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# A Hybrid Clinical Decision Support System for Heart Attack Risk Prediction with SHAP-Based Explainability and Evidence-Based Clinical Interpretation

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***Abstract: Heart disease is a major cause of death globally, therefore leading to the need for reliable and interpretable predictive models to support early diagnosis. Current machine learning techniques for predicting heart disease predominantly concentrate on boosting accuracy, while overlooking interpretability and clinical actionability. Here we present a combined clinical decision support system that leverages machine learning and explainable AI to deliver predictive performance with meaningful clinical explanations. Our approach integrates an XGBoost machine learning model (optimised for non-ECG datasets) with a second ECG-informed feature stream, which is then meta-learnt to better account for variations in predictions and increase model robustness. To retain the crucial aspect of explainability in medical scenarios, SHAP (SHapley Additive exPlanations) explanations are used and translated into reliable evidence-based clinical interpretations through well-accepted medical thresholds and guidelines. Two-layer explanation interface to the clinicians and patients also characterize the framework and enhance explainability and usability. It is experimentally and tested using the UCI Heart Disease data set where the system has good predictive performance (with a predicted area of about 0.911) and predictive probability. Additionally, the stability test of the noisy and missing data situation warrants the stability of the proposed system. The findings suggest that the methodology that relies on the combination of hybrid models with explainable and clinically reasoning may make AI-based solutions more utilized in clinical environments in predicting the risks of cardiovascular complications.***
***Keywords: Heart Disease Prediction, Hybrid Machine Learning, Explainable AI, SHAP, Clinical Decision Support System, XGBoost, Cardiovascular Risk***

## I. INTRODUCTION

Heart disease is one of the biggest killers around the world, claiming many lives each year. Predictions of patients at risk of heart attack at an early stage are essential for early treatment and positive outcomes. Current clinical risk prediction is often based on a combination of patient history, laboratory tests and medical tests, which can be time-consuming and require specialised knowledge. Thus, there is a need for rapid and automated cardiovascular risk prediction using machine learning techniques. A number of machine learning algorithms have applied to prediction of heart disease on structured clinical data over the last ten years [1]-[3]. More conventional techniques such as logistic regression, support vector machines, and ensemble learning have been shown to have quite good predictive capabilities. However, current models primarily aim to generate the highest possible accuracy, while offering little opportunity for interpretation, which limits their use in clinical practice. For clinical applications, it is essential to provide transparent and meaningful predictions since clinicians need to know what factors are driving model predictions.

A second major limitation of the current approaches is the use of a single data modality. Typically, existing approaches use only clinical attributes of the tabular representations, neglecting other potentially useful cardiac features that may be important for predicting cardiovascular risk. In addition, while deep learning approaches have achieved great success in applications for medical imaging and signal processing [4]-[6], they have limited success on small tabular data, and frequently lead to overfitting and poor generalization. Indeed, recent research has demonstrated that tree-based ensemble methods are still superior to deep learning methods for tabular data, especially on smaller-sized datasets [20], [21].

To overcome these challenges, this paper proposes a multi-stage clinical support system for heart attack risk assessment that combines predictive models, explainable artificial intelligence (XAI) and clinical interpretation. Our approach leverages a primary model, XGBoost, which is trained on a subset of tabular features and an additional set of features derived from ECG information using a meta-learning strategy to improve performance and robustness. To achieve interpretability, explanations encoded by SHAP are used to calculate the feature contributions, which are then mapped to clinically sound interpretations, based on medical guidelines and thresholds.

The main findings of the research are presented:

1) Proposed a hybrid machine learning model, the combination of tabular and ECG-derived features and a stacking technique.
2) Explainability of SHAP, systematized grouping and interpretation of attributes.
3) Evidence-based clinical decision support module translating the predictions into clear clinical knowledge and instructions.
4) Performance tests of the model when there is noise and missing data to evaluate its implications in practice.

Our system seeks to translate the predictive accuracy into clinical utility in that we will guild the accurate, interpretable and actionable information to the doctors and the patients.

