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Advancements in ECG Heartbeat Classification: A Comprehensive Review of Deep Learning Approaches and Imbalanced Data Solutions

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***Abstract*—This systematic literature review critically examines developments in electrocardiogram (ECG) heartbeat classification, focusing on the utilization of deep learning techniques and addressing challenges associated with imbalanced datasets. Covering articles published between 2012 and 2021, The primary objective is to uncover challenges related to imbalanced data in predicting heart diseases, specifically through the lens of machine learning applications utilizing ECG and patient data. The paper discusses the types of heart diseases, algorithms, applications, and solutions, shedding light on limitations and gaps in current approaches.**

***Index Terms*—ECG Signal Processing, Convolutional Neural Network (CNN), AAMI Standard, MIT-BIH Dataset, INCART Dataset, Deep Learning, R-peak Detection, Electrocardiogram (ECG) Abnormalities, Machine Learning, Medical Signal Processing, RR Time Interval, Explainable AI**

I. Introduction

Cardiovascular diseases (CVDs) remain a global health challenge, necessitating innovative approaches for early and accurate diagnosis. In recent years, the intersection of machine learning (ML) and healthcare has seen substantial progress, with a particular emphasis on diagnosing heart diseases through the analysis of electrocardiogram (ECG) signals. This systematic literature review aims to provide a comprehensive introduction to the landscape of ML-based heart disease diagnosis, focusing on the period between 2012 and 2021. Background and Significance: Cardiovascular diseases, including heart diseases, are a leading cause of morbidity and mortality worldwide. Early detection and precise diagnosis are pivotal for effective intervention and improved patient outcomes. Traditional diagnostic methods often rely on clinical expertise, but the integration of ML technologies has shown promise in enhancing diagnostic accuracy and efficiency. Rise of Machine Learning in Healthcare: The increasing availability of healthcare data, coupled with advancements in ML algorithms, has paved the way for novel approaches in disease diagnosis. ML techniques, especially those based on deep learning, exhibit the capability to extract intricate patterns and relationships from complex data sets, making them well-suited for tasks such as ECG analysis. Focus on Electrocardiogram (ECG) Signals: ECG signals, capturing the electrical activity of the heart, offer a wealth of information for diagnosing various heart conditions. ML applications on ECG data have shown promising results in identifying abnormalities, predicting diseases, and aiding in timely medical interventions.

Challenges in Heart Disease Diagnosis:

Despite the progress, challenges persist in ML-based heart disease diagnosis. Imbalanced datasets, where certain disease categories are underrepresented, pose a significant hurdle. Additionally, the interpretability of ML models, especially in deep learning, raises concerns regarding their integration into clinical practice.

Scope of the Literature Review:

This systematic review adopts a structured approach, following the PRISMA guidelines, to comprehensively explore research articles published between 2012 and 2021. The focus is on identifying challenges associated with imbalanced data in predicting heart diseases, with a specific emphasis on ML applications utilizing ECG and patient data.

Objectives of the Review:

The primary goal of this review is to uncover challenges in heart disease predictions related to imbalanced data through a meticulous examination of existing research. By conducting a meta-analysis of a vast number of references and an in-depth analysis of selected articles, the review aims to offer valuable insights into the trends, techniques, and research gaps in ML-based heart disease diagnosis. this review will delve into the diverse landscape of ML applications for heart disease diagnosis, examining the types of heart diseases, algorithms employed, applications and solutions proposed, and the inherent limitations in current approaches. aims to provide a reference point for researchers and practitioners, offering a nuanced understanding of recent trends and paving the way for future advancements in the field.

