine (SVM), to the MIT-BIH arrhythmia database. Cross-validation results show high accuracy, precision, recall, and F1 score, making the proposed method possess a good discriminative ability. Moreover, the research reveals the benefits of the Heartbeat dynamics in the separation of various classes of the heartbeat. This approach is much more feasible than other complicated deep learning models as the later has a major limitation in its interpretability. It postulates that incorporating heartbeat dynamics into other static parameters will improve the generalizability of the arrhythmia identification models.

[9] suggests a new classification method of ECG signals for the energy-constrained wearable devices, utilizing some power-saving and efficient approaches. The paper presents a method which implements the Delta-Sigma Modulators (DSMs) for arrhythmias' detection, along with the Random Forest classifiers for their classification. As used in this paper, the proposed method has a lower sampling rate than the conventional techniques in hopes of minimizing the power requirement which is ideal for wearable ECG gadgets. An analysis of the method was carried out using the CinC 2017 A fib and QT datasets, and the method showed high accuracy in locating the QRS complexes and quite stable performance even under noisy conditions. This work underscores the benefits of the presented method over several other benchmark procedures, particularly in categorization precision and energy consumption. Random forest(RF) is also preceded with robustness because this algorithm can handle missing values and noise. They conclude that integrating resource-saving architectures with sophisticated classification algorithms will improve the efficiency and reliability of ECG monitoring solutions particularly in applications in wearable technology.

[13] presents a novel methodology for classifying cardiac arrhythmias by combining traditional parametric features with visual pattern features of ECG morphology. It focus on improving classification accuracy by proposing a new feature extraction algorithm, Adaptive K-means Clustering (AKMC), which clusters QRS complex morphologies into visual patterns. To improve the classification system's discrimination power, these patterns are combined with parametric data including wave amplitudes, intervals, and durations. Three popular classifiers—k-nearest neighbors (KNN), support vector machines (SVM), and neural networks (NN)—are used to classify the collected feature sets. While the methodology achieves high classification accuracy across multiple arrhythmia types, the study highlights some limitations. One of the challenges faced is that certain features, like RR intervals, are not sufficient to distinguish between different arrhythmia types, especially more complex ones like bundle branch blocks. Additionally, the reliance on a novel visual morphological pattern feature introduces a degree of complexity, particularly in the training phase where multiple clusters must be identified and mapped accurately.

B. CNN Based Approaches

Paper [1] suggests a hybrid model that combines particle swarm optimization (PSO) with convolutional neural networks (CNNs) for the classification of arrhythmias. This method minimizes manual design work by automating the selection of the best CNN hyperparameters. MIT-BIH Arrhythmia Database ECG data is used to train the model, and PSO optimizes the architecture to reduce cross-entropy loss and improve classification accuracy. The hybrid CNN-PSO model has difficulties because of its computational burden and the dataset's imbalance, where some arrhythmia classes have a disproportionately small number of samples, even though it shows better accuracy and automatic adjustment.

[6] presents NEO-CCNN, presents an innovative algorithm named NEO-CCNN for arrhythmia classification tailored for wearable ECG devices. The primary focus is on developing an embedded arrhythmia classifier that can operate efficiently on a simple microcontroller, addressing the limitations posed by the high-power consumption of continuous ECG data transmission to mobile phones. The suggested approach achieves excellent accuracy and sensitivity by combining a compact 1D convolutional neural network (CCNN) for classification with a nonlinear energy operator (NEO) based thresholding algorithm for R-peak detection. The work highlights the difficulties in developing a reliable embedded arrhythmia classifier because of the differences in ECG morphology brought on by age, gender, physical condition, and environmental factors. R-peak identification is made more accurate and sensitive by the algorithm's integration of the NEO with a time-dependent thresholding technique. This is essential for the subsequent arrhythmia classification. Additionally, to address the possible influence of R-peak location errors (RLE) on the classification performance, the research presents a QRS complex augmentation method. Using a stacked k1k2-fold cross-validation technique, the algorithm's performance is robustly assessed. The proposed NEO-CCNN algorithm's ability to efficiently detect and classify arrhythmias on a simple microcontroller highlights its potential for early detection and monitoring of heart conditions, potentially alleviating the need for continuous hospital monitoring and providing significant relief to patients with arrhythmia.

[8] offers a complex framework for precise arrhythmia classification utilizing ECG signals called the Deep Multi Scale Convolutional Neural Network Ensemble (DMSCE). In order to optimize their combined knowledge through a gating network for efficient decision fusion, this ensemble approach combines many Single-Task Deep Convolutional Neural Networks (SD-DCNNs) that concentrate on various facets of ECG analysis. By focusing on clinically significant ECG segments, like aberrant P-waves and ectopic beats, this method not only increases classification accuracy but also improves model interpretability, closely matching medical diagnostic criteria. The DMSCE framework demonstrates significant advantages over traditional methods by effectively managing model complexity while maintaining high diagnostic accuracy. By leveraging diverse predictions from multiple expert models, it reduces the risk of overfitting and improves generalizability across various patient populations. The study validates its efficacy utilizing publicly accessible datasets such as CinC-training2017 and PTBXL-2020, showcasing superior performance compared to baseline models. Despite its strengths, the paper notes the challenge of limited information on non-linear equation reduction, which may impact the model's effectiveness.

[10] presents a comprehensive survey of advancements in using deep convolutional neural networks (CNNs) for the automated detection and classification of arrhythmias from ECG signals. It address several key challenges, including data imbalance and the necessity for effective feature extraction from ECG beats. They introduce DeepArrNet, a novel CNN architecture that incorporates depthwise separable convolutions and multiple parallel temporal convolutions to enhance computational efficiency and feature extraction capabilities. Wavelet-based denoising of raw ECG signals before classification is a key component of DeepArrNet that lowers noise and increases the network's resilience to changes in ECG signals. To efficiently collect and combine data from various temporal scales, the architecture is made up of successive DeepArrNet Unit Blocks, each of which has residual connections and pointwise-temporal-pointwise (PTP) convolutions. According to experimental results on

benchmark datasets, DeepArrNet outperforms other deep learning techniques and conventional methods in terms of accuracy, sensitivity, and specificity, achieving state-of-the-art performance in arrhythmia identification. All things considered, DeepArrNet makes a substantial contribution to the area by providing a robust and lightweight deep learning framework designed for accurate and effective arrhythmia identification.