## II. RELATED WORK

The use of machine learning models to predict heart disease using structured clinical data has had a lot of work done on it. Selective predictoric models, such as logistic regression, support vector machines and ensemble activity have shown good predictive accuracy of a relative handful of benchmark datasets such as the Heart Disease data at UCI. Newly created works too have enhanced prediction using advanced ensemble techniques and class balancing techniques such as XGBoost algorithm using Synthetic Minority Over-sampling Technique (SMOTE) in case of class imbalance. These methods, however, are disadvantaged in that, they only observe predictive performance, not interpretability, and this may pose a problem when used in a clinical setting that may more often than not, be interested in an explanation [1]-[3]. In other cases, applications of deep learning methods in predicting risk of a cardiovascular disease have been utilized in medical image classification tasks and in the classification of electrocardiogram (ECG) signal tasks. Hybird deep learning and convolutional neural networks have demonstrated promising results in feature extraction from ECG signals and multi-modal medical features. However, deep learning models often demand big data and powerful computational infrastructure for model development and installation. In addition, overfitting and poor performance can occur when deep learning models are used to learn from a small sample of structured tabular data, as shown in recent research on predictive modelling with tabular data [4]-[6], [20], [21]. Hybrid and ensemble learning models have been developed to address the shortcomings of individual models. These approaches use multiple models or representations of data to enhance predictive accuracy and generalisation. A recent study has proposed hybrid ensemble learning and explainable AI to improve interpretability. Although such methods show enhanced performance, they often do not take into account the integration of domain knowledge and clinical reasoning processes to generate explanations that are easier to understand from a medical standpoint [7]-[9].

The field of explainable artificial intelligence (XAI) has emerged in healthcare to explain AI systems predicting medical data. Methods like SHAP have been successfully applied to explain feature importance and enhance trust in models. A number of works have used SHAP-based explanations for explaining heart disease prediction models, offering insights into feature relevance and model behaviour. But most current research offers statistical explanations without translating them into clinically relevant explanations or practical insights for clinicians [10]-[13].

Clinical decision support systems (CDSS) have been designed to help practitioners in diagnosing diseases and planning treatments. These have recently evolved to support machine learning and explainable AI for better decision making. However, current CDSS systems either emphasise either predictions or interpretations, without combining these features with evidence-based clinical reasoning [14], [15]. Unlike previous research, our system combines hybrid machine learning, SHAP explainability and evidence based clinical interpretations into a comprehensive system. The system leverages both predictive accuracy and explanation based on clinical evidence to offer reliable decision support for predicting heart disease.

## III.METHODOLOGY

### *A. Dataset*

Our system is trained and tested on publicly available Heart Disease (HD) data from the UCI machine learning repository [19]. The data contains patient records with several attributes such as some demographic, physiological and diagnostic attributes. It includes instances that correspond to patient records, labeled as either afflicted or not by heart disease, thus it is a binary classification problem.

 

It contains a combination of continuous and discrete attributes, including age, cholesterol, resting blood pressure, chest pain type and electrocardiogram. Some features, such as number of major vessels and thalassemia, are missing values, which need to be preprocessed to ensure the accuracy of the model. Table I summarizes the dataset features to be used in the study.

To facilitate reliable model assessment, the data are split into 80% training and 20% hold-out samples. The holdout set is only used for final model evaluation, and it is not used in model development or hyperparameter tuning, enabling a fair evaluation of the final model.

TABLE I
DATASET FEATURES

| Feature | Description |
|---|---|
| Age | Age of the patient |
| Sex | Gender (0 = female, 1 = male) |
| Cp | Chest pain type |
| Trestbps | Resting blood pressure |
| Chol | Serum cholesterol |
| Fbs | Fasting blood sugar |
| Restecg | Resting ECG results |
| Thalach | Maximum heart rate |
| Exang | Exercise induced angina |
| Oldpeak | ST depression |
| Slope | Slope of ST segment |
| Ca | Number of vessels |
| Thal | Thalassemia |

### *B. Data Preprocessing*

A pre-processing pipeline is established for the experiments to ensure consistency and reproducibility. All numerical features undergo missing value imputation by the median and then are standardized to ensure they are independent of their scales. Categorical features are handled using most frequent imputation and one-hot encoding to convert them into an encoding suitable for machine learning.

To avoid inconsistencies between the train and test phases, consistent mappings are used for encoding the categories. This guarantees consistency of the feature space when the model is applied to new data. Preprocessing strategies are grouped into a pipeline, which is only fitted on the training data to prevent data leakage.

### *C. Feature Selection*

Features are selected to increase model speed, avoid noise and to improve model performance. A feature importance method using XGBoost model is used to assess the importance of different features for prediction. Importance scores are calculated across cross-validation fold to provide a robust feature selection.

A subset of 15 features were chosen from the ranked features for model training, considering both accuracy and complexity of the model. This is useful in removing extraneous or irrelevant features and selecting those that are important for clinical purposes. The first set of features selected are symptoms of chest pain, ST depression (oldpeak), number of major vessels and other clinical factors known to influence the risk of developing heart disease.

### *D. Model Development*

A variety of machine learning models are considered to create a baseline and prompt the search for the best performing model for the task. This includes linear baseline (logistic regression), neural network-based learning (multilayer perceptron - MLP), and an ensemble method known as gradient boosting (XGBoost) [17].

