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Multimodal ECG-PPG Clinical Fusion for Myocardial Infarction Classification Using Ensemble Learning

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Abstract: *This study presents a comparative analysis of multimodal ECG, PPG, and clinical feature fusion for Myocardial Infarction (MI) classification using four ensemble learning algorithms: Random Forest, XGBoost, LightGBM, and CatBoost. The experiments were conducted in two classification scenarios: binary classification for Normal vs MI and multi-class classification for Normal, STEMI, NSTEMI, and Old MI. Five feature scenarios were evaluated, including Clinical-only, ECG-only, PPG-only, ECG + PPG, and ECG + PPG + Clinical. The results show that ECG features were the most dominant modality for MI classification. In binary classification, XGBoost with ECG-only features achieved perfect performance with accuracy, macro F1-score, macro recall, and MCC of 1.0000. For multi-class classification, the best result was obtained by CatBoost using ECG + PPG + Clinical features, achieving accuracy of 0.9000, macro F1-score of 0.5394, and MCC of 0.6912. These findings indicate that multimodal fusion is more beneficial for MI subtype classification, while ECG-only features are highly effective for binary MI detection.*

Keywords: Myocardial Infarction, ECG, PPG, multimodal fusion, ensemble learning.

1. Introduction

Cardiovascular disease remains one of the major global health problems due to its substantial contribution to mortality worldwide. The World Health Organization reports that cardiovascular diseases are the leading cause of death globally, with an estimated 19.8 million deaths in 2022, most of which were related to heart attacks and strokes[1]. This condition highlights the importance of early detection and accurate classification of heart diseases, including Myocardial Infarction (MI), to support clinical decision-making and the development of computer-aided diagnostic systems.

Myocardial Infarction is a condition involving damage to the heart muscle, commonly caused by impaired coronary blood flow. In clinical practice, MI may appear in several forms, including ST-Elevation Myocardial Infarction (STEMI), Non-ST-Elevation Myocardial Infarction (NSTEMI), and Old MI. STEMI is generally associated with coronary artery occlusion that causes transmural ischemia and myocardial injury, while risk factors such as hypertension, hyperlipidemia, smoking, and diabetes increase the likelihood of MI occurrence.

One of the primary modalities used in MI examination is the Electrocardiogram (ECG) [2]. ECG records the electrical activity of the heart and provides important diagnostic information through features such as ST elevation, ST depression, QRS duration, QT interval, T-wave inversion, and pathological Q-wave[3]. Clinical guidelines also emphasize that ST-segment changes, ST depression, and conduction abnormalities on ECG are important indicators in evaluating patients with chest pain or suspected acute coronary syndrome[4], [5].

In addition to ECG, Photoplethysmography (PPG) has increasingly been used in cardiovascular health monitoring [6], [7] because it can capture hemodynamic and vascular information non-invasively. PPG features such as pulse transit time, augmentation index, stiffness index, pulse wave velocity, perfusion index, and reflection index can represent arterial elasticity, peripheral perfusion, and hemodynamic response. Therefore, PPG can provide complementary information related to vascular characteristics and cardiovascular risk[8].

However, the use of a single modality may not be sufficient to represent a patient's condition comprehensively. ECG is more effective in describing the electrical activity of the heart, whereas PPG provides information related to vascular and hemodynamic conditions. Meanwhile, clinical features such as age, sex, body mass index, smoking status, diabetes, hypertension, total cholesterol, and family history of coronary artery disease provide additional context regarding patient risk factors[9]. Therefore, a multi-modal feature fusion approach that integrates ECG, PPG, and clinical features has the potential to produce a more comprehensive data representation for MI classification[10].

