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ECG Heartbeat Classification Using Ensemble of Efficient Machine Learning Approaches

Sonam Sirohi
Department of Electronics and Communication Engineering
Greater Noida Institute of Technology (Enginnering Institute)
Gautam Budh Nagar, Greater Noida, India
sonamsirohi.2012@gmail.com

Diya Rastogi
Department of Electronics and Communication Engineering
Greater Noida Institute of Technology (Enginnering Institute)
Gautam Budh Nagar, Greater Noida, India

Ankit Jindal
Department of Electronics and Communication Engineering
Greater Noida Institute of Technology (Enginnering Institute)
Gautam Budh Nagar, Greater Noida, India

Vishwas Sharma
Department of Electronics and Communication Engineering
Greater Noida Institute of Technology (Enginnering Institute)
Gautam Budh Nagar, Greater Noida, India

Abstract— **Electrocardiogram, an established method for cardiac health analysis, has attracted significant research interest in accurate heartbeat classification. Despite numerous studies in this field, achieving high accuracy scores remains a challenge. This paper employs and fine-tunes well-known machine learning techniques, comparing them with additional cutting-edge techniques. The study utilizes highly imbalanced datasets, addressing this issue by adjusting the Artificial Neural Network (ANN) and Residual Network (ResNet) models loss value through class weight assignment. Two enriched ECG datasets are used: the PTB Diagnostic ECG dataset, which has two classes, and the MIT-BIH Arrhythmia dataset, which has five classes. For the MIT-BIH Arrhythmia dataset, the suggested methods attain accuracies of roughly 98% (ANN) and 95% (ResNet); for the PTB Diagnostic ECG dataset, they obtain accuracies of 97% (ANN) and 94% (ResNet). The results of this study outperform those of other cutting-edge approaches in both cases.**

Keywords—Convolutional Neural Networks, Machine Learning, SVM, RESNET, ANN.

Introduction

In India as well as throughout the world, cardiovascular disease (CVD) is one of the leading causes of death. Peripheral vascular disease (PVD), myocardial infarction, angina, and cerebrovascular accidents are the main types of CVD. CVD involves cardiac abnormalities, resulting in impaired heart function and reduced oxygen delivery to vital bodily organs. This oxygen deficiency affects the brain, lungs, internal organs, and the heart itself, leading to additional health complications. Risk factors such as tobacco use can disrupt the heart's natural electrical impulse generation, potentially triggering various CVD conditions and increasing symptoms like dizziness and palpitations. Severe cases may involve irregular blood flow and heightened risk of heart attacks. According to a recent study, CVDs were responsible for 17.1 million deaths in 2004, or 29% of all deaths worldwide. An estimated 7.2 million of these deaths were ascribed to coronary heart disease, and 5.7 million to stroke [1]. Men and women are nearly equally affected by CVD, which accounts for 82% of deaths in low- and middle-income countries, placing a disproportionate burden on developing nations. Projections indicate that by 2030, CVD-related deaths may reach 23.6 million, predominantly due to stroke and heart disease, which are anticipated to continue to be the main causes of death. The Eastern Mediterranean Region is anticipated to experience the highest percentage of CVD-related deaths. Early symptom recognition, which allows for prompt and ideal clinical intervention, is now the most successful method for lowering death rates from complex diseases [2]. Medical treatment has been enhanced by computerized processes.

An electrocardiogram (ECG) serves as a diagnostic instrument for assessing and evaluating cardiac activity. The ECG device detects electrical impulses generated by the heart. These ECG readings are essential for detecting a number of heart anomalies. The ECG equipment monitors electrical activity and generates signals on paper, which are subsequently examined by a specialist to assess the health of the heart. Any change from the typical electrical signal pattern is seen as quite concerning. Several factors, including family history, obesity, diabetes, and high cholesterol, are potential contributors to most heart diseases [1]. Timely diagnosis and treatment have become increasingly vital for the patients. Precise identification of irregularities in heart rate indicators can assist physicians in identifying cardiac conditions. Accurate classification provides sufficient details on anomalous data, enabling physicians to prescribe appropriate treatment for patients. This underscores the significance of classifying arrhythmic heartbeats [2]. ECG signal classification faces various challenges. Due to their high beat-to-beat variability, lack of consistency in ECG characteristics, and error-prone nature, current approaches may not provide adequate diagnostic performance [3].

Extensive research has been conducted on heartbeat classification. ECG categorization has been more popular among computer scientists working in the field of artificial intelligence research in recent years [4]. Many models and methods have been proposed by researchers in recent years for computer-aided ECG categorization. These approaches range from straightforward ones like decision trees [5] to more intricate and condensed ones like SVM and conventional neural networks [6]. For categorization purposes, deep learning techniques have recently attracted a lot of interest from researchers.

