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A Hybrid ECG-PPG Fusion Model for Cardiac Arrhythmia Detection.

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***Abstract*—Cardiac arrthymia is a major healthcare concern that requires continuous monitoring and timely diagnosis. Multi-modal physiological signal analysis has emerged as a promising approach to enhance diagnostic reliability by leveraging complementary information from electrocardiogram (ECG) and photoplethysmogram (PPG) signals. This study presents a hybrid framework for early arrhythmia prediction through ECG–PPG signal fusion integrated with machine learning and deep learning techniques. Raw signals are acquired in WFDB format and undergo preprocessing, including synchronization, normalization, and fixed-length standardization. Statistical feature selection using ANOVA-based SelectKBest is employed to extract discriminative features, followed by multi-modal feature fusion to construct an optimized input space. The classification stage utilizes Gaussian Naïve Bayes, XGBoost, Deep Neural Networks (DNN), and RNN-LSTM models, while regression analysis incorporates Bayesian Ridge, Random Forest Regressor, and XGBoost Regressor for heart rate estimation. Data imbalance is addressed using SMOTE, and performance is evaluated using standard classification and regression metrics. Experimental results demonstrate that the XGBoost classifier achieves superior performance with 99.2% accuracy and 99.8% AUC, while the XGBoost regressor attains an R^2 score of 96.6% with minimal error rates. A Flask-based web application is developed to enable real-time inference, automated preprocessing, and clinical report generation through a secure user interface.**

Keywords— ECG, PPG, arrhythmia prediction, feature fusion, XGBoost, deep learning, heart rate estimation, Flask web application.

I. INTRODUCTION

Cardiovascular diseases remain one of the leading causes of mortality worldwide, with arrhythmia representing a critical condition that requires timely detection and monitoring. The increasing prevalence of cardiac disorders has created a demand for intelligent and automated systems capable of analyzing physiological signals efficiently and accurately. Advances in artificial intelligence have significantly contributed to improving diagnostic capabilities by enabling the extraction of meaningful patterns from complex biomedical data [1]. The integration of intelligent prediction models has further enhanced the ability to identify cardiac abnormalities at early stages, supporting improved clinical outcomes and patient care [2].

Electrocardiogram and photoplethysmogram signals are widely utilized for monitoring cardiac activity due to their non-invasive nature and accessibility. ECG provides detailed electrical activity of the heart, while PPG reflects blood volume changes, offering complementary physiological information. However, challenges such as noise interference, signal variability, and large data volumes make manual interpretation difficult and less reliable [3]. Recent developments in deep learning and signal processing techniques have enabled automated extraction of features and improved classification of cardiac conditions, reducing dependence on manual analysis [4]. Additionally, advancements in biomedical research have emphasized the importance of integrating multiple physiological signals to enhance diagnostic accuracy and reliability [5].

Artificial intelligence-based techniques have been increasingly applied to analyze ECG signals for detecting cardiac abnormalities, providing improved performance over traditional approaches [6]. The growing significance of early disease detection highlights the need for scalable and efficient systems capable of continuous monitoring [7]. Hybrid approaches that combine multiple data sources and intelligent models have demonstrated improved capability in capturing complex physiological patterns [8]. The use of multi-model fusion and advanced computational methods further strengthens the ability to process high-dimensional data and improve predictive performance [9]. Furthermore, the adoption of modern analytical techniques continues to address challenges related to feature extraction, classification, and real-time monitoring [10]. Signal processing combined with intelligent classification methods has shown promising results in identifying arrhythmia patterns from physiological data [11].

This work focuses on developing an integrated system that processes ECG and PPG signals for signal quality assessment and heart rate estimation. The objective is to design an

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efficient framework that performs automated signal handling, preprocessing, feature representation, and analysis, while enabling real-time interaction through a web-based interface to support accurate and reliable cardiac monitoring.

