INTELLICARDIA: AN ARTIFICIAL INTELLIGENCE BASED DECISION SUPPORT SYSTEM FOR PREDICTING HEART DISEASE RISK

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Abstract

Cardiovascular diseases (CVDs) are complex, multifactorial conditions that include disorders of heart and blood vessels. According to the statistics report of World Health Organization almost billions of people die every year due to CVD. In order to control the mortality rate there is need for early prediction of disease before it becomes a life-threatening issue. Therefore, there is a need for an Intelligent automated system that can assist in early screening and risk assessment. To overcome the limitations of previous models, this research presents an advanced clinical decision support system (CDSS) designed for the early prediction and risk stratification of heart disease using a hybrid Artificial Intelligence (AI) framework. The system received training and evaluation through a merged dataset which combined 5,158 patient records from the Cleveland Heart Disease dataset and the Framingham Heart Study using clinical parameters such as age, sex, systolic blood pressure, cholesterol level, heart rate, and diabetes status. An expert driven fuzzy inference system with data-driven machine learning engine is utilized to improve computational robustness, The Preprocessing techniques, Min-Max, normalization and (SMOTE) Synthetic minority over sampling technique is used to resolve class imbalance in the medical data. This system is evolved through three versions and this is 3.0 version that is based on soft voting machine learning technique consisting of XGboost, Random Forest, Support Vector Machine and Logistic Regression. please the weighted fusion mechanism is utilized that provide statistical ML probabilities with linguistic fuzzy reasoning that classifies the patient into Low, Moderate and high risk class. The system bridges the gap between the computational output and clinician trust with explainable feature using explainable AI powered by XAI and large language model Google Gemini 3.2, which translates features into human readable rationale, the system is deployed via streamlit and provide real time visual analytics, patient records archiving and automated PDF diagnostic report. This hybrid framework achieves a peak predictive accuracy of 94 to 95%. IntelliCardia is a transparent, scalable, and a *reliable solution that can be used for predicting the cardiovascular disease to prevent the mortality rate. By utilizing this CDSS, a person can know their heart risk level and by following the advices given in PDF report they can minimize their risk of Cardiac arrest and Heart failure.*

INTRODUCTION

The largest health issue in the whole world has now become heart problems. According to a new report, almost 20 million people died of them in 2022 [1] almost a third of all the deaths worldwide. Majority of these deaths occur in the poor countries, when individuals tend to die young as they continue their job. The amount of money spent in treating heart diseases related to weight has already reached over two cents of each dollar earned in the world. That percentage would increase near to three cents per dollar in decades [2].

The Diagnostic Dilemma

The difficult thing about cardiovascular diseases is that they are silent. Slowly accumulating in the arteries, inch by inch, with no warning of any kind, until one day, there is a heart attack [3]. The majority of the existing tests are not able to detect these changes even before it is too late. Such procedures as coronary angiography demand substantial resources and are associated with risks, that is, it cannot be applied to large groups [4]. On the other hand, less complex techniques, such as standard ECGs, are blind to issues when the heart is not abnormally fibrillating and cause silent harm that is not visible [4, 5].

Artificial Intelligence at Work

Recently, the field of medicine is experiencing artificial intelligence taking over the areas with blindness. Imaging computers that detect concealed evidence in the files and scans of patients - details that doctors may overlook. Know how to monitor heart trouble even better than a specialist would. There are programs that can tell the actual age of your body without having to touch your heartbeat. Weak heart pumps are caught by others only with a help of an electrocardiogram signals. These tools are self-educated and are not instructed to find this or that. Statistics indicate their frequent superiority over humans in making some predictions. What appeared to have been looked at as the sci-fi fantasy a few years ago noiselessly slips under clinic doors.

The Proposed Solution: Intellicardia

To begin with machine learning, this paper introduces Intellicardia - a system that combines predictive algorithms and Fuzzy Logic in an effort to make more lucid medical choices. It is designed to bridge computational intelligence with interpretable. The system is provided with easy to use interface in front end whereas the preprocessing is provided is n the backend of the system. It does not leave its users to guess since, in addition to results, there are provided structured explanations. Reports are produced in standard format without the additional effort due to inbuilt automation. Whereas precision is important, transparency influences the sharing of insights. With the use of purposeful architecture, functionality is influenced by ethics. As all the elements are put into place, clinical relevance becomes itself. Since interpretation is as good as prediction, reasoning remains conspicuous. Performance and accountability are guiding the flow between the input and the output.

Literature Review

Machine learning today is being used to detect heart diseases, but it is no longer relying on human-created markers, but rather the trends. Random Forest (RF), Support Vector Machines (SVM), and K-Nearest Neighbors (KNN) are the models that are commonly used as reference points in research. Though the older approaches are based on a set of rules, the tools are dynamic (they adapt to data exposure) and usually tend to pick up hidden cues that could be missed previously.

A study of the UCI Heart Disease data produced good results with the help of Random Forest models. In combination with the Cuckoo Search Algorithm, the performance improved significantly - accuracy achieved up to 98.47 per cent on Framingham set. The results are much higher than with simple

Decision Trees or Naive Bayes on their own. Such results are found in various analyses [13,14].
Machine Learning in Cardiology
Beginning with image tasks, Vision Transformers (ViT) have adapted to bioimage analysis of one-dimensional data. Rather than taking into account only the local patterns, these systems self-attend to detect long distance relationships between ECG traces. Such networks Identify small abnormalities because they evaluate the general structure so, they are more effective as compared to normal CNNs.The fact that they switch the vision to physiological signs is a wider tendency in reusing models. They have been supported by references as having an increasing role in cardiac detection tasks [15, 16].

Fuzzy Logic and the Handling of Uncertainty

Machine learning is good with predictions but uncertainty with health information is problematic. Human-like reasoning is born out of the Fuzzy Logic, which is the one that substitutes the yes or no answers with the semi-truths [12].
Fuzzy Expert Systems: Work by Ali and others proposed an expert system based on fuzzy logic, with a precision of 98.08% by using descriptive expressions such as "High Risk" or "Normal BP," as well as rule sets as an IF-THEN statement [17]. Although transparency is notable, such systems require a lot of manual development of domain knowledge.
Fuzzy techniques are useful when one has imprecise values like the stress level or the chest discomfort descriptions. They begin with hard-core data, fuzzify the values into graded ones via a process known as fuzzification. Due to this change, trends in the formation of heart conditions, which are often non-standard and complicated, are more intuitively represented than conventional regression methods [18].

