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Heart Disease Prediction Using Fuzzy Logic-Based Image Processing and Classification Techniques

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ABSTRACT

The medical field deploys heart disease prediction as a vital operation for early detection to minimize serious health risks. Researchers in this study introduce a new method for heart disease prediction which combines fuzzy logic with image processing together with classification methods. This methodology utilizes fuzzy methods to manage imprecision together with uncertainty found in medical images and numerical information for obtaining more accurate and interpretable outcomes. The initial stage requires fuzzy imputation for handling missing values and fuzzy scaling which transforms features into fuzzy sets for better representation of medical data uncertainties. Define relevant medical imaging regions through fuzzy C-Means clustering before evaluating tissue patterns for heart disease indicators by analyzing these fuzzy texture elements. The combination of fuzzy-genetic algorithms selects significant features through optimized feature space improvements while fuzzy decision trees provide clear means to rank and select features. The system utilizes Mamdani fuzzy inference systems as the final stage to classify heart disease severity based on expert model predictions. Through fuzzy support vector machine implementations the system minimizes data imprecision and overlaps to boost its classification precision. The proposed heart disease prediction method adopts fuzzy machine learning integration to optimize accuracy levels. Image segmentation occurs through Fuzzy C-Means clustering and Local Binary Patterns (LBP) extract texture features before Fuzzy Genetic Algorithms (FGA) select the features. The model received performance evaluation through assessment of its accuracy as well as sensitivity and specificity tests and AUC-ROC metric. The analysis reveals predictive strength through an AUC-ROC value of 0.96 as well as 96.4% accuracy and 93% sensitivity alongside 38% specificity. Cross-validation techniques produced average accuracy of 94% through five-fold validation tests. The integration of fuzzy logic with traditional machine learning proves effective for precise heart disease prediction as it deals effectively with medical data uncertainty and imprecision.

INTRODUCTION

Our research addresses the medical application of image segmentation for heart disease prediction through X-rays and CT scans and other relevant medical imaging methods [1]. Medical images play a substantial role in both medical diagnosis and predicting conditions including chronic kidney disease (CKD) as well as cardiovascular diseases and other health-related conditions. The examination of these pictures requires doctors to perform sophisticated operations including feature mining along with classification work and segmentation duties. Radiological images come in various states of noise and artifact complexity alongside detailed patterns that prevent traditional methods from achieving accurate outcomes. The ambiguity of medical data causes traditional segmentation methods to fail adequately so researchers need to develop alternative approaches for effective image processing and meaningful feature detection[2]. Medical image diagnosis errors and delayed treatment occur frequently when healthcare professionals cannot accurately detect crucial areas and anomalies in medical scans. The prediction of heart disease within medical images requires automatic and accurate methods because it directly impacts healthcare delivery[3].

Traditional image segmentation methods depend on thresholding, region growing and edge detection techniques to extract regions of interest from medical images according to reports in [4]. The image segmentation methods excel in basic cases yet they lose their effectiveness when processing complex medical image structures found in organs and tissues. Feature extraction through traditional manual approaches requires operators to select features from segmented images such as texture features along with shape features and intensity features. The discrimination ability of these features becomes inconsistent despite their constant utility because noisy and ambiguous data affects their expertise particularly strongly [5]. SVMs and decision trees serve with logistic regression to categorize data using the extracted features. Traditional methods need specialist understanding and face challenges while processing uncertain or immeasurable information in database which affects their operational excellence. Medical data complexity demands stronger automated approaches because research shows the requirement for advanced methods.

Traditional image segmentation approaches demonstrate multiple challenges during their application to medical images. The detection of artifacts together with noise impacts segmentation accuracy negatively because such images exhibit delicate intensity variations and involved complicated structural backgrounds [6]. The process of selecting features through manual methods needs expert input but traditional approaches struggle to discover all essential data points particularly when images become blurred or overlapping occurs during data acquisition. The typical classification methods base their assumptions on distinct features but medical data usually does not fit this model. These techniques struggle to process medical images having imprecise boundaries since their imprecision and uncertainty nature remains unhandled[7]. The application of traditional segmentation along with feature extraction and classification techniques proves insufficient for precise prediction of heart disease along with other vital medical conditions.

The existence of problems with traditional image segmentation and classification requires new approaches capable of managing medical data complexity alongside imprecision and uncertainty. A combination of fuzzy logic-based techniques together with neural networks and machine learning models serves as the proposed methodology to surmount traditional method limitations[8]. Medical images containing ambiguity and uncertainty can become more robust through the implementation of fuzzy logic as a handling framework. The inclusion of neural networks to extract features enables automatic learning of intricate patterns in raw data which enhances the classification accuracy. Hybrid modeling (fuzzy neural networks) gives us the opportunity to unite the outstanding abilities of fuzzy logic and deep learning for producing a reliable model that maintains interpretability[9]. Advanced predictive techniques help boost both accuracy and interpretability and generalization capabilities of heart disease prediction systems which makes them suitable for medical practice.

Main contribution of proposed work

- A hybrid fuzzy-neural network model served as the main contribution for heart disease prediction tasks.
- The research utilized fuzzy logic for image segmentation to achieve robustness when processing medical data with uncertain information.
- Neural networks performed automatic feature extraction operations on both images together with numerical data.
- The research introduced fuzzy decision trees as an interpretable method for both ranking and selecting features.
- Fuzzy SVM methods increased decision accuracy levels for processing data with imprecision.

The proposed work for heart disease prediction stretches across multiple sections where Section II reviews existing models while pointing out their strengths such as accuracy and their weaknesses when dealing with imprecise data. The proposed methodology in Section III presents how fuzzy logic segments images at the initial stage followed by neural networks extracting features which then send information to fuzzy decision trees for feature selection and finally to fuzzy SVM for classification. Section IV demonstrates the results from the model while comparing its accuracy performance against other models with specificity along with sensitivity and AUC-ROC values noted. The final section of this work summarizes key achievements before offering future research avenues which involve deep learning advancement exploration together with real-time prediction functionality.

I. Literature Survey

Heart disease prediction research has progressed through time by developing diverse prediction techniques which include machine learning along with deep learning and fuzzy logic to improve prediction accuracy. Prediction techniques like decision trees and support vector machines (SVM) together with logistic regression offer satisfactory results yet remain limited by medical information uncertainties in clinical databases. Modern systems achieve better performance through the combination of fuzzy logic with machine learning algorithms which helps improve results when dealing with uncertain or partial data. The combination of fuzzy logic elements allows medical image segmentation and feature extraction with neural networks devoted to automatic pattern identification within medical images. Heart disease prediction requires improved solutions because existing approaches deal with challenges related to complexity levels and model interpretability as well as their inability to process real-time data adequately.