The development of machine learning provides significant opportunities for building medical data-based classification systems. Algorithms such as Random Forest, XGBoost, LightGBM, and CatBoost are widely used for tabular data because they can capture non-linear patterns, model feature interactions, and perform well on datasets with multiple feature types[11]. In the context of MI classification, machine learning can be used to distinguish Normal and MI patients as well as classify MI subtypes such as STEMI, NSTEMI, and Old MI[12]. Based on these issues, this study proposes a comparative analysis of four ensemble learning algorithms, namely Random Forest, XGBoost, LightGBM, and CatBoost, for Myocardial Infarction classification using multi-modal feature fusion[13]. This study not only compares the performance of different algorithms, but also evaluates the contribution of each feature modality through five scenarios: Clinical-only, ECG-only, PPG-only, ECG + PPG, and ECG + PPG + Clinical [14].

The main research gap lies in the limited number of studies that systematically compare the contributions of ECG, PPG, and clinical features within a unified MI classification framework [15], [16]. Many MI classification approaches focus on a single modality, particularly ECG, while the potential integration of PPG features and clinical risk factors has not been fully evaluated in a comparative ensemble learning setting. In addition, class imbalance remains a significant challenge, especially in recognizing minority classes such as STEMI, NSTEMI, and Old MI.

Therefore, this study aims to evaluate the effectiveness of multi-modal feature fusion involving ECG, PPG, and clinical features for Myocardial Infarction classification using Random Forest, XGBoost, LightGBM, and CatBoost. The results are expected to contribute to the development of machine learning-based MI classification models that not only achieve strong predictive performance, but also demonstrate the role of each feature modality in supporting heart disease classification [26].

2.Literatur Review

Previous studies have explored the use of ECG and PPG signals for various cardiac-related classification tasks, including arrhythmia detection, hypertension prediction, ECG reconstruction, and cardiovascular monitoring. As summarized in Table 2, most existing studies focused on arrhythmia classification, blood pressure estimation, or PPG-to-ECG reconstruction, while direct Myocardial Infarction classification using combined ECG, PPG, and clinical features remains limited. Therefore, this study addresses this gap by evaluating multimodal feature fusion for both binary and multi-class MI classification using ensemble learning modelssummarized in the Table 1.

Table 1. Comparison of Previous Studies on ECG, PPG, and Multimodal Features for Myocardial Infarction Classification

Author	Dataset	Method	Best Performance	Limitation
Neha et al. (2021)[17]	MIT-BIH, MIMIC-II, PhysioNet Challenge 2015, AHA, European ST-T, and self-generated datasets	SVM, k-NN, NN, fuzzy classifier, CNN, LSTM, wavelet features	ECG methods showed high performance; PPG single-class detection reached around 97%	Review study only; mainly focused on arrhythmia, not MI subtype classification. PPG studies were limited by noise, motion artifacts, and lack of annotated datasets.
Bassiouni et al. (2021)[18]	MIMIC I, MIMIC II, and ECG–PPG subject-based datasets	KNN, SVM, ANN, BNN, RF, AdaBoost, MARS, LR, DT	KNN reached 94.84% for hypertension; SVM reached 95% for alcohol detection	Focused on hypertension, blood pressure, epilepsy, and alcohol detection; did not address MI classification or ECG–PPG–clinical fusion.
Ji et al. (2025)[19]	MIMIC-II, MIMIC-III, and MIMIC-IV	P2Es diffusion framework, KNN clustering, contrastive learning	MSE 0.0902 and DTW 0.0583 for PPG-to-ECG generation; 87.5% specificity for MI detection	Focused on ECG reconstruction, not direct MI classification from multimodal tabular features.
Saranya et al. (2025)[20]	225 patients and 109,736 ECG/PPG waveform segments	DenseNet-ABiLSTM with attention	Mean F1-score 87.74%, accuracy 89.14%, ROC-AUC 0.98	Focused on multiclass arrhythmia classification, not MI detection or MI subtype classification.