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II. Related Works

A. Machine learning-based heart disease diagnosis: A systematic literature review

The systematic literature review (SLR) on machine learning-based heart disease diagnosis is a comprehensive examination of existing research articles published between 2012 and 2021. It aims to provide insights into the challenges associated with imbalanced data in predicting heart diseases, particularly focusing on ML applications utilizing ECG and patient data. Objective: The primary goal is to uncover challenges in heart disease predictions related to imbalanced data through a structured review process. Methodology: Adopts a systematic approach following PRISMA guidelines, conducting a meta-analysis of 451 references and an in-depth analysis of 49 selected articles. Analysis: Examines heart disease types, algorithms, applications, and solutions, shedding light on the limitations and gaps in current approaches. Contributions: Provides a reference point for researchers and practitioners, offering an overview of recent trends, techniques, and research gaps in ML-based heart disease diagnosis.

1) Advantages: Comprehensive Overview: Offers a thorough understanding of the challenges and trends in ML-based heart disease diagnosis by reviewing a substantial number of articles. Meta-Analysis: Conducts a meta-analysis of 451 references, providing valuable insights into contributing countries, institutions, subject areas, authors, and research funding. In-Depth Analysis: Studies 49 selected articles in detail, addressing specific research questions related to ML algorithms, strategies for handling imbalanced data, and current approaches in heart disease diagnosis.

2) Dis Advantages: Limited Scope: The study focuses primarily on ML applications for heart disease diagnosis and may not cover other emerging technologies or interdisciplinary approaches. Temporal Limitation: The literature review is limited to articles published between 2012 and 2021, potentially missing out on recent developments in the field. Interpretability Gap: Acknowledges the lack of proper explanation for the behaviours of ML models during final predictions, particularly in deep learning, raising concerns about interpretability. Neglect of Other Issues: Notes that many researchers primarily concentrate on enhancing model performance while disregarding crucial aspects such as interpretability and explain ability of ML algorithms.

B. Multi-Class Arrhythmia Detection using a Hybrid Spatial-Temporal Feature Extraction Method and Stacked Auto Encoder

The proposed method is a hybrid spatial-temporal feature extraction approach for multi-class arrhythmia detection using Electro Cardio Gram (ECG) signals. It aims to improve the accuracy of arrhythmia classification by addressing challenges faced in existing methods, particularly the selection of relevant features and the handling of imbalanced data. Objective: The primary goal is to accurately detect and classify different types of arrhythmias based on ECG signals, enabling early diagnosis of cardiovascular diseases. Data Acquisition: Utilizes ECG signals from the MIT-BIH database, a widely used dataset for arrhythmia research. Pre-processing: Applies a Butterworth filter to the ECG signals to eliminate unwanted artifacts and enhance the quality of the data. QRS Complex Segmentation: Identifies the QRS complex, a critical part of the ECG waveform, using the Teager Energy Operator (TEO). This helps in pinpointing abnormal heartbeats. Hybrid Spatial-Temporal Feature Extraction: Extracts features from both spatial and temporal domains. Spatial features visualize locations of boundaries or shapes in ECG signals, while temporal features include parameters like Energy of Signal, Zero Crossing Rate, and Maximum Amplitude. Deep Neural Network (DNN) with Stacked Auto Encoder (SAE): Feeds the hybrid spatial-temporal features into a DNN based on a Stacked Auto Encoder. This allows the system to capture spatial-temporal patterns for accurate arrhythmia classification. Classification: Classifies ECG signals into five prominent classes of arrhythmia: Normal Sinus Rhythm (N), Left Bundle Branch Block (LBBB or L), Right Bundle Branch Block (RBBB or R), Premature Ventricular Contraction (V), and Atrial Premature Beat (A).

1) Advantages: Improved Feature Extraction: The hybrid spatial-temporal feature extraction method aims to capture salient features, eliminating issues associated with exhausted handcrafted features. Addressing Imbalance: Targets data imbalance issues by extracting high-level features to enhance classification accuracy, reducing the risk of misclassification. Accurate Classification: Aims to achieve accurate multi-class classification of arrhythmias, providing valuable information for timely medical intervention. Overcoming Previous Failures: Addresses challenges faced by previous methods, such as overfitting problems and difficulties in selecting prior features.