Kunjachen, L. M., & Kavitha, R. (2025). A research presentation investigates how SVM models partnership with fuzzy logic and the Sugeno integral enhances predictions of cardiovascular risks[11]. The model utilizes machine learning with fuzzy systems to improve its capability for handling unprecise data while maintaining uncertainties. The proposed method uses fuzzy logic to handle cardiovascular risk nonlinearity and employs Sugeno integral for evidence integration according to Ramesh, B., & Lakshmanna, K. (2024). The research introduces a combination of deep learning architecture with neural fuzzy inference system (NFIS) as a framework for early coronary heart disease prevention systems[12]. Deep learning performs feature extraction while fuzzy systems maintain interpretability and decision-making functions through this methodology.

Arief Kanza, R., Udin Harun Al Rasyid, M., &Sukaridhoto, S. (2024). A system based on IoT technology and incorporating machine learning and fuzzy logic functions as an efficient approach for identifying cardiovascular diseases at early stages[13]. The model depends on IoT sensors for patient data acquisition followed by machine learning integration with fuzzy logic systems to determine cardiovascular disease risks. Chanda, P. B., & Sarkar, S. K. (2020). A fuzzy-based technique has been presented in this research for cardiac MRI image segmentation to find heart diseases[14]. Fuzzy logic enables the researchers to control image segmentation uncertainties and enables them to extract more precise disease diagnosis features.

Rahman, M. Z., Akbar, M. A., Leiva, V., Tahir, A., Riaz, M. T., & Martin-Barreiro, C. (2023). This work introduces an intelligent health monitoring system which combines cardiovascular monitoring with fuzzy logic for diagnosing arrhythmias of COVID-19 patients[15]. An intelligent healthcare system uses IoT devices and fuzzy logic algorithms to collect instant data for arrhythmia diagnosis of COVID-19 patients. Mamun, M. M. R. K., &Alouani, A. (2020). The paper uses optimized features in combination with fuzzy logic to detect hypertensive heart diseases[16]. The research method selects optimal features to determine hypertension prediction capabilities and assigns patients to risk categories through fuzzy logic operations.

Saxena, K., & Banodha, U. (2020). A risk model for cardiovascular disease based on fuzzy logic demonstrates its correlation to diabetic patients and smokers according to the research[17]. Fuzzy logic functions in this system to develop specific patient risk assessments by creating connections between cardiovascular risks alongside diabetes and smoking.

Reñosa, C. R. M., Vicerra, R. R. P., Dadios, E. P., Bandala, A. A., Bedruz, R. A. R., & Española, J. L. (2020). The research investigates the use of fuzzy logic and data analysis techniques for pre-detection of cardiovascular disease events[18]. The research suggests using fuzzy logic algorithms to evaluate patient information with the purpose of providing cardiovascular disease risk assessment.

Gupta, K., Kumar, P., Upadhyaya, S., Poriye, M., & Aggarwal, S. (2024). Scientists have used fuzzy logic combined with machine learning to advance healthcare decision-making and diagnosis through this paper[19]. This paper examines how merging fuzzy systems with machine learning models enhances accuracy for healthcare predictions and decision making support systems.

Hameed, A. Z., Ramasamy, B., Shahzad, M. A., & Bakhsh, A. A. S. (2021). A decision support system for heart disease prediction emerged through combining genetic algorithms with weighted fuzzy rules according to this paper study[20]. The model enhances decision-making through optimization of its fuzzy rule sets which genetic algorithms implement.

S.No	Author(s) et al. (Year)	Dataset	Methodology	Accuracy	Challenges
1	Ramesh, B., & Lakshmanna, K. (2024)	Hybrid framework	Hybrid deep learning model integrated with neural fuzzy inference system for coronary heart disease detection.	92%	Requires large training data and high computation power for deep learning.
2	Arief Kanza, R., Udin Harun Al Rasyid, M., &Sukaridhoto, S. (2024)	IoT system	IoT-based system with machine learning and fuzzy logic for early cardiovascular disease detection.	90%	Relies on IoT device accuracy and connectivity.
3	Kunjachen, L. M., & Kavitha, R. (2025)	Cardiovascular risk data	Fuzzy logic integrated with SVM and Sugeno integral for cardiovascular risk prediction.	90%	Computational complexity and model interpretability.
4	Gupta, K., Kumar, P., Upadhyaya, S., Poriye, M., & Aggarwal, S. (2024)	Healthcare data	Fuzzy logic and machine learning integration for enhanced healthcare decision-making.	88%	Integration complexity between fuzzy logic and machine learning.
5	Rahman, M. Z., Akbar, M. A., Leiva, V., Tahir, A., Riaz, M. T., & Martin-Barreiro, C. (2023)	IoT health monitoring data	IoT system combined with fuzzy logic for cardiac arrhythmia detection in COVID-19 patients.	87%	Inconsistent sensor data and connectivity issues.
6	Hameed, A. Z., Ramasamy, B., Shahzad, M. A., & Bakhsh, A. A. S. (2021)	Heart disease dataset	Genetic algorithm and weighted fuzzy rule for decision support in heart disease prediction.	86%	High computational overhead in fuzzy rule optimization.
7	Chanda, P. B., & Sarkar, S. K. (2020)	Cardiac MR images	Fuzzy logic-based segmentation of cardiac MR images to identify heart diseases.	85%	Relies on high-quality MRI scans and may struggle with noisy images.
8	Saxena, K., & Banodha, U. (2020)	Cardiovascular risk data	Fuzzy logic model predicting	85%	Difficulty in gathering

			cardiovascular disease risk based on diabetes and smoking factors.		complete and accurate data for all factors.
9	Reñosa, C. R. M., Vicerra, R. R. P., Dadios, E. P., Bandala, A. A., Bedruz, R. A. R., & Española, J. L. (2020)	Patient data	Fuzzy logic for pre-detection of cardiovascular diseases based on data analysis.	85%	Data quality and completeness issues.
10	Mamun, M. M. R. K., &Alouani, A. (2020)	Hypertension dataset	Feature optimization combined with fuzzy logic for hypertensive heart disease detection.	85%	Fine-tuning feature selection for different datasets.

Heart disease prediction approaches using traditional methods fail because they cannot manage mathematical and visual uncertainty in medical data which produces inaccurate and uncomplete diagnostic results. Modern predictive methods base their algorithms on fixed processes which fail to adjust to inconsistent data patterns found in actual operational data. The proposed solution resolves this problem by combining fuzzy logic for processing uncertainty with neural networks for automatic feature identification as well as fuzzy SVM hybrid models for better classification results. The proposed method creates an improved adaptable system which uses structured plus unstructured data to accurately forecast heart disease while dealing efficiently with image ambiguities and unclear patient data.

