iJRASET
International Journal For Research in
Applied Science and Engineering Technology

INTERNATIONAL JOURNAL FOR RESEARCH

IN APPLIED SCIENCE & ENGINEERING TECHNOLOGY

Volume: 14 **Issue:** VI **Month of publication:** June 2026

DOI: https://doi.org/10.22214/ijraset.2026.83499

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International Journal for Research in Applied Science & Engineering Technology (IJRASET)
ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.538
Volume 14 Issue V May 2026- Available at www.ijraset.com

Stacked Ensemble Model for Myocardial Infarction Prediction Using Sleep Data

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Abstract: Pre-emptive forecasting of myocardial infarction (MI) remains a clinical imperative; however, relying strictly on standard electrocardiogram (ECG) infrastructure limits prolonged, uninterrupted patient observation due to inherent logistical and financial constraints. To overcome these limitations, non-invasive sleep-derived physiological signals, such as heart rate and respiratory rate, offer a highly practical alternative for continuous risk stratification. However, applying machine learning to such medical data often encounters severe class imbalance. To address this, our pipeline leverages SMOTE for synthetic data generation, achieving class equilibrium while preserving all original baseline subject profiles. We propose a novel stacked ensemble framework that integrates five diverse base classifiers—Multilayer Perceptron, XGBoost, LightGBM, Random Forest, and Support Vector Machine (SVM) —whose outputs are unified by a Logistic Regression meta-learner to maximize predictive robustness. Evaluated on a refined 924-patient dataset, the proposed architecture achieved an exceptional accuracy of 95.68% and a high recall of 0.96 for MI cases, effectively minimizing critical false negatives. These findings demonstrate that combining synthetic sampling with a heterogeneous ensemble architecture provides a highly accurate, scalable, and cost-effective system for continuous early MI prediction using non-ECG sleep data.

Keywords: Myocardial Infarction, Stacked Ensemble Learning, SMOTE, Sleep Physiological Data, Non-ECG Monitoring, Predictive Healthcare.

I. INTRODUCTION

Myocardial infarction (MI) represents a severe cardiac emergency that consistently ranks among the top contributors to global death rates. A myocardial infarction takes place when a blockage in the coronary circulation prevents adequate oxygen delivery to a portion of the heart muscle. This lack of oxygen can damage or destroy heart tissue. Early identification of individuals at high risk of MI is essential for timely medical intervention, lifestyle modification, and the reduction of mortality rates. However, traditional predictive and diagnostic methods heavily depend on electrocardiogram (ECG) analysis and clinical hospital examinations. While ECG provides valuable electrical activity information, it presents significant limitations for early warning systems: it requires specialized medical equipment, is typically performed episodically in clinical settings, and has a limited ability to capture long-term physiological trends prior to an acute event. Recent advancements in wearable devices and sleep monitoring technologies have introduced a highly practical alternative. By enabling the continuous and non-invasive collection of physiological signals—specifically heart rate (HR) and respiratory rate (RR) dynamics—during sleep, long-term risk assessment becomes possible outside the hospital. Sleep offers a naturally controlled physiological state where external physical activity and emotional stress are minimized, allowing cardiovascular and respiratory baseline signals to be recorded with high consistency. Unlike short-term clinical measurements, sleep-based physiological monitoring captures extended biological behaviour under natural conditions, making it a highly cost-effective and scalable source for early MI risk assessment.

Despite the clinical potential of sleep-based data, existing machine learning applications in cardiovascular risk assessment face several technical bottlenecks. First, medical datasets inherently suffer from severe class imbalance, where minority MI cases are vastly underrepresented compared to healthy subjects. Traditional approaches often utilize destructive undersampling techniques to balance the data, which results in significant information loss by discarding valid majority-class samples. Furthermore, many existing predictive systems rely on single-model algorithms (such as standalone neural networks or decision trees). These single models often hit an accuracy ceiling, suffer from limited generalization on unseen data, and struggle to simultaneously capture the complex, non-linear correlations between respiratory and cardiac signals.