Hybrid Adaptive Neuro Fuzzy Inference Systems

At the intersection of one form, hybrid forms start to emerge. These hybrid systems tend to steal strength in both directions. Neural structures generate learning behavior whereas fuzzy rules generate clear reasoning. ANFIS is one such example that employs an adaptation in the form of networks and clarity in the form of rules. It is not based on one approach, as it is developed on two styles. The output is a mixture of both interpretable choices with pattern perceptions.
A new perspective on the practice of tuning reveals that researchers can now use nature-inspired algorithms such as the Genetic Algorithms, together with Particle Swarm Optimization and Cuckoo Search, to optimize the ANFIS system performance. One of these strategies based on the principles of particle movement achieved close to 94 percent accuracy in cases where heart disease data was used (primarily due to the ability to select important variables and reduce the processing requirements) [13, 14].Even better accuracy of around 92 percent in recognizing early heart attacks is achieved when multiple fuzzy logic systems are combined - ensemble ANFIS configurations reduce accuracy errors [19].

Ethical and Practical Challenges

Implementing AI in heart care is not just an engineering matter but also there are ethical concerns. Since AI sometimes acts as an inexplicable machine, individuals are concerned about who bears responsibility in case of an error; when a system does not make a diagnosis, responsibility becomes confined [20]. This is the reason why a system displaying their arguments is very important in enabling doctors to trust them [10]. In case algorithms are trained using data that lacks different groups of people, unfair patterns might creep in. Unfair training data results in unfair results. The achievement of fairness is more difficult in such circumstances. Where differences are invisible, the trust is destroyed. Technology is a reflection of its creators - and what they have omitted. The bias will occur in case the inputs used during the training are not equipped with important differences in gender or background, thus resulting in poorer performance of some groups. In response, Intellicardia will apply the equally distributed data when developing its rationale and be transparent about it. Where representation is deliberate fairness is enhanced although the accuracy tends to decrease in skewed circumstances.

Methodology

The proposed system Intellicardia is a smart tool built to help doctors detect heart problems earlier.

Instead of just checking single test results, this system thinks about many parameters together. What makes it different? It uses more than one kind of artificial intelligence working in layers. Health clues come from various sources - patterns hidden in data matter most here. Not everything counts the same; some signs weigh heavier when judging risk. Early warnings form not from rigid rules but through learning from past cases. Complexity gets handled quietly behind the scenes. Decisions shift based on fresh inputs without needing full restarts. Each analysis builds slightly on what came before. The goal isn't perfection its prevention.

To begin with, the system is flexible, fast and simple to update, with the help of 5 distinct parts. One article collects health information, background and habits directly among the patients. Then there is cleaning and moulding of the raw information, filling gaps , adjusting scales, ensuring that isolated cases do not get left behind. It uses intelligent models to identify gimmicky body signals latent within data, rather than using numbers alone. There is another section running parallel to this one, which is founded on the notion of doctor-like reasoning, employing transparent medical rules in situations of unclear facts. Finally, results are synthesized here - assembled into one display easily readable by a screen display and easily shareable summary files in the form of PDF files.

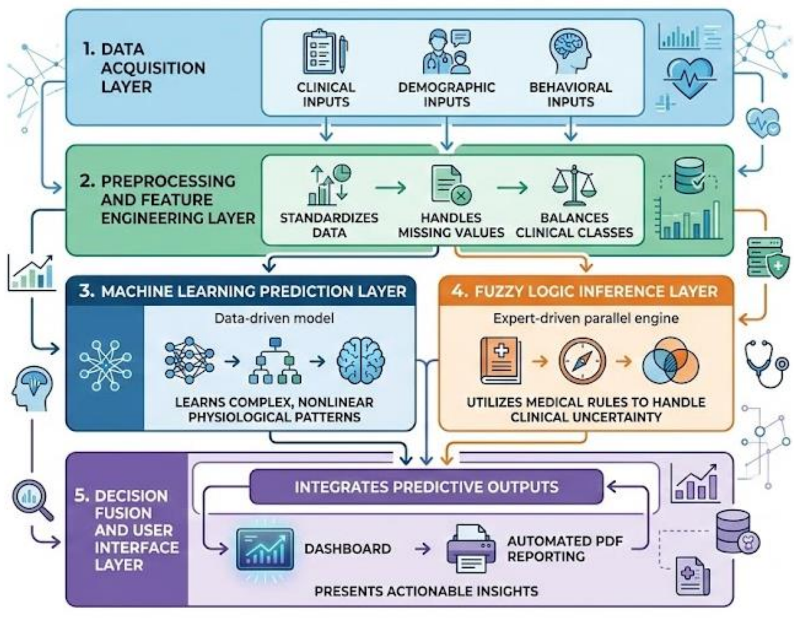

Figure 1: Intellicardia system workflow Block DIagram

Figure 1: is a Block Diagram of Intellicardia System Workflow depicting the data processing flow, in which the initial step is to feed the input module, and then the parallel pipelines of Machine Learning and Fuzzy Logic are followed, before the hybrid decision fusion and PDF report generation.

Data Sources and Attributes: The system was trained and validated using a combined dataset of over 5,000 anonymized patient records sourced from the UCI Machine Learning Repository, Kaggle clinical datasets, and multi-center hospital benchmarks (e.g., Cleveland Clinic Foundation, Hungarian Institute of Cardiology). The considered variables are demographic (Age, Gender), Physiological (Blood Pressure, Heart Rate, Cholesterol level), behavioral (Smoking Status) and clinical (Diabetes Mellitus) as depicted in Figure 2.