II. Related Work

Recent advancements in arrhythmia detection have focused on leveraging intelligent techniques to improve the analysis of physiological signals, particularly electrocardiogram data. X. Chen, J. Chen, et.al., proposed a method based on multi-feature extraction combined with convolutional neural networks to enhance detection performance. Their approach emphasizes automated feature learning from ECG signals, enabling improved identification of atrial fibrillation patterns through deep representation learning [12]. Similarly, N. Arora, B. Mishra, et.al., provided a comprehensive review of the evolution of ECG analysis, highlighting the transition from traditional signal processing techniques to modern automated approaches that improve efficiency and accuracy in cardiac monitoring [13].

Further developments include domain adaptation techniques for improving model generalization across different patient data. G. Wang, M. Chen, et.al., introduced an unsupervised domain adaptation method for inter-patient arrhythmia classification, addressing variability in ECG signals and enhancing robustness in diverse clinical conditions [14]. In another approach, S. Mandal, P. Mondal, et.al., explored the use of heart rate variability and ECG beat images for detecting ventricular arrhythmia, demonstrating the importance of combining temporal and morphological features for improved classification [15].

Advanced classification methods have also been proposed for handling long-term ECG recordings. Y. Li, Z. Zhang, et.al., presented a multi-label classification framework that incorporates feature learning techniques to detect multiple arrhythmia types simultaneously, improving the capability of handling complex cardiac conditions [16]. Similarly, Y. Lu, X. Li, et.al., developed a depthwise separable convolutional neural network with focal loss to enhance classification accuracy, particularly in imbalanced datasets, by focusing on difficult-to-classify samples [17].

Ensemble learning methods have also shown promising results in arrhythmia detection. P. Yang, D. Wang, et.al., proposed an ensemble approach combining kernel extreme learning machines with random forest classifiers to improve classification performance and stability. Their method effectively integrates multiple learning strategies to capture diverse patterns in ECG signals [18]. Additionally, A. García-Escobar, S. Vera-Vera, et.al., investigated subtle variations in ECG signals and their association with cardiac dysfunction, highlighting the role of artificial intelligence in identifying clinically significant patterns that may not be easily detectable through conventional analysis [19].

Recent research has also emphasized the integration of multiple physiological signals to enhance detection accuracy. C. Rathnayake, W. Chen, et.al., explored multimodal wearable technologies combining ECG and PPG signals, demonstrating the potential of signal fusion techniques in improving arrhythmia detection and continuous monitoring capabilities [20]. Similarly, D. D. Gupta, A. Singhal, et.al., introduced a multi-modal deep learning framework that leverages both ECG and PPG data, showcasing the effectiveness of combining multiple signal sources for improved classification performance [21].

Feature fusion techniques have further advanced the field by enabling efficient handling of high-dimensional data. J. Cui, L. Wang, et.al., proposed a deep learning-based multidimensional feature fusion approach that enhances classification accuracy by integrating diverse feature representations. Their work highlights the importance of combining multiple feature types to capture comprehensive information from physiological signals [22]. These studies collectively demonstrate significant progress in arrhythmia detection through the use of intelligent models, multi-modal data integration, and advanced feature learning techniques.

III. Materials And Methods

An integrated framework is introduced for early arrhythmia prediction by combining ECG and PPG signal analysis with hybrid machine learning and deep learning techniques. The system begins with acquisition of physiological signals, followed by preprocessing operations including synchronization, normalization, and fixed-length standardization to ensure uniformity and consistency in data representation. Feature extraction is performed to obtain meaningful characteristics, and statistical feature selection is applied to retain the most relevant attributes. Multi-modal feature fusion is then carried out to combine ECG and PPG features into a single optimized representation, enabling comprehensive analysis of physiological patterns. The classification stage incorporates Gaussian Naïve Bayes, XGBoost Classifier, Deep Neural Network, and RNN-LSTM to evaluate signal quality and capture complex relationships within the data. For continuous estimation, regression models such as Bayesian Ridge, Random Forest Regressor, and XGBoost Regressor are utilized to predict heart rate values accurately. Data balancing techniques are included to handle class imbalance and improve generalization. The system is further supported by a Flask-based web application for secure interaction, automated processing, and real-time output generation [23] [24] [25].

