DEPARTMENT OF COMPUTER TECHNOLOGY

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Review I Report

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Optimized CNN-Based Hybrid Model for Multi-Label Classification of Cardiovascular Diseases in 12-Lead ECG Images

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Title: Optimized CNN-Based Hybrid Model for Multi-Label Classification of Cardiovascular Diseases in 12-Lead ECG Images

Domain: Machine Learning, Deep Learning, Cardiovascular Disease Detection, Biomedical Signal Processing

Introduction:

Cardiovascular diseases (CVDs), including stroke, arrhythmias, and myocardial infarction (MI), cause 17.9 million deaths annually, comprising 32% of global mortality. Early detection improves outcomes, but manual ECG interpretation is time-consuming and variable. Machine learning and deep learning enhance automation, reducing errors and improving efficiency.

This research proposes an optimized CNN-based hybrid model for 12-lead ECG image analysis, combining deep learning for feature extraction with machine learning for classification. A multi-label approach identifies multiple CVDs, integrating adaptive preprocessing and optimization (Adam, RMSprop) to enhance performance, reduce complexity, and improve generalization.

Problem Statement:

Cardiovascular diseases (CVDs) are major causes of morbidity and mortality. Traditional ECG diagnosis is manual, time-consuming, and variable, while existing deep learning models often overlook multiple CVDs. Feature extraction from 12-lead ECG images remains challenging.

This research proposes an optimized CNN-based hybrid model for efficient multi-label classification of stroke, arrhythmias, and MI. It integrates adaptive preprocessing and optimization techniques (Adam, RMSprop) to enhance performance and accuracy.

Objectives:

- Compare and optimize training performance using Adam and RMSprop for better accuracy and faster convergence.
- Optimize preprocessing techniques such as image resizing (800KB to 300KB), adaptive enhancement, and efficient labeling using LabelImg.
- Implement a CNN-based model for multi-label classification of cardiovascular diseases from ECG images.
- Evaluate the model using standard ECG datasets and benchmark its performance against existing approaches.

Literature Survey:

S.No.	Title	Publications & Year	Methodology	Limitations
1.	**Comparison of Machine Learning and Deep Learning Methods for Heart Disease Prediction**	Bharti et al., IEEE Access, 2022	• Used UCI heart disease dataset. • Applied DL (three fully connected layers) and ML models (RF, LR, K-NN, SVM, DT, XGBoost). • DL model used ReLU activation and dropout for regularization. • ML models applied feature selection and outlier detection	• ML models achieved lower accuracy than DL. • Class imbalance was not addressed, leading to potential biases. • Limited generalization due to dataset constraints. • Hyperparameter tuning for ML models was not extensively explored.

2.	**Extended Heterogeneous Oscillator Model for 12-Lead ECG Waveform Generation**	Mario et al., Computers in Biology and Medicine, 2023	• Used modified van der Pol and FitzHugh-Nagumo equations to model the cardiac conduction system. • Generated realistic ECG waveforms. • Incorporated statistical heart rate variability and noise to simulate real-world	• Does not consider pathological ECG variations. • Limited applicability for diagnosing specific cardiovascular diseases. • Requires high computational power for real-time applications. • Model validation lacks large-scale clinical
3.	**Deep Learning Approach for Cardiac Disorder Classification Using 12-Lead ECG Images**	Ali Haider Khan et al., Scientific Reports, 2023	• Used SSD MobileNet v2-based CNN. • Classified MI, abnormal heartbeat, past MI, and normal class. • Trained on 11,148 ECG images using data augmentation and transfer learning.	• Does not consider co-occurrence of multiple cardiovascular diseases. • Lacks interpretability, making it difficult for medical professionals to trust the model. • Dataset may not be diverse enough for generalization