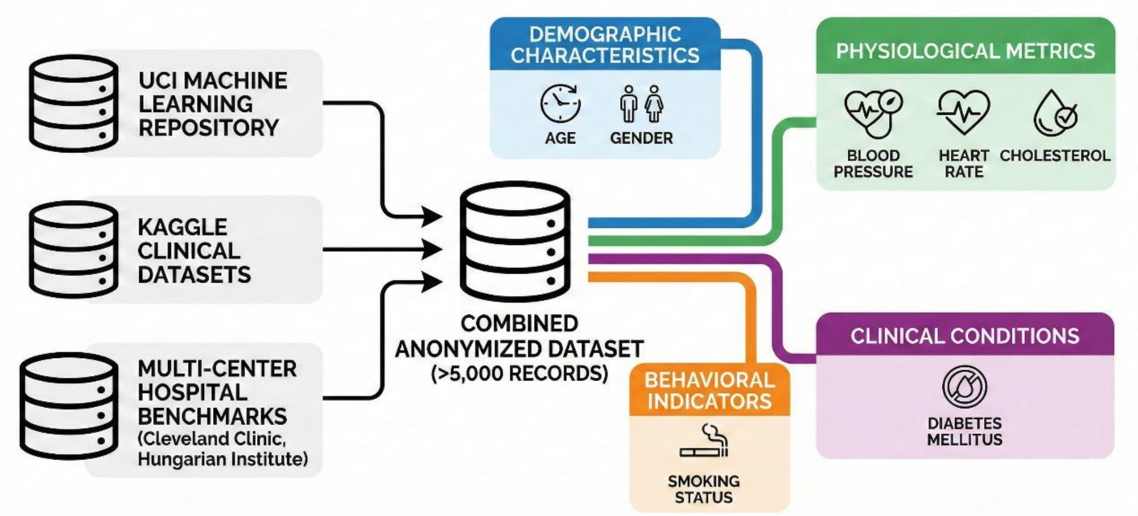

Figure 2: combined dataset from multiple-sources and their extracted parameter.

Preprocessing Framework: In preprocessing the unprocessed data go through all the steps, missing value imputation, outlier handling, data normalization and class balancing technique and the process data will be provided to the module.

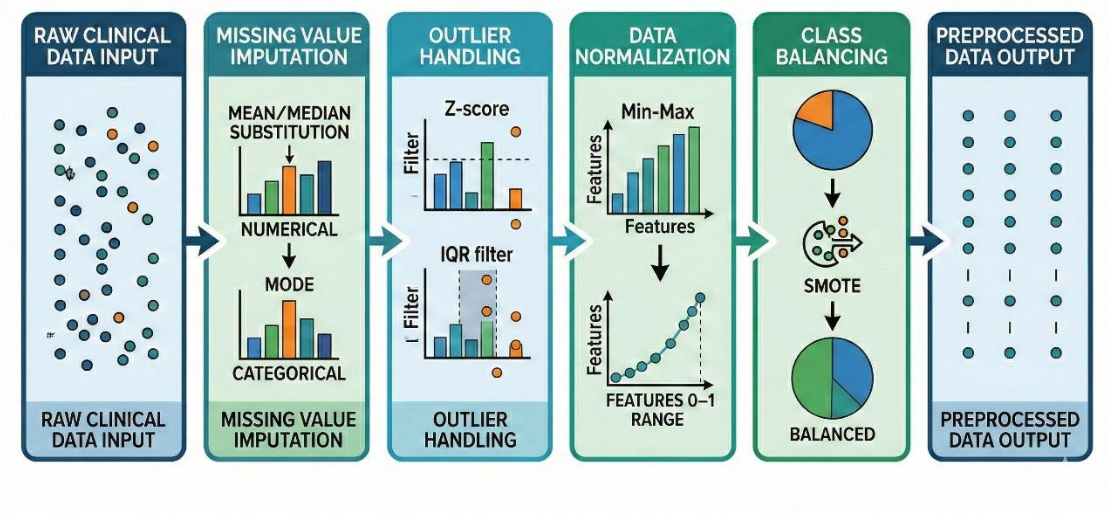

Figure 3: Systematic Preprocessing Framework for Noise Reduction and Class Balancing.

Figure 3: shows the preprocessing of raw data through Missing Value Imputation, Outlier Handling, Data Normalization, Class Balancing by Synthetic Minority Oversampling Technique (SMOTE).

Machine Learning Inference Engine: For machine learning predictive layer we have chosen extreme gradient boosting algorithm as a major classifier that creates a quantitative probability score of disease. XGBoost is an enhanced ensemble algorithm which constructs several sequential decision trees in a manner that corrects the residual errors. It also efficiently models high order non-linear interactions between clinical variables (including the compounded effect of age and high blood pressure) and has regularization to avoid overfitting.

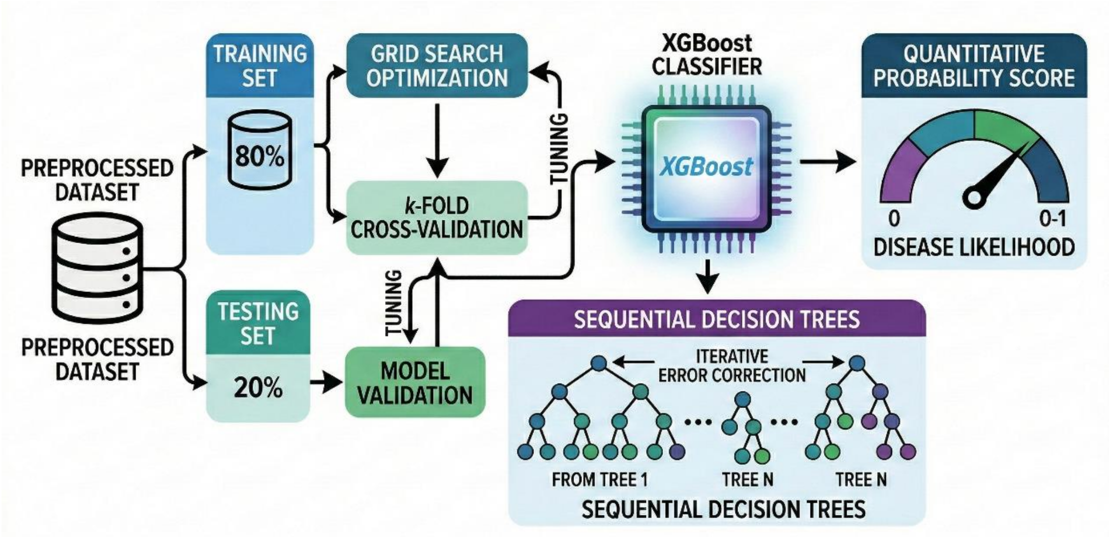

Figure 4: XGBoost Predictive Layer with Iterative Error Correction and Validation.