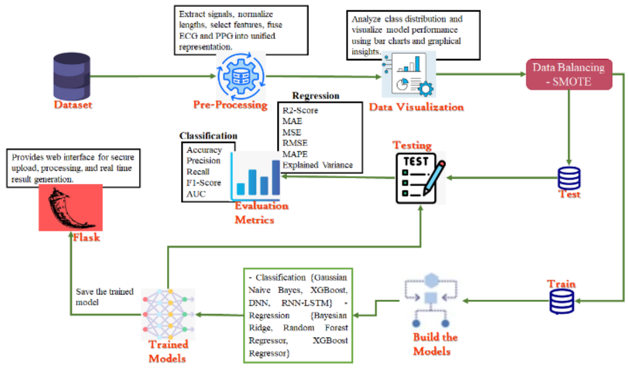

Fig.1 System Architecture

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The proposed framework, illustrated in Fig. 1, presents an end-to-end machine learning pipeline for ECG and PPG signal analysis. It integrates rigorous pre-processing and SMOTE-based data balancing before transitioning to model building for classification and regression tasks. Finally, the trained models are evaluated using comprehensive metrics and deployed via a Flask web interface to ensure secure, real-time result generation.

A) Dataset Collection:

Dataset collection involves gathering physiological signal data required for analyzing ECG and PPG signals for quality assessment and heart rate estimation. The data consists of raw signal recordings stored in standardized formats such as WFDB, along with corresponding metadata stored in structured files like CSV. Each record includes synchronized ECG and PPG signals associated with individual subjects, ensuring proper mapping between signal data and their respective labels such as signal quality and heart rate values.

The dataset used in training and evaluating of the cardiac Arrythmia system consisted of a total of 3,888 synchronized recordings of PPG and ECG signals. Each recording has a fixed duration of 10 seconds which is suitable for segment level analysis. The PPG signals acquired using smartphone cameras (Xiaomi Mi9 and Huawei p20 pro). The ECG signal recorded using medical grade wearable devices (Bittium Faros 360/180).

The signals are sampled at different frequencies, PPG at 30HZ and ECG at 1000HZ.All signals are provided in the Wave Form Database (WFDB) format, where each modality is stored in separate files. Each recording is associated with annotations stored in CSV file, which contains patient ID, Signal quality label and Heart rate (HR). The median 10-second segment computed and considered the ground truth.

Special attention is given to maintaining data integrity by verifying signal completeness, removing corrupted entries, and ensuring proper alignment between ECG and PPG recordings. The dataset is structured to support efficient retrieval and processing, enabling seamless integration into subsequent stages such as preprocessing, feature extraction, and model training. By organizing and managing the data effectively, the collection phase establishes a strong foundation for accurate analysis, ensuring that the system can learn meaningful patterns and deliver reliable outputs in real-time cardiac monitoring applications.

B) Pre-Processing:

Pre-processing plays a crucial role in preparing raw ECG and PPG signals for effective analysis. It involves transforming unstructured and inconsistent data into a standardized and usable format. By ensuring signal quality, uniformity, and relevance, this stage enhances the reliability of subsequent processing steps and supports accurate classification and estimation of physiological parameters.

a) Data Processing: Data processing involves transforming raw ECG and PPG signals into a structured format suitable for analysis. Initially, signal extraction is performed to obtain the primary ECG and PPG channels from raw recordings. These signals are then mapped with corresponding ground-truth labels to ensure proper alignment between input data and expected outputs. Synchronization is carried out to maintain temporal consistency across both signal types, which is essential for accurate multi-modal analysis.

Following extraction, uniform data normalization is applied to standardize signal lengths. Since raw signals may vary in duration, techniques such as zero-padding and truncation are used to convert all signals into fixed lengths. This ensures consistency and enables efficient batch processing during model training. Standardization also helps in reducing variability caused by inconsistent recording durations.

Next, statistical feature selection is performed to identify the most relevant features from the extracted signals. This step reduces dimensionality and eliminates redundant or less informative data, improving computational efficiency and model performance. Finally, multi-modal feature fusion is carried out by combining selected ECG and PPG features into a single unified representation. This fusion enhances the richness of information and enables comprehensive analysis by leveraging complementary characteristics from both signal types.

b) Data Visualization: Data visualization is an essential step for understanding the characteristics and distribution of the dataset. It provides graphical representations that help in identifying patterns, trends, and potential issues within the data. Initially, class distribution is analyzed to determine the balance between different categories, such as signal quality labels. This helps in identifying whether the dataset is skewed or evenly distributed, which is important for model performance.