3.Methods

The overall research methodology is illustrated in Figure 1. The workflow shows the sequential process for classifying Myocardial Infarction using multimodal ECG, PPG, and clinical features. As shown in Figure 1, the research process consists of eight stages: dataset collection, data integration, data preprocessing, feature scenario construction, model training, model evaluation, feature importance analysis, and comparison and discussion. This workflow was designed to systematically evaluate the contribution of each feature modality and compare the performance of Random Forest, XGBoost, LightGBM, and CatBoost in both binary and multi-class MI classification.

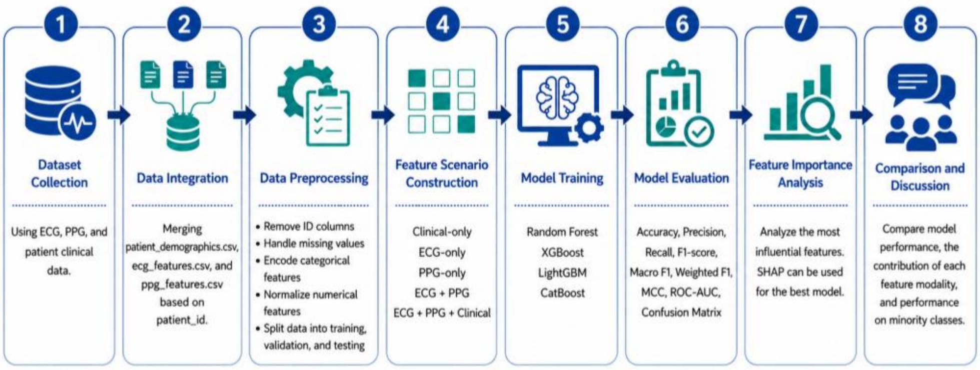

Figure 1. Research Methodology Workflow

Dataset Collection

The first stage of this study is dataset collection. As shown in Table 2, the dataset consists of structured patient data, including clinical information, extracted ECG features, and extracted PPG features. This dataset was obtained from a public repository https://www.kaggle.com/datasets/meruvakodandasuraj/ecg-ppg-features-for-mi-classification dataset designed for machine learning experimentation. Since the dataset is already available in feature-based tabular format, it can be directly used for machine learning modeling without raw signal extraction. Summarized in the Table 2. The dataset sources include patient_demographics.csv, ecg_features.csv, ppg_features.csv, and combined_cardiac_dataset.csv.

Table 2. Research dataset sources

No	File Name	Number of Records	Number of Features	Description
1	patient_demographics.csv	5,000	11	Patient clinical data, risk factors, and MI labels
2	ecg_features.csv	5,000	23	ECG features, morphological intervals, and HRV
3	ppg_features.csv	5,000	18	PPG, hemodynamic, and vascular features
4	combined_cardiac_dataset.csv	5,000	50	Merged dataset ready for modeling

The data integration stage is performed by merging clinical data, ECG features, and PPG features based on the patient_id column. This column acts as a unique identifier for each patient, so each row in the final dataset represents one patient with complete feature information. As shown in Table 3, the integration process begins by reading the clinical data, ECG feature data, and PPG feature data separately.

Table 3. Data integration process

Stage	Input	Process	Output
1	patient_demographics.csv	Read clinical data and classification targets	Patient clinical data
2	ecg_features.csv	Read ECG features based on patient_id	ECG feature data
3	ppg_features.csv	Read PPG features based on patient_id	PPG feature data
4	Clinical + ECG + PPG data	Merge data using patient_id	Multimodal dataset
5	Multimodal dataset	Validate number of rows, columns, and targets	Dataset ready for preprocessing

Description of Clinical Features

Clinical features are used to represent patient risk factors for heart disease. As presented in Table 4, these features include demographic information and health conditions related to MI risk, such as age, BMI, smoking status, diabetes, hypertension, total cholesterol, and family history of coronary artery disease. These variables are used to evaluate whether clinical risk factors can independently support MI classification and whether they can improve model performance when combined with ECG and PPG features[21].

Table 4. Clinical features used in the study.