The logistic regression model is straightforward and linear, while the MLP is able to learn non-linearity in the data. But given the limited sample size and tabular nature of the features, neural network approaches can overfit the data and lack generalisation capability. On the other hand, XGBoost outperforms other models on tabular data by effectively capturing feature interactions, and modelling non-linearity.

The XGBoost model's hyperparameters are tuned with a Bayesian approach to find the best possible settings [18]. This is done with cross-validation to avoid overfitting. The best model is chosen according to a range of performance criteria, including area under the receiver operating characteristic (AUC), precision-recall, and calibration.

### *E. Hybrid Architecture*

A hybrid predictive approach is developed using a two-stream architecture, fusing complementary feature representations, to improve model robustness and provide interpretability by harnessing domain experts' knowledge. The architecture includes a primary machine learning model based on tabular clinical data, a secondary model based on ECG-driven features, and a fusion approach to predict the outcome. The primary stream employs the XGBoost model built on the chosen feature subset, enabling it to capture complex non-linear relationships and interactions between clinical features. The secondary stream model is built using a subset of ECG-related features, such as ST depression (oldpeak), slope of the ST segment, exercise-induced angina, and thalassemia status. These variables are linked to stress responses and ischemia in the heart, and serve to supply additional domain-specific knowledge. The two streams are merged using a stacking approach. In particular, a meta-learner (logistic regression) is trained on the probabilities of both streams. In order to avoid any bias in the fusion process, the meta-learner is trained on the out-of-fold predictions, avoiding leakage and preserving the ability to generalise. The resulting prediction from the hybrid system is a calibrated probability measure of heart disease. This design enables the model to tap into generic tabular clinical information for predictions, as well as specific cardiac risk factors extracted from the ECG-informed features. The hybrid solution enhances reliability due to superior incorporation of diverse source of information, which gives better predictions. Fig. 1 demonstrates the general system framework of the proposed hybrid system of clinical decision support.

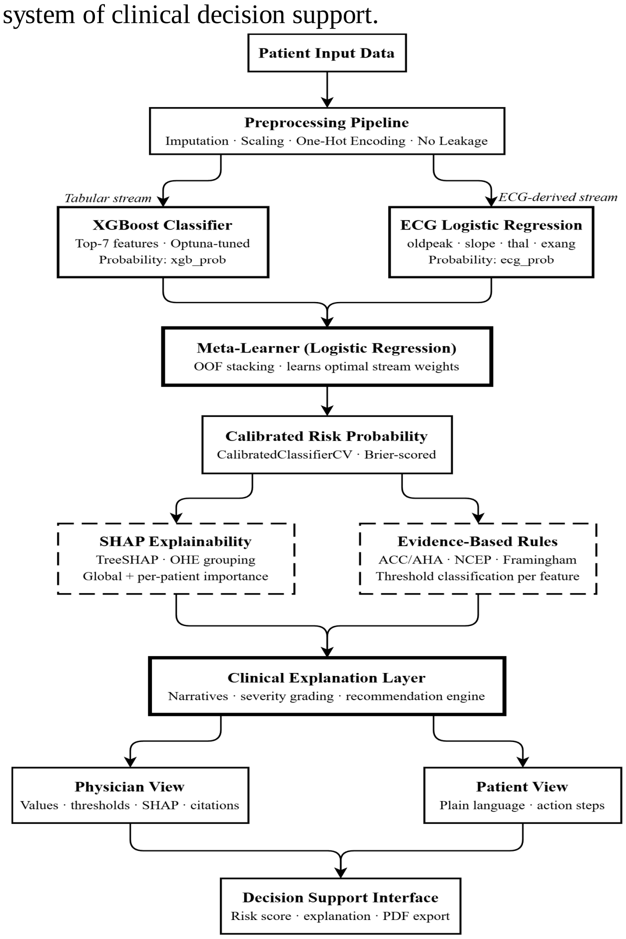


Fig. 1 Proposed hybrid clinical decision support system architecture

### *F. Probability Calibration*

Accurate probability predictions are crucial for clinical decision making. Although machine learning models, like XGBoost, offer excellent predictive capability, their probability estimates are not necessarily calibrated. This can result in over- or under-confidence and potentially confuse clinicians.

Therefore, the prediction process includes an additional step of calibrating probabilities. This involves using calibration methods to bring predicted probabilities in line with observed frequencies, thus enhancing risk prediction. This helps the predicted risk scores be applied appropriately in a clinical setting, in which intervention thresholds are usually defined in terms of probabilities rather than class membership.

