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Hybrid Deep Learning and Machine Learning Approach for ECG-based Arrhythmia Classification and Multi-Class Disease Identification

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Abstract:- This Study shows a thorough hybrid technique for the classification of arrhythmias utilizing ECG signals, incorporating both Deep Learning (DL) and Machine Learning (ML) methods. We assess a pasture of ML classifiers to decide the most efficient model for arrhythmia discovery, with Adaboost discovered as the dominant classifier, attaining a precision of 96.9%. In the deep learning section, we exploit VGG16 for robotic feature extraction, succeeded by classification of these features applying a Support Vector Machine (SVM), which outcome in an accuracy of 96.6%. To develop an expansion of our study, we concoct a multi-class disease classification approach predicate on a hybrid CNN-LSTM framework, which attains an impressive accuracy of 99.53%. These experiment outcomes feature the conclusiveness and strength of our hybrid approach in enhancing ECG-based arrhythmia identification and multi- class CVD classification..

Keywords: *Deep Learning, Arrhythmia identification, Classification.*

1. Introduction

1.1 Background Study & Important of ECG

Cardiovascular disease (CVD) relates to a collection of medical hells that impact the heart and blood vessels, leading to a disruption in the normal operation of the CV system [1]. The primary role of this network is centered on the heart, which is responsible for circulating blood throughout the entire body. CVD has surfaced as a suggestive prompt of death widely. The Australian Institute of Health and Welfare shared especially in 2021, CVD considered for 42,700 casualties, describing 25% of fully demises[2]. Cardiovascular diseases, specifically arrhythmias, persist to be a substantial universal benefactor to homicide standards. Electrocardiography (ECG) is a vital record for tracing and decreasing the threats connected with arrhythmias [3].

ECG imposes the breathtaking exercise of the heart, furnishing sensitivity not only into instantaneous cardiac result but also into the incremental modifications connected to chronic ailments [4]. lately, models exploiting artificial intelligence for electrocardiography (AI- ECGs) have surfaced, suitable of diagnosing 12-lead ECGs to assess a patient's biologically [5].

1.1.2 Function of ML and DL in enhancing classification precision

Machine learning approach have been extensively applicable in the classification of ECGs due to their volume to clarify complex patterns. The wonder of machine learning in improving classification accuracy mostly depends on the techniques of feature engineering, feature selection, and the utilize of higher learning approaches. Deep Learning (DL) take off the necessity for manual feature extraction by independently distinguishing hierarchical figures inside raw ECG signals.

1.2 Research Gap

1.2.1 Restricts of Existing techniques in ECG classification

In spite of illustrious process in the field of ECG classification, conventional procedures meet some boundaries that rear their accuracy, generalizability, and impressive in real-time scenarios. The fundamental challenges include:

Dependence on Feature Engineering in Machine Learning Models:

Conventional Machine Learning (ML) methodologies, such as Support Vector Machines (SVM), AdaBoost, Random Forest based on manually bespoken features inferred from ECG waves. The success of classification is mostly delegation upon the standard of these manually extracted features, which requires technical knowledge and may dominate cunning interpretations in ECG waveforms. There is also a finite capability to generalize around varied datasets due to differences in ECG signal characteristics, noise levels, and recording environments.

Computational Demands of Deep Learning Models

Convolutional Neural Networks (CNNs) and Long Short-Term Memory networks (LSTMs) have exhibited excitable accuracy; still, they require significant datasets and substantial computational power for effective training. The shortage of illustrate in deep learning methods suggests questions for clinicians, who may discover it hard to trust the automated classification results. furthermore, there is an elevated risk of overfitting when operating with small datasets, necessitating the use of extensive data augmentation and transfer learning strategies.

Difficulties in Multi-Class Arrhythmia Classification

While several existing methods excel in binary classification (distinguishing between normal and abnormal), they frequently stumble with multi-class classification consequent the resemblances in ECG signals connected with different arrhythmias [6]. Certain rare arrhythmias give a challenge due to the shortage of labeled samples, complicating the ability of profound learning models to identify strong features.

Hybrid CNN-LSTM for Temporal and Morphological Analysis

CNNs are adept in capturing adept characteristics (such as waveform shape), while Long Short-Term Memory networks (LSTMs) are adept at understanding temporal collaborations within ECG sequences. The blending of CNN and LSTM models. Connections the classification of multi-class arrhythmias, with recent research indicating accuracy levels surpassing 99.53%.

1.3 Research Objectives

• Distinguish the best ML classifier for ECG arrhythmia:

Assess a range of machine learning classifiers, comparable as Decision Tree (DT), Gaussian Naïve Bayes, Extra Tree classifier, reinforcement Vector Machine (SVM), Multi-Layer Perceptron (MLP), SGD, Hist Gradient Boosting, RF and AdaBoost, for the detection of arrhythmias using ECG data. Enhance the rendition of these version through hyperparameter optimization and value the classifiers using essential metrics, as well as accuracy, precision, recall, and F1- score.