[11] investigates how to create a convolutional neural network (CNN) architecture that is most suited for using ECG data to classify arrhythmias. It solves the urgent demand for precise and effective models that can be used for medical diagnostics in real time. The use of ShuffleNet, a lightweight CNN design renowned for its computational efficiency and parameter reduction strategies, is essential to the strategy. The researchers sought to reduce model complexity while preserving high classification accuracy by utilizing ShuffleNet's design principles. This is crucial for resource constrained scenarios such as wearable technology or remote healthcare settings. The suggested ShuffleNet-based CNN was trained and assessed using benchmark ECG datasets as part of the technique, and it was rigorously validated against predetermined metrics. The results showed encouraging performance, delivering notable benefits and competitive accuracy levels when compared to more intricate models in terms of computational efficiency and model size. This approach holds substantial promise for deploying AI-driven arrhythmia detection systems in practical healthcare applications, contributing to improved diagnostic capabilities and patient outcomes.

[15] suggests utilizing a two-dimensional Convolutional Neural Network (2D-CNN) to categorize arrhythmias in ECG signals. The authors use the Short-Time Fourier Transform (STFT) to convert ECG signals from the time domain into time-frequency spectrograms in order to overcome the difficulty of automatic arrhythmia detection. The 2D-CNN then uses these spectrograms as input to classify the heartbeats into five categories: atrial premature contraction beat, premature ventricular contraction beat, left bundle branch block beat, and normal beat. The first step in the multi-phase technique is the gathering of ECG data from the MIT-BIH arrhythmia database. 2D spectrograms are created by preprocessing the ECG signals. The 2D-CNN model uses these spectrograms as input to categorize the various types of arrhythmias. The authors also compare their proposed 2D CNN model with a traditional 1D-CNN model, demonstrating the superior performance of the 2D approach. The proposed method offers significant advantages, including the elimination of manual feature extraction, which is often required in traditional methods. However, it also involves complex transformations and requires substantial computational resources for training the deep learning model.

C. Other Approaches

[2] introduces a novel method for arrhythmia detection by combining Group Sparse Mode Decomposition (GSMD) with the Superlet Transform (SLT) to classify ECG signals. This methodology addresses the challenges of analyzing nonstationary ECG data by decomposing signals into Intrinsic Mode Functions (IMFs) using GSMD, followed by transforming the signals into two-dimensional time-frequency spectrograms using SLT. The spectrograms are subsequently fed into deep learning models, such as VGG19, RESNET-18, GoogleNet, and AlexNet, for arrhythmia classification into healthy heartbeats, atrial fibrillation (AF), and ventricular fibrillation (VF). The use of SLT enhances the resolution of time-frequency representations, eliminating the need for additional denoising steps while maintaining the integrity of crucial ECG features like QRS complexes.Despite its high accuracy, the proposed methodology has some limitations. The computational complexity of the GSMD + SLT approach, as shown by a training time of several hours, poses a significant drawback, particularly when applied to larger datasets or real-time systems. Additionally, the datasets used in the study are not balanced, with fewer samples in minority classes such as AF and VF. This imbalance can lead to biased classification results, where the model may perform well on majority classes but struggle with minority class detection, affecting its generalization ability. This limitation underscores the need for further work in addressing class imbalance, potentially through data augmentation or more robust balancing techniques.

[3] introduces HA-ResNet, an ECG arrhythmia detection model that uses a hidden attention method and residual connections. The attention method improves interpretability and classification performance by assisting the model in concentrating on important ECG segments. Experimental tests on benchmark datasets such as MITDB and CUDB demonstrate that HA-ResNet reaches cutting-edge robustness and accuracy. Additionally, the design incorporates BConvLSTM layers and SE blocks, which enhance temporal dependencies and feature representation. However, patient demographics and dataset heterogeneity can affect the model's performance, making it difficult to generalize across various clinical situations.

[4] presents a complex method that uses multimodal neural networks (MM-NN) to increase the accuracy of cardiac arrhythmia identification. The work tackles the difficult problem of correctly categorizing ECG data, which is essential for timely heart disease diagnosis and therapy. By integrating patient-specific metadata with ECG data through a linear perceptron and employing LSTM networks for signal classification, the MM-NN achieves a recognition accuracy. This accuracy represents a notable improvement of 2 percentage points over existing state-of-the-art methods. Key contributions of the research include the

effective preprocessing of ECG signals using wavelet transforms and robust data balancing techniques like ROS, which collectively contribute to improved classification outcomes. The findings underscore the significance of personalized medicine approaches that integrate multimodal data sources for more accurate disease diagnosis and management. Future research directions include optimizing MM-NN architectures, exploring additional preprocessing methods, and evaluating the scalability and applicability of the proposed approach across diverse patient populations and clinical settings.

[5] uses deep learning models to address the crucial problem of interpretability in arrhythmia classification. Conventional deep learning techniques frequently operate as "black boxes," providing excellent accuracy but with opaque decision making. This work suggests a novel approach to improve interpretability while preserving good classification performance by fusing machine-encoded and human-encoded information. Electrocardiogram (ECG) signals are encoded in this work using an Autoencoder into two separate parts: machine-encoding knowledge that is obtained from the data and hand-encoding information that incorporates human skill. Arrhythmia heartbeats are classified using this dual encoding, with the potential to further refine the classification by using human-in-the-loop (HIL) interaction. Tests conducted using the MIT-BIH Arrhythmia Database show that this method not only increases classification accuracy but also yields results that are easy to understand, making it easier for medical professionals to trust and understand the model's decisions. Thus, the paper contributes a two-task learning method to ensure the hidden layers of the model contain both human interpretable and machine-generated features. The integration of HIL mechanisms allows for human adjustments to the model, enhancing its performance and trustworthiness. This work represents a significant step towards making deep learning models for medical diagnosis more transparent and trustworthy. But it faces Complexity in integrating human knowledge and ensuring accurate HIL adjustments