To get rid of these constraints, this study proposes a stacked ensemble framework for myocardial infarction prediction using non-ECG sleep data. The framework introduces a constructive data-balancing approach by utilizing the Synthetic Minority Oversampling Technique to synthesize minority class representation without discarding any healthy patient data. To maximize predictive robustness, the system integrates a heterogeneous stack of multiple base classifiers—including Multilayer Perceptron, XGBoost, LightGBM, Random Forest, and Support Vector Machine (SVM) —whose predictions are synthesized using a Logistic

Regression meta-learner. By capturing diverse physiological patterns and successfully achieving the accuracy of 95.68% and a recall of 0.96 on a refined dataset, this research demonstrates a highly accurate, scalable, and clinical-grade alternative to traditional ECG-dependent MI prediction.

II. RELATED WORK

Historical approaches to forecasting cardiac events have heavily documented the shift from rudimentary statistical evaluation toward sophisticated deep learning methodologies. However, the predominant share of these prior investigations remains fundamentally anchored to standard clinical electrocardiogram datasets to map and isolate myocardial damage. Recent efforts to enhance MI identification have incorporated attention-guided, optimized CNN architectures applied to standard clinical datasets like PTB-XL [1]. Similarly, Ma et al. [2] applied Convolutional Dendrite Nets for MI detection via ECG, and Xiong et al. [3] proposed a 2D vectorcardiogram (2D-VCG) tensor combined with a Depthwise Separable Convolutional Network (DSC-Net) to capture spatial cardiac electrical activity. Several other studies [4], [5], [6] have also explored various deep neural architectures to achieve highly accurate localization. While these models achieve impressive accuracy, they are fundamentally limited by their reliance on high-quality, clinical-grade ECG signals. Such approaches require specialized medical equipment and computationally intensive preprocessing, making them unsuitable for continuous, cost-effective, home-based patient monitoring.

Researchers are increasingly adopting ensemble learning and data-balancing approaches to address the prediction of cardiovascular illness using structured clinical information. A framework merging multiple distinct classifiers specifically XGBoost, Logistic Regression, KNN, and SVM was introduced by Tripathy et al. [7] for heart disease prognostication. Implementing both stacking and voting strategies, the authors verified that such ensemble configurations yield better results than single, isolated models. Various other clinical approaches, such as the work by Yilmaz et al. [8], have similarly utilized structured datasets and explainable artificial intelligence to predict acute events. However, to handle the severe class imbalance inherent in medical datasets, Abbas et al. [9] integrated the Synthetic Minority Oversampling Technique with deep neural networks for binary and multi-label MI classification. Similarly, Li et al. [10] applied SMOTE alongside XGBoost and LightGBM to predict acute MI mortality risk using the MIMIC-IV clinical database. While these studies successfully proved the efficacy of SMOTE and ensemble methods, they were applied exclusively to hospital-derived clinical or mortality datasets rather than non-invasive, continuous physiological monitoring.

Recognizing the limitations of episodic ECG and hospital-bound monitoring, recent studies have begun exploring non-ECG physiological signals collected during sleep. Li et al. [11], whose work forms the basis of the present research, predicted MI using non-ECG sleep-related information, with heart rate and respiratory features extracted from records available in the SHHS dataset. They evaluated standalone models including Multilayer Perceptron (MLP), SVM, and XGBoost, identifying the MLP as the best baseline performer with an accuracy of 71.1%, which modestly improved to 73.1% upon embedding age-based medical rules. While this work successfully validated the use of sleep-derived signals, it highlighted significant methodological gaps. To handle class imbalance, previous sleep-based studies relied on K-Means under sampling, a destructive technique that discards valuable majority-class information. Furthermore, performance was restricted by a reliance on single-model architectures. Therefore, a clear gap exists in the current literature: there is no framework that applies constructive synthetic sampling (SMOTE) combined with a heterogeneous stacked ensemble architecture specifically tailored to non-ECG sleep physiological data. The proposed system addresses this gap directly, engineering a robust pipeline to elevate non-invasive prediction to clinical-grade accuracy.

III. PROPOSED METHOD

This architecture aims to detect possible heart attack vulnerabilities early by using biosignals collected during sleep, independently of conventional medical systems. Leveraging resting patient states provides an optimal observation window, capturing consistent respiratory and cardiac baseline fluctuations without subjecting the individual to cumbersome clinical hardware. The proposed pipeline is built in seven stages: data loading, preprocessing, data splitting, class balancing, base model training, ensemble stacking, and explainability. The complete workflow is shown in Figure 1. The dataset first goes through preprocessing using median imputation and Z-score scaling. The data is then apart into two parts which are training and testing datasets, and class balancing is applied exclusively to the training data using SMOTE. Five diverse base classifiers are trained on this balanced data, and a Logistic Regression meta-learner is applied to combine them into a highly accurate Stacked Ensemble model. Finally, feature importance analysis is applied to explain the ensemble's predictions and identify the most critical clinical warning signs.