• Enhance classification rendition using DL-based feature extraction:

Engage Deep Learning (DL) methodologies, as well as Convolutional Neural Networks (CNNs), Long Short-Term Memory (LSTM) networks, and interbred CNN-LSTM frameworks, to infer significant features from unprocessed ECG signals. sway pretrained models, such as VGG16 and ResNet, to augment feature representation and enrich the accuracy of classification. Impose the effectiveness of DL-driven feature extraction when dual with machine learning classifiers, such as CNN-SVM and CNN-RF, in equivalence to conventional machine learning models. Interrogate how DL-based feature extraction leverages classification precision in the discovery of multi-class arrhythmias.

• Evolve a multi-class illness classification architecture:

Demonstrate a complete classification system focused at distinguishing varied ECG-related diseases, such as arrhythmias, myocardial infarction, and other cardiovascular disorders. Tackle results related with class imbalance by employing data augmentation and synthetic data generation methods. Generate a hybrid ensemble method that unites machine learning, deep learning, and AI-driven optimization to enhance generalization and facilitate real-time application. Impose the framework's rendition using standard ECG datasets to confirm its Professional dependability and effectiveness.

2. Literature Review

2.1 Deep Learning in ECG Analysis

• Existent RNN and CNN methods for ECG classification:

Deep Learning (DL) has produce curious strides in the element of ECG-based arrhythmia classification by assisting robotic feature extraction and improving classification accuracy. In diversity to conventional Machine Learning (ML) approaches that based on manually crafted feature engineering, DL models independent learn hierarchical depictions from crude ECG signals. The primary DL architectures engaged in ECG assessment is are Convolutional Neural Networks (CNNs) [8]and Recurrent Neural Networks (RNNs)[9]. Current CNN and RNN Models for ECG Classification

1. Convolutional Neural Networks (CNNs)

CNNs are considerably applied in ECG classification consequent their experience in gaining spatial and morphological attributes of ECG signals. Illustrious CNN-based models for ECG classification contain:

General CNN Architectures: Basic CNN models featuring combined convolutional layers have displayed notable accuracy in distinguishing arrhythmias by understanding local patterns within ECG waveforms.

ResNet: These improved CNNs enhance feature extraction by relieving the passing gradient result, thus assisting efficient learning from broad ECG datasets.

CNN-LSTM Hybrid Models: This methodology combines CNNs for spatial feature extraction with Long Short-Term Memory (LSTM) networks for literacy temporal sequences, thereby enhancing arrhythmia classification effects.

1D-CNN vs 2D-CNN: While 1D-CNN methods ECG signals straightly, 2D-CNN propagates waveforms into spectrogram images, which refines pattern recognition abilities.

Advantages of CNNs in ECG Classification:

• Effective feature extraction without the need for manual preprocessing.

• Capability to learn spatial relationships within ECG waveforms.

• Superior performance in identifying arrhythmias and myocardial infarctions.

2. Recurrent Neural Networks (RNNs)

RNNs, particularly Long Short-Term Memory (LSTM) networks and Gated Recurrent Units (GRUs), are specifically efficient for classifying electrocardiogram (ECG) waveforms consequent their expertise to attain temporal relationships within successive ECG facts.

LSTM Models: These models exceed in preserving long-term reliance in ECG waveforms, potential them specifically applicable for arrhythmia classification, where factual waveform data significantly crashes future results.

Advantages of RNNs in ECG Classification:

• Capability to model time-series dependencies inherent in ECG signals.

• Effectiveness in multi-class arrhythmia classification.

• Aptness for identifying abnormalities in extended ECG recordings.

Advantages of VGG16-Based Feature Extraction

VGG16, a deep convolutional neural network (CNN) initially developed for image classification, has been successfully repurposed for ECG feature extraction by interpreting ECG signals as two-dimensional representations or raw waveforms. Rather than depending on manually crafted features, VGG16 autonomously extracts high-level representations, which can subsequently be classified using conventional machine learning models such as Support Vector Machines (SVM) or Random Forest.

Key Benefits of VGG16-Based Feature Extraction in ECG Analysis

• Pretrained Feature Extraction

• Enhanced Classification Precision

• Robustness Against Noise and Variability

• Decrease in Computational Demands

• Integration with Hybrid Models.

3. Methodology

3.1 Dataset & Preprocessing

The given dataset is collected from blended libraries of heartbeat rhythms. It includes two heartbeat classification datasets. One dataset from the MIT-BIH Arrhythmia dataset and another one is obtained from PTB diagnostic ECG database[7]. This dataset utilized Deep learning Neural Network architectures in heartbeat classification, and attending certain facilities of higher knowledge on it. The ECG waves inter communicate with the heartbeats of ECG in the ordinary case and the simulated by distinguishable arrhythmias and myocardial infraction of heartbeats. These waveforms are pre-processed and limited with every portion similar to a heart rhythm[10].