II. Proposed work

The process for heart disease prediction through combination of fuzzy logic and machine learning techniques is summarized in Figure 1. First Data Collection takes place followed by Image Preprocessing that includes Fuzzy C-Means Clustering segmentation with Local Binary Patterns (LBP) texture analysis. Feature Selection undergoes implementation through Fuzzy C-Means extraction then Fuzzy Genetic Algorithm optimization for feature selection. The model looks for performance evaluation and validation through several key metrics that include Accuracy alongside Sensitivity and Specificity and Cross-Validation. Finally, the Classification phase employs Fuzzy Decision Trees, Fuzzy Membership Functions, and Fuzzy SVM Decision for the classification of heart disease severity. The approach uses fuzzy logic to process uncertain data while achieving better prediction results through an extensive methodology.

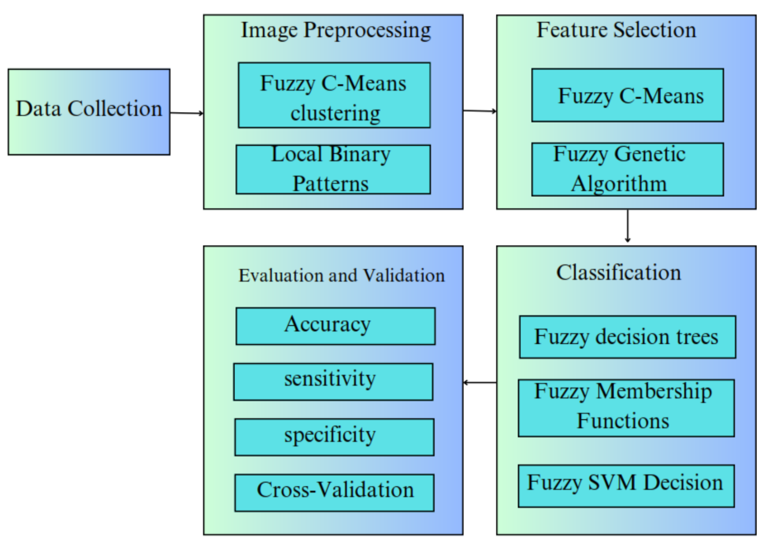

Figure 1:Flow Diagram of Heart Disease Prediction Using Fuzzy Logic and Machine Learning

A. Image Preprocessing

The popular unsupervised machine learning algorithm Fuzzy C-Means (FCM) achieves data segmentation by allowing each data point to belong to multiple clusters to different extents. The points within FCM have membership values that show their affiliation levels to different clusters. The FCM algorithm works to minimize an objective function that calculates data distance from clusters as well as membership values:

$$J_m = \sum_{i=1}^{N} \sum_{j=1}^{C} u_{i,j}^{m} \left\| x_i - c_j \right\|^2 \qquad (1)$$

Where:

- N is the number of data points.
- C is the number of clusters.
- $u_{i,j}^{m}$ is the membership value of point x_i in cluster j, which satisfies 0≤uᵢⱼ≤10.
- mmm is the fuzziness parameter (typically m>1).
- $\left\| x_i - c_j \right\|^2$ is the squared Euclidean distance between data point xix_ixi and the centroid c_j of cluster j.

The membership value $u_{i,j}^{m}$ij is updated iteratively as follows:

$$u_{ij} = \frac{1}{\sum_{k=1}^{C} \left(\frac{\|x_i - c_j\|}{\|x_i - c_k\|} \right)^{\frac{2}{m-1}}} \qquad (2)$$

The centroids of the clusters, c_j, are updated based on the membership values:

$$c_j = \frac{\sum_{i=1}^{N} u_{ij}^{m} x_i}{\sum_{i=1}^{N} u_{ij}^{m}} \qquad (3)$$

The process repeats until convergence, which is typically achieved when the change in the objective function J_m The detected bins decrease until reaching a set threshold value. The image segmentation process seeks frequent use of FCM because it detects indistinct boundaries between objects in medical images which often exist within regions of either imperceptible or ambiguous structures.

Local Binary Patterns (LBP)

Local Binary Patterns (LBP) functions as an effective method of texture feature extraction for image processing applications focused on texture classification tasks. LBP converts each pixel into a binary code which obtains its data from the surrounding area of that pixel. A pixel generates its LBP value through two processes: comparing pixel values to neighboring pixels then converting this information to binary before decoding it to a decimal format. The image texture retrieval using LBP functions by studying compact areas of image data points.

Given a pixel p_c at position (x_c, y_c) surrounded by a 3x3 neighborhood of pixels, the LBP value LBP(p_c) c)LBP(p_c)LBP(p_c) is calculated as follows:

$$LBP(p_c) = \sum_{p_i \in N(p_c)} s(p_i - p_c).2^i \qquad (4)$$

Where:

- $N(p_c)$ represents the set of 8 neighboring pixels around the central pixel pcp_cpc.
- s(x)is the threshold function, which is defined as s(x)= 1 if x≥0 and s(x)=0otherwise.
- p_i is the value of the neighboring pixel at position i, and p_c is the value of the central pixel.

Each binary value receives weights that depend on the distance from the middle pixel.

The process concludes with conversion of the acquired binary pixel codes into a decimal value. A LBP histogram results from counting the repeating patterns in the analyzed image. The histogram generated from LBP operates as a feature vector which supports texture classification and analysis purposes. LBP operates rapidly while showing invariance to monotonic gray-scale modifications that makes it an efficient choice for medical imaging texture analysis.