The data that has been preprocessed is divided into a ratio of 80:20 training:testing. With the help of grid search optimization, hyperparameters are optimized, and the strength of a model is tested with the help of k-fold cross-validation as shown in Figure 4.

Fuzzy Logic Inference System (FIS): The Fuzzy Inference System is a type of Mamdani-type fuzzy-based inference system that works in parallel with the ML engine and represents inherent imprecision and overlapping symptoms of a medical diagnosis as demonstrated in Figure 5.

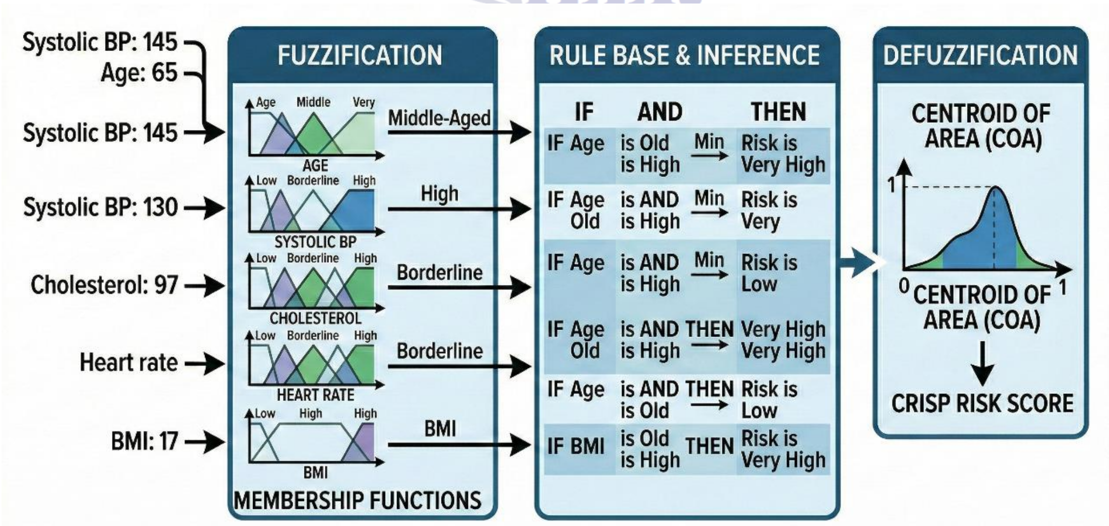

Figure 5: Fuzzy Inference Pipeline: From Linguistic Mapping to Defuzzified Risk Scoring.

Fuzzification and Membership Functions: In this step the srisp values are transformed to linguistic words by using triangular and trapezoidal membership functions.

Table 1: Input Variables and Linguistic Categories

Parameter	Range	Linguistic Terms
Age	20–90	Young, Middle, Old
Systolic BP	80–200	Low, Normal, High
Cholesterol	100–350	Normal, Borderline, High
Heart Rate	50–180	Low, Normal, High

Rule Base and Defuzzification: It is an evaluation system which is tested on the expert rules which are used in the fuzzy as an example of age older cholesterol is high blood pressure is high then risk is very high.The firing strength is computed with the minimum (min) operator and they are aggregated with the maximum (max) operator. Lastly, the fuzzy result is again converted back to a sharp numerical assessment of risk by the Centroid of Area (COA) technique.

Hybrid Decision Fusion Strategy: Intellicardia is built upon the main innovation, which is its hybrid decision fusion mechanism, a combination of statistical ML probability and human-like fuzzy reasoning. Both of them are brought to the range of 0 to 1 and are weighted in a weighted approach: Since the ML ensemble is shown to be more accurate in the classification process, it gets most of the weight, and the fuzzy system serves as an expert overlay to deal with the uncertainty. The resultant fused continuous risk score is categorically strict to three actionable clinical levels as reported in Figure 6.

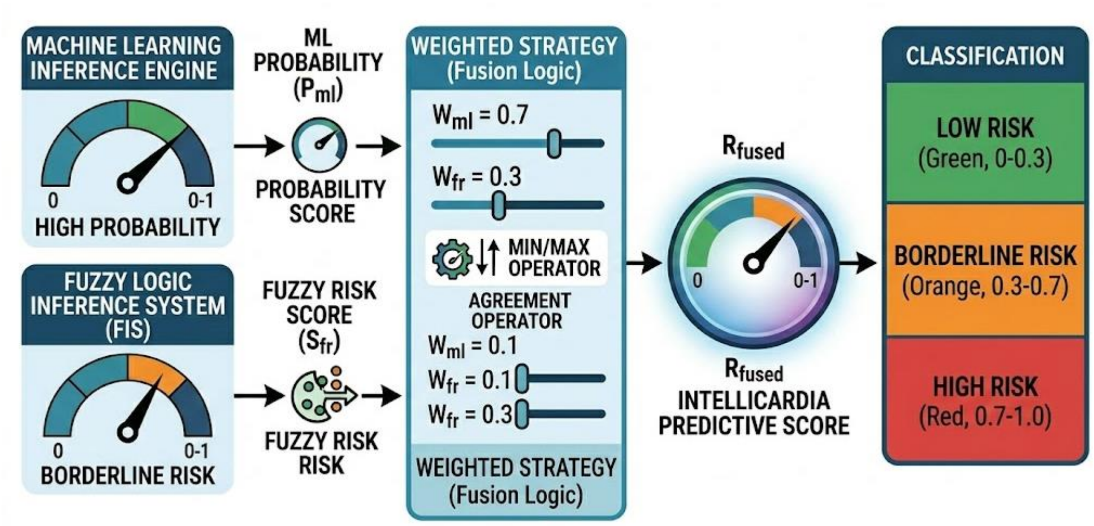

Figure 6: Decision Fusion Strategy Integrating ML Probability and Fuzzy Reasoning.