3.1.1. Dataset

Data set found from (https://www.kaggle.com/datasets/erhmrai/ecg-image-data/data & Data Source: Physio net's MIT-BIH Arrhythmia Dataset) & The data set contains 109446 samples under 5 categories with 125 Hz frequency and 5 classes. Classes are 'N': 0, 'S': 1, 'V': 2, 'F': 3, 'Q': 4. This dataset is generated by conservation of every ECG arrhythmia in the picture form. of total pictures between all classes were split into train and test data where training sample are 80% of the total data and test samples are 20%[11].

3.1.2. Preprocessing steps applied to ECG signals

a) Dataset attentiveness:

(i) Find out the Dataset Structure:

• Initially, verify the format of ECG signals and their labels.

• Recording the allocation of the 'Q', 'V','F','S','N' are the 5 classes and an assured whether it is stable or not. If not, look upon the sampling techniques.

b) Separate verification data:

o The dataset previously has considered an 80% of training data and 20% of testing data (80:20 Train: test). It's not specifically furnished.

3.2. Preprocessing for ECG Images

As the ECG waveforms are in the form of an image and the below techniques are required:

3.2.1. Image Resizing

o Formalizing a dimension of an image to guarantee consistence. Resizing all images to 256x256 pixels.

3.2.2. Normalization

o Enhance the model performance and intensities of the pixels range between [0,1] or [-1,1].

3.3. Preprocessing for Signal Features

3.3.1. Denoising

o Use baseline a wander technique to remove noise.

o Baseline wander is the outcome where X-axis of an ECG signal shows to wander or rise and drop rather than be straight. This impetus the whole signal to shift from its ordinary base[12].

3.3.2. Resampling

o Resampling the ECG waveform images if necessary.

3.3.3. Segmentation

o Signals were split by equalization the size of the input among all classes.

3.4. Label Encoding

Table 1. The classes are labeled below

Class name	Label name
N	0
S	1
V	2
F	3
Q	4

• Make sure that the labels were placed in the dataset for training.

3.5. Train-Test Data Split-up

• Couple of times the data split-up checked (80/20 = train/test). Training and test data should not mix with each one. The split is based on the classes to maintaining a class balance in both sets.

3.4. Machine Learning Approach

3.4.1. Model Selection

3.4.1.1. Implementation of multiple classifiers:

In this research [7], a range of machine learning algorithms, such as Decision Tree (DT), Gaussian Naïve Bayes, ExtraTrees, Support Vector Machine (SVM), and Multi-Layer Perceptron (MLP) classifiers,SGD classifier, Hist Gradient Boosting, Ada boost classifer,RF were assessed for the classification of ECG arrhythmias.

Table 2. Various Algorithms and its accuracy

S.NO	NAME OF THE ALGORITHM	ACCURACY
1	Decision Tree	0.6140
2	Gaussian	0.5380

3	Extra Tree classifier	0.6742
4	SVM	0.6627
5	MLP classifier	0.6742
6	SGD classifier	0.6742
7	Hist Gradient boosting	0.8965
8	Ada Boost Classifier	0.96
9	Random Forest	0.6785

3.4.1.2. Identification of Adaboost as the best classifier

Among the different machine learning algorithms evaluated for ECG classification, the AdaBoost Classifier demonstrated the highest accuracy at 0.96, greatly surpassing other models, including Decision Tree (0.614), SVM (0.6627), and Random Forest (0.6785). This exceptional performance can be attributed to its ensemble learning methodology, which progressively refines weak classifiers, thereby increasing the overall robustness and accuracy of the model.

3.4.2 Hyper parameter Tuning

• Tuning Adaboost parameters:

Among these algorithms, the AdaBoost classifier exhibited the highest level of accuracy. To enhance performance, the number of estimators in the AdaBoost model was adjusted to 50, 75, 100, 125, and 150.

Table 3.

S.NO	Parameter	Accuracy
1	50	0.949
2	75	0.954
3	100	0.96
4	125	0.963
5	150	0.969

• Achieved highest accuracy:

The optimal classification accuracy of 0.969 was attained with 150 estimators, underscoring the efficacy of boosting techniques in improving the accuracy of ECG classification.

3.5. Deep Learning Approach

3.5.1Feature Extraction Using VGG16

VGG16, a pre-trained deep learning model initially developed for image classification, was utilized for transfer learning to derive significant features from ECG signals [13]. In contrast to conventional machine learning feature extraction techniques, VGG16 identifies more profound hierarchical patterns, thereby enhancing classification accuracy by maintaining essential morphological traits of ECG signals.