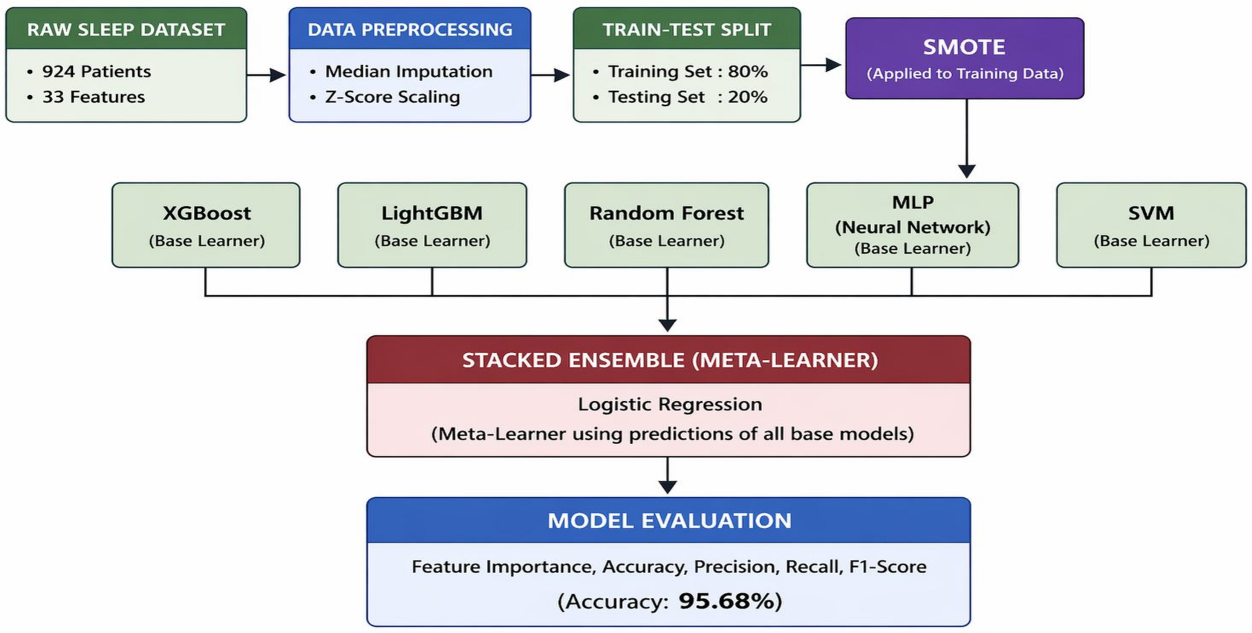

Figure 1. Working of Proposed System

A. *Data Preprocessing*

Before any learning can occur, the raw dataset containing 924 patient records and 33 physiological features must be cleaned and standardized. Rather than discarding incomplete subject profiles, hardware-corrupted sensor entries were mathematically repaired via median substitution. Subsequently, to neutralize the vast discrepancies in measurement scales—particularly between respiration cycles and cardiac rhythms—every continuous variable underwent Z-score standardization. This adjusts each feature to have a standardized distribution, ensuring the data is clean, uniformly scaled, and ready for further processing.

B. *Train/Test Split*

Once preprocessing is complete, we divide the dataset into training and testing subsets to develop the models and evaluate their performance. We use a strict 80/20 approach, dedicating 80% of the information to build the model while saving the other 20% as entirely unseen testing data. By securely isolating the test data *before* any balancing techniques are applied, we prevent data leakage and get a much more accurate picture of how the system will actually perform in real-world clinical scenarios.

C. *Class Imbalance Correction using SMOTE*

Medical datasets frequently suffer from an unequal distribution of class samples, and the MI sleep dataset is no exception. When a classifier is trained on data where one class dominates (healthy patients), it tends to favour the majority group and systematically miss cases belonging to the minority, which in this context means failing to detect actual MI events. To tackle this issue, the proposed framework employs SMOTE solely on the training data to improve class balance and enhance model performance. This algorithm mathematically synthesizes realistic minority-class profiles, transforming the imbalanced data into a perfectly balanced training environment of 473 healthy and 473 MI instances.