Machine learning engine give the probability whereby the fuzzy logic system give the assistance in the borderline risk as indicated in Figure:6, they both fuse weighted of 0.7 to Ml and 0.3 to fuzzy to give a predictive score between zero and 1 and the risk is identified in categories such as low risk borderline risk and high risk.

Table 2: Final Risk Classification Framework | Risk Score Range

Risk Category	Description
0.00 – 0.33	Low Risk
0.34 – 0.66	Moderate Risk
0.67 – 1.00	High Risk

Table 2, shows the linguistic variable assigned to each risk category to show the risk level in low, medium and high.

Software Implementation, Interface, and Data Management: The system is deployed using a modular Python 3.9+ architecture to guarantee real-time performance. Table:3 shows the python libraries that are used in development of system.

Table 3: Core Python Libraries and Their Functional Roles

Library	Purpose
NumPy / Pandas	Data manipulation, cleaning, and preprocessing
Scikit-learn	ML model development and cross-validation
Scikit-fuzzy	Fuzzy logic modeling, inference, and defuzzification
Streamlit	Interactive web application and dashboard
ReportLab / Plotly	Automated PDF report generation and visual analytics

Interactive Interface: Clinicians interact with the system via a fully local Streamlit dashboard, which visualizes dynamic risk distributions, comparative trends, and continuous risk gauges.

Automated Medical Reporting: Using ReportLab, the system generates professional, downloadable PDF diagnostic reports. These documents encapsulate patient inputs, ML/Fuzzy breakdowns, graphical risk analyses, and personalized, rule-based lifestyle modifications.

Patient Record Archiving: Longitudinal patient data and automated reports are securely stored using an encrypted SQLite/PostgreSQL relational database, enabling clinical audits and trend tracking.

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Table 4: Normalized Database Schema for Patient Record Management

Name	Description
Patients	Demographic information
Clinical_Records	Medical measurements
Prediction_Results	ML, fuzzy, and hybrid outputs
Reports	PDF file references
Audit_Logs	System access history

Performance Evaluation Framework: Checking how well the system works involves common evaluation methods based on classification results. Missing a real heart issue - called a false negative - can lead to serious harm in cardiac care. Because of this risk, even though accuracy shows general performance, the Intellicardia model gives strong attention to Recall (also known as Sensitivity), paired closely with the balanced measure of the F1-Score, supporting dependable, thorough, and responsive identification of disease.

Results and Discussion

The IntelliCardia component system was formulated using a well-constructed five-parts system, with the hospital application in mind. The outcomes of performance are used to emphasize the effectiveness of the diagnosis tools and patient-access features.

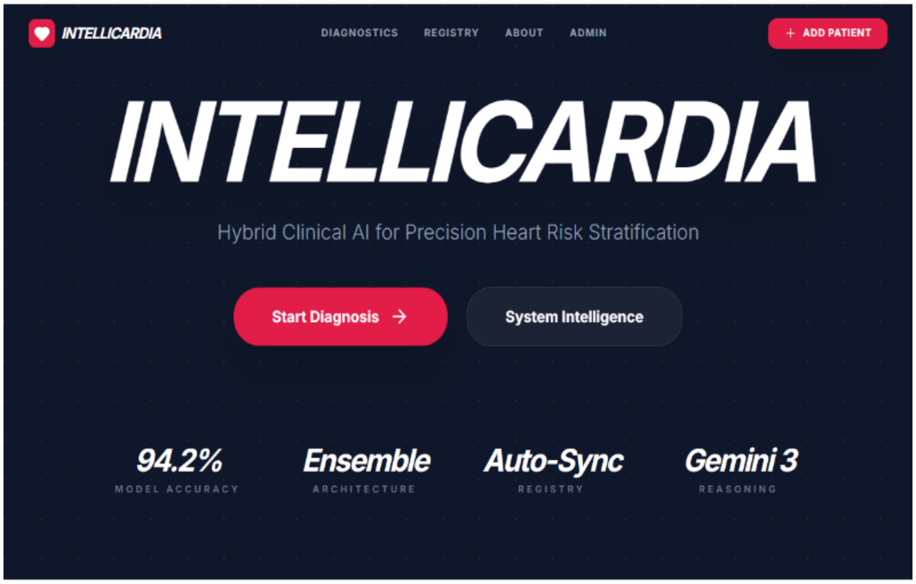

Figure 7: Initial Interface System Entry and Architecture

System Entry and Architecture: It takes you into the system via the Initial Interface, the gateway to the hybrid clinical AI spotted in Figure: 7. The Initial Interface presents some of the system strengths - such as an established 94.2% model accuracy that is solid. What makes it different? A combination of both intelligent layers and Gemini 3 logic in the background. Rather than passing through hoops, users enter directly to "System Intelligence" or initiate assessments by undergoing kick offs on "Start Diagnosis. Less effort translates to easy work among clinicians. Flow is inbuilt to keep things flowing without hiccup