Related Work

The classification of ECG heartbeats for normal and abnormal heartwave detection has been a prominent focus within medical research, with advancements in machine learning methods enhancing diagnostic accuracy despite the challenges posed by imbalanced datasets. Because arrhythmia datasets, such as the MIT-BIH arrhythmia database, are inherently unbalanced, early research (1995–2005) mostly relied on conventional classifiers like K-Nearest Neighbors (KNN) and Support Vector Machines (SVM), which had trouble correctly classifying minority classes [7]. In order to solve class imbalance, researchers started investigating resampling strategies in the mid-2000s, such as the Synthetic Minority Over-sampling Technique (SMOTE), which improves sensitivity in minority classes without substantially affecting majority class accuracy [8]. Deep learning models, especially Convolutional Neural Networks (CNNs), emerged as machine learning advanced, showed promise in handling large ECG datasets. Techniques such as data augmentation, cost-sensitive learning and advanced sampling strategies emerged to tackle the issue of imbalanced data within these complex networks [9].

From 2015 onwards, hybrid models integrating Recurrent Neural Networks (RNNs) and CNNs were developed, allowing for enhanced temporal feature extraction from ECG signals and improved classification across imbalanced datasets. Ensemble learning methods like AdaBoost and Random Forest have also been explored, often yielding improved performance for minority class detection by leveraging bagging and boosting techniques [10]. Additionally, Generative Adversarial Networks (GANs) have been utilized to synthetically generate minority samples, proving particularly effective in recent studies by helping neural networks learn representative features from both major and minor classes [11]. The importance of interpretability has driven further developments, with recent models incorporating explainable AI frameworks to enhance clinical usability [12]. This evolution from traditional to complex, deep-learning-based approaches underscores the ongoing commitment to refining ECG heartbeat classification models, as researchers continue to improve classification accuracy on imbalanced datasets while ensuring reliable deployment in clinical settings. In this study, the data preprocessing part combines and describes the chosen datasets. The final forecast is produced once the datasets are pooled through a rigorous voting process after being trained using five distinct techniques. Figure 4 shows the suggested ANN and ResNet structures, while Fig. 3 in the technique section shows the entire procedure. Additionally, this work is contrasted with other cutting-edge techniques detailed in Table I , with superior performance achieved through our proposed ensemble approach.

DATA SETS

The MIT-BIH Arrhythmia data set [13] and the PTB Diagnostic ECG dataset [14] are two sources of heartbeat signals that were used in the study's ECG categorization [2]. The PTB Diagnostic ECG dataset contains 14552 samples in two categories, whereas the Arrhythmia dataset contains 109446 samples in five categories. The sampling frequency for both datasets remains at 125 Hz. Every sample was subjected to zero-padding, downsampling, and cropping.

(a) A normal and premature ventricular contraction heart wave from the MIT-BIH data set

(b) An abnormal and normal heart wave from the PTB Diagnose ECG data set

Proposed Design

- Preprocessing the data

As stated in [2], the original dataset was previously cleaned and standardized. For training and testing, several preprocessing procedures were used. The training and testing datasets for the MIT-BIH heartbeat signal dataset, which had 87554 and 21892 rows, respectively, were already divided at the source [2]. The PTB Diagnostic ECG dataset was separated into normal and pathological subsets, and these subsets were then joined to generate a composite dataset. This combined dataset was then randomized, with 20% allocated for model testing. In both the PTB Diagnostic ECG datasets and MIT-BIH, the final column contained the label information, which was extracted separately. The preprocessing steps ensured that the data was appropriately formatted for model training and evaluation.

- Implementing the k-Nearest Neighbor Algorithm (KNN) for Training

The KNN classification technique operates based on the closest training data points. A key benefit of this method is its minimal tuning requirements, necessitating only adjustments to K and the distance metric to attain a high level of precision [15]. The highest rate of accurate classifications is obtained by calculating the K value. According to this study, K=3 created the best confusion matrix for the MIT-BIH Arrhythmia dataset, whereas K=1 worked best for the PTB Diagnostic ECG dataset.

- Implementing the Decision Tree (DT) Algorithm for Training

In the research presented in [16], decision tree-based methods were also employed for ECG classification. Decision trees, a common supervised learning approach, function as both classification and regression tools by creating tree-structured models. When applying the decision tree algorithm to the MIT-BIH Arrhythmia data set, the most effective confusion matrix was produced at a tree depth of 21. Similarly, for PTB Diagnostic ECG dataset, the optimal confusion matrix resulted from a tree depth of 43. This supervised learning technique has gained popularity due to its adaptability to a range of regression and classification problems.