### *G. Explainability and Clinical Interpretation*

To make the system explainable and facilitate adoption, an explainability layer is also built on the proposed system with the help of SHAP (SHapley Additive exPlanations) [16]. SHAP offers a consistent approach to measuring the feature contribution to individual predictions and provides global and local explanations.

Global explanations are used to identify the most important features globally, while local explanations are used to explain feature importance for individual patients. SHAP allows for efficient and theoretically justified calculation of feature contributions for tree-based models, resulting in stable and robust explanations. The importance of individual features with SHAP is shown globally as shown in Fig. 2.

To improve clinical readability, the SHAP explanations are translated into clinical interpretations. Key factor contributions are mapped to medically meaningful categories by pre-defined thresholds based on medical guidelines. The summary of these thresholds and their interpretations is given in Table II. For instance, ST depression, levels of cholesterol and blood pressure are considered in terms of severity according to medical literature.

The model produces explanations that explain the impact of various clinical features on the risk. These explanations are displayed in two versions: a technical version for doctors and a layman version for patients. The clinician view provides feature contributions and medical context, while the patient view is a more intuitive explanation of contributing risk factors and their meaning.

Finally, a recommendation engine is integrated to suggest appropriate actions based on the risk level and feature contributions. These recommendations may range from lifestyle changes to additional diagnostic tests or doctor's referrals, based on the level of predicted risk.

TABLE II
CLINICAL THRESHOLDS

| Feature | Threshold | Interpretation | Severity | Source |
|---|---|---|---|---|
| oldpeak (ST depression) | ≥ 2.0 mm | Significant ischemia | Severe | ACC/AHA Exercise Testing (2002) |
| oldpeak | 1.0 – 2.0 mm | Moderate ischemia | Moderate | ACC/AHA |
| chol (mg/dL) | ≥ 240 | High cholesterol | Severe | NCEP ATP III |
| chol | 200–239 | Borderline high | Moderate | NCEP ATP III |
| trestbps (mmHg) | ≥ 140 | Hypertension Stage 2 | Severe | ACC/AHA 2017 |
| trestbps | 130–139 | Hypertension Stage 1 | Moderate | ACC/AHA 2017 |
| thalach | < 85% expected | Chronotropic incompetence | Moderate/Severe | Circulation (Brubaker, 2011) |
| ca (vessels) | ≥ 2 | Multi-vessel disease | Severe | AHA CAD Guidelines |
| exang | = 1 | Exercise-induced angina | Severe | ACC/AHA |
| cp | asymptomatic | Silent ischemia | Severe | ACC/AHA Chest Pain 2021 |
| thal | reversible defect | Active ischemia | Severe | Nuclear Cardiology Guidelines |
| age | ≥ 60 | Elevated risk | Moderate | Framingham Study |
| fbs | ≥ 120 mg/dL | Diabetes indicator | Moderate | ADA 2023 |

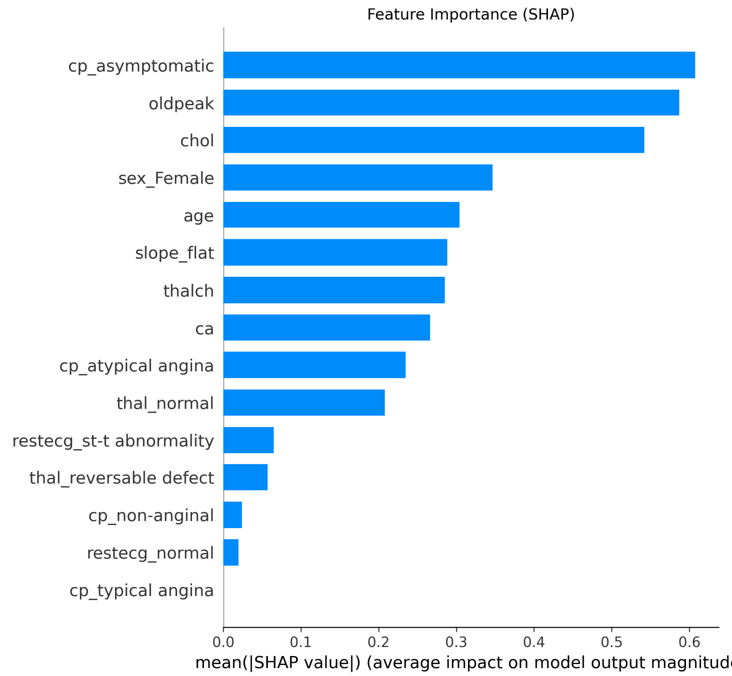


Fig. 2 SHAP feature importance at a global scale including contribution of clinical features

## IV. EXPERIMENTS AND RESULTS

### *A. Evaluation Metrics*

In order to assess the level of performance of the suggested models, we consider a combination of some measures that will help us fully assess the classification. The first one is the area under the receiver operating characteristic curve (AUC) which provides an idea of the discrimination of the model. The other performance measure is the area under the precision-recall curve (AUPRC) that is utilized when the classes are not equally distributed.