No	Feature	Data Type	Description
1	age	Numeric	Patient age in years
2	sex	Categorical	Patient sex
3	bmi	Numeric	Patient Body Mass Index
4	smoking_status	Categorical	Patient smoking status
5	diabetes	Binary	Patient diabetes status
6	hypertension	Binary	Patient hypertension status
7	total_cholesterol_mg_dl	Numeric	Total cholesterol level
8	family_history_cad	Binary	Family history of coronary artery disease

Data Preprocessing

Data preprocessing As presented in Table 5 is performed to ensure that the dataset is ready for model training. The preprocessing stage consists of several steps, including removing the identity column, handling missing values, encoding categorical features, normalizing numerical features, and splitting. The patient_id column is removed because it only serves as a patient identifier and is not used as a predictive feature [22]. Missing values are then handled to prevent interference during model training. Categorical features are transformed into numerical representations using encoding, while numerical features are adjusted to ensure a suitable format for modeling[23].

Table 5. Preprocessing

Step	Method Used	Description
ID removal	Drop patient_id	Removed because it is not predictive
Missing value handling	Median and mode imputation	Median for numerical features and mode for categorical features
Categorical encoding	One-Hot Encoding	Applied to sex, smoking status, st_slope, recording_lead, and measurement_site
Numerical scaling	Not mandatory for tree-based models / optional StandardScaler	Tree-based models can handle numerical scale differences
Data split	Stratified split	70% training, 15% validation, 15% testing
Imbalance consideration	Macro F1, macro recall, MCC	Used to avoid majority-class-biased evaluation

Data Splitting

The dataset is divided into three subsets: training, validation, and testing. Training data are used to train the model, validation data are used to monitor and evaluate model performance during the experiment, and testing data are used to evaluate the final model performance on unseen data. The data are split using a proportion of 70% training**,** 15% validation, and 15% testing . A stratified split technique is applied to ensure that the class distribution in each subset remains consistent with the original dataset distribution.

Model Training

The model training stage is performed using four ensemble learning algorithms: Random Forest**,** XGBoost**,** LightGBM, and CatBoost As presented in Table 6. Each model is trained on all feature scenarios and both classification target scenarios. Random Forest is used as a bagging-based ensemble model. XGBoost, LightGBM, and CatBoost [24] are used as gradient boosting models with strong capabilities in handling tabular data and non-linear patterns.

Table 6. Models used in the study

No	Model	Model Type	Characteristics
1	Random Forest	Bagging ensemble	Combines multiple decision trees to improve prediction stability
2	XGBoost	Gradient boosting	Includes regularization and performs strongly on tabular data
3	LightGBM	Gradient boosting	Efficient and fast for training data with many features
4	CatBoost	Gradient boosting	Effective in handling categorical features and reducing overfitting [25]

Hyperparameter tuning was not the main focus of this study As presented in Table 7. Therefore, all models were trained using fixed baseline hyperparameter settings to ensure a fair comparison across feature scenarios. Future work may include systematic hyperparameter optimization using grid search, random search, Bayesian optimization, or metaheuristic algorithms.

Table 7. Hyperparameter tuning

Model	Main Hyperparameters
Random Forest	n_estimators=300, class_weight=balanced, random_state=42
XGBoost	n_estimators=300, learning_rate=0.05, max_depth=5, subsample=0.9, colsample_bytree=0.9
LightGBM	n_estimators=300, learning_rate=0.05, num_leaves=31, class_weight=balanced
CatBoost	iterations=300, learning_rate=0.05, depth=6, loss_function=Logloss/MultiClass

Model Evaluation

Model evaluation is conducted to measure the performance of each algorithm under each feature scenario. Several evaluation metrics are used so that model performance can be analyzed comprehensively, especially because the dataset has an imbalanced class distribution. Accuracy is used to measure the overall number of correct predictions. Precision is used to measure the correctness of positive predictions. Recall is used to measure the model's ability to identify a specific class. F1-score is used to balance precision and recall. Macro F1-score is used as the main metric because it treats all classes equally regardless of the number of samples in each class.