D. *Multi-Classifier Base Layer (Layer 1)*

To capture the complex, non-linear correlations between respiratory and cardiac signals, the balanced training data is fed into five well-established machine learning models acting as specialized feature extractors. Within this parallel layer, multiple distinct models are deployed simultaneously: LightGBM, XGBoost, MLP networks, Random Forest, and SVM. The purpose of this layer is not merely to pick one algorithm, but to utilize different algorithmic approaches—ranging from tree-based logic to neural networks—to analyse the specific physiological data characteristics from multiple mathematical angles.

E. Stacked Ensemble Meta-Learner (Layer 2)

Among all the classification strategies evaluated, relying on a single model often leaves gaps in decision boundary mapping. Therefore, the proposed system employs a Stacked Ensemble architecture. A Logistic Regression meta-learner is deployed as the final decision-making layer. This model processes the continuous probability outputs of the five base classifiers and dynamically learns to weight their predictions, minimizing individual algorithmic biases and maximizing overall diagnostic reliability.

F. Model Explainability

To complement the predictive capability of the Stacked Ensemble with a deeper layer of interpretability, Feature Importance analysis is incorporated into the evaluation process. This analysis assigns a contribution value to the input features, immediately revealing which physiological characteristics exert the greatest influence on the model's decisions. This level of detail allows clinicians and researchers to connect model behavior directly to known biomarkers of a cardiovascular event, fostering trust and supporting the practical adoption of the system in a clinical environment.

IV. RESULTS AND DISCUSSION

This study utilizes a sleep-derived physiological dataset comprising features from healthy individuals and patients susceptible to Myocardial Infarction (MI). Our experimental cohort consists of 924 distinct subject profiles, with each entry mapped across 33 numerical physiological variables (including nuanced respiratory and cardiac tracking metrics) alongside their definitive diagnostic category. A label of 0 denotes a healthy subject, while a label of 1 identifies an MI-positive case. Examining the initial distribution of these labels revealed a clear imbalance: healthy samples were significantly more numerous (591 cases) than disease samples (333 cases). This disproportion is a known obstacle in medical data analysis because models trained on such data tend to favor the majority group and overlook the minority, which in this case represents the very patients the system is meant to detect. By applying the proposed methodology step-by-step—including preprocessing, strict data splitting, SMOTE data balancing, and Stacked Ensemble training—highly reliable results were obtained. This structured approach helped improve the model's now have knowledge to learn meaningful physiological patterns from the data and produce accurate predictions.

A. Performance Assessment of Various Machine Learning Algorithms

To evaluate the proposed Stacked Ensemble against the five base models (SVM, MLP, Random Forest, LightGBM, and XGBoost), we benchmarked their performance using accuracy, precision, recall, and F1-score. In medical diagnostics, Recall is especially critical as it evaluate the model's metrics to accurately determine actual MI cases, minimizing false negatives. As shown in Table I, the proposed Stacked Ensemble system outclasses the individual base models in the overall evaluation area.

Model	Accuracy	Precision	Recall (MI)	F1-Score
MLP	85.95%	0.8154	0.7910	0.8030
SVM	85.41%	0.8226	0.7612	0.7907
Random Forest	92.97%	0.9091	0.8955	0.9023
LightGBM	95.68%	0.9403	0.9403	0.9403
XGBoost	95.68%	0.9275	0.9552	0.9412
Stacked Ensemble	95.68%	0.9275	0.9552	0.9412

Table 1. Outcome Analysis for All Models

B. Graphical Analysis of Model Performance

A comparative bar chart was utilized to visualize the success of each algorithm across all four primary metrics. This graphical representation confirms that the Stacked Ensemble model, alongside the leading base model (XGBoost), offers a significant improvement over baseline techniques like MLP and SVM. The similarity in the metric scores across the ensemble framework reflects its stable and dependable performance, ensuring strong precision and recall throughout the evaluation.