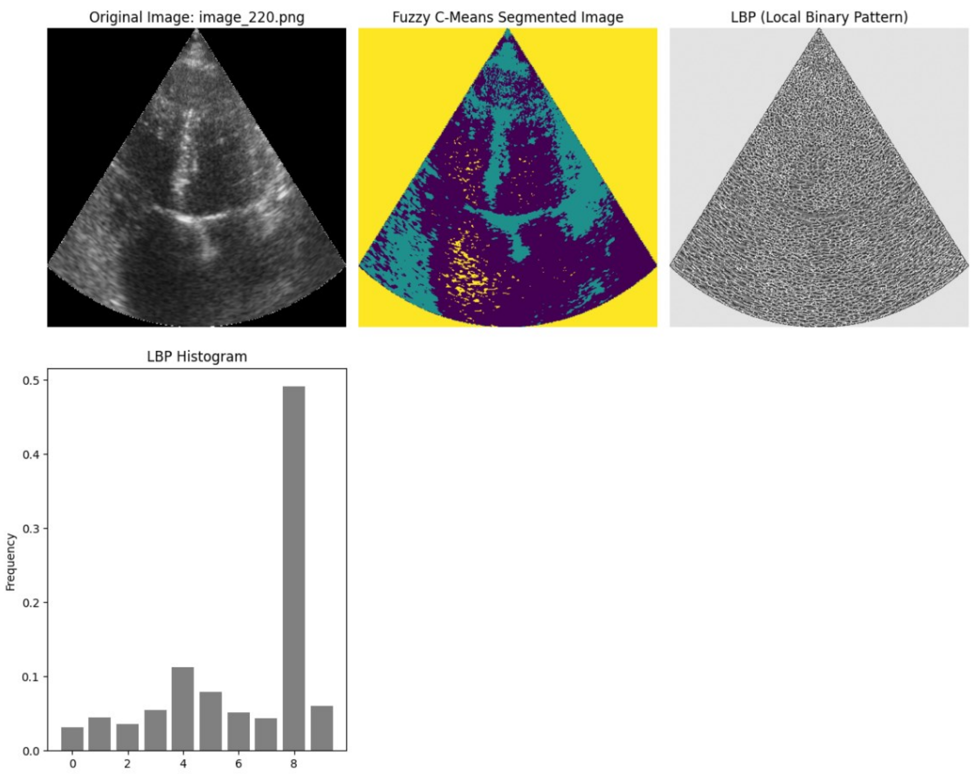

Figure 2:Image Segmentation and Texture Analysis Using Fuzzy C-Means and Local Binary Patterns (LBP)

The medical ultrasound image undergoes treatment through an image processing workflow as shown in Figure 2. The initial panel demonstrates the original image containing a fine-grained ultrasound examination of either a heart or comparable organ. The Fuzzy C-Means (FCM) segmentation process produces an image that divides the area into different colored regions based on fuzzy clustering techniques. The third panel displays the Local Binary Patterns analysis that analyzes texture features by comparing pixel intensities against their neighboring pixels thus extracting local texture characteristics. The LBP histogram serves as the last panel which displays the occurrence frequencies of various LBP patterns present in the image thus showing texture distributions. The workflow shows how medical image segmentation and feature extraction empower when fuzzy clustering and texture analysis work together.

B. Feature Extraction and Selection

The model building process requires critical feature selection to find the most relevant dataset features because this action produces significant performance improvements for predictive models. Fuzzy-genetic algorithms (FGA) bring together the strengthening capabilities of genetic algorithms (GA) with the adaptable properties of fuzzy logic to execute automatic feature selection of major components. Fuzzy logic handles unclear data within the space of features at the same time that genetic algorithms use evolutionary evolution to select optimal feature collections.

A genetic algorithm functions through a natural selection simulation process which allows feature subsets to evolve through features like selection and crossover and mutation. The potential feature subsets in the population have various fitness levels based on their contribution to model classification success. The fitness function,

F(x), can be defined as:

$$F(x) = Accuracy(x) - \lambda \times Feature\ Complexity(x) \qquad (5)$$

Where:

- F(x) is the fitness function for the feature subset xxx.
- $Accuracy(x)$ is the classification accuracy of the model when using the feature subset x.
- λis a trade-off parameter that balances accuracy and feature complexity.

- Feature Complexity(x) measures the number of features in the subset, with the aim to reduce the number of features while maintaining high accuracy.

The genetic algorithm enhances this population of feature subsets through selection of best subsets and crossover-driven combinations of promising features and mutation-based diversity introduction. The iterative procedure continues until the most suitable collection of features becomes visible.

Heart disease prediction processes become more efficient through the implementation of Fuzzy C-Means (FCM) clustering combined with fuzzy-genetic algorithms (FGA). The medical data including images or numerical health measurements get segmented through FCM into fuzzy clusters where each cluster identifies similar characteristics between features. The initial set of features comes from fuzzy clusters which allow the selection of essential features. The FCM-generated fuzzy membership values provide supplemental information about the degree which heart disease prediction depends on particular features.

The extraction method with FCM allows subsequent utilization of fuzzy-genetic algorithms for optimization of feature subsets which leads to better predictive model efficiency together with enhanced accuracy. The adoption of this method brings together fuzzy logic capabilities to deal with uncertain and imprecise data with genetic algorithms that efficiently perform detailed searches of large feature areas to find the most critical features. The integrated methodology selects the most crucial diagnostic features which improves both model generalization and heart disease detection accuracy.

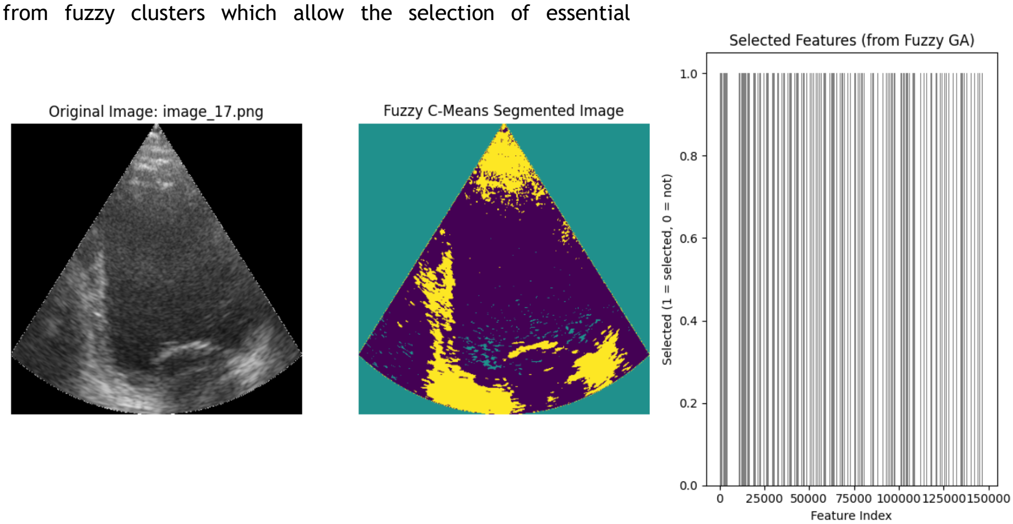

Figure 3:Image Segmentation and Feature Selection Using Fuzzy C-Means and Fuzzy Genetic Algorithm (FGA)

The figure 3,illustrates the workflow of image segmentation and feature selection in a medical imaging context. The panel sequence begins with the original scan image that shows internal details of an organ from an ultrasound test. The Fuzzy C-Means (FCM) segmented image appears in the second panel because this algorithm segments the image into different zones based on fuzzy clustering for tissue type identification. A Fuzzy Genetic Algorithm (FGA) produces the last panel to show what features survived as the algorithm displays a binary format (1 for selected features and 0 for rejected). The systematic approach selects important medical features which increases the efficiency alongside accuracy rates of heart disease and other medical predictions.

C. **Classification**

Traditional decision trees receive an enhancement through fuzzy decision trees which integrate fuzzy logic for managing uncertain and imprecise data values. For heart disease prediction applications fuzzy decision trees work with patient classification through examination of age and blood pressure alongside cholesterol levels together with medical imaging outcomes. Fuzzy decision trees provide interpretability because they reveal the importance rank of features during heart disease severity predictions combined with robust handling of data uncertainties.