To measure the calibration of the predictions a Brier score is used. We also report sensitivity and specificity to identify the performance of the model in regards to detection of positive and negative cases respectively. False positives and false negatives can be crucial as such actions are needed in medical practice.

### *B. Model Comparison*

To benchmark the performance, several models, such as logistic regression, multilayer perceptron (MLP) and XGBoost, are considered as shown in Table III. Logistic regression offers a simple and interpretable baseline model, whereas the MLP model allows for learning non-linearly. XGBoost (k=15), being an ensemble method, performs well on tabular data.

The findings suggest that XGBoost performs better than logistic regression and MLP in terms of the various evaluation metrics, especially the area under the curve (AUC) and the probability calibration. The MLP, on the other hand, exhibits lesser performance due to the small size of the data and the structured feature set, which may not be the optimal choice for a deep learning model.

TABLE III
PERFORMANCE COMPARISON OF MODELS

| Model | AUC | AUPRC | Brier | Sensitivity | Specificity |
|---|---|---|---|---|---|
| LogisticRegression | 0.874 | 0.881 | 0.132 | 0.861 | 0.702 |
| MLP | 0.842 | 0.857 | 0.148 | 0.835 | 0.681 |
| XGBoost (k=15) | 0.909 | 0.912 | 0.116 | 0.912 | 0.732 |
| Hybrid | 0.911 | 0.917 | 0.119 | 0.902 | 0.756 |

### *C. Hybrid Model Evaluation*

The hybrid model is assessed using the performance of the streams and the fused model. The XGBoost model provides general prediction patterns and the ECG-informed features provide domain-specific knowledge related to heart disease. The ROC curve (Fig. 3) compares XGBoost, Hybrid model and ECG.

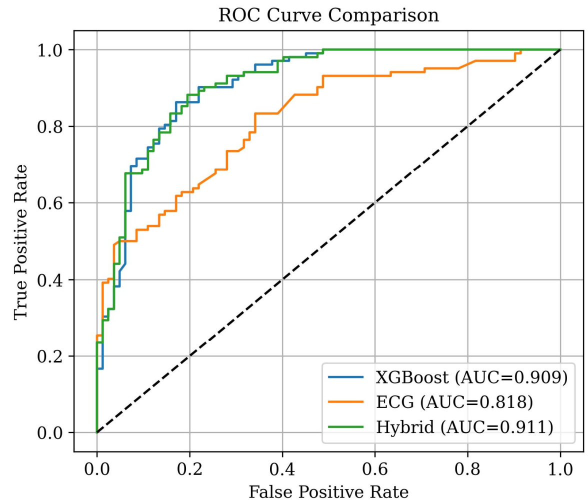


Fig. 3 ROC curve comparison of XGBoost and hybrid models

The pooled streams show a very slight improvement in AUC as compared to the baseline XGBoost model, and have better specificity. This implies that feature integration based on ECG provides complementary features. This is an indication of the two streams capturing complementary information that is useful in balancing the model.

Decision curve analysis (DCA) is used to assess the clinical utility of the proposed model. DCA quantifies the net value of a model over a set of threshold probabilities, and relates a model to real-world decision-making situations. As illustrated in Fig. 4, the hybrid model has a superior net benefit with a range of clinically viable thresholds than XGBoost baseline, suggesting an increased practical utility in the trade off between false positives and false negatives.

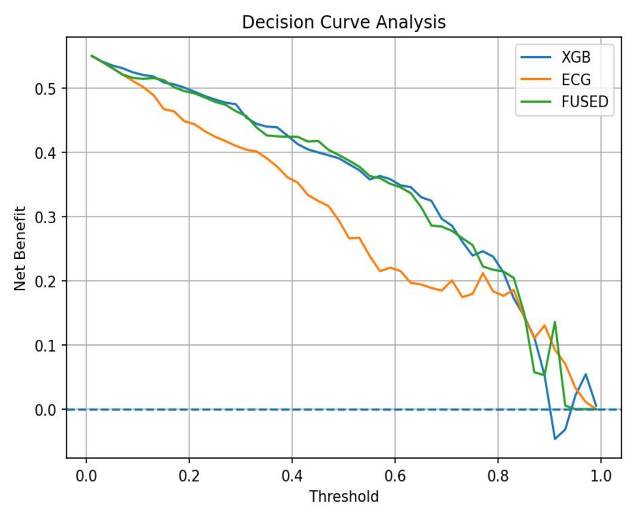


Fig. 4 Decision curve analysis illustrating net clinical benefit across threshold probabilities.