- Implementing Artificial Neural Networks (ANN) for Training

ANNs have been employed in various ECG studies [2]. This study implements an ANN architecture model that incorporates class weights to address the issue of imbalanced datasets. The scikit-learn library is used to determine the class weights [17]. Fig.3 illustrates the complete architecture of the model.

- Implementing Support Vector Machine (SVM) for Training

By identifying data points, known as support vectors, that optimize the distance between classes, the SVM classification method focuses on a set of labeled training samples in order to produce a hyperplane that offers an ideal decision boundary [18]. Hyperplanes have the following mathematical equation:

$$W.Y + P = 0 \qquad (1)$$

where b stands for the scalar data and W for the weighted vector.

Making a grid of hyper-parameters is a better way to identify the ideal one. Grid SearchCV is the name of this technique. Grid SearchCV is used to fine-tune the SVM. "c"=1 and "gamma"=1 are the optimal parameters.

- Implementing ResNet for Training

The ResNet architecture, known for its residual connections that mitigate vanishing gradients, was adapted for 1D ECG signal processing. The input convolutional layer was modified for single-channel signals, while the final fully connected layer was tailored for multi-class classification. The network was trained using an 80-20 train-test split and cross-validation for robustness. Adam optimizer with a learning rate of 0.001 and a batch size of 32 was used. The architecture of this is briefly described in Fig. 4.

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- Methodology for Hard Voting Classification

The hard voting method [17] combines predictions from multiple classifiers to improve overall model performance. Given an input (x), the predicted label ($Y_{predcted}$) is determined by the majority vote across all classifiers. Mathematically, this can be expressed as:

$$Y_{predicted}=\text{mode}\ (C1(x), C2(x),\ldots,Cn(x)) \qquad (2)$$

Here, C1,C2,…,Cn represent the individual classifiers, and mode() calculates the most frequent predicted label among the classifiers for the input x. This approach ensures that the final decision leverages the collective strength of all classifiers, reducing the impact of individual errors.

The confusion matrices for the ensemble classifiers, depicting the prediction performance, are illustrated in Fig. 6. These matrices provide insights into true positives, false positives, true negatives, and false negatives, aiding in performance evaluation and model comparison.

- MIT-BIH dataset.

- PTB Diagnostic dataset.

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MIT-BIH Arrhythmia dataset

Method

Accuracy %

Decision Tree

96.11

ANN with class weights

98.06

Support Vector Machine

97.58

RESNET

95.53

Ensemble Approach

97.78

PTB Diagnostic ECG dataset

Decision Tree

97.28

ANN with class weights

97.26

Support Vector Machine

96.84

RESNET

94.50

Ensemble Approach

97.66

Tables I illustrate the comparative analysis between this study and previous research. The investigation employed various methods, comprising ensemble methods, RESNET, decision trees, ANN with class weights, SVM. For the MIT-BIH Arrhythmia dataset, the ANN with class weights method yielded the highest accuracy of 98.06%. The ensemble method produced the best results for the PTB Diagnostic ECG dataset.

Other established machine learning approaches also achieved relatively good accuracy, precision, and recall scores. Figure 6 displays the optimal confusion matrix obtained at K=3 for the MIT-BIH Arrhythmia dataset and K=1 for the PTB Diagnostic ECG dataset. In the decision tree classification method, the best confusion matrix was achieved at depth 21 for the MIT-BIH Arrhythmia dataset and depth 43 for the PTB Diagnostic ECG dataset. The study also incorporated some hyperparameter tuning. Grid Search CV was utilized to fine-tune the SVM model, resulting in optimal parameters of 'c'=1 and 'gamma'=1.

Conclusion

This study aims to develop a system capable of effectively identifying patients and aiding specialists in determining suitable treatments. The research examined two heartbeat signals: the Arrhythmia dataset, comprising 109446 samples across five categories, and the PTB Diagnostic ECG dataset, containing 14552 samples in two categories, both with a 125 Hz sampling frequency. To address class imbalance, class weights were assigned during training with ANN and LSTM. Various optimized approaches, including KNN, DT, ANN, SVM, and LSTM, were applied to both ECG datasets, yielding higher accuracy than previous studies in this field. The research utilized five established machine learning algorithms, which were combined through ensemble methods after training. For the MIT-BIH dataset, ANN with class weights achieved the highest accuracy of 98.06%, while the ensemble approach reached 97.664% accuracy for the PTB Diagnosis ECG dataset. Although these results surpass existing research, there is potential for improvement using enhanced datasets. Future work could involve deploying the proposed method as a web server to assist specialists in efficiently classifying signals.

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