[12] describes a system for grading cardiac arrhythmias according to their intensity, with a focus on wearable medical equipment' energy efficiency. The work tackles the problem of striking a balance between low energy consumption and high classification accuracy, which is essential for wearables that run on batteries. According to their system, arrhythmias are categorized into a hierarchy of severity categories, ranging from normal to severe. By allowing neural network components to be activated only when required, this hierarchical design effectively lowers total energy consumption. The study suggests employing Superlet Transforms (SLT) and Group Sparse Mode Decomposition (GSMD) to extract features from ECG data, which are then classified using neural networks. The innovative aspect of this severity-based approach lies in its ability to simplify classification at higher levels (normal, mild, moderate, severe) and conduct finer classification only when needed, enhancing diagnosis speed and device efficiency. However, a major disadvantage highlighted is the imbalanced nature of the dataset, with a higher frequency of normal heartbeats compared to severe arrhythmia types. Additionally, the complexity introduced by utilizing hierarchical classifiers requires distinct neural network configurations for different arrhythmia severities, posing a challenge for effective system design.

[14] suggests a sophisticated method for classifying various arrhythmia types using long-term ECG readings. Multi-label feature selection (MS-ECG) and multi-label classification (MC-ECG) are the two approaches that the authors suggest. Conventional classification techniques for arrhythmias frequently handle each type of arrhythmia separately, which results in information loss, particularly when several arrhythmias happen at the same time. In order to address this issue, a multi-label system that captures correlations between various arrhythmia types is introduced in this research. By optimizing ECG feature selection using kernelized fuzzy rough sets, the MS-ECG feature selection technique minimizes the feature space while maintaining the essential ECG features for arrhythmia identification. The MC-ECG classifier then uses these selected features, optimizing for multiple objectives while handling the sparsity of the data, which improves the overall classification performance. The complexity of dealing with multi-label data is significantly higher than traditional multiclass problems. Large data sets and processing power might be problematic, particularly for real-time applications such as wearable ECG monitors. Additionally, though the authors emphasize the discovery of correlations between different arrhythmias, such correlations can vary between datasets, possibly affecting generalizability.

[16] presents a novel method for using a 12-lead ECG to classify arrhythmias. The classification performance is improved by the suggested MLBF-Net architecture's efficient acquisition and integration of the various types of data from each lead. A multi-loss optimization technique is used to guarantee the model's correctness and resilience, a cross-lead fusion mechanism merges these features, and several lead specific branches that learn features from individual leads. The shortcomings of earlier approaches, which frequently ignore the distinctive qualities of every ECG lead, are addressed with MLBF-Net. Through the use of a fusion module and a lead specific branch network (BranchNet), MLBF-Net is able to learn and integrate features from every lead, offering a thorough examination of the ECG signals. The authors also introduce a multi-loss co-optimization approach that balances the learning of individual lead features and the overall integrated features, resulting in improved

classification performance across multiple arrhythmia types. The evaluation of MLBF-Net on benchmark datasets demonstrates its superior performance compared to existing models. The outcomes demonstrate the model's potential for useful clinical applications by demonstrating its accuracy in classifying a variety of arrhythmias. For practical implementation, the model's intricacy and the amount of computing power needed for training and inference are significant drawbacks that must be resolved.
[17] presents a deep learning approach aimed at classifying raw ECG signals into different heartbeat types, such as normal and arrhythmic beats. The methodology focuses on eliminating the need for handcrafted feature extraction by using deep neural networks (DNNs) that process raw ECG signals directly. To improve accuracy, the paper align the heartbeats by using the R-peak as an anchor point and include the P and T waves alongside the QRS complex. The study highlights the advantages of an end-to-end approach, including eliminating reliance on expert-annotated data for feature extraction and enabling the system to automatically learn the most informative features from raw ECG signals. However, the reliance on DNNs introduces computational complexity, which may be challenging for real-time or resource-constrained environments.

D. Research Gaps and Objectives

The categorization of arrhythmias using deep learning and other machine learning techniques has advanced significantly in recent years. Even though these techniques have demonstrated potential in raising diagnostic precision and effectiveness, there are still a number of obstacles and restrictions. In order to provide more useful and efficient solutions for actual medical applications, these gaps must be filled. Some of the major research gaps that still impede advancement in this area and require more investigation are covered in this study.
Computational Intensity and Resource Constraints: The accuracy and feature extraction of the hybrid models and deep learning architectures employed in arrhythmia classification, like the CNN-PSO method [1] or models like VGG19 and ResNet-18, are impressive. Nevertheless, these methods frequently have large computing costs, especially when training and inferring in real time. These techniques' scalability in low-resource settings, such as wearable technology or remote monitoring systems, where memory and battery consumption are crucial limitations, is limited by their computational intensity. Furthermore, whereas models like [6] NEO-CCNN and [11] ShuffleNet seek to strike a balance between accuracy and efficiency, the difficulty is in developing a method that does not compromise either. Therefore, there is a need to create lightweight algorithms that preserve classification accuracy while using fewer resources, especially for real-time continuous monitoring on low-power devices.

Dataset Imbalance:

A pervasive issue across many studies is the class imbalance inherent in datasets like MIT-BIH, where normal heartbeats are disproportionately represented compared to less common arrhythmias. This imbalance causes models to become biased towards detecting common arrhythmias at the cost of missed diagnoses of rare but clinically significant conditions. While approaches such as ROS (Random Over Sampling) are widely used, these methods are often prone to overfitting on the minority class, leading to a drop in generalization performance. Furthermore, the dataset imbalance can negatively impact model validation, making it difficult to assess performance on unseen cases reliably. A significant research gap lies in developing advanced balancing techniques that ensure accurate classification across both majority and minority classes while maintaining robustness during real-world deployment. New techniques such as generative adversarial networks (GANs) to create synthetic samples for minority classes or adaptive weighting schemes in loss functions could offer potential solutions.