3. Results and Discussion

Dataset and Experimental Setup

This study used a multimodal cardiac health dataset containing 5,000 patient records and 50 columns, including clinical data, ECG features, PPG features, and MI labels. As shown in Table 8, two classification scenarios were applied: binary classification using mi_label for Normal vs MI, and multi-class classification using mi_subtype for Normal, NSTEMI, STEMI, and Old MI. The dataset was imbalanced, with Normal as the dominant class. In the binary scenario, Normal represented 81.52% and MI 18.48% of the data. In the multi-class scenario, Normal accounted for 81.52%, followed by NSTEMI 8.44%, STEMI 6.30%, and Old MI 3.74%. The data were split using a stratified approach into 70% training, 15% validation, and 15% testing. Five feature scenarios were evaluated using Random Forest, XGBoost, LightGBM, and CatBoost: Clinical-only, ECG-only, PPG-only, ECG + PPG, and ECG + PPG + Clinical.

Table 8. Feature scenarios used in the study

Scenario	Number of Features	Description
Clinical-only	8	Demographic and clinical risk factor features
ECG-only	22	ECG morphology and HRV features
PPG-only	17	Hemodynamic and vascular features from PPG
ECG + PPG	39	Combination of ECG and PPG features
ECG + PPG + Clinical	47	Combination of all multimodal features

Binary Classification Results: MI vs Normal

The binary classification results show that ECG and multimodal features achieved very high performance in distinguishing Normal and MI patients, as presented in Table 8. The Clinical-only scenario produced the lowest performance, with CatBoost achieving an accuracy of 0.7227, macro F1-score of 0.6170, and MCC of 0.2568, indicating that clinical risk factors alone were less discriminative for MI detection. In contrast, the ECG-only scenario achieved the strongest result, where XGBoost obtained accuracy, macro F1-score, and MCC of 1.0000. However, this perfect performance should be interpreted cautiously. To minimize data leakage, mi_label, mi_subtype, and patient_id were excluded from the feature set before training. Nevertheless, ECG-derived features such as ST elevation, ST depression, T-wave inversion, and pathological Q-wave are strong clinical indicators of MI and may create highly separable class boundaries. Therefore, the binary classification results should be considered preliminary and require further validation using cross-validation, external datasets, or independent clinical cohorts.

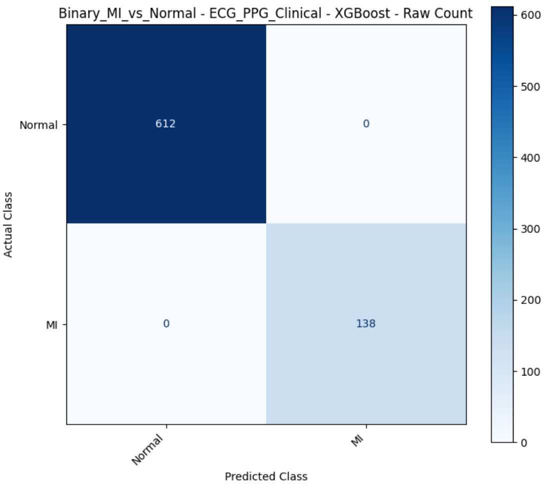

Figure 2. Confusion matrix binary classification

The PPG-only scenario also performed well, with LightGBM achieving an accuracy of 0.9853, macro F1-score of 0.9754, and MCC of 0.9508, indicating that PPG features provide useful vascular and hemodynamic information. Furthermore, the ECG + PPG and ECG + PPG + Clinical scenarios achieved perfect performance using XGBoost, LightGBM, and CatBoost. Overall, ECG features were the most dominant modality for binary MI classification, while PPG and clinical features served as complementary information.