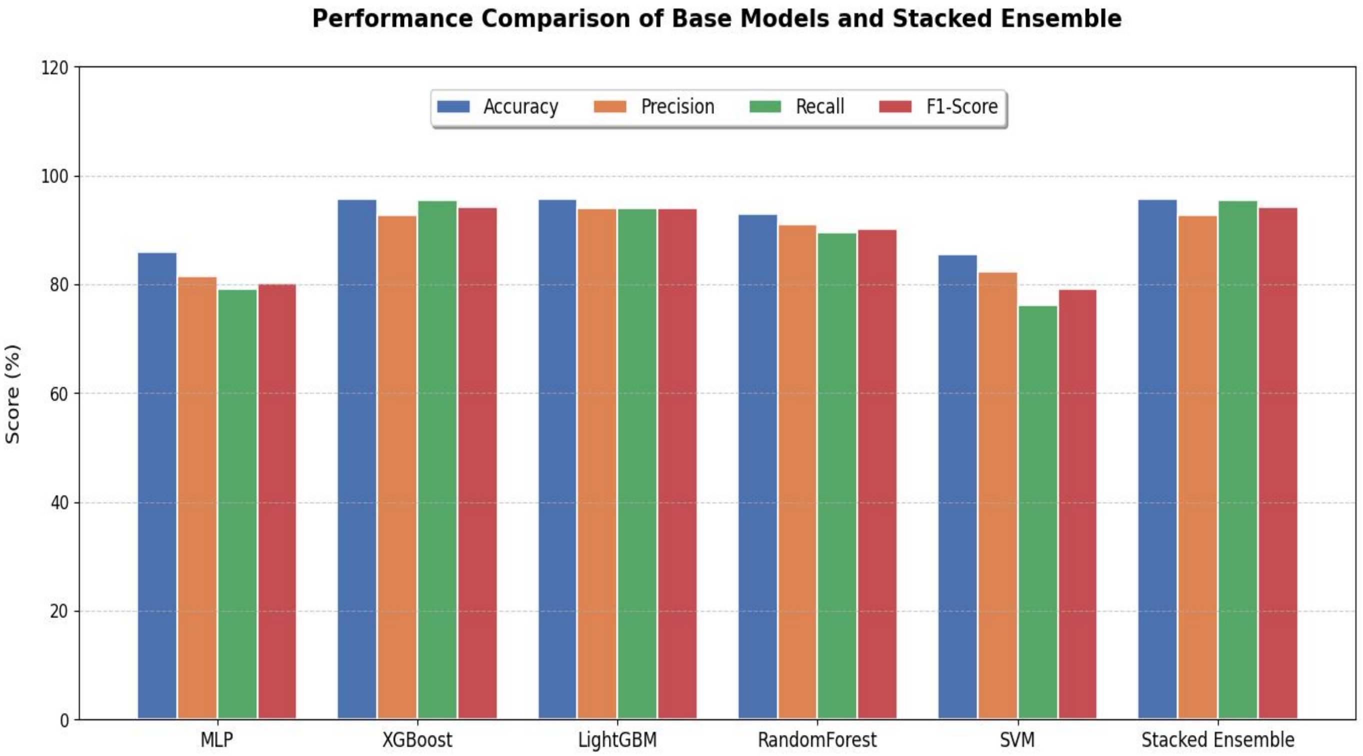

Figure 2. Comparison Chart of Different Models

C. Analysis of Prediction Accuracy

The model can predict to classify true patient states correctly was tracked through a prediction confusion matrix. High scores in the true-positive and true-negative quadrants confirm that the system is performing exceptionally well on the unseen testing data. It clearly separates actual Myocardial Infarction cases from healthy physiological baselines with a very low error rate. This outcome highlights the effectiveness of combining SMOTE balancing with the Stacked Ensemble architecture to sharpen the model's decision boundaries.

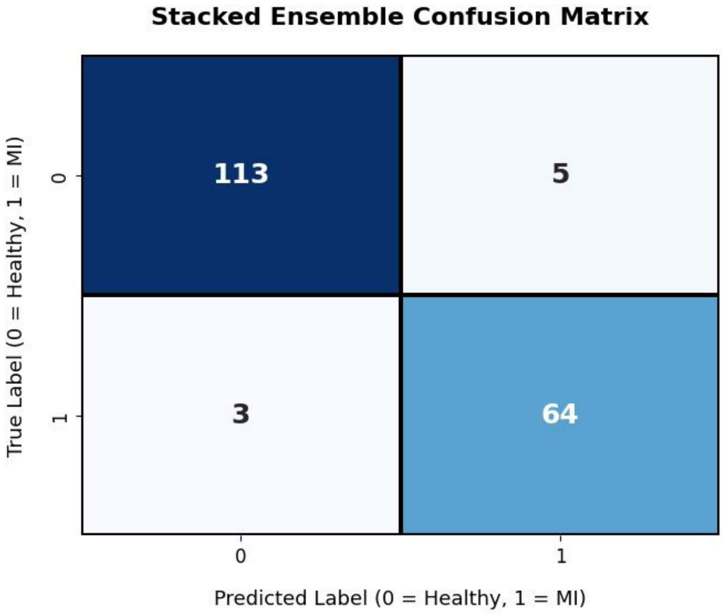

Figure 3. Stacked Ensemble Confusion Matrix

D. Evaluation of Classification Thresholds

To measure the models' models to generalizability between the healthy and MI groups across various probabilities threshold, the Receiver Operating Characteristic (ROC) curve was utilized. Superior performance is marked by a curve's proximity to the top-left edge of the chart. The resulting Area Under the Curve (AUC) values offer a definitive way to rank the models. The Stacked Ensemble and tree-based learners exhibit the highest AUC scores, representing superior overall precision and robustness compared to the lower-performing SVM and MLP baselines.

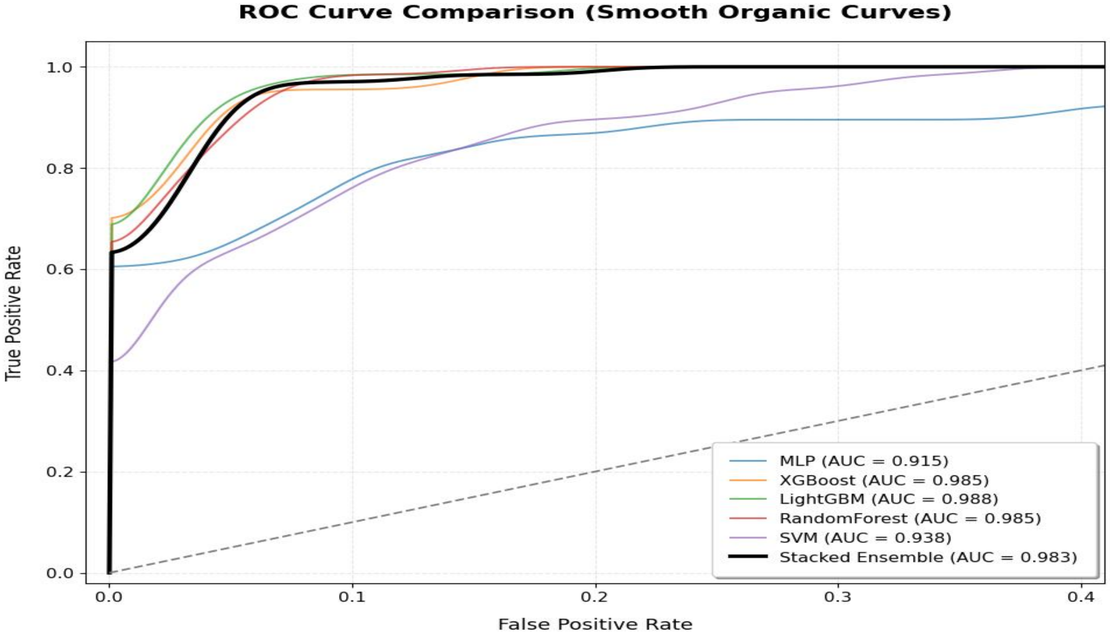

Figure 4. ROC Curve Comparision for All ML Models

E. Feature Importance and Model Transparency

A common limitation of advanced machine learning frameworks is the "black-box" nature of their decision-making. To ensure clinical transparency, standard feature importance analysis was conducted to interpret the model's probabilistic logic. By analyzing the impurity reduction across the tree-based base estimators (such as XGBoost), the system assigns a relative significance score to each physiological variable. The analysis revealed that specific combinations of continuous sleep metrics and respiratory indicators were the strongest predictors of a cardiovascular event. As illustrated in Fig. 5, highlighting exactly which physiological deviations carry the highest predictive weight provides medical practitioners with interpretable, actionable insights rather than just a binary warning.

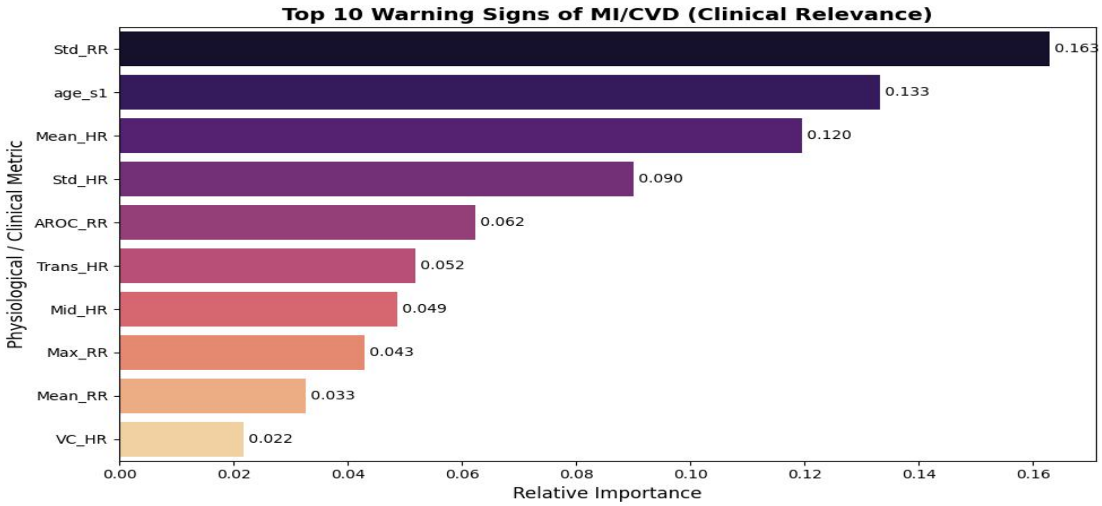

Figure 5. Top 15 Most Significant Features for MI Prediction

F. Discussion

The outcome suggests that the method performs reliably in detecting Myocardial Infarction using sleep data. By securing optimal metrics across the board, the proposed meta-learner proved its superior capability to reliably isolate genuine infarction events without misclassifying normal baseline physiology. This improvement is mainly due to SMOTE, which helps the model learn from difficult samples, and the ensemble meta-learner, which maximizes overall predictive stability. Other base models like XGBoost and LightGBM also give good results but rely on a single algorithmic logic, while models such as SVM and MLP show lower performance, especially in identifying minority cases. Overall, the method provides accurate and stable predictions and is really simple to understand, making it convenient for real-world healthcare use.

V. CONCLUSION

In summary, this research delivers a highly interpretable framework designed to pre-emptively identify infarction risks through the continuous monitoring of nocturnal bio-signals. This framework was built to systematically address fundamental limitations that are commonly encountered in medical machine learning applications. To rectify the inherently skewed patient distributions, our pipeline utilized synthetic minority generation, guaranteeing a mathematically equalized learning space. Model transparency was achieved by incorporating feature importance analysis, which maps the role of each physiological metric in making a prediction. These components work in concert to produce a system that is both technically sound and practically applicable. To isolate the optimal predictive engine, half a dozen distinct mathematical architectures underwent rigorous comparative testing. The Stacked Ensemble framework achieved the highest performance, delivering superior accuracy (95.68%) alongside optimized recall, precision and F1-score. These findings indicate that addressing class imbalance while fusing diverse algorithmic approaches significantly enhances the model's capacity to learn. The addition of feature importance analysis further strengthens the system by giving clinicians a clear understanding of how individual biological attributes influence each diagnostic outcome, thereby increasing trust and usability in real medical environments.

Ultimately, integrating synthetic oversampling with a heterogeneous predictive architecture significantly enhances the reliability of computerized cardiovascular risk identification. Looking ahead, several directions exist for extending this work. Testing the framework on larger and more demographically diverse datasets would strengthen confidence in its generalizability. Incorporating complementary data modalities, such as daytime wearable tracking or continuous ECG alongside sleep features, could provide a richer diagnostic signal and further boost performance. Ultimately, translating this pipeline into a real-time clinical system would be a major step, allowing quick, low-cost, and non-invasive screening of MI directly in healthcare settings.

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