### *D. Robustness Analysis*

To assess the robustness of the proposed system in practical scenarios, robustness testing is carried out, introducing different levels of noise and missing values to the data. It remains stable even with moderate noise, resulting in slight decrement of the AUC as shown in Fig. 5.

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Furthermore, as the percentage of missing data increases, the model has graceful degradation, implying that preprocessing and imputation plan are effective. Fig. 6 demonstrates the effects of increasing quantities of missing data on the model performance, where degradation is slow. It has shown in our results the stability of the system and its applicability in the real-world clinical environment where the quality of the data may be non-deterministic.

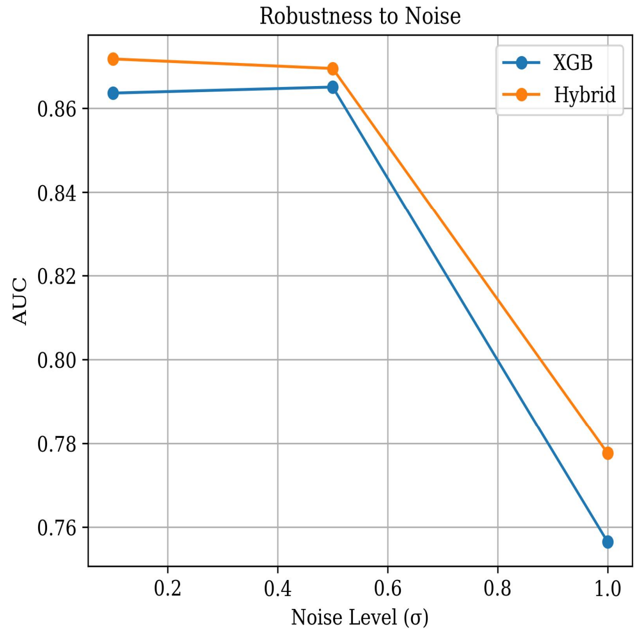


Fig. 5 Model robustness under varying levels of noise

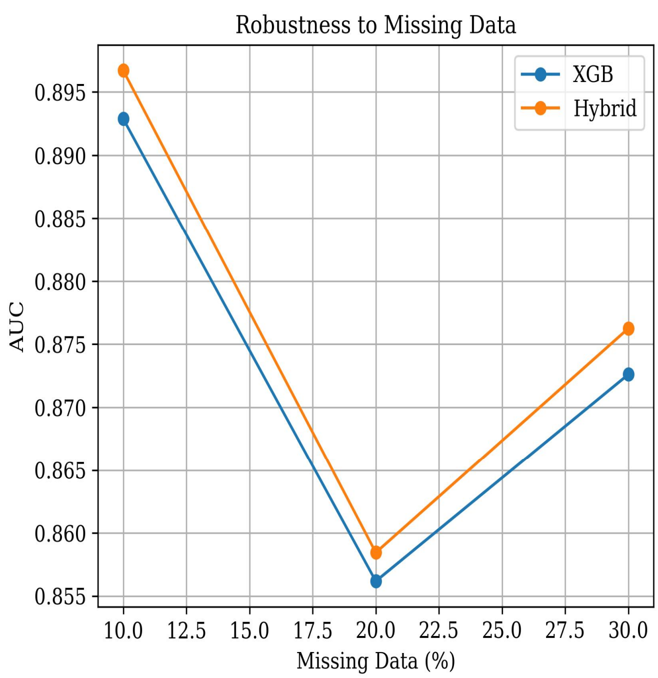


Fig. 6 Model robustness under varying levels of missing data

To assess the calibration of the predicted probabilities, we conduct further analyses. The calibration plot (Fig. 7) shows the relationship between predicted likelihoods and the observed frequencies. The results show that the model's predicted probabilities are well-calibrated, which is important for clinical use.