Visual tools such as bar charts are used to represent the number of samples in each class, providing a clear overview of data distribution. These visualizations enable quick identification of class imbalance and assist in making informed decisions regarding data balancing techniques. Additionally, visualization helps in examining the variation and spread of data, which is crucial for understanding the complexity of physiological signals.

During evaluation, graphical representations are used to compare the performance of different models. Metrics are plotted using bar charts to visually assess how each model performs across various evaluation criteria. This comparative visualization aids in selecting the most suitable model for the task. Overall, data visualization enhances interpretability, supports better decision-making, and ensures a deeper understanding of both data characteristics and model performance.

c) Data Balancing: Data balancing is an important step in ensuring that the dataset does not favor one class over another. In many real-world scenarios, datasets are imbalanced, meaning that one class has significantly more

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samples than others. This imbalance can lead to biased models that perform well on the majority class but poorly on minority classes. To address this issue, data balancing techniques are applied to create a more uniform distribution.

Synthetic data generation methods are used to increase the number of samples in underrepresented classes. These techniques generate new data points based on existing samples, helping to improve representation without duplicating data. By balancing the dataset, the model is encouraged to learn patterns from all classes equally, leading to more reliable and unbiased predictions.

Balanced data also improves the generalization capability of the model, allowing it to perform well on unseen data. It reduces the risk of overfitting to dominant classes and ensures fair evaluation across all categories. This step is particularly important in classification tasks, where accurate identification of all classes is critical. Overall, data balancing enhances model robustness and contributes to improved predictive performance.

d) Train & Test: Splitting the dataset into training and testing sets is a fundamental step in building a reliable analytical system. The dataset is divided into two parts, typically using an eighty to twenty ratio, where the larger portion is used for training and the smaller portion is reserved for testing. The training set is used to learn patterns, relationships, and representations from the data, enabling the model to understand underlying structures.

The testing set is used to evaluate how well the model performs on unseen data. This helps in assessing the generalization capability of the system and ensures that the model is not simply memorizing the training data. By keeping the testing data separate, a realistic evaluation of performance is achieved.

Proper splitting also helps in detecting issues such as overfitting and underfitting. If a model performs well on training data but poorly on testing data, it indicates overfitting. Conversely, poor performance on both sets suggests underfitting. This process ensures that the system maintains a balance between learning and generalization. Overall, train and test splitting is essential for validating the effectiveness and reliability of the analytical framework.

C) Algorithms:

Gaussian Naïve Bayes: Gaussian Naïve Bayes is a probabilistic classification method based on Bayes' theorem, assuming independence among features and normal distribution. It computes posterior probabilities using mean and variance of input data. In ECG and PPG analysis, it classifies signal quality efficiently from extracted features. It performs well on high-dimensional datasets, offering fast computation, simplicity, and stable results, making it suitable for quick and effective physiological signal classification tasks.

XGBoost Classifier: XGBoost Classifier is an ensemble learning technique based on gradient boosting, where decision trees are built sequentially to minimize errors. It incorporates regularization, parallel processing, and optimized learning strategies. In ECG and PPG signal classification, it analyzes fused features to distinguish signal quality accurately. It handles large datasets, captures complex patterns, manages missing values, and improves performance iteratively, making it highly effective for robust biomedical signal classification.

Deep Neural Network (DNN): Deep Neural Network is a multi-layer neural model consisting of input, hidden, and output layers that learn hierarchical feature representations. It uses nonlinear activation functions to model complex relationships in data. In ECG and PPG signal analysis, it learns patterns from fused features to classify signal quality. Its layered structure captures intricate dependencies, making it suitable for high-dimensional data, though it requires sufficient training data and computational resources.