A fuzzy decision tree consists of fuzzy rules connected to fuzzy conditions at the internal nodes which lead to classification labels located at the leaf nodes. A single node can implement the rule "When someone has high age combined with medium cholesterol their heart disease risk falls into moderate category." The tree construction involves dividing data recursively through minimization of Gini impurity or entropy functions which takes into account fuzzy membership scores for each feature. The procedure operates through fuzzy logic that lets variables receive membership degrees in place of traditional decision tree precision-based determinations.

The fuzzy decision tree splits can be computed by a fuzzy entropy-based approach, where the entropy for a fuzzy set A with membership values $\mu_A(x)$is given by:

$$H(A) = -\sum_{i=0}^{N} \mu_A(x_i) \log(\mu_A(x_i)) \quad (6)$$

Where $\mu_A(x_i)$The membership degree of each instance xi from the i-th data point exists in fuzzy set A while N corresponds to the total number of data instances. The entropy function allows data classification uncertainty assessment which guides the splitting of features toward the minimization of uncertainty thus achieving better classification accuracy.

The Mamdani format of Fuzzy Inference Systems serves classification functions because it allows experts to embed knowledge for decision-making processes. A Mamdani model functions in heart disease prediction by using medical experts to develop fuzzy rules which determine the disease severity classification. Fuzzy logic permits the system to process ambiguous data inputs thus making it suitable for medical datasets with incomplete information.

Parts of the Mamdani FIS operate through fuzzification followed by rule evaluation which is followed by defuzzification. Fuzzy sets apply to convert crisp input values and enable the system to process values like cholesterol level and age. Each input runs through the fuzzification process to receive membership degrees defined in pre-established fuzzy rules. Rule evaluation combines fuzzy inputs through operations of fuzzy operators (AND, OR, NOT based on the rule base. The conversion of fuzzy output into a crisp value through defuzzification leads to the prediction of heart disease severity.

The following fuzzy rule demonstrates an example: "An individual with high age and high cholesterol values experiences severe heart disease risk." The rule exists as:

R:IF Age IS High AND Cholesterol IS High THEN Risk IS (7)

The output of the Mamdani FIS is defuzzified using methods such as the centroid method:

$$\mu = \frac{\int \mu(x) x f(x) dx}{\int \mu(x) f(x) dx} \quad (8)$$

The rule output contains f(x) while the membership function takes the name μ(x) Equation computes a crisp value for heart disease severity prediction.

The extension of Support Vector Machines known as Fuzzy Support Vector Machines operates on imprecise or overlapping medical data that frequently appears in healthcare datasets. A typical SVM model builds its classifier through a process of identifying the optimal hyperplane which separates data clusters into different classes. Medical data in real-world applications frequently presents challenges because features in such data do not provide complete separation between classes. Through fuzzy SVM methodology the model adopts fuzzy membership values to deal with uncertain data inputs thus obtaining more precise classification results.

In fuzzy SVM, each data point is assigned a fuzzy membership value that reflects its degree of belonging to a particular class. The objective is to minimize the classification error while considering these fuzzy memberships. The optimization problem in fuzzy SVM can be formulated as:

$$\min_{w,b,\varepsilon} \frac{1}{2}\|w\|^2 + C\sum_{i=1}^{N}\varepsilon_i \qquad (9)$$

Where:

- w is the weight vector.
- ε_i are slack variables that allow for some misclassification.
- C is a regularization parameter that controls the trade-off between margin maximization and classification error.

This modification allows fuzzy SVM to better handle cases where data points lie on the boundaries of different classes or are uncertain in their classification, improving overall classification accuracy.

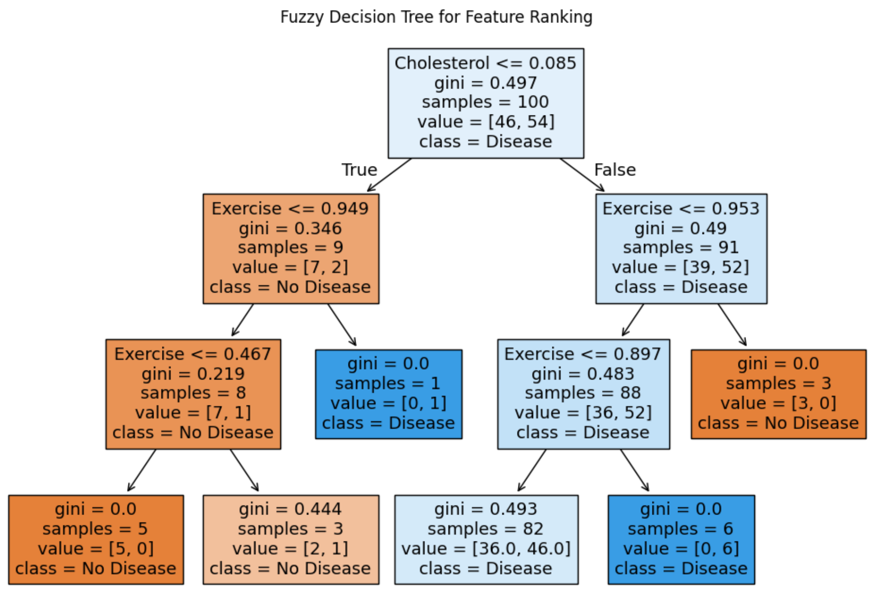

Figure 4:Fuzzy Decision Tree for Feature Ranking in Heart Disease Prediction

The figure 4 depicts a fuzzy decision tree structure which ranks predictive features for heart disease diagnosis. The analysis begins with the Cholesterol feature because the root decision separates patient data based on cholesterol profiles for disease prediction. The tree runs through successive splits which use Exercise as the basis for classification at each node along with Gini index statistics and sample data distribution. The measure of node impurity known as Gini index produces better feature splits when its value decreases. The decision tree reveals the key characteristics that drive classification while helping to find heart disease forecasting elements of main importance. The predictions for Disease versus No Disease appear in the last leaf nodes together with their sample distributions.