Table 9. Best models in each binary classification scenario

Scenario	Best Model	Accuracy	Macro F1	Macro Recall	MCC
Clinical-only	CatBoost	0.7227	0.6170	0.6505	0.2568
ECG-only	XGBoost	1.0000	1.0000	1.0000	1.0000

PPG-only	LightGBM	0.9853	0.9754	0.9714	0.9508
ECG + PPG	XGBoost / LightGBM / CatBoost	1.0000	1.0000	1.0000	1.0000
ECG + PPG + Clinical	XGBoost / LightGBM / CatBoost	1.0000	1.0000	1.0000	1.0000

Based on these results, ECG features can be considered the strongest modality for binary MI classification. PPG features also produced high performance, although slightly lower than ECG features. Meanwhile, clinical features alone were not optimal, with the best macro F1-score reaching only 0.6170.

Multi-Class Classification Results: Normal, STEMI, NSTEMI, and Old MI

Unlike binary classification, the multi-class classification task was more challenging due to the larger number of classes and the highly imbalanced distribution of Old MI, STEMI, and NSTEMI cases, as presented in Table 10. The Clinical-only scenario produced the weakest performance, with XGBoost achieving the best macro F1-score of only 0.2592, indicating that clinical features alone were not sufficient to distinguish MI subtypes. Performance improved substantially when ECG features were used. In the ECG-only scenario, XGBoost achieved an accuracy of 0.8840, macro F1-score of 0.5054, and MCC of 0.6403, showing that ECG features provide strong information for subtype classification. The PPG-only scenario also contributed relevant vascular and hemodynamic information, with XGBoost achieving a macro F1-score of 0.4644. The best overall result was obtained by CatBoost in the ECG + PPG + Clinical scenario, achieving an accuracy of 0.9000, macro F1-score of 0.5394, MCC of 0.6912, ROC-AUC of 0.9516, and PR-AUC of 0.5038.

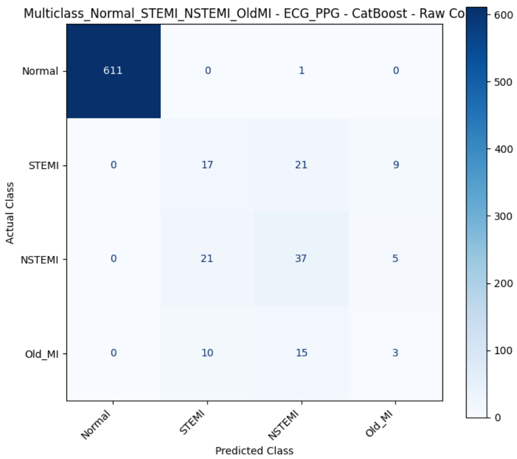

Figure 3. Confusion matrix multi-class classification

Table 10. Best models in each multi-class classification scenario

Scenario	Best Model	Accuracy	Macro Precision	Macro Recall	Macro F1	MCC
Clinical-only	XGBoost	0.5667	0.2694	0.2760	0.2592	0.0784
ECG-only	XGBoost	0.8840	0.5070	0.5051	0.5054	0.6403
PPG-only	XGBoost	0.8707	0.4646	0.4650	0.4644	0.5977
ECG + PPG	CatBoost	0.8920	0.4964	0.5085	0.4960	0.6666
ECG + PPG + Clinical	CatBoost	0.9000	0.5545	0.5468	0.5394	0.6912