Interpretability:

First of all, deep learning models are black box like systems which specifically remains as big drawback when used in diagnosis and prognosis in the field of medicine as doctors require specific reasons for coming to their conclusions. Though in [5] methods such as attention layers or human-in the-loop (HIL) interventions are described, the methods remain only partially explainable in ways that medical practitioners can confidently put their reliance in. For example, in HIL models, manual adjustments need to be applied that can cause either bias or increase the model’s complexity and it is considered that the performance will not necessarily be the same for different users or in another dataset. The development of models which have similar prediction performance to the default deep learning structures, but contain clear and explainable decision making logic that could be audited by the clinicians has been left unaddressed. This also involves continuing work on the explain-ability of AI (XAI) methods in the hope of shedding light on the inner mechanisms of deeper models and making the output diagnosable to clinicians.
To enhance the effectiveness of arrhythmia classification, it is essential to establish specific research objectives that address current challenges in the field. A primary focus is on advancing data balancing techniques to tackle the severe class imbalances prevalent in ECG datasets. This involves not only refining traditional methods but also exploring innovative approaches such as generative models that synthesize new data points for underrepresented arrhythmia classes and dynamic re-weighting strategies during the training process. We can guarantee good classification accuracy for both common and uncommon arrhythmias while preserving model resilience and generalization by

refining these approaches. Making these systems more usable for practical applications requires lowering the computational complexity associated with preprocessing and feature extraction. The model's performance can be greatly improved by looking at automated feature extraction techniques that are adaptive to changing signal conditions and require little manual involvement. Meaningful feature extraction from raw signals can be facilitated by self-supervised learning techniques, which let models learn from unlabeled data. By addressing these research gaps and pursuing these objectives, the field of arrhythmia classification can move toward the development of more robust, efficient, and clinically viable models, ultimately leading to improved cardiac health outcomes through timely and accurate detection of arrhythmias.

III. PROPOSED ALGORITHM

A. Dataset Description

MIT-BIH Arrhythmia Dataset is the heartbeat classification dataset most commonly used, especially in ECG analysis. It contains 109,446 samples of heartbeat signals, categorized into five distinct classes: Type A: Normal (N), Supraventricular ectopic (S), Ventricular ectopic (V), Fusion of ventricular and normal (F), Paced beats or Unclassifiable (Q). These ECG signals are of various heartbeats which include normal as well as abnormally beating hearts caused by one kind of arrhythmia or the other. The use of the ECG signals contained in Dataset, recorded under real-life clinical conditions, makes the database valuable for developing and comparing algorithms for detecting and diagnosing arrhythmias. The signal is tagged by human annotators for confident and consistency of data labels for each of the classes of the arrhythmia. People have employed this dataset to confirm whether or not data can be used to classify heartbeat with reasonable accuracy. This make the MIT-BIH dataset not only valuable for the establishment of reliable classification systems, but also for training models that can be used in real time healthcare environments, aimed at the early identification of fatal types of heart diseases.

B. Motivation for hybrid model of CNN and LSTM

The dynamic nature of heart rhythms and the existence of noise in the data make it difficult to classify arrhythmias from electrocardiogram (ECG) measurements. Although somewhat successful, traditional approaches frequently fail to capture the minor variations among arrhythmia types and are ill-suited to simulate the temporal dependencies present in ECG signals. The suggested approach makes use of a hybrid model that combines Long Short-Term Memory (LSTM) networks with Convolutional Neural Networks (CNN) to overcome these difficulties. This combination of two potent deep learning architectures makes it possible to model sequential relationships (using LSTM) and extract significant features from the ECG data (using CNN), which makes it a viable method for classifying arrhythmias. ECG signals are typically time-series data with both spatial (morphological) and temporal patterns. Different types of arrhythmias exhibit specific waveforms that require careful analysis to identify key features such as the QRS complex, P-wave, and T-wave, as well as subtle shifts in rhythm over time. Traditional machine learning models, while useful for static or feature engineered inputs, often fall short when dealing with the sequential nature of ECG data. The capacity of CNNs to automatically identify hierarchical patterns in data through convolutional layers has led to their widespread application in image processing jobs. CNNs are particularly good at detecting local, spatial patterns, including characteristic peaks and troughs in the ECG waveform, when applied to 1D ECG signals. These features are essential for distinguishing various arrhythmia types. The temporal connections that can exist between successive heartbeats or variations in rhythm over time, however, are not captured by CNNs alone. However, by preserving temporal information and long-term relationships, LSTM networks are made to handle sequential data. LSTMs are very good at examining the temporal progression of heartbeats in the context of ECG signal classification, which aids in the detection of arrhythmias that gradually or irregularly develop over time. The hybrid CNN-LSTM model seeks to capture both spatial and temporal patterns, improving arrhythmia classification performance by fusing CNN's feature extraction skills with LSTM's capacity to handle temporal data. The suggested CNN-LSTM hybrid model combines the advantages of recurrent and convolutional neural networks to offer a reliable and effective solution for arrhythmia classification. This approach tackles the particular difficulties of classifying arrhythmias, including minute morphological variations and temporal connections between heartbeats, by capturing both spatial and temporal characteristics from ECG data. With its ability to automate feature extraction and improve classification accuracy, the CNN-LSTM hybrid model holds significant potential for enhancing cardiovascular disease diagnosis, reducing manual labor, and improving patient outcomes in real-world clinical settings.