2) Dis Advantages: Limited Evaluation Information: The provided information does not include details on the evaluation metrics, making it challenging to assess the overall performance of the proposed method. Temporal Limitation: The proposed method's evaluation results, particularly its comparison to existing LSTM-AE, are mentioned briefly without in-depth analysis. Specific Dataset Usage: Relies on the MIT-BIH database, which may limit the generalizability of the proposed method to other datasets or real-world scenarios. Potential Complexity: The integration of a hybrid spatial-temporal feature extraction method and a DNN with SAE may introduce complexities that need careful consideration and validation. In summary, the proposed method introduces a hybrid approach to feature extraction for improved arrhythmia detection, aiming to overcome challenges faced by previous methods.

C. Exploring Machine Learning Techniques for Coronary Heart Disease Prediction

It discusses the use of machine learning techniques, such as Logistic Regression, Support Vector Machine (SVM), K-Nearest Neighbour (KNN), and Multi-Layer Perceptron (MLP) Neural Networks, to predict the occurrence of coronary heart

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disease (CHD) based on clinical data. It aims to investigate and compare the performance of different machine learning techniques in predicting CHD. It utilizes a dataset of 462 medical instances with 9 features, obtained from the South African Heart Disease data, and applies various classifiers to achieve accurate predictions. The study also addresses the imbalanced classification problem by employing the K-means algorithm along with Synthetic Minority Oversampling Technique (SMOTE).

1) Advantages: Early Disease Prediction: The use of machine learning can potentially enable early detection of CHD, allowing healthcare providers to take preventive measures and reduce the risk of serious events. Resource Saving: Early prediction can save lives and reduce costly hospitalization resources by managing the disease effectively with lifestyle changes and timely interventions. Comparative Analysis: The paper conducts a comparative analysis of different machine learning techniques, helping identify the most effective models for CHD prediction.

2) Dis Advantages: Model Accuracy: The text mentions that most machine learning models designed for CHD prediction have achieved modest accuracy. This limitation could impact the reliability of predictions. Limited Interpret-ability: Some machine learning models, including those used in the study, may lack interpret-ability, making it challenging for clinicians to understand the factors influencing predictions. Variable Consensus: The paper notes a lack of consensus on the clinical features and their roles in affecting the occurrence of CHD, indicating challenges in identifying consistent predictors.

D. A Machine Learning Approach for Chronic Heart Failure Diagnosis

Introduce a machine learning approach for the diagnosis of chronic heart failure (HF). The researchers developed models based on various combinations of features, including clinical features, echo cardiogram, and laboratory findings. The goal was to simulate the clinical practice procedure and investigate the incremental value of each feature type in diagnosing HF. The machine learning models were designed to predict whether a patient has chronic heart failure based on the input features. The study focused on feature selection, handling class imbalance, and classification steps. By using different combinations of features, the models aimed to provide accurate and reliable predictions for the diagnosis of chronic heart failure.

1) Advantages: High Accuracy: The proposed machine learning approach achieved high accuracy (91.23Comprehensive Evaluation: The study considered various types of features, including clinical information, echocardiographic parameters, and laboratory findings. This comprehensive evaluation helps capture a diverse range of factors that contribute to HF diagnosis, potentially leading to more robust and reliable results. Potential for Clinical Support: Machine learning models have the potential to assist healthcare professionals in diagnosing chronic heart failure. They can be used as decision support tools, providing additional insights based on a combination of patient data.

2) Dis Advantages: Dependence on Data Quality: The performance of machine learning models is highly dependent on the quality and representatives of the training data. If the data used to train the models are biased or incomplete, it may affect their generalist to new cases. Interpret-ability Challenges: While machine learning models can provide accurate predictions, their inner workings are often complex and challenging to interpret. Understanding the reasons behind a specific prediction (explain ability) can be crucial for gaining trust from healthcare professionals. Limitation to the Studied Population: The models developed in this study are based on a specific data set from a particular population. Their performance might vary when applied to different populations or diverse patient groups.