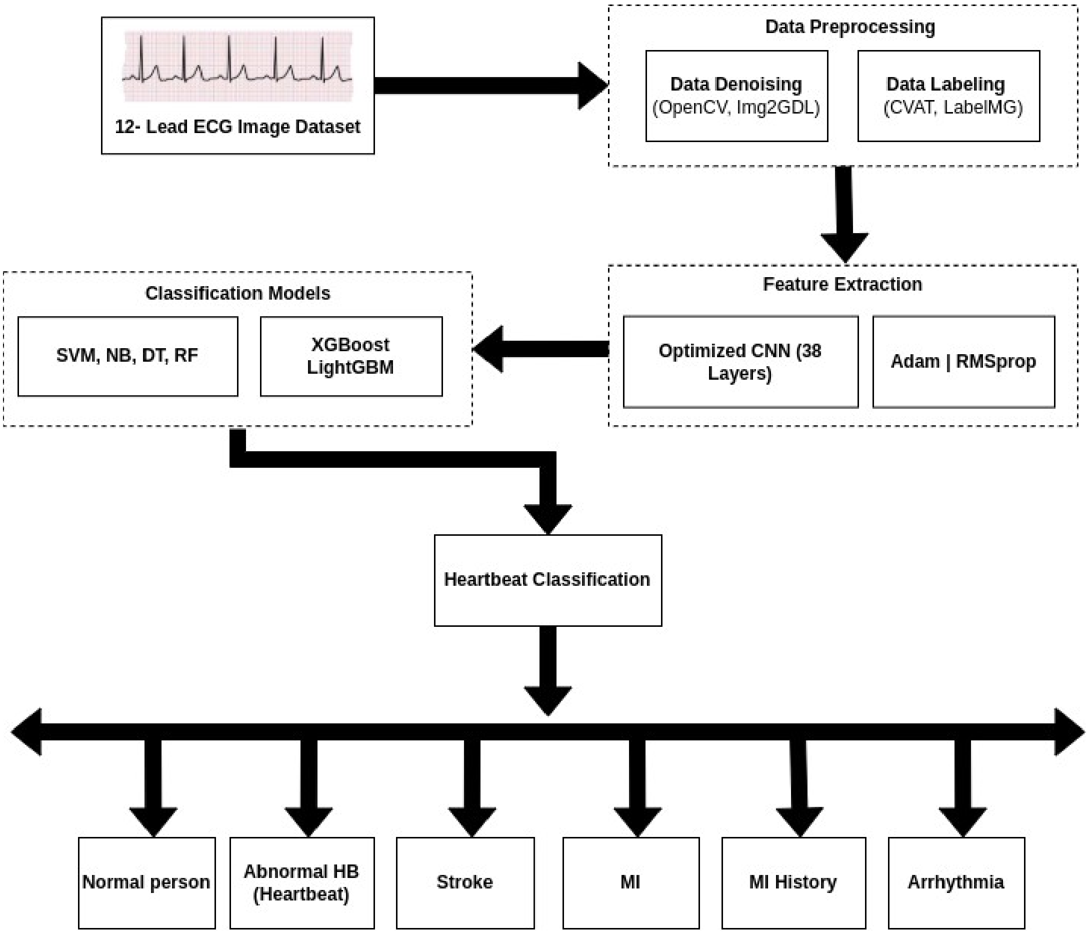
4.	**ECG Heartbeat Classification Using CNN-BiLSTM and SMOTE**	Neenu Sharma et al., Biomedical Signal Processing and Control, 2023	• Combined CNN-BiLSTM with SMOTE to handle class imbalance. • Used the MIT-BIH arrhythmia dataset. • CNN extracts spatial features, while BiLSTM captures temporal dependencies. •	• May not generalize well to other datasets. • Prone to overfitting to specific characteristics of MIT-BIH data. • High computational requirements due to combined CNN-BiLSTM model. • SMOTE-based synthetic data generation might introduce unrealistic ECG patterns.
5.	**1D Self-Operational Neural Networks (Self-ONNs) for ECG Classification**	Junaid Malik et al., Neural Computing and Applications, 2023	• Used Self-ONNs with generative neurons for patient-specific ECG classification. • Model dynamically adjusts kernel functions for better feature learning. • Focused on arrhythmia detection.	• Higher computational complexity compared to traditional CNNs. • Challenging for real-time deployment on edge devices. • Requires large datasets for effective training.

6.	**ECGMatch: Semi-Supervised Learning for Multi-Label Cardiovascular Disease Prediction**	Rushuang Zhou et al., IEEE Transactions on Biomedical Engineering, 2022	• Used the ECGMatch framework. • Applied data augmentation, pseudo-label learning, and label correlation alignment. • Incorporated both labeled and unlabeled data for improved generalization.	• Performance on real-world unseen data needs further validation. • Model might be biased towards its training dataset. • Semi-supervised learning approach may struggle with high intra-class variations. • Computationally expensive training process.
7.	**CNN-Based Heart Abnormality Classification with Transfer Learning**	Mohammed B. Abubaker et al., Sensors, 2023	• Used CNN with transfer learning. • Applied Naïve Bayes (NB) algorithm. • Achieved 99.79% accuracy on ECG images. • Used pre-trained feature extraction layers for faster convergence.	• Limited generalizability due to reliance on a specific dataset. • May not capture diverse ECG variations. • Transfer learning might not be optimal for ECG data compared to specialized architectures. • Requires fine-tuning of pre-trained layers for different datasets.

8.	**BayeSlope: Adaptive R-Peak Detection for Wearable ECG Sensors**	Elisabetta De Giovanni et al., IEEE Journal of Biomedical and Health Informatics, 2023	• Combined Bayesian filtering, unsupervised learning, and non-linear normalization for ECG peak detection. • Adaptive design adjusts computational complexity based on real-time error estimation.	• Performance during extreme motion artifacts needs improvement. • Excessive movement can introduce significant noise. • Adaptive complexity control might lead to performance fluctuations. • Requires hardware optimization for wearable applications.
9.	**CNN-Based Automatic ECG Diagnosis**	Roberta Avanzato et al., Medical & Biological Engineering & Computing, 2022	• Used CNN to classify normal beats, atrial premature beats, and premature ventricular contractions. • Trained on a dataset of 4,000 ECG instances.	• Limited dataset size (4,000 ECG instances), reducing model robustness. • Potential overfitting due to small dataset size. • No cross-validation with other large-scale ECG datasets. • Lacks interpretability for clinicians.