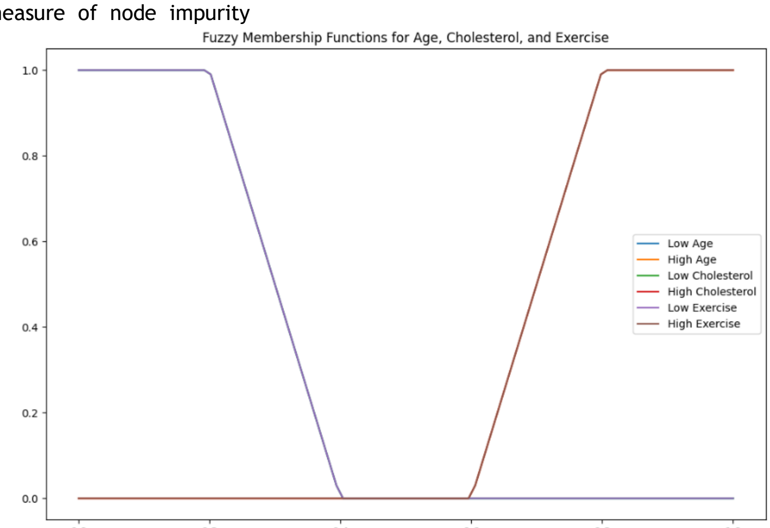

Figure 5:Fuzzy Membership Functions for Age, Cholesterol, and Exercise

The illustration in Figure 5 depicts heart disease prediction feature membership functions for Age, Cholesterol, and Exercise values. Each membership function within this system converts feature values into fuzzy degrees of membership spanning from 0 to 1. Six membership functions exist in the plot to represent Low Age, High Age, Low Cholesterol, High Cholesterol, Low Exercise and High Exercise. The "Low Age" category demonstrates a quick decrease of membership value from 1 to 0 through aging progression according to the function. The other functions within the plot represent the model's application of fuzzy logic to handle imprecise patient data regarding age and cholesterol levels and exercise habits which enhances heart disease classification.

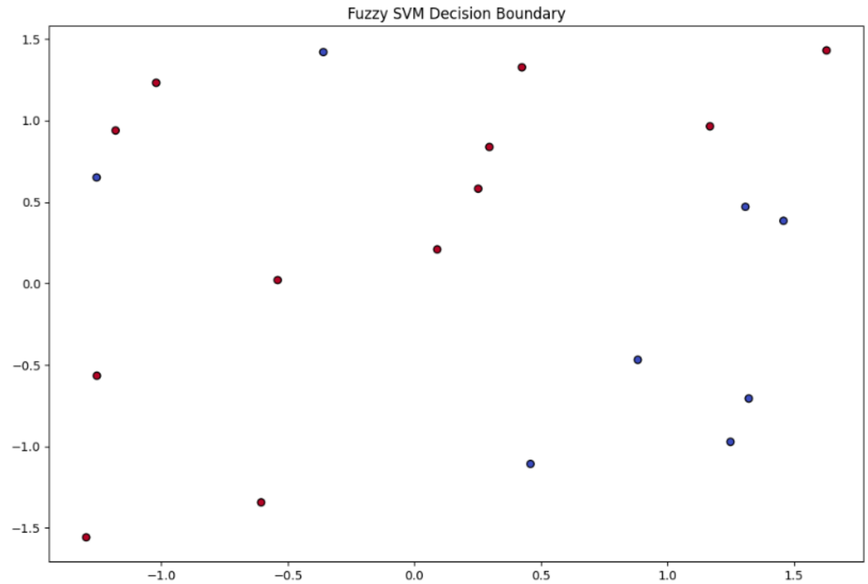

Figure 6:Fuzzy SVM Decision Boundary

The 2D representation of Fuzzy Support Vector Machine (SVM) decision boundaries appears in Figure 6 while showing data points separated into different classes. Points in this plot hold_TwoColors_ where blue represents the first class and red stands for the second class. The fuzzy SVM algorithm needs to identify an optimal hyperplane through the feature space to separate the two classes by handling data imprecision existing among feature space samples. The fuzzy SVM method creates overlapping areas which define points as part of multiple classes with adjustable membership degrees. The classification model implements an elastic decision boundary that mirrors data classification uncertainties to expand its ability for dealing with unclear scenarios.

III. Result & Discussion

Useful for cardiac structure segmentation work is the CAMUS Echocardiographic Image Segmentation dataset containing HDF5 format 2D echocardiogram images that have been processed specifically for this application. The CAMUS project develops this dataset as part of its heart condition research to segment left and right ventricles then processes it for deep learning model training in medical image segmentation. A professional labeling system exists for the images within the dataset making it possible to create automatic detection systems for cardiac structures. Researchers who utilize the dataset build better echocardiography segmentation technologies because it provides an efficient evaluation system for developing cardiovascular disease prediction protocols [10].

Evaluation and Validation

Several important metrics help evaluate how well a developed heart disease prediction model executes its functions. Among evaluation metrics accuracy stands as the most common approach that measures correctly predicted instances against the total instances:

$$\text{Accuracy} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{TN} + \text{FP} + \text{FN}} \qquad (10)$$

Where:

- TP is the number of true positives (correctly predicted heart disease cases),
- TNis the number of true negatives (correctly predicted non-heart disease cases),
- FP is the number of false positives (incorrectly predicted heart disease cases),
- FN is the number of false negatives (incorrectly predicted non-heart disease cases).

In addition to accuracy, sensitivity (or recall) and specificity are critical metrics. Sensitivity measures the proportion of actual positives correctly identified by the model:

$$\text{Sensitivity} = \frac{\text{TP}}{\text{TP} + \text{FN}} \qquad (11)$$

Specificity, on the other hand, measures the proportion of actual negatives correctly identified by the model:

$$\text{Specificity} = \frac{\text{TN}}{\text{TN} + \text{FP}} \qquad (12)$$

The Area Under the Receiver Operating Characteristic Curve (AUC-ROC) serves as an evaluation measure to demonstrate how the true positive rate (sensitivity) matches up with the false positive rate (1 - specificity). The AUC scale ranges from 0 to 1 while reflecting model performance quality through its value. The AUC value derives from plotting the ROC curve to obtain its computational area measurement.