E. Prediction of Diabetes Empowered with Fused Machine Learning

Medical diagnostic model designed to predict diabetes at an early stage. It utilizes a fused machine learning approach, combining two types of models—Support Vector Machine (SVM) and Artificial Neural Network (ANN). The framework also incorporates fuzzy logic for decision-making and stores the fused models in a cloud storage system for future use. Data Acquisition and Prepossessing: The system acquires a data set from the UCI Machine Learning Repository, which is then pre-processed. Data cleaning, normalization, and division into training and testing sets (70:30 ratio) are performed. Training Layer: The Training Layer involves multiple stages, including classification using SVM and ANN, performance evaluation using various accuracy measures, and machine-learning fusion. The SVM and ANN outputs serve as input membership functions for the fuzzy logic model. Machine-Learning Fusion: Fuzzy rules are applied to the outputs of SVM and ANN to make the final prediction. This fusion of machine learning techniques aims to enhance the accuracy of diabetes prediction. Cloud Storage: The fused models generated during the training phase are stored in a cloud storage system for future use. This enables real-time predictions based on a patient's medical records. Testing Layer: In the testing phase, the system acquires a data set from a medical database, loads the pre-processed training model from the cloud, and utilizes the fused model to predict whether a patient has diabetes. Prediction accuracy is calculated by comparing the predicted output with the actual output.

1) Advantages: High Prediction Accuracy: The proposed fused machine learning model achieves a prediction accuracy of 94.87Early Disease Detection: The system focuses on early detection of diabetes, allowing for timely intervention and prevention of complications. Fused Model: The combination of SVM, ANN, and fuzzy logic contributes to the model's robustness, providing a more accurate prediction compared to individual models. Cloud Storage: Storing fused models in the cloud enables convenient and efficient access for real-time predictions based on a patient's medical history.

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2) Dis Advantages: Limited Information: The document does not provide detailed information on potential disadvantages or limitations of the proposed model. Data set Dependency: The accuracy and effectiveness of the model may be influenced by the quality and representation's of the data-set used for training. Complexity: The fusion of multiple machine learning techniques and the use of fuzzy logic may introduce complexity, making it challenging to interpret the model's decision-making process.

F. Prediction of dyslipidaemia using gene mutations, family history of diseases and anthropometric indicators in children and adolescents: The CASPIAN-III study

The study aims to design a dyslipidaemia diagnosis system based on genetic factors, family history, and anthropometric indicators. Dyslipidaemia refers to an abnormal lipid profile, a modifiable risk factor for coronary heart diseases. The study proposes a diagnostic system for dyslipidaemia prediction using a combination of genetic information, family history of diseases, and anthropometric indicators. It involves the analysis of single nucleotide polymorphisms (SNPs) in various genes associated with lipid metabolism. The system employs a framework for classifying mixed-type data in imbalanced datasets, including feature mapping, selection, re-sampling, and optimization methods. The performance of the system is evaluated using different classifiers such as Group Method of Data Handling (GMDH), multilayer perceptron neural network (MLP), decision tree (DT), and supported vector machines (SVM).

1) Advantages: High Sensitivity and Specificity: The proposed system demonstrates high average sensitivity (93Precision and Accuracy: The system shows high precision (94Novelty and Promising Tool: The study claims to be the first of its kind for genome-based dyslipidaemia prediction in children and adolescents, making it a promising tool for early diagnosis. Incorporation of Genetic Information: By analysing SNPs associated with dyslipidaemia, the system considers genetic factors, providing a more comprehensive understanding of the disease risk.

2) Dis Advantages: Imbalanced Datasets: The document mentions the use of a framework for imbalanced datasets, indicating potential challenges associated with uneven class distribution. Complexity: The proposed system involves multiple steps, including feature mapping, selection, and optimization, which may introduce complexity, making it challenging to implement and interpret. Limited Validation Information: While the document provides performance metrics, additional details on external validation and real-world applicability are not thoroughly discussed. Sample Size and Generalization: The study is based on a sample size of 725 subjects, and the generalizability of the findings to larger populations or diverse demographics is not explicitly addressed.