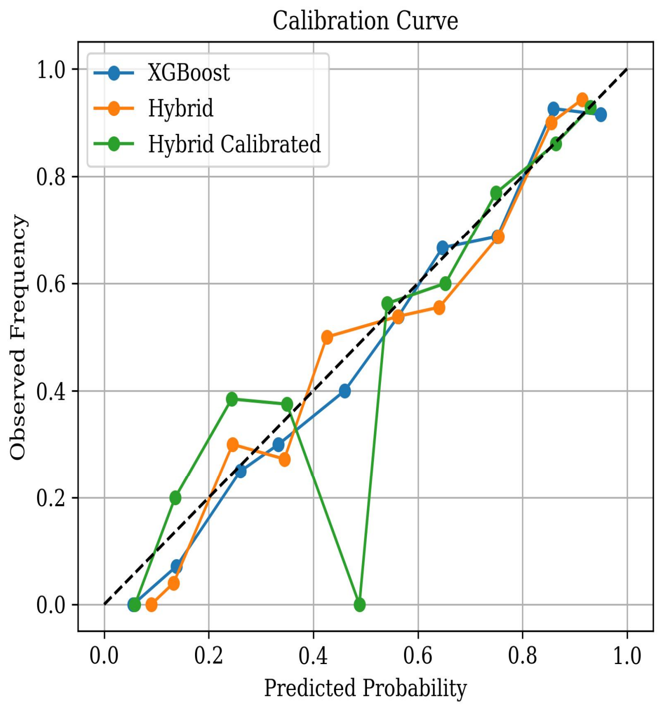


Fig. 7 Calibration curve showing reliability of predicted probabilities

## V. DISCUSSION

The findings indicate that the hybrid model performs well, and is interpretable and robust, which are key requirements for medical decision-making. The XGBoost model performs better than the logistic regression and MLP models, validating the use of tree-based approaches on tabular data. The relatively lower performance of the MLP model also corroborates findings that deep learning models may not be the best choice for small tabular datasets [20], [21].

The use of ECG-derived features in the hybrid model makes the model more robust by taking the clinically relevant ECG measures into account. While the absolute AUC shows a slight but consistent improvement over the XGBoost model, the hybrid model outperforms the original XGBoost model in terms of specificity (fewer false positives). This is especially critical in the medical practice, when false positives can cost them an extra price and pain.

The other significant aspect is the interpretation of the proposed system. The system also has easily readable and understandable results in the form of SHAP explanations, as well as, the contribution that features make in the development of significant medical thresholds. As opposed to the traditional models, the suggested system will not just give predictions but also present the risk factors as per the context in order to ease the decision making process of the clinician.

The robustness analysis suggests that the system has been applied in practice as well. The system does not mandate the performance of noisy and incomplete clinical data that is inherent with the clinical data. This has rendered it so stable, courtesy of the preprocessing of data and the complementary power of the hybrid architecture.

However, some of the weaknesses cannot be left out. This validating is performed with the help of little set of data and may need the procedure to validate with bigger set of data in more practicalities. In addition to this, the data used to feed the model i.e. the ECG data are structured, in place of raw ECG signal hence they can restrict information that is present concerning the heart in the data. Additional research like incorporation of the raw ECG signal into the model, and training a model which uses a larger and more diversified dataset could be considered.

To demonstrate that the suggested system can be applied in practice, Fig. 8 demonstrates the sample of the dual-view clinical explanation output. The system develops a rich clinical interpretation and medical sources to assist clinicians, and a clear description to patients, enhancing clarity and trust.

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| DOCTOR VIEW | PATIENT VIEW |
|---|---|
| **CLINICAL RISK REPORT**<br><br>**Predicted Risk:** 72.8% (High Risk)<br><br>**Key Risk Factors:**<br>• ST Depression (oldpeak = 1.5 mm)<br>→ Moderate ischemia (≥1.0 mm threshold)<br>→ Ref: Gibbons RJ et al., Circulation, 2002<br>→ SHAP: +0.287<br><br>• Male sex<br>→ Elevated baseline CAD risk<br>→ Ref: Framingham Heart Study<br>→ SHAP: +0.222<br><br>**Protective Indicators:**<br>• Chest pain: non-anginal<br>→ Ref: Gulati M et al., JACC, 2021<br>• Max heart rate: 155 bpm (94% expected)<br>→ Ref: Brubaker & Kitzman, Circulation, 2011<br>• No major vessel blockage detected<br>→ Ref: Boden WE et al., COURAGE Trial<br><br>**Clinical Interpretation:**<br>Findings indicate moderate ischemic stress with elevated cardiovascular risk.<br><br>**Recommendation:**<br>Urgent cardiology referral and further diagnostic evaluation. | **YOUR HEART HEALTH SUMMARY**<br><br>**Risk Level:** HIGH (72.8%)<br><br>**Why is your risk high?**<br>• Your stress test shows reduced blood flow<br>• Some personal factors increase your heart risk<br><br>**What is good?**<br>• Your cholesterol and heart response are healthy<br>• No major artery blockages detected<br><br>**What should you do?**<br>• Visit a heart specialist soon<br>• Share this report with your doctor<br><br>⚕ This is a decision-support tool. Final diagnosis is made by your doctor. |

Fig. 8 Sample of a clinical explanation output in dual-view with doctor-oriented and patient-oriented explanations.