RNN-LSTM: Recurrent Neural Network with Long Short-Term Memory is designed for sequential data by maintaining memory of previous inputs. LSTM units use gates to control information flow and capture long-term dependencies. In ECG and PPG analysis, it processes time-series signals to identify temporal patterns. It effectively models signal variations over time, improving understanding of sequential relationships and enabling accurate classification in physiological signal-based sequence analysis tasks.

Bayesian Ridge Regression: Bayesian Ridge Regression is a linear regression approach that applies Bayesian inference to estimate parameters using prior distributions. It updates coefficients based on observed data, producing probabilistic predictions. In ECG and PPG analysis, it estimates heart rate values from features. It handles multicollinearity, reduces overfitting through regularization, and provides uncertainty estimation, making it suitable for stable and interpretable continuous value prediction in physiological signal processing.

Random Forest Regressor: Random Forest Regressor is an ensemble method that builds multiple decision trees using random subsets of data and features. It combines their outputs to generate accurate predictions. In ECG and PPG analysis, it estimates heart rate by capturing nonlinear relationships. It is robust to noise, handles high-dimensional data, and improves stability through averaging, while also providing insights into feature importance for better understanding of influencing variables.

XGBoost Regressor: XGBoost Regressor is a gradient boosting-based regression technique that builds decision trees sequentially to minimize residual errors. It uses regularization and optimized computation to improve accuracy. In ECG and PPG analysis, it predicts heart rate by learning complex feature relationships. It handles large datasets, missing values, and enhances performance iteratively, making it a powerful and scalable solution for precise continuous value prediction tasks.

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IV. Experimental Results

Classification performance was evaluated using Accuracy, Precision, Recall, F1_Score and AUC metrics, while regression performance was measured using R2 Score, MAE, RMSE and MAPE

Accuracy:

$$Accuracy = \frac{\mathrm{TP} + \mathrm{TN}}{\mathrm{TP} + \mathrm{FP} + \mathrm{TN} + \mathrm{FN}} \quad (1)$$

Precision:

$$Precision = \frac{\text{True Positive}}{\text{True Positive } + \text{False Positive}} \quad (2)$$

Recall:

$$Recall = \frac{\mathrm{TP}}{\mathrm{TP} + \mathrm{FN}} \quad (3)$$

F1Score:

$$F1\ Score = 2 * \frac{Recall\ \mathrm{X}\ Precision}{Recall + Precision} * 100(1)$$

AUC-ROC Curve:

$$AUC = \sum_{i=1}^{n-1} (FPR_{i+1} - FPR_i) \cdot \frac{TPR_{i+1} + TPR_i}{2} \quad (5)$$

R2 Score:

$$R^2 = 1 - \frac{\sum_{i=1}^{n} (\hat{y}_i - y_i)^2}{\sum_{i=1}^{n} (y_i - \bar{y}_i)^2} \quad (6)$$

MSE:

$$MSE = \frac{1}{n} \sum_{i=1}^{n} (Y_i - \hat{Y}_i)^2 \quad (7)$$

RMSE:

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n} ||y(i) - \hat{y}(i)||^2}{N}} \quad (8)$$

MAE:

$$MAE = \frac{1}{n} \sum_{i=1}^{n} |y_i - \hat{y}_i| \quad (9)$$

MAPE:

$$MAPE = \frac{1}{n} \sum_{i=1}^{n} \left| \frac{A_i - P_i}{A_i} \right| \times 100 \quad (10)$$

Table.1 Performance Evaluation – Classification

Model	**Accuracy**	**Precision**	**Recall**	**F1 Score**	**AUC**
GaussianNB	0.617	0.642	0.617	0.599	0.628
XGBoost	**0.992**	**0.992**	**0.992**	**0.992**	**0.998**
DNN	0.571	0.628	0.571	0.517	0.621
RNN-LSTM	0.668	0.687	0.668	0.660	0.716

Table.1 shows classification performance comparison across models using accuracy, precision, recall, F1, AUC