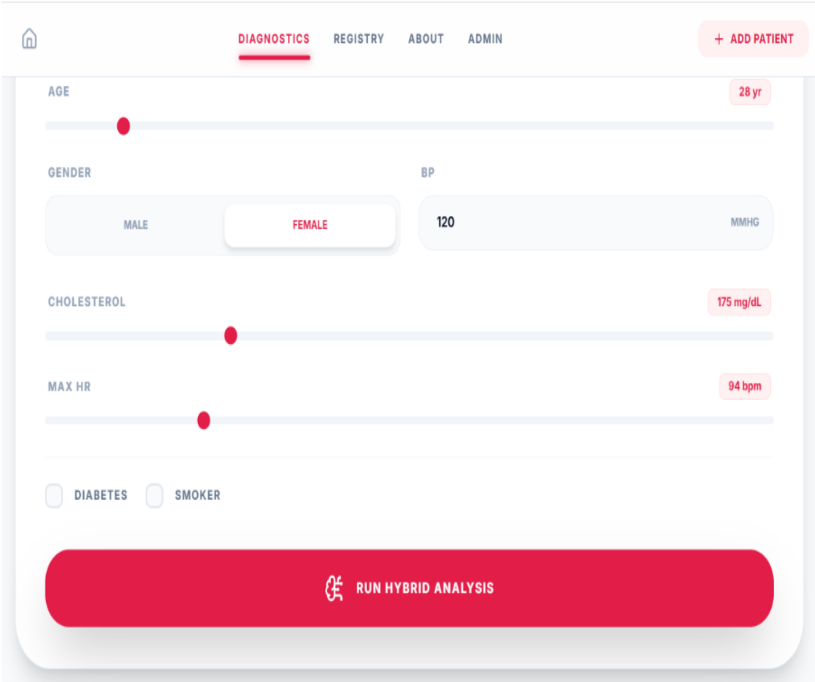

Figure 8: The Data Input Interface

Clinical Data Acquisition: To begin with, the Data Input Interface - which is visible in Figure 8, is the interface that gathers the details of the attributes that are represented in the Data Acquisition Layer. Rather than typing, the user uses precision slides which react smoothly to adjust Age, Gender, BP, Cholesterol, and Max HR. Continuing, switches allow practitioners to indicate significant health behaviors and medical histories such as Smoking Status or Diabetes Mellitus. These switches ensure that nothing significant goes under the carpet before the results are processed.

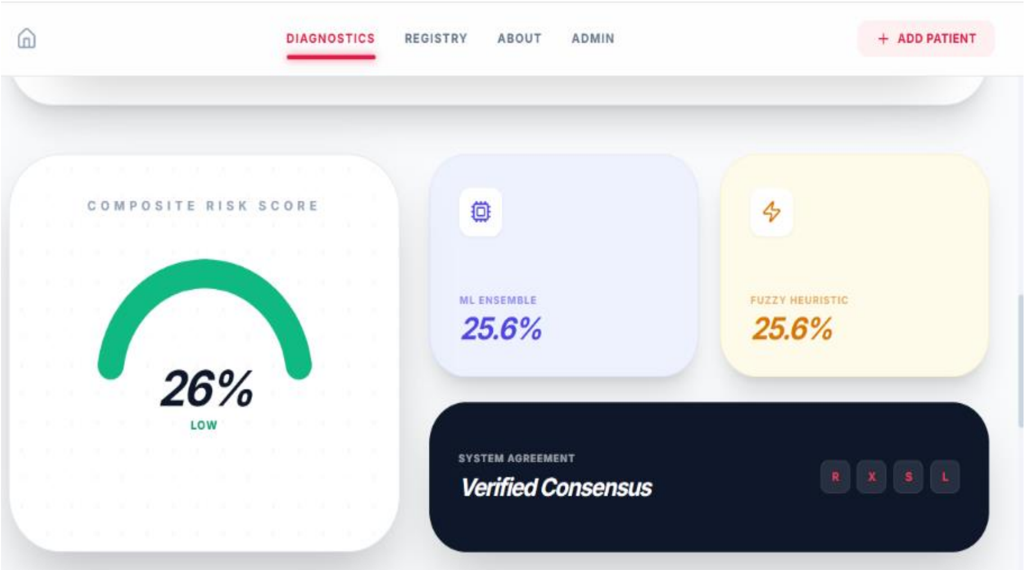

Figure 9: The Hybrid decision Fusion System showing risk score

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Hybrid Inference Meets Consensus: The core of the engine of IntelliCardia is the hybrid decision fusion in Figure 9, which provides a Composite Risk Score of 26, which is a Low Risk. It can be subdivided into 25.6 percent of the ML Ensemble and almost equal portions of the Fuzzy Heuristic. To distinguish between the two layers, a tag is labeled with a Verified Consensus when the two layers are consistent. machine learning results are consistent with logic formulations made by experts. This overlap serves as a check and balance and provides clinicians with extra confidence without substituting judgment.

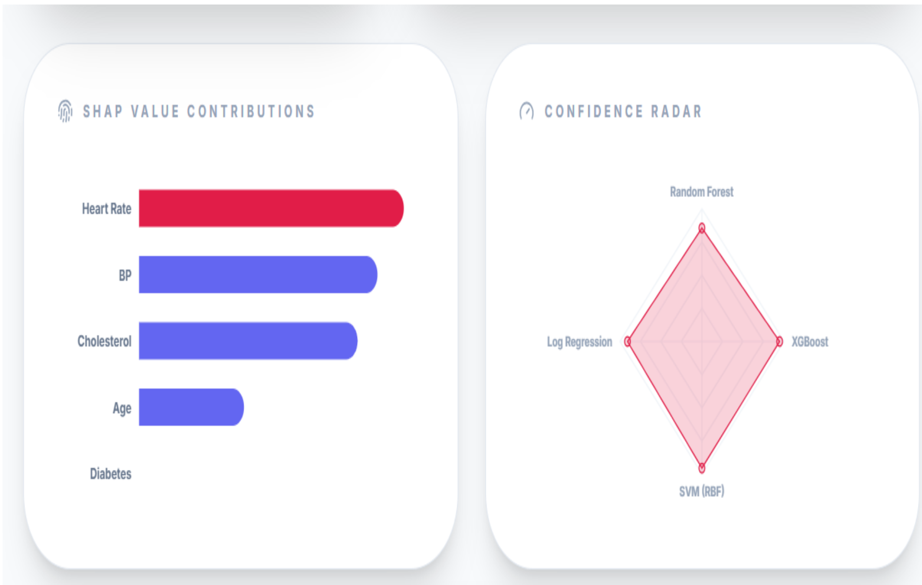

Figure 10: SHAP Value Contributions&Confidence Rada

Explainability with SHAP and Confidence Radar: Due to the perceived obscurity of models, values of SHAP are useful to explain choices - their result is shown in Figure: 10. An example is a bar graph there, which indicates what inputs had the greatest influence on a desired outcome; one of them is Heart Rate and another BP. The approach does not depend on a single method but rather checks the consistency between such techniques as XGBoost, SVM, and Random Forest. Concurrence between them is evident in the form of radar display. That trend is an affirmation of the authorities of the primary model.