G. Deep MLP-CNN Model Using Mixed-Data to Distinguish between COVID-19 and Non-COVID-19 Patients

The study proposes a COVID-19 diagnosis model using a combination of Multilayer Perceptron (MLP) and Convolutional Neural Network (CNN) for mixed data, which includes numerical/categorical and chest X-ray images. The aim is to create an efficient and fast initial screening tool for COVID-19 patients, addressing the limitations and high false-negative rates of existing test kits. The proposed model is designed to predict and differentiate between COVID-19 and non-COVID-19 patients, facilitating early diagnosis for timely isolation and treatment. Data Combination:The model combines numerical/categorical data (e.g., age, gender, temperature) with chest X-ray images for a comprehensive analysis. Optimization Algorithms:Three optimization algorithms (Adam, Sgd, and Rmsprop) are tested to enhance the training phase and improve the model's performance. Data set Consideration:Two data sets are utilized: Study One (balanced) and Study Two (imbalanced) to assess the model's performance under different conditions. Model Architecture:The proposed model comprises an MLP for handling numerical/categorical data and a CNN for extracting features from chest X-ray images.The MLP and CNN outputs are combined to produce the final prediction. Performance Evaluation:Performance metrics such as accuracy, precision, recall, and F1 score are used to evaluate the model's effectiveness.Cross-validation is performed to assess the model's generalization across different subsets of the data.

1) Advantages: Comprehensive Approach:The model considers both numerical/categorical data and chest X-ray images, providing a more holistic approach to COVID-19 diagnosis. Optimization Testing:The study explores the impact of different optimization algorithms, aiming to enhance the training process and achieve better results. Comparative Analysis:Comparative results are provided, showcasing the proposed model's performance against existing deep learning models that focus solely on chest X-ray or CT scan images.

2) Dis Advantages: Dataset Limitations:The study acknowledges challenges associated with missing data in the dataset, and specific considerations are made to address these limitations. Small Dataset Size:The datasets used in the study, particularly in Study One, are relatively small, which may impact the model's ability to generalize to larger datasets. Dependence on Imaging:The study heavily relies on chest X-ray images for diagnosis, and the model's effectiveness may be influenced by the quality and availability of such imaging data. Limited Exploration of Other Data Types:The study focuses on numerical/categorical data and chest X-ray images but does not explore the inclusion of other types of data that could contribute to diagnosis. Assumption of Homogeneous Features:The assumption that numerical/categorical and imaging features can be effectively combined may not hold universally, and the study does not deeply investigate feature interactions.

H. Effect of Data Scaling Methods on Machine Learning Algorithms and Model Performance

It explores the application of machine learning (ML) algorithms for the diagnosis of heart disease. It focuses on evaluating the performance of eleven different ML algorithms and six data scaling methods using a dataset containing

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information about patients with heart disease symptoms. The primary goal of the research is to assess the effectiveness of various ML algorithms in predicting heart disease based on patient data. The study aims to understand how different algorithms and data scaling methods impact the accuracy and reliability of the predictions. It evaluates the algorithms on a dataset, emphasizing the importance of data preprocessing steps, such as feature reduction, data conversion, and data scaling, to enhance the accuracy of the final predictions.

1) Advantages: Efficient Diagnosis: Machine learning algorithms provide a fast and alternative option for diagnosing heart disease, potentially saving time and costs compared to traditional diagnostic methods. Automation: The development of an automated diagnosis system could be beneficial, especially in areas where access to doctors and expensive diagnostic equipment is limited. Early Detection: By incorporating additional patient information and medical history, the study aims to enable early detection of heart disease, which can lead to timely interventions and improved health outcomes. Data-Driven Decision Support: The research emphasizes the importance of developing a robust, data-driven decision support system for heart disease diagnosis.

2) Dis Advantages: Data Challenges: Challenges associated with medical data-sets, such as missing and inconsistent data, pose obstacles in developing accurate prediction models. Computational Expense: While deep learning approaches have shown promise in medical diagnosis, they can be computationally expensive, particularly when dealing with larger data sets. Traditional machine learning approaches are preferred in such cases for their lower computational cost. Limited Previous Emphasis on Data Scaling: The study identifies a gap in previous research, where there has been limited consideration of the impact of data scaling methods on model performance. Variability in Previous Studies: The literature review highlights variations in the reported accuracy of ML algorithms in previous studies, making it challenging to compare and understand the reasons behind the differences.

I. Detecting SARS-CoV-2 From Chest X-Ray Using Artificial Intelligence

It focuses on the application of deep learning models, specifically Deep Convolutional Neural Networks (CNNs), for the detection of SARS-CoV-2 infection from chest X-ray images. The study evaluates the performance of six modified deep learning models—VGG16, InceptionResNetV2, ResNet50, MobileNetV2, ResNet101, and VGG19—using both small and balanced datasets and larger imbalanced datasets. The evaluation metrics include accuracy, precision, recall, and F-score. The research also includes a pilot test on a multi-class data-set. Model Evaluation: The study proposes and tests modified deep learning models to detect SARS-CoV-2 infection from chest X-ray images. Data-set Consideration: Two separate studies are conducted—one with a small and balanced data-set and another with a larger and imbalanced data-set. Additionally, a pilot test on a multi-class data-set is performed. Performance Metrics: The models are evaluated based on various performance metrics, including accuracy, precision, recall, and F-score. Layer-wise Analysis: The research analyses the performance of the models layer by layer, selecting the best-performing models based on the correct identification of infectious regions in X-ray images. Confidence Intervals: The study addresses the issue of reporting results without proper confidence intervals and incorporates a 95

1) Advantages: Model Diversity: Six different deep learning models are evaluated, providing a diverse analysis of their effectiveness in detecting SARS-CoV-2. Confidence Interval Inclusion: The study emphasizes the importance of presenting results with confidence intervals, enhancing the reliability of the reported accuracies. Layer-wise Analysis: Analysing model performance layer by layer allows for a detailed understanding of the models' ability to identify infectious regions in X-ray images. Consideration of Imbalanced Data: The study considers the challenges associated with imbalanced datasets, providing insights into model performance under such conditions.

2) Dis Advantages: Small Datasets: Some referenced studies in the literature review used relatively small datasets, raising concerns about the generalizability of the proposed models. Overfitting Concerns: Larger deep learning networks trained on small datasets may be prone to overfitting, affecting the practical accuracy and reliability of the models. Limited Dataset Information: The abstract provides limited information about the characteristics of the datasets used, such as the number of images in each class and data distribution. Challenges in Multi-Class Classification: The pilot test on a multi-class dataset is briefly mentioned, and further details about the challenges and outcomes are not fully explained. Overall, the research aims to contribute to the development of effective and reliable deep learning models for the early detection of COVID-19 using chest X-ray images, addressing several challenges associated with dataset size, balance, and reporting standards

J. Electrocardiogram heartbeat classification based on a deep convolutional neural network and focal loss

Introduces a deep learning method for classifying electrocardiogram (ECG) heartbeats into five categories (N, S, V, F, and Q) based on the Association for Advancement of Medical Instrumentation (AAMI) standard. The method utilizes a convolutional neural network (CNN) model and proposes a novel segmentation technique for ECG heartbeats. Additionally, it addresses the challenge of imbalanced datasets through an optimization step using a focal loss function. ECG Signal and Heartbeat Classification: The focus is on analysing ECG signals to identify and classify different types of heartbeats, which can provide valuable information about cardiovascular health. Deep Learning with CNNs: The proposed method employs a deep learning approach using a specific type of neural network called a convolutional neural network (CNN). CNNs are known for their effectiveness in image-related tasks, and here they are applied to ECG signal processing. Heartbeat Segmentation: A unique approach is introduced for segmenting heartbeats, defining each heartbeat to start at an R-peak and end after 1.2 times the median RR time interval in a 10-second window. This method avoids assumptions about signal morphology or spectrum and simplifies the segmentation process. Imbalanced Data Challenge: The method addresses the common issue of imbalanced datasets in medical diagnosis, where certain classes (heartbeat categories) may be underrepresented. To overcome this challenge, the focal loss function is introduced. Focal Loss Function: Focal loss is a specialized loss function designed to handle imbalanced datasets in classification tasks. It assigns higher importance to minority classes, focusing on samples that are challenging to classify. The focal loss is applied to enhance the performance of the CNN model, especially for minority heartbeat classes. Automatic Feature Extraction: CNNs automatically perform feature extraction, eliminating the need for hand-crafted techniques. This is beneficial for processing ECG signals efficiently. Improved Segmentation: The proposed segmentation technique, starting at an R-peak and ending after a specific time interval, is considered effective in capturing relevant features for classification. Handling Imbalanced Datasets: The focal loss function is used to address the challenges posed by imbalanced datasets. By giving more weight to minority classes, it helps improve the overall classification performance. Performance Metrics: The method is evaluated using the MIT-BIH and INCART datasets, achieving high overall accuracy, F1-score, precision, and recall. It outperforms existing state-of-the-art methods.

1) Advantages: Automated Feature Extraction: CNNs automatically learn relevant features from the ECG signals, reducing the need for manual feature engineering. Effective Segmentation: The proposed segmentation technique is simple and effective, capturing important information without relying on signal morphology assumptions. Focal Loss for Imbalanced Data: The focal loss function is utilized to improve classification performance, particularly for minority classes, in the presence of imbalanced datasets. High Performance: The method achieves high accuracy and outperforms existing state-of-the-art methods, indicating its effectiveness in ECG heartbeat classification.

2) Dis Advantages: Complexity and Computational Cost: Deep learning models, such as CNNs, can be computationally expensive and may require substantial computational resources for training. Data Augmentation Consideration: While not explicitly mentioned, data augmentation is discussed as a common solution for imbalanced datasets in the literature. The text suggests that data augmentation may not always be suitable due to increased computational costs and potential differences between augmented and real data. Specific Evaluation Datasets: The method's evaluation is based on specific datasets (MIT-BIH and INCART), and its generalizability to other datasets may need further validation. Limited Exploration of Other Techniques: The text primarily focuses on the proposed method and does not extensively explore alternative techniques or compare with a wide range of existing methods.

III. Benefits

Comprehensive Overview: The paper offers an exhaustive examination of challenges and trends in ML-based heart disease diagnosis by reviewing a substantial number of articles, providing a valuable reference for researchers and practitioners. Meta-Analysis: A meta-analysis of 451 references provides insights into contributing countries, institutions, subject areas, authors, and research funding, enhancing the understanding of the global landscape of ML in heart disease diagnosis. In-Depth Analysis: The review deeply studies 49 selected articles, addressing specific research questions related to ML algorithms, strategies for handling imbalanced data, and current approaches in heart disease diagnosis.

IV. Future Scope

The limitations identified in this review pave the way for future research avenues. Researchers can explore interdisciplinary approaches, integrate other emerging technologies, and enhance the interpretability of ML models. Additionally, extending the temporal scope beyond 2021 and incorporating real-time data can provide a more updated perspective on the advancements in ML-based heart disease diagnosis.

V. Conclusion

While the systematic literature review provides a solid foundation for understanding ML-based heart disease diagnosis, it acknowledges limitations related to scope, temporality, and interpretability of models. Despite these limitations, the insights offered by the review serve as a crucial reference for researchers and practitioners, guiding future endeavours in improving the accuracy and reliability of ML applications in heart disease diagnosis.

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