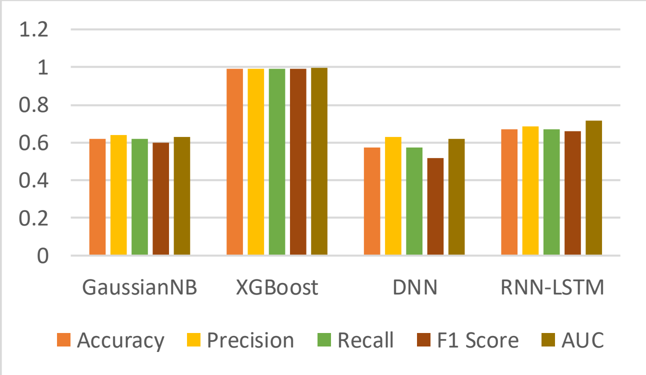

Fig.2 Comparison Graph – Classification

Fig. 2 compares the classification performance of GaussianNB, XGBoost, DNN, and RNN-LSTM across five key metrics.

Table.2 Performance Evaluation – Regression

Model	**R2 Score**	**MAE**	**MSE**	**RMSE**	**MAPE**	**Explained Variance**
Bayesian Ridge	0.017	10.244	191.529	13.839	0.130	0.019
Random Forest	0.882	3.519	23.063	4.802	0.045	0.882
XGBoost	**0.966**	**1.331**	**6.691**	**2.587**	**0.017**	**0.966**

Table.2 shows regression performance comparison across models using R2, MAE, MSE, RMSE, MAPE metrics

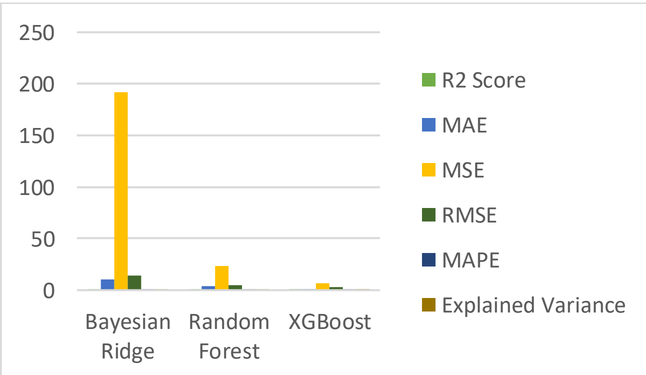

Fig.3 Comparison Graph – Regression

Fig. 3 illustrates regression performance metrics for Bayesian Ridge, Random Forest, and XGBoost machine learning models.

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V. CONCLUSION

Accurate early detection of arrhythmia is achieved through effective fusion of ECG and PPG signals combined with hybrid learning techniques. The integration of statistical feature selection and multi-modal fusion significantly enhances discriminative capability, enabling reliable signal quality assessment and heart rate estimation. Among the evaluated models, the XGBoost classifier demonstrates superior performance with 99.2% accuracy and 99.8% AUC, indicating highly robust classification capability. For regression tasks, the XGBoost regressor achieves the best performance with an R^2 score of 96.6% and minimal error values, confirming its effectiveness in precise heart rate prediction. The incorporation of SMOTE improves class balance, contributing to stable and unbiased model performance. Deep learning models such as DNN and RNN-LSTM provide additional insights into temporal dependencies, though ensemble-based methods outperform them in this context. The end-to-end pipeline ensures efficient preprocessing, feature optimization, and model inference, making the system suitable for real-time applications. A Flask-based web application further enhances practical usability by providing a secure interface for data upload, automated analysis, and instant clinical report generation. The overall framework demonstrates strong potential for deployment in healthcare environments, supporting clinicians with accurate, fast, and scalable decision-making tools for cardiac monitoring and diagnosis.

Future advancements can focus on integrating additional physiological signals such as blood pressure, respiration rate, and oxygen saturation to enable more comprehensive cardiovascular assessment. Incorporating advanced deep learning architectures like Transformers and attention-based models may further improve temporal feature extraction and long-range dependency modeling. Real-time wearable device integration can enhance continuous monitoring and enable proactive healthcare interventions. Expanding datasets with diverse populations and multi-center clinical data would improve generalizability and robustness. Federated learning approaches can be explored to ensure privacy-preserving model training across distributed healthcare systems. Furthermore, explainable AI techniques can be incorporated to provide interpretability, increasing clinical trust and adoption in critical decision-making environments.

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