10.	**Feature Engineering vs. Deep Learning for ECG-Based Diagnosis**	Eran Zvuloni et al., Nature Communications, 2023	• Compared feature engineering (FE) and deep learning (DL) on 2.3M ECGs. • Evaluated diagnosis, risk prediction, and age estimation. • Analyzed feature importance and hybrid approaches.	• Combining FE and DL did not improve results over DL alone. • Suggests feature extraction techniques might be redundant for deep models. • Feature importance analysis might be dataset-specific. • Requires extensive computational resources for large-scale processing.

Block Diagram:



New Contributions:

- **Optimized Training Performance**: Comparison and fine-tuning of Adam and RMSprop optimizers to achieve better accuracy and faster convergence.
- **Advanced Preprocessing Techniques**: Implementation of adaptive image resizing (reducing size from 800KB to 300KB), enhancement, and efficient labeling using LabelImg.
- **Multi-Label ECG Classification**: Development of a CNN-based model for identifying multiple cardiovascular diseases from ECG images.
- **Performance Benchmarking**: Evaluation of the proposed model using standard ECG datasets and comparison against existing approaches to establish improvements in classification accuracy and computational efficiency.

Module Design:

1. Input: 12-Lead ECG Image Dataset

- The system begins with an ECG dataset consisting of 12-lead ECG images.
- These images are used as input for further processing.

2. Data Preprocessing

- **Data Denoising (OpenCV, Img2GDL):** Techniques such as filtering and noise reduction are applied to enhance ECG signals/images.
- **Data Labeling (CVAT, LabelIMG):** Images are labeled with corresponding conditions to prepare for supervised learning.

3. Feature Extraction

- **Optimized CNN (38 Layers):** A deep convolutional neural network with 38 layers is used to extract critical ECG features.
- **Adam | RMSprop:** These are optimization algorithms used to fine-tune the CNN's performance.

4. Classification Models

- Traditional machine learning models (SVM, Naïve Bayes, Decision Tree, Random Forest) are used for classification.
- Advanced boosting models (XGBoost, LightGBM) are also considered for improved performance.

5. Heartbeat Classification

- The extracted features are passed to the classification models to predict the heartbeat type.

6. Output: Final Classification

- The system classifies the heartbeat into one of six categories:
    - **Normal person, Abnormal Heartbeat (HB), Stroke, Myocardial Infarction (MI), MI History, Arrhythmia**

Evaluation Metrics:

Metric	Purpose	Formula
Accuracy	Measures the proportion of correctly classified ECG signals.	Accuracy = (TP + TN) / (TP + TN + FP + FN)
Precision	Indicates how many of the predicted positive cases are actual positives.	Precision = TP / (TP + FP)
Recall (Sensitivity)	Measures the model's ability to correctly detect positive cases.	Recall = TP / (TP + FN)
F1-score	Harmonic mean of precision and recall, balancing false positives and false negatives.	F1-score = 2 * (Precision * Recall) / (Precision + Recall)
AUC-ROC Curve	Evaluates the trade-off between true positive rate (TPR) and false positive rate (FPR) across different thresholds.	-
Confusion Matrix	Provides a detailed breakdown of classification results, showing TP (True Positive), TN (True Negative), FP (False Positive), and FN (False Negative) values.	-

Test Cases:

To ensure robustness and reliability, the following test cases are designed:

Test Case ID	Component	Test Case	Expected Outcome	Remarks
TC-001	Data Preprocessing - Denoising	Input noisy ECG images and apply OpenCV, Img2GDL filters	Noise should be significantly reduced while preserving signal features	Check for over-smoothing or loss of important features

TC-002	Data Preprocessing - Labeling	Verify manually labeled ECG images using CVAT, LabelIMG	Labels should be correctly assigned to ECG signals	Ensure inter-annotator agreement for consistency
TC-003	Feature Extraction - CNN	Pass ECG images through the optimized CNN (38 layers)	Features should be extracted correctly without distortion	Validate using sample input-output pairs
TC-004	Feature Extraction - Optimizer	Compare Adam vs RMSprop for training	Model should converge with optimal learning performance	Track loss function behavior for both optimizers
TC-005	Classification - ML Models	Train and test SVM, NB, DT, RF	Models should classify ECG data accurately	Compare accuracy, precision, recall for each model
TC-006	Classification - Boosting Models	Train and test XGBoost, LightGBM	Expected improvement in classification accuracy compared to other models	Hyperparameter tuning required
TC-007	Heartbeat Classification	Test model with ECG images of different heart conditions	Model should correctly classify each condition	Measure performance using confusion matrix
TC-008	Output Validation	Verify classification results for different cases (Normal, Abnormal HB, Stroke, MI, MI History, Arrhythmia)	Correct classification with high confidence score	Cross-check with clinical diagnosis

TC-009	System Performance	Test execution time for each step	Model should complete classification within an acceptable time	Optimize computations if needed
TC-010	Edge Cases	Input ECG images with extreme variations, artifacts, or missing segments	Model should handle such cases gracefully without crashes	Consider fallback mechanisms

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