Comparison Between Machine Learning Models

Overall, the four ensemble learning models showed different performance patterns, as presented in Table 11. In binary classification, XGBoost, LightGBM, and CatBoost achieved the highest performance in the ECG-only and fusion scenarios, while Random Forest also performed well but was slightly lower than the boosting-based models. For multi-class classification, CatBoost produced the best result in the full fusion scenario, with a macro F1-score of 0.5394 and MCC of 0.6912. This indicates that CatBoost was effective in utilizing combined numerical and categorical features from ECG, PPG, and clinical data. XGBoost also showed strong performance, particularly in the ECG-only and PPG-only scenarios, with macro F1-scores of 0.5054 and 0.4644, respectively. Meanwhile, LightGBM performed competitively, especially in binary classification and the PPG-only scenario, where it achieved a macro F1-score of 0.9754. However, its multi-class performance was generally lower than CatBoost and XGBoost. Random Forest tended to produce lower macro F1-score values, particularly in Clinical-only and multi-class scenarios, indicating limited ability to recognize minority classes despite achieving relatively high accuracy.

Table 11. Best models based on classification task

Task	Best Model	Feature Scenario	Accuracy	Macro F1	MCC
Binary MI vs Normal	XGBoost	ECG-only	1.0000	1.0000	1.0000
Multi-class MI Subtype	CatBoost	ECG + PPG + Clinical	0.9000	0.5394	0.6912

Discussion

Overall, the results show that ECG features are the most dominant modality in Myocardial Infarction classification. In binary classification, ECG-only features with XGBoost produced perfect performance. In multi-class classification, ECG-only features also produced strong performance, with a macro F1-score of 0.5054. This indicates that ECG features are strongly related to MI characteristics.

PPG features also proved to have an important contribution. Although their performance was lower than ECG-only, PPG-only still achieved a macro F1-score of 0.9754 in binary classification and 0.4644 in multi-class classification. These results show that PPG features can be used as a supporting modality in MI classification systems.

Clinical features alone produced the lowest performance. However, when combined with ECG and PPG, clinical features improved multi-class classification performance. This indicates that clinical risk factors such as age, diabetes, hypertension, cholesterol, BMI, and family history of CAD are more useful as complementary features rather than as primary features.

From the algorithmic perspective, boosting models such as XGBoost, LightGBM, and CatBoost generally outperformed Random Forest. CatBoost achieved the best performance in full fusion for multi-class classification, while XGBoost was very strong in ECG-only and binary classification scenarios. These results indicate that gradient boosting algorithms are more effective in capturing complex patterns in multimodal tabular data.

4. Conclusions

This study compared multimodal ECG, PPG, and clinical feature fusion for MI classification using Random Forest, XGBoost, LightGBM, and CatBoost. Two classification tasks were evaluated: binary classification for Normal vs MI and multi-class classification for Normal, STEMI, NSTEMI, and Old MI. Five feature scenarios were tested, including Clinical-only, ECG-only, PPG-only, ECG + PPG, and ECG + PPG + Clinical.

The results indicate that ECG features provided the strongest contribution to MI classification in the evaluated dataset. In binary classification, XGBoost with ECG-only features achieved the highest performance, with accuracy, macro F1-score, macro recall, and MCC of 1.0000 on the current test split. Similar results were obtained in the ECG + PPG and ECG + PPG + Clinical scenarios. However, these perfect results should be interpreted cautiously and require further validation to rule out data leakage, feature-label dependency, or overly separable dataset characteristics. PPG features also showed promising performance, particularly in the PPG-only scenario, where LightGBM achieved an accuracy of 0.9853, macro F1-score of 0.9754, and MCC of 0.9508. In contrast, clinical features alone produced lower performance, indicating that clinical risk factors were less effective when used independently.

For multi-class classification, the best result was achieved by CatBoost using ECG + PPG + Clinical features, with an accuracy of 0.9000, macro F1-score of 0.5394, MCC of 0.6912, ROC-AUC of 0.9516, and PR-AUC of 0.5038. This suggests that multimodal fusion may improve MI subtype classification, although minority class recognition remains challenging.

Overall, ECG appeared to be the primary modality for MI classification, while PPG and clinical features served as complementary information, especially for MI subtype classification. Future studies should apply cross-validation, external validation, imbalance handling techniques, and explainable AI methods such as SHAP to improve robustness, minority class performance, and interpretability.

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