3.5.2. Classification Using SVM

Following the extraction of deep features with VGG16, a Support Vector Machine (SVM) classifier was developed to categorize ECG arrhythmias utilizing these high-dimensional features. The VGG16- SVM methodology accomplished an accuracy of 96.6%, denoting that deep feature extraction significantly enhances classification interpretation in association to traditional machine learning techniques

3.6. Multiple Class disease Classification

3.6.1. Implementation of CNN – LSTM model:

3.6.1.1. CNN for Spatial Feature Extraction

Convolutional Neural Networks (CNNs) were applied to understand spatial features out of ECG waveforms by detecting local patterns such as QRS complexes, P waves, and T waves. This spatial assessment aides in distinguishing various types of arrhythmias depends on the morphological differences followed in ECG waveforms.

3.6.1.2. STM for Sequential Pattern Recognition

Long Short-Term Memory (LSTM) networks were applicable to interrogate temporal dependencies within ECG waveforms, successfully gaining sequential patterns in heartbeat rhythms. By deciphering long-term dependencies, LSTM enhances the model's volume to classify arrhythmias based on interpretations in heartbeat sequences.

3.6.1.3. Achieved 99% Classification Accuracy:

Among the combination of CNN for feature extraction and LSTM for sequence modelling, the current hybrid deep learning model attained 99% accuracy in multi-class ECG signal classification. This result features the conclusiveness of merging spatial and temporal learning to improve the finding of cardiovascular diseases.

4. Results

4.1. Performance Comparison

The assessment of all models was supervised utilizing metrics such as accuracy, precision, recall, and F1- score, immolation an unconditional assessment of their classification performance. Amidst the models imposed, CNN-LSTM listed the highest accuracy at 99%, with Adaboost next nearly at 96.9% and VGG16-SVM at 96.6%, featuring the advantages of deep learning techniques in ECG classification.

4.2 Comparison with Previous Studies

4.2.1 Opportunities of the Proposed Methods Over Existing ECG Classification Methodology:

The proposed CNN-LSTM mothodolgy, attaining an accuracy of 99%, across with the Adaboost classifier at 96.9% accuracy, exhibit prominent advances when equated to conventional machine learning (ML) and detached deep learning (DL) models. These advances are initially due to superior feature extraction, advanced classification methods, and the manifestation of dual spatial and temporal learning for ECG waveforms.

4.2.2 Rationale for the Hybrid ML-DL-AI Approach

The hybrid DL-ML methods leverage an opportunity of ML-based boosting (Adaboost), improved feature extraction (VGG16), and consequence modeling (LSTM) to redeem unique classification results. This amalgamation expands the model's robustness, its capability to tailor to complicated ECG patterns, and its generalizability, depiction it more efficient than using individual DL or ML approach alone.

4.3 Discussions on Findings:

4.3.1 Influence of Hyperparameter Tuning on Adaboost:

The procedure of hyperparameter tuning has accompanied to a illustrious improvement in the performance of Adaboost, with accuracy revolt from less levels to 96.9% at 150 estimators. This signifies that fine- tuning the number of weak learners significantly enhances the method's expertise to classify ECG arrhythmias more precisely.

4.3.2 Efficacy of Feature Extraction Utilizing VGG16:

Feature extraction predicated on VGG16 succumbed rich, high-dimensional depictions of ECG waveforms, which intensified classification accuracy when dual with an SVM classifier. The hierarchical features incidental exceeded those derived from conventional machine learning approaches, underscoring the advantages of deep learning in ECG signal analysis.

4.3.3 Advantages of CNN-LSTM for Multi-Class Disease Classification:

The CNN-LSTM hybrid method achieved an impressive accuracy of 99%, successfully capturing both spatial characteristics (through CNN) and temporal relationships (through LSTM) in ECG signals.

This integration facilitated precise classification of various cardiovascular diseases, showcasing its superiority compared to individual machine learning and deep learning methods.

5. Conclusion and Future Enhancements

5.1. Brief of Findings

This research has shown that hybrid machine learning and deep learning models significantly enhance the accuracy of ECG classification, with Adaboost achieving an accuracy of 96.9% and the CNN- LSTM model reaching 99%. The CNN-LSTM model has demonstrated exceptional effectiveness in identifying multiple diseases by utilizing both spatial and temporal dependencies present in ECG signals.

5.2. Future Research Directions

Future endeavours will concentrate on the creation of real-time ECG monitoring systems powered by AI models, facilitating early detection and ongoing patient surveillance in clinical environments.

There will be a concerted effort to enhance the interpretability of AI models through the application of attention mechanisms, SHAP values, and various visualization techniques, thereby fostering greater trust and acceptance within the healthcare sector.The hybrid methodology proposed in this study can be adapted for the analysis of other biomedical signals, such as EEG for neurological disorders and PPG for cardiovascular assessments, thereby expanding its relevance in medical diagnostics.

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