C. Addressing Data imbalance with SMOTE

In the realm of ECG signal analysis, particularly for arrhythmia detection, imbalanced datasets present a significant challenge, with certain heartbeat types like normal beats vastly outnumbering others such as arrhythmic beats. Various techniques have been developed to address this imbalance, each with its own advantages and drawbacks. Random Over Sampling increases the size of the minority class by duplicating existing samples, which can enhance model performance but risks overfitting due to a lack of diversity in the training data. Conversely, Random Under-Sampling reduces the number of instances in the

majority class, helping to focus the model on minority classes, but it often results in information loss that can negatively affect overall accuracy. Tomek Links cleans datasets by removing instances that contribute to class overlap, thereby enhancing class distinction; however, it can be computationally expensive, particularly with high-dimensional data, and may also remove useful information. Cluster-Based Over-Sampling generates synthetic samples within clusters formed from the minority class but can be computationally intensive and may fail to accurately capture the data's underlying structure. Cost Sensitive Learning incorporates class imbalance directly into model training by assigning different penalties for misclassifications based on class membership, yet this approach can be complex and requires careful tuning of the cost matrix, potentially increasing training time. In contrast, SMOTE (Synthetic Minority Over-sampling Technique) effectively creates synthetic examples by interpolating between existing minority class samples, which enhances diversity without merely duplicating instances, thereby reducing the risk of overfitting. SMOTE avoids the information loss typically associated with under-sampling, as it preserves the majority class while enriching the minority class representation. It is also less computationally intensive than more advanced techniques like clustering or Tomek Links, as it primarily involves identifying nearest neighbors and interpolating between them rather than complex calculations of distances across the dataset. By filling gaps in the minority class distribution and reflecting the underlying data patterns more accurately, SMOTE allows classifiers to learn more robust decision boundaries, ultimately leading to improved performance in recognizing arrhythmias across varied datasets.
SMOTE interpolates between existing samples to produce synthetic samples of the minority class. This synthetic oversampling is done in the feature space rather than duplicating original samples, which helps to avoid overfitting while improving model generalization on minority classes.

Identifying k-Nearest Neighbors
In the case of each object from the minority set (arrhythmic beats), SMOTE finds k nearest neighbors applying distance measure (normally Euclidean distance) within the feature space.

The feature space is constructed based on derived features from the ECG signal, such as:
- RR intervals: The difference in time between two successive R-peaks.
- QRS duration: The length of the right and left ventricles' depolarization in the QRS complex form (the waveform representing the depolarization of the right and left ventricles).
- Amplitude features: For example, the height of the P wave, QRS complex, or T wave.

The algorithm identifies the closest neighbors of each sample in the minority class. These neighbors are other samples from the same class, representing similar ECG patterns. After selecting one of the k-nearest neighbors for a given sample, SMOTE generates a new synthetic sample by linear interpolation between the two:

$$\text{New Sample} = \text{Sample A} + \delta \times (\text{Sample B} - \text{Sample A}) \quad (1)$$

The (1) equation explains that,
• Sample A represents the minority class sample (arrhythmic beat).
• Sample B is one of its k-nearest neighbors. • δ is a random number between 0 and 1 that determines how far along the line between Sample A and Sample B the new sample will be placed.

This process creates a new, synthetic minority class sample by combining features of Sample A and Sample B. The synthetical samples to generate will be in between the chosen sample and its neighbor, thus providing variety without duplication.
Fig 1. illustrates the distribution of classes in the original, unbalanced dataset, providing a clear visualization of the significant disparity between different arrhythmia categories.

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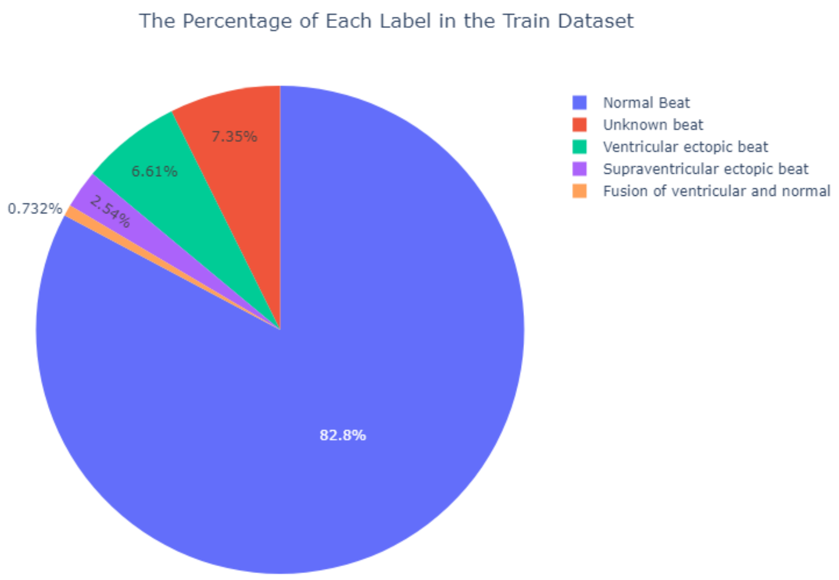

Fig. 1. Class distribution of unbalanced data

After addressing the class imbalance in the original dataset using the Synthetic Minority Over-sampling Technique (SMOTE), the balanced dataset is shown in Fig 2. The distribution of samples throughout the five categories is clearly shown in the pie charts.

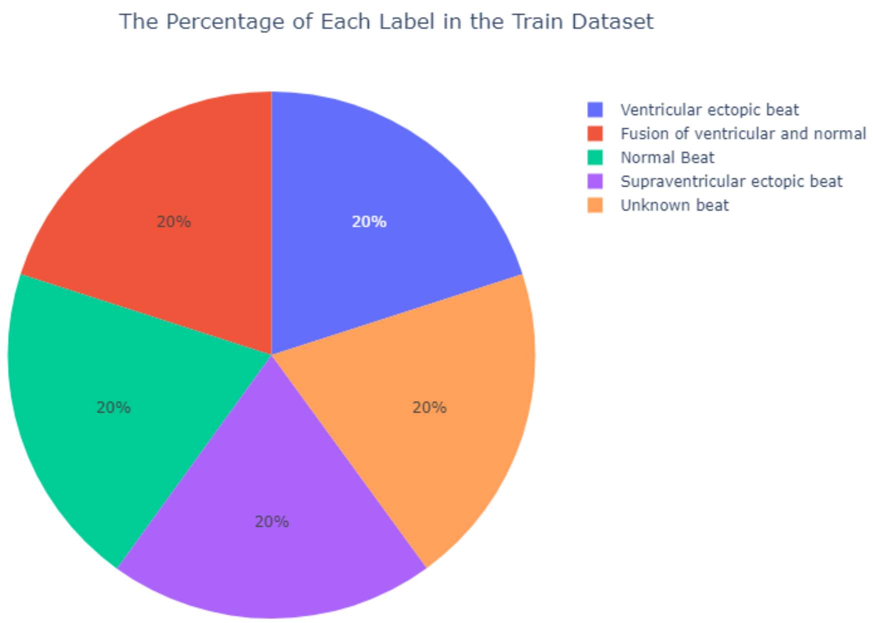

Fig. 2. Class distribution of balanced dataset

D. System Architecture

The approach that combines CNN and LSTM networks into a single framework is shown in Fig. 3. Time-series ECG data are used as the model's input. These signals are first processed through CNN layers to extract features, and then they are passed through LSTM layers to simulate the temporal dependencies. The architecture is broken down in detail below.

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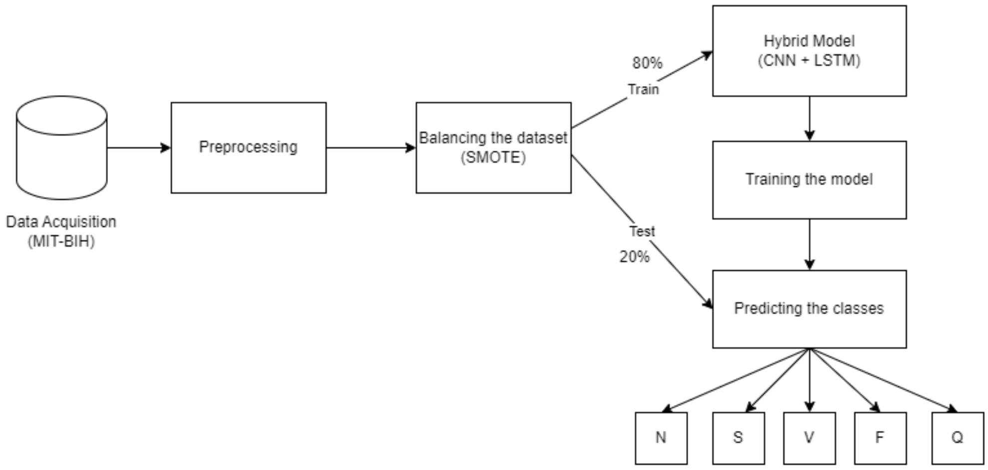

Fig. 3. Architecture

Data Acquisition: ECG signals comes from MIT-BIH Arrhythmia Database which is one of the most famous databases in the biomedical signal processing filed. It consists of different types of heartbeat which is used for training and testing of developed model. The input data is the raw ECG signals in form of one dimensional array, the size of which represents the number of samples taken over timeThis dataset provides a foundation for detecting arrhythmias using deep learning models.
Preprocessing: In the preprocessing stage, raw ECG signals were prepared for model training by converting the data to the int64 type to ensure compatibility with the neural network architecture. This step was crucial to standardize the input data and ensure consistency in the format fed into the model. Proper preprocessing enhances the quality of the data and improves the model's ability to generalize during training.
Balancing the Dataset: The MIT-BIH dataset is known to have had some class imbalance initially, some types of arrhythmias were not appropriately represented. To overcome this, the SMOTE technique was practiced; more specifically, synthetic samples for minority classes were produced through interpolation. The effect of balancing the data was that the model was trained in such a way that it did not overlearn from the biggest class of data, while it was also useful in making better predictions when it came to cases of minor classes such as arrhythmias.
Hybrid Model Architecture: The proposed hybrid model uses a combination of CNN and LSTM layers. The CNN layers apply 1D convolutions to extract spatial features from the ECG waveform, such as P, QRS, and T waves. These feature maps are then passed to the LSTM layers, which capture temporal relationships in the data. The LSTM handles both short-term and long-term dependencies, enabling the model to distinguish between arrhythmias with similar spatial features but different temporal patterns.
Training the Model: The CNN-LSTM model was trained on labeled ECG data using several optimization techniques. Early Stopping prevented overfitting by halting training when validation accuracy plateaued. Model Checkpoint saved the best-performing model, while Reduce LROn Plateau adjusted the learning rate when the validation performance stopped improving. These methods ensured that the final model was well-optimized, leading to high accuracy and generalization.
Predicting the Classes: When all the needed features are extracted by LSTM layers, fully connected dense layers at the final of the model complete the classification task. Each dense layer learn features and summarise, and the final layer, after a non-linear transformation with a softmax activation function, classify the input into one of the arrhythmia forms. The model then classifies ECG signal into five categories which are N, S, V, F, Q respectively offering a full classification.

IV.EXPERIMENT AND RESULT

This demonstrates how well the SMOTE approach works to mitigate class imbalance problems, which are a frequent occurrence in medical datasets. The other models showed good performance on majority classes, but they struggled with minority class detection, which is critical in clinical settings where accurate identification of rare but dangerous arrhythmias is crucial for patient outcomes. The improvements achieved through our approach are further evidenced by a higher overall accuracy, as well as improved sensitivity and specificity when compared to the algorithms in the literature.

The comparison of the proposed hybrid model with other algorithms before balancing the large dataset is shown in Table 1. Substantial works and papers showed high levels of identification and classification of arrhythmias of using number of algorithms like conventional artificial intelligence and modernistic deep learning algorithms. However, these studies were often undertaken on the data with a strong imbalance where the number of samples for specific types of arrhythmias especially the minority classes was significantly fewer than those for the majority types. On the other hand, the suggested hybrid model, which combines CNN for feature extraction and LSTM for temporal analysis, achieved an impressive accuracy rate of almost 98% on both the training and test datasets even before the dataset was balanced. This high accuracy highlights the robustness of the hybrid model in handling complex time-series ECG data, even in the presence of imbalanced class distributions. The ability to perform well on imbalanced data sets the proposed model apart from other algorithms, showcasing its potential for real-world applications where rare arrhythmia events are often critical to diagnose. Although further improvement can be achieved by applying data balancing techniques, the hybrid model's performance indicates its effectiveness and reliability in arrhythmia classification, making it a promising tool for enhancing cardiovascular diagnosis and care.

Table -1 Reported accuracy of models with imbalanced datasets

SI.NO	Algorithm	Accuracy
1	**CNN + PSO**	**97%**
2	**Random Forest**	**95%**
3	**Neural Network**	**98.2%**
4	**KNN**	**97.70%**
5	**Multi Lead Branch Fusion Network**	**85%**
6	**CNN + LSTM**	**98.3%**

While the initial accuracy of the model seemed promising, with values surpassing those achieved by other algorithms, a deeper analysis of the training process revealed significant over fitting. This was evident from the divergence in the loss curves between training and validation data, as depicted in Fig 4. As a result, it became clear that a more robust strategy was necessary to address this imbalance and mitigate over fitting, ensuring better model performance across all classes.

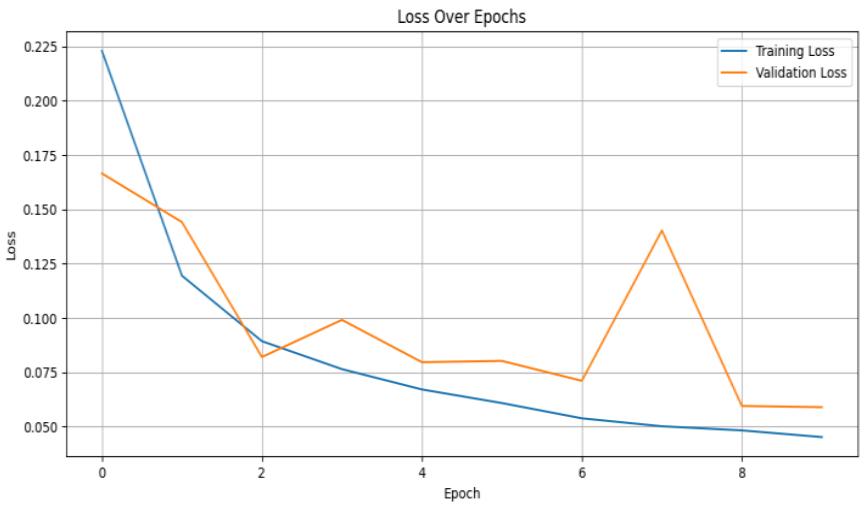

Fig. 4. Examining the loss curves with imbalance data

To address this, the Synthetic Minority Over-sampling Technique (SMOTE) is used. With the balanced dataset, the model was retrained using the same hybrid CNN-LSTM architecture, and the results showed a remarkable improvement in the model's ability to generalize across all classes. The model's performance after balancing is seen in Figs. 5 and 6, where the model accuracy and loss graphs have smoother patterns. While the accuracy showed steady progress over the epochs, the loss values steadily declined, indicating that the model was learning more efficiently from the balanced dataset.

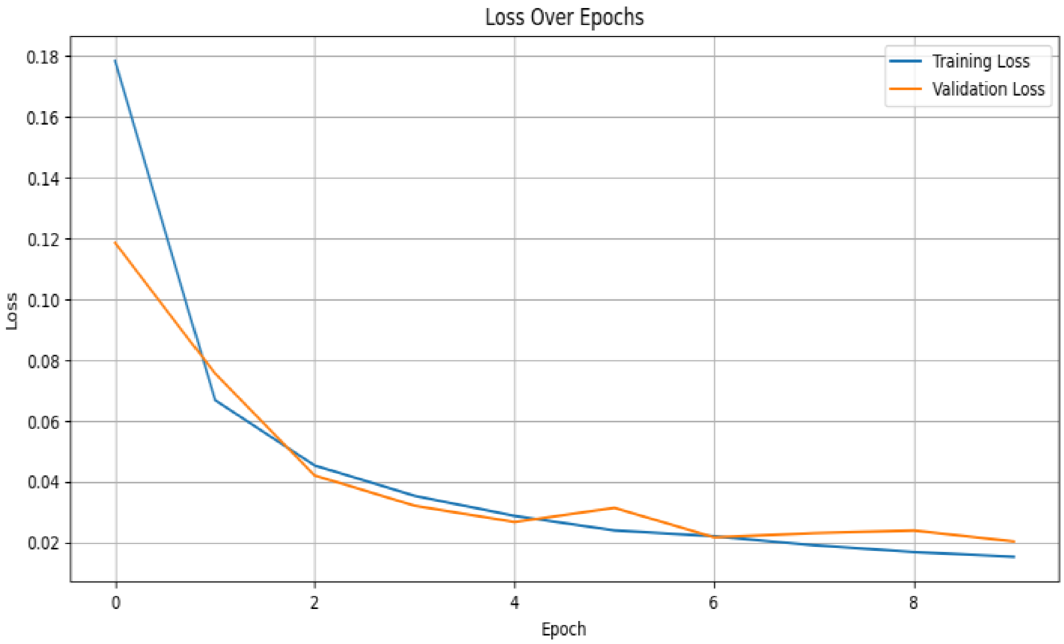

Fig. 5. Graph of model loss with balanced data

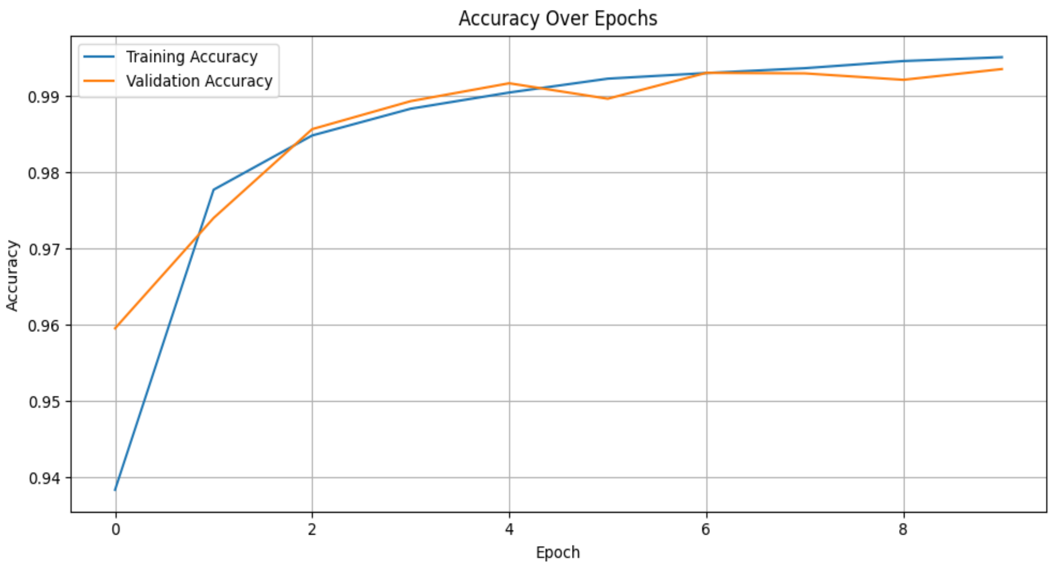

Fig. 6. Graph of model accuracy with balanced data

Following the SMOTE technique, the model achieved a significantly improved performance. The model's ultimate accuracy on training data was 98.06%, while its validation accuracy was a remarkable 99.36%. With no indications of over fitting, the model was now able to generalize well, as evidenced by the tight alignment between training and validation accuracy. By allowing the model to learn from all arrhythmia classes equally, the balanced dataset made sure that minority classes were adequately represented throughout the training process.

In Fig 7, a bar chart illustrates the comparative performance of various balanced methodologies for arrhythmia classification, highlighting the effectiveness of our proposed hybrid model. It emphasizes the critical role of balancing techniques in enhancing arrhythmia classification accuracy. Each algorithm displayed in the chart represents a different balanced methodology, allowing for a analysis of their effectiveness in addressing data imbalance issues inherent in arrhythmia detection. By comparing our results with those of other models, we provide insights into how various approaches manage classification challenges and improve diagnostic capabilities. This visual representation not only highlights the superior performance metrics achieved by our methodology but also reinforces the notion that balancing data significantly contributes to the robustness and reliability of arrhythmia detection systems.

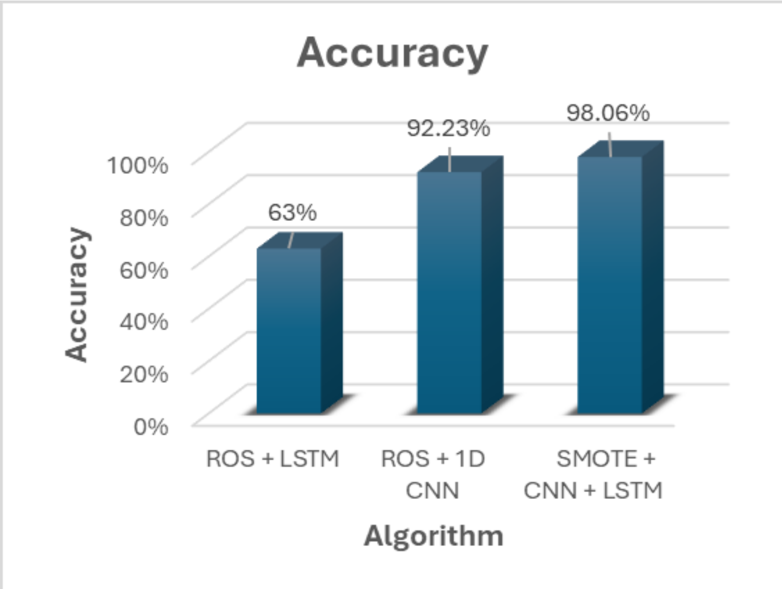

Fig. 7. Comparative Analysis of Classification Accuracy Across Balanced Algorithms

Ultimately, this visual representation serves to reinforce the significance of our contributions to the field, demonstrating that effective handling of data imbalance can lead to substantial gains in classification performance across diverse algorithms.

V. CONCLUSION

This study has brought to light substantial progress in the field of arrhythmia classification by integrating innovative methods and balanced data techniques. Through the exploration and comparative analysis of various models, it has been demonstrated that balanced approaches, particularly those addressing the challenges of imbalanced datasets, significantly enhance the performance of classification systems. This improvement is crucial for medical applications, where data imbalance is a common issue, often leading to inaccurate predictions. In addition to increasing accuracy, the hybrid model that combines Convolutional Neural Networks (CNN) and Long Short-Term Memory (LSTM) networks has also been shown to improve the system's interpretability and generalization capabilities across a range of arrhythmia types. These findings highlight the significance of continuous attempts to improve classification methods since they are critical to the prompt and precise identification of arrhythmias, which is crucial for patient treatment. The study has cleared the path for the development of more robust and dependable arrhythmia detection systems that may be used in real-time, clinical settings by utilizing these cutting-edge frameworks and methods. Looking forward, there is significant potential for enhancing the proposed model through further optimization and the incorporation of cutting-edge deep learning techniques. Expanding the dataset to include more diverse patient profiles will enable better generalization, ensuring the model's robustness across a wider range of arrhythmia cases. As wearable devices and real-time health monitoring technologies continue to gain attention, the need for highly efficient and responsive arrhythmia classification systems will grow. Further research could focus on integrating advanced deep learning techniques, such as Transformer models, and exploring ensemble methods to improve detection accuracy and processing speed. Moreover, emerging technologies like edge computing and federated learning offer promising opportunities to decentralize the processing of health data, enhancing privacy and security while enabling real-time analysis directly on wearable devices. This could significantly improve the practicality and scalability of arrhythmia detection systems in everyday health monitoring. By embracing these advancements, future models can achieve greater accuracy, real-time capability, and wider adoption in both clinical and non-clinical settings, ultimately contributing to more effective cardiovascular health management and preventive care.

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