## VI. CONCLUSION

In the present paper, a hybrid clinical decision support mechanism to predict the risk of heart attack based on a combination of machine learning and explainable artificial intelligence with clinical interpretation is presented. The technique combines XGBoost prediction, ECG-inspired feature stream/stacking fusion to enhance the accuracy and stability of models.

The experimentation of the system depicts high predictive accuracy, precise modeling of probability and resilience to missing and spurious data. SHAP interpretation and evidence-based clinical reasoning helps the system to offer both clinical interpretability and practical information to both clinicians and patients.

The system surpasses the weak points of existing methods by creating a system that integrates predictive performance with clinical interpretability. With such orthogonal properties as interpretability, robustness and knowledge, the system fosters the development of actionable AI-based systems in healthcare. Future research is directed at one of the priorities to expand the proposed system to accommodate bigger datasets, raw sensor data streams, and test its feasibility in clinical practice.

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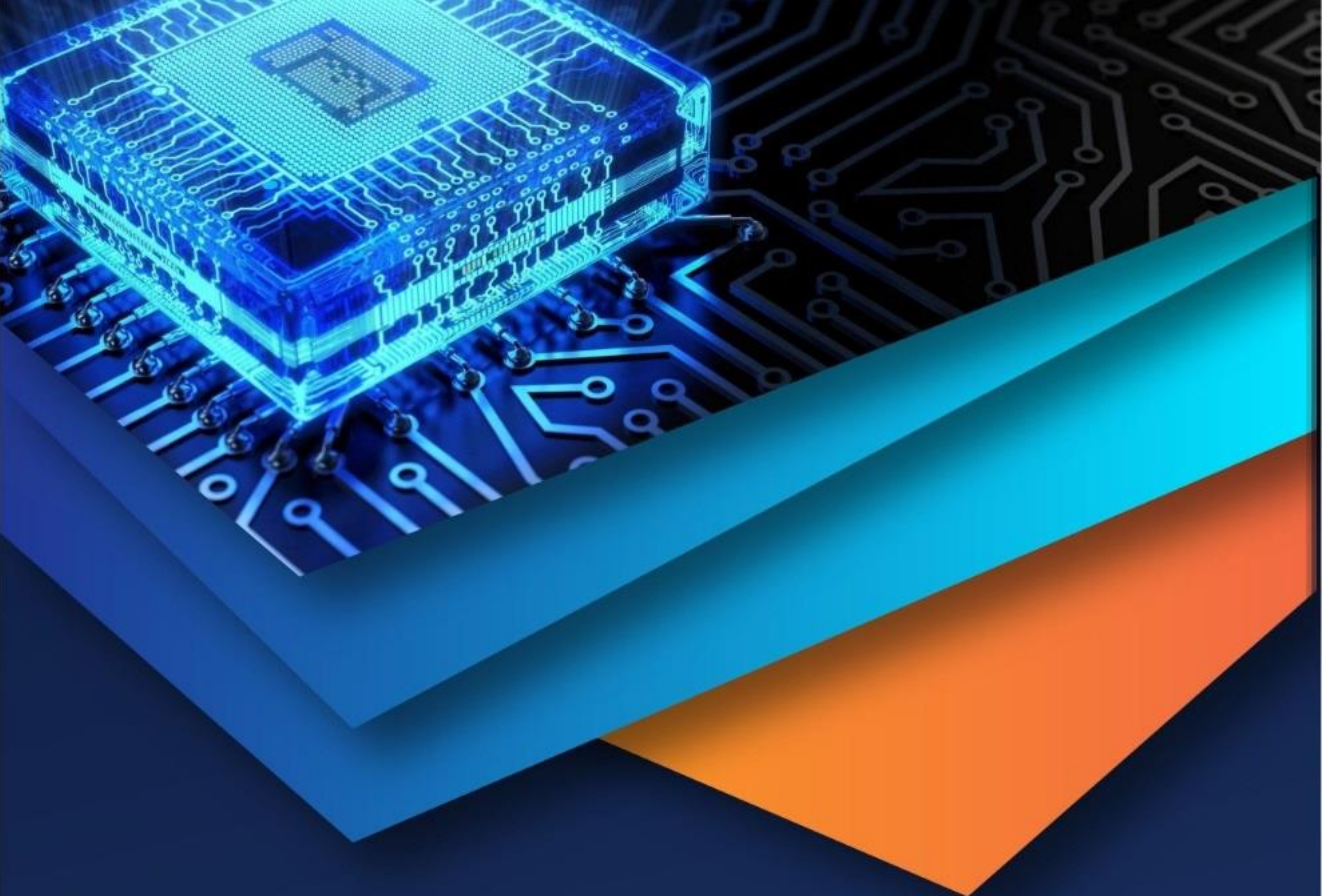


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