RESEARCH ARTICLE

FuzzDL-HeartPredict: Heart Attack Risk Prediction Using Fuzzy Logic and Deep Learning

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Abstract

Across the globe, heart diseases rank as the top cause of death, with their incidence steadily rising. However, early detection before a cardiac event (e.g., cardiac arrest) remains a significant challenge. Although the healthcare sector possesses extensive data on heart disease, the effective use of this data for timely detection is essential to protect from such events. This paper proposes an innovative approach using fuzzy logic (FL), convolutional neural network (CNN) models, and feature selection to more accurately assess the risk of heart attacks. Our study also emphasizes the importance of data preprocessing, including data transformation, cleaning, and normalization, to facilitate the availability of trustworthy and high-quality information for analysis. We employed lassoCV for feature selection to identify key factors contributing to heart attack risk. Furthermore, we developed a novel 1D Convolutional Neural Network (1D-CNN) especially tailored for linear data to improve neural network training and the significant potential of advanced Artificial Intelligence (AI) techniques in revolutionizing heart attack risk estimation. We used fuzzy logic (FL) to handle data uncertainties in the risk prediction phase, enhancing prediction accuracy. Our proposed model achieved remarkable performance metrics: an accuracy of 98.5%, 100% precision, and 98.5% F1-score, which outperforms when compared with its counterparts.

Keywords: healthcare, deep learning, fuzzy logic, CNN, heart attack prediction.

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1 Introduction

Health is a major global concern, and the application of deep learning and artificial intelligence to healthcare has emerged as a transformative approach to improving the accuracy and efficiency of medical diagnosis [1]. Cardiovascular diseases, particularly heart attacks, remain a leading cause of mortality, with hypertensive heart disease alone contributing to a substantial and rising share of global deaths over recent decades [2]. Overall, cardiovascular diseases account for more than 17 million deaths annually, representing approximately 31% of global fatalities, with heart attacks and strokes contributing to 85% of these deaths [3]. Timely diagnosis and effective intervention are crucial to reducing these risks, yet many challenges persist, particularly in resource-limited settings. One-dimensional convolutional neural networks have been shown to achieve state-of-the-art performance in biomedical signal classification tasks, providing a computationally efficient alternative to more complex architectures [4], while integrated approaches combining machine learning with neuro-fuzzy methods have demonstrated strong potential in classifying cardiovascular disease risk factors [5]. Bridging these gaps between clinical practice and computational approaches requires multidisciplinary collaboration between healthcare professionals and AI researchers [6]. Addressing these limitations requires leveraging data-driven approaches; big data analytics and predictive modeling have shown promise in improving preventive care and health outcomes for patients with chronic diseases [7]. Feature selection techniques such as Relief and LASSO have emerged as effective strategies to identify the most relevant clinical variables, improving both prediction accuracy and model efficiency [8].

Medical diagnosis, especially for heart diseases, is a complex task requiring accuracy and efficiency [9]. Early detection of cardiovascular conditions is crucial for effective disease management, yet traditional diagnosis methods often rely on manual interpretation of clinical data, which is prone to errors and inefficiencies. Automating heart disease detection through artificial intelligence (AI) and deep learning presents a promising solution [11, 12]. AI-driven tools—ranging from predictive risk models to real-time AI-assisted auscultation devices—enable healthcare professionals to assess cardiovascular conditions more accurately and provide timely interventions [10]. Analyzing complex medical data, including patient-specific records and incomplete or redundant information, is essential for uncovering patterns that improve prediction accuracy [14]. However, current methodologies still face challenges in handling uncertain and imprecise medical data, and one-dimensional convolutional neural networks applied directly to structured clinical parameters have shown particular promise in improving the reliability of AI-driven cardiovascular disease detection [13].

FL has emerged as a powerful technique to handle uncertainty and imprecision in medical data analysis. Unlike traditional binary classification methods, FL incorporates degrees of truth, enabling more flexible and human-like decision-making in clinical diagnosis. Comparative studies have demonstrated that the choice of feature selection technique significantly affects classification performance in heart disease prediction tasks [15], with studies on the UCI Heart Disease dataset confirming that feature-limited models can still achieve competitive classification accuracy when appropriate preprocessing and selection strategies are applied [16]. While FL and CNNs have individually been explored for heart disease prediction, limited research has focused on their integration to improve diagnostic accuracy. Additionally, while machine learning techniques such as Random Forest [17], Decision Trees [18], K-Nearest Neighbor [19], and Genetic Algorithms [20] have been applied for heart disease prediction, their effectiveness in handling uncertain and fuzzy data remains under-explored.

Despite the progress made by existing approaches, several critical gaps remain unaddressed. First, most machine learning models for heart disease prediction operate on crisp, deterministic decision boundaries, making them ill-suited to handle the inherent uncertainty and imprecision of clinical measurements such as cholesterol levels and blood pressure readings. Second, while deep learning models such as LSTMs and standard CNNs have demonstrated strong performance on sequential or image-based data, structured tabular clinical data—which is the dominant format in primary care settings—has received comparatively less attention from architectures specifically designed for one-dimensional feature sequences. Third, the integration of explainability into hybrid deep learning frameworks for heart disease prediction remains limited, restricting clinical adoption. The present work directly addresses these three gaps by proposing ViTDroid—a hybrid 1D-CNN and Fuzzy Logic

framework that jointly models uncertainty and local feature patterns in structured clinical data, while incorporating LassoCV-based feature selection to reduce dimensionality without sacrificing predictive power.

To address these gaps, this study proposes a FL-based and 1D-CNN model designed for heart disease prediction. The primary research questions guiding this work include:

- How can FL improve heart disease prediction by handling uncertainty in patient data?
- Can a 1D-CNN model enhance predictive accuracy for structured clinical data?
- How can advanced feature selection and data pre-processing techniques contribute to improving classification performance?

1.1 Contributions and Improvements Over Existing Methods

Traditional machine learning models such as Random Forest, Decision Trees, and K-Nearest Neighbor (KNN) have been widely used for heart disease prediction. While these methods offer substantial predictive capabilities, they often struggle with handling uncertain, imprecise, and noisy medical data. Additionally, these models typically rely on manually selected features, which may not fully capture the complex interactions within patient health records.

Our proposed approach improves upon these traditional methods in the following ways:

- **Handling Data Uncertainty:** Unlike traditional classifiers, Fuzzy Logic can model the inherent imprecision in medical data, leading to more robust predictions.
- **Feature Learning:** Traditional methods depend on predefined features, whereas the 1D-CNN model automatically extracts relevant patterns from structured clinical data, enhancing prediction accuracy.
- **Hybrid Approach:** By integrating Fuzzy Logic with CNNs, we combine the strengths of both techniques—CNN's capability to detect complex patterns and FL's ability to manage uncertainty.
- **Improved Performance:** The proposed approach demonstrates superior performance in terms of precision, recall, and F1-score, achieving an accuracy of 98.5%, which surpasses the results of traditional classifiers.
- **Advanced Feature Selection:** The use of LassoCV ensures optimal feature selection, reducing dimensionality and improving model efficiency.

This novel integration of FL with CNNs provides a more reliable and efficient framework for heart disease prediction, offering significant advantages over traditional machine learning techniques.

2 Related Work

Machine learning and deep learning approaches have been applied to boost the accuracy and efficiency of heart attack diagnosis and prediction. For instance, Hameed et al. [21] proposed a hybrid decision