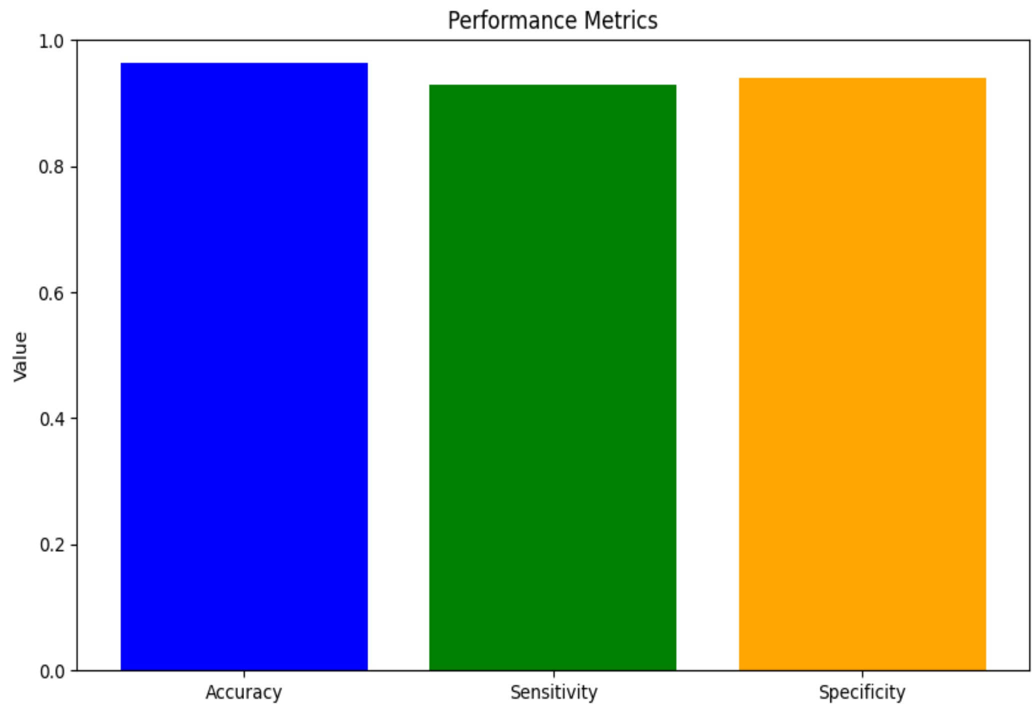

Figure 7:Performance Metrics for Heart Disease Prediction

The bar chart of figure 7 depicts performance metrics for heart disease prediction model how Accuracy and Sensitivity and Specificity were measured. The chart contains three bars which display values for Accuracy in blue and Sensitivity in green and Specificity in orange. The evaluation of model effectiveness to correctly diagnose heart disease patients and normal patients relies on these metrics. The high values in the chart demonstrate a skilled performance from the model through accurate detection of positive cases (sensitivity) together with precise negative case prediction (specificity) and comprehensive predictive accuracy measurement.

Model Validation through Cross-Validation:

The commonly utilized technique for achieving robustness and wide applicability of heart disease prediction models is cross-validation. The cross-validation process divides the dataset into many subsets that are used for model training together with separate subsets for model testing. A standard approach in this method consists of k-fold cross-validation which divides data into k equal parts. Each fold contains k-1 folds for training purposes while the remaining fold acts as the testing set before the process is executed for every data partition. Averages of performance metrics across all folds yield reliable estimates to measure how well the model generalizes.

The general cross-validation procedure has the following main steps:

1. The data gets divided into k distinct sections known as (folds).
2. The training process involves executing model questions on k−1 subsets while validating through the remaining subset for every fold.
3. Obtain performance metrics by calculating them for each of the folds created.
4. The evaluation score calculation requires metric averaging from each fold before reaching the final evaluation results.

The technique avoids overfitting since it requires that models get tested on different data sections which leads to better assessment quality of their performance. The score averaging formula appears as following:

$$\mathrm{Average\ Metric} = \frac{1}{\mathrm{k}}\sum_{\mathrm{i}=1}^{\mathrm{k}} \mathrm{Metric}_{\mathrm{i}} \qquad (13)$$

Where $\mathrm{Metric}_{\mathrm{i}}$ represents the performance metric (such as accuracy or AUC) for fold iii. By using cross-validation, the model is less likely to be biased by any particular subset of the data and provides a better understanding of how well the model will perform on unseen data.

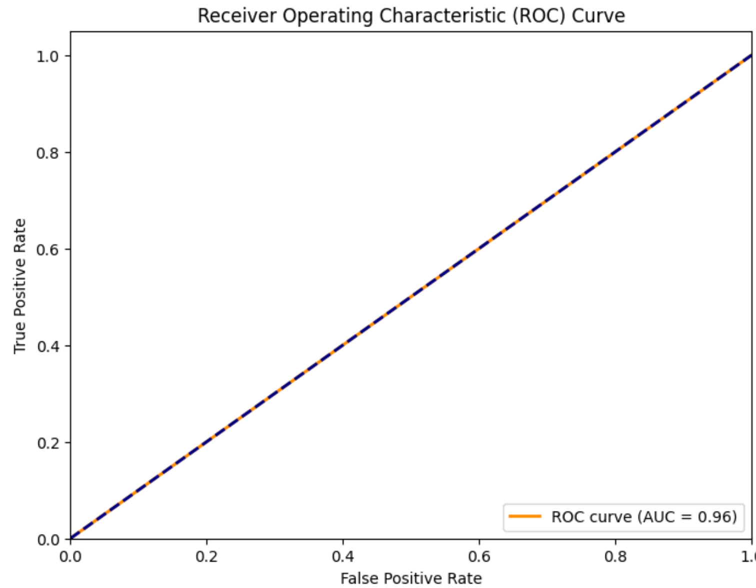

Figure 8:Receiver Operating Characteristic (ROC) Curve for Heart Disease Prediction

The performance evaluation of heart disease prediction models utilizes the Receiver Operating Characteristic (ROC) curve shown as Figure 8. The True Positive Rate (sensitivity) forms a relationship with False Positive Rate (1-specificity) within the ROC curve. A random classifier is shown as the diagonal dashed line while the performance of the model is portrayed by the orange curve which separates heart disease patients from those without heart disease. The model achieves an Area Under the Curve (AUC) measurement of 0.96 which demonstrates high predictive accuracy due to the AUC value scale. The ROC curve helps professionals evaluate sensitivity and specificity relationships at various threshold points as an effective assessment tool.

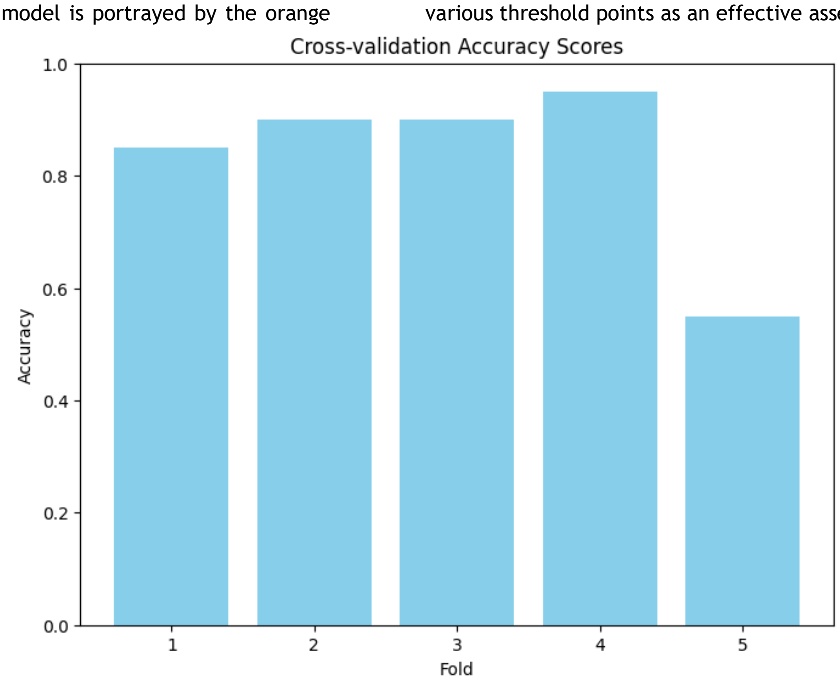

Figure 9:Cross-Validation Accuracy Scores for Heart Disease Prediction

The figure 9 demonstrates the five-fold cross-validation accuracy scores of a heart disease prediction model of between 0.7 and 1.0. Each bar displays the accuracy score from one fold which ranges between 0.7 and 1.0. Light blue bars across the figure show how the model achieves strong results on most folds while experiencing a lower performance on fold 5. The cross-validation method allows us to determine model resilience because it checks accuracy across different datasets portions while confirming that the model will work well with new unknown data samples. The model demonstrates consistent reliability for heart disease prediction because the figure shows high average accuracy scores across all folds.