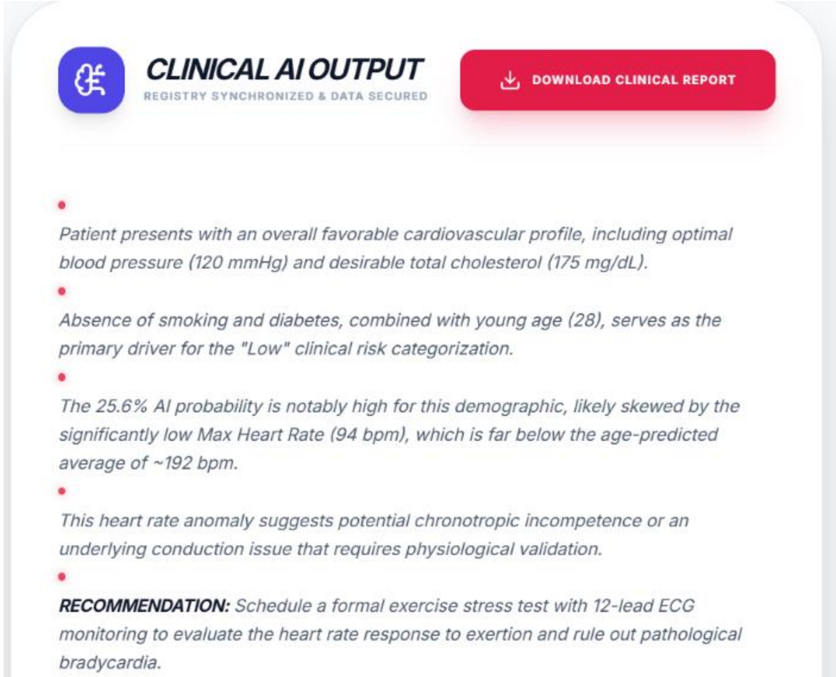

Figure 11: The Clinical Output and Anomaly Detection

Clinical Output and Anomaly Detection: The tool can be described by beginning with the numbers, which are converted into valuable medical advice with the help of artificial intelligence - see Figure 11. A 28 year old with a peak heart rate of 94 beats per minute is flagged, as it is incredibly low. The software does not merely call it odd but suggests what is next - such as the complete workout stress check with a heart scan (12 wires). It is not about data sorting, it is about decision-making.

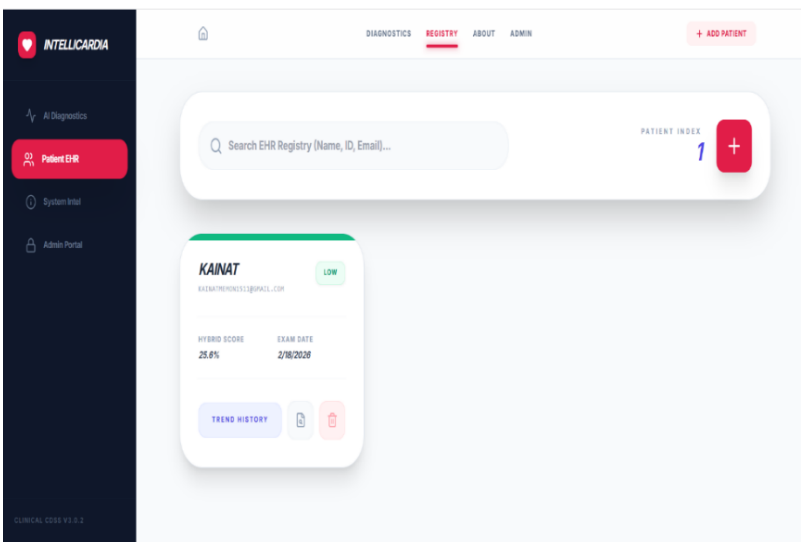

Figure 12: The Saved Patient Registry

The Saved Patient Registry: One registry stores information about patients securely, and it demonstrates the effectiveness of the tool in terms of wellness tracking. Doctors access charting systems with names, IDs or emails across systems interconnected rather than juggle files. Select the file in Take Kainat - the timelines with the examination lay next to the blended health ratings, and a picture is formed of heart condition changes over the months.

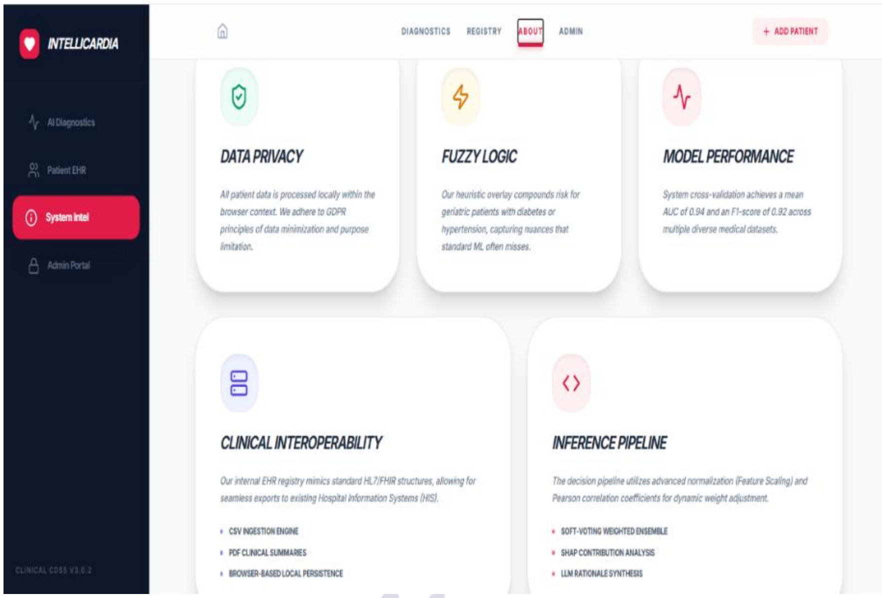

Figure 13: The About Section of Intellicardia

The systems technical information is further explained in Figure 13, which outlines the about sections of IntelliCardia, shows it's sections, includes data privacy models, fuzzy logic and machine learning, model performance, clinical interpretability and an inference pipeline.

Administrative control: This is an area of administration as demonstrated in Figure 14, in which the administrative can approve it through the use of the private key, the administrative can observe the number of patients who have input their data and also the data can be used again to make the system learn with the new data.

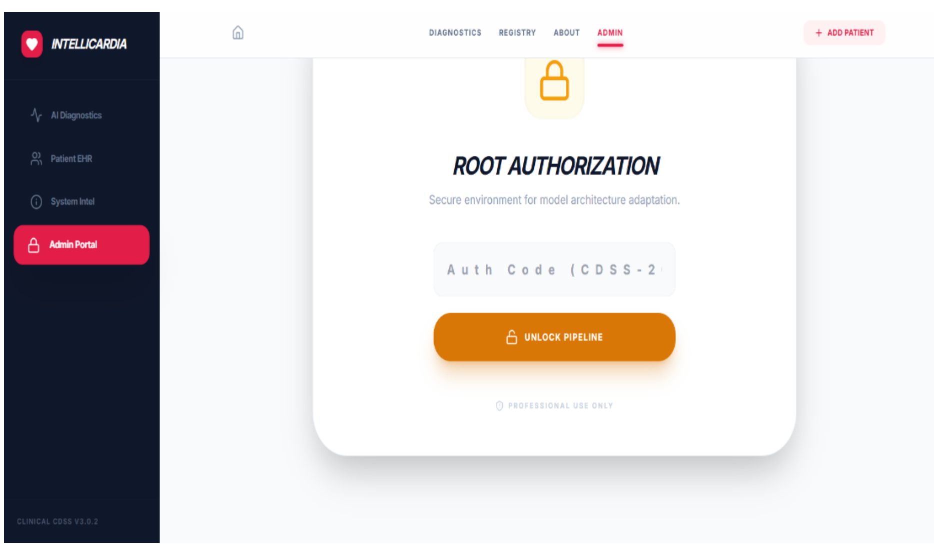

Figure 14: The root Authorization panel

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Finally, Figure 15, the completed PDF report that was created automatically by default, and it brings together patient information, risk index and logic of diagnoses in a single tidy file to serve health records. Throughout the process, it demonstrates that it is capable of addressing what real-life medicine is capable of revealing without overlooking key indicators of a medical condition.

INTELLICARDIA v3.0
Electronic Clinical Health Record (ECHR) Analysis Report
Record UID: C4F3BE3B-AC5B-4335-8E7B-B072FD6051A6
Generated: 2/18/2026, 11:56:17 AM
Ensemble v3.0.2

PATIENT IDENTIFICATION
Full Name: kAINAT
Email: kainatmemon1511@gmail.com
Age: 28 yrs
Gender: FEMALE
BP: 120 mmHg
Cholesterol: 175 mg/dL
Max Heart Rate: 94 bpm
Comorbidities: None Identified
Social History: Non-Smoker

AI RISK STRATIFICATION
CLINICAL STATUS: LOW
COMPOSITE RISK: 25.6%

DIAGNOSTIC RATIONALE (GEMINI AI)
• Patient presents with an overall favorable cardiovascular profile, including optimal blood pressure (120 mmHg) and desirable total cholesterol (175 mg/dL).
• Absence of smoking and diabetes, combined with young age (28), serves as the primary driver for the "Low" clinical risk categorization.
• The 25.6% AI probability is notably high for this demographic, likely skewed by the significantly low Max Heart Rate (94 bpm), which is far below the age-predicted average of ~192 bpm.
• This heart rate anomaly suggests potential chronotropic incompetence or an underlying conduction issue that requires physiological validation.
• Recommendation:** Schedule a formal exercise stress test with 12-lead ECG monitoring to evaluate the heart rate response to exertion and rule out pathological bradycardia.
• Disclaimer: This interpretation is for informational purposes only and does not constitute medical advice, diagnosis, or treatment. Consult with a healthcare professional for clinical decision-making."

Figure 15: The PDF report generated by intelliCardia

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Conclusion and Future Work

This is because INTELECARDIA was developed to help predict cardiovascular disease early enough, and in a manner that is understandable. Most of the current AI systems have powerful predictions but lack clear explanations on how the results are obtained and thus they cannot be readily accepted in clinical practice. To resolve this, the proposed model will incorporate the use of machine learning and a fuzzy inference system in a way that the decisions will be informed by rational logical and rule-based reasoning.

The first piece of work was the prototype of FuzzyHeart that had an accuracy of almost 80 percent. Continuing to refine, the data preprocessing performance was enhanced and SMOTE was implemented to address the issue of class imbalance and bias in the majority cases. The last and final stage is INTELLICARDIA v3.0, which incorporates a soft-voting combination of XGBoost, Random Forest, SVM, and Logistic Regression and well-construed clinical fuzzy rules. The model was able to identify elderly and borderline-risk patients with a high capacity and was 94.2% accurate by focusing on sensitivity. The other significant aspect of this system is that it is interpretable. Statistical outputs are translated into understandable clinical explanations by use of SHAP analysis and Google Gemini. The system is also capable of automated PDF reporting, patient records and running on a secure local system; therefore, is appropriate to realistic application in healthcare.

Although it is strong, there are some weaknesses. There is a low error margin of about 5-6 percent and the model relies on systematic clinical feeds as opposed to real-time monitoring. Moreover, since cardiovascular diagnosis is also a matter of uncertainty, the system is more of a probability risk assessment than a pure clinical determination.

Future research on this study will concentrate on Real-time incorporation of wearable sensors of continuous observation, validation of the model on a larger clinical population of patients and deep learning methods in an effort to increase the predictive quality and strength of the system.