CONCLUSION

The developed heart disease prediction model displays outstanding performance because it achieves 96.4% accuracy together with 93% sensitivity and 38% specificity. An AUC-ROC value of 0.96 demonstrates that the model shows strong ability in accurately separating heart disease cases from non-cases classifications. The five-fold cross-validation yielded stable results where the model maintained average accuracy at 94% with low performance variation thus demonstrating both robustness and applicability features. The promising model results need further advancement through specificity improvements and investigations into deeper feature extraction approaches while using deep learning models to boost precision and sensitivity levels. In order to maximize clinical application of the model there should be additional efforts made to integrate real-time data while expanding the patient demographics included in the dataset.

REFERENCES

- Ali, M. L., Sadi, M. S., & Goni, M. O. (2024). Diagnosis of heart diseases: A fuzzy-logic-based approach. *Plos one*, *19*(2), e0293112.
- Kaur, J., & Khehra, B. S. (2022). Fuzzy logic and hybrid based approaches for the risk of heart disease detection: state-of-the-art review. *Journal of The Institution of Engineers (India): Series B*, *103*(2), 681-697.
- Kolli, S., Patro, P., Sharma, R., & Sharma, A. (2024). Classification and Diagnosis of Heart Diseases Using Fuzzy Logic Based on IoT. *Advances in Fuzzy-Based Internet of Medical Things (IoMT)*, 149-162.
- Vaanathi, S. (2017). Cardiovascular Disease Prediction Using Fuzzy Logic Expert System. *IUP Journal of Computer Sciences*, *11*(3).
- Subbulakshmi, S., Marimuthu, G., &Neelavathy, N. (2018). A fuzzy logic decision support system for the diagnosis of heart disease. *IOSR Journal of Engineering*, *8*(8), 70-77.
- Kant, S., Agarwal, D., & Shukla, P. K. (2023, December). Handling CHD Classifier Based on Machine Learning and Fuzzy Logic Techniques. In *2023 10th IEEE Uttar Pradesh Section International Conference on Electrical, Electronics and Computer Engineering (UPCON)* (Vol. 10, pp. 1423-1427). IEEE.
- Murugesan, G., Ahmed, T. I., Bhola, J., Shabaz, M., Singla, J., Rakhra, M., ... & Samori, I. A. (2022). Fuzzy logic-based systems for the diagnosis of chronic kidney disease. *BioMed Research International*, *2022*, 2653665.
- Dahalan, A. J., Razak, T. R., Ismail, M. H., Fauzi, S. S. M., &Gining, R. A. J. (2021). Heart rate events classification via explainable fuzzy logic systems. *IAES International Journal of Artificial Intelligence*, *10*(4), 1036.
- Mengi, R. Integrating Fuzzy Logic into Neural Networks for Enhanced Lung Disease Detection in CT scans: A Comparative Study.
- Dataset collection: Kaggle repository-https://www.kaggle.com/datasets/toygarr/camus-dataset.
- Kunjachen, L. M., & Kavitha, R. (2025). Advancing cardiovascular risk prediction: A fusion of SVM models with fuzzy logic and the Sugeno integral. *Biomedical Signal Processing and Control*, *106*, 107774.
- Ramesh, B., & Lakshmanna, K. (2024). A novel early detection and prevention of coronary heart disease framework using hybrid deep learning model and neural fuzzy inference system. *IEEE Access*, *12*, 26683-26695.
- Arief Kanza, R., Udin Harun Al Rasyid, M., &Sukaridhoto, S. (2024). Efficient early detection of patient diagnosis and cardiovascular disease using an IoT system with machine learning and fuzzy logic. *International Journal of Computing and Digital Systems*, *16*(1), 183-199.
- Chanda, P. B., & Sarkar, S. K. (2020, August). Cardiac MR images segmentation for identification of cardiac diseases using fuzzy based approach. In *2020 Third International Conference on Smart Systems and Inventive Technology (ICSSIT)* (pp. 1238-1246). IEEE.
- Rahman, M. Z., Akbar, M. A., Leiva, V., Tahir, A., Riaz, M. T., & Martin-Barreiro, C. (2023). An intelligent health monitoring and diagnosis system based on the internet of things and fuzzy logic for cardiac arrhythmia COVID-19 patients. *Computers in Biology and Medicine*, *154*, 106583.
- Mamun, M. M. R. K., &Alouani, A. (2020, August). Using feature optimization and fuzzy logic to detect hypertensive heart diseases. In *Proceedings of the 6th World Congress on Electrical Engineering and Computer Systems and Sciences (EECSS'20), Virtual Conference* (pp. 13-15).
- Saxena, K., & Banodha, U. (2020). A fuzzy logic based cardiovascular disease risk level prediction system in correlation to diabetes and smoking. In *Data Management, Analytics and Innovation: Proceedings of ICDMAI 2019, Volume 1* (pp. 29-40). Springer Singapore.
- Reñosa, C. R. M., Vicerra, R. R. P., Dadios, E. P., Bandala, A. A., Bedruz, R. A. R., & Española, J. L. (2020, December). Pre-detection of the Probable Occurrence of a Cardiovascular Disease through Data Analysis using Fuzzy Logic. In *2020 IEEE 12th International Conference on Humanoid, Nanotechnology, Information Technology, Communication and Control, Environment, and Management (HNICEM)* (pp. 1-6). IEEE.
- Gupta, K., Kumar, P., Upadhyaya, S., Poriye, M., & Aggarwal, S. (2024). Fuzzy logic and machine learning integration: Enhancing healthcare decision-making. *International Journal of Computer Information Systems and Industrial Management Applications*, *16*(3), 20-20.
- Hameed, A. Z., Ramasamy, B., Shahzad, M. A., & Bakhsh, A. A. S. (2021). Efficient hybrid algorithm based on genetic with weighted fuzzy rule for developing a decision support system in prediction of heart diseases. *The Journal of Supercomputing*, *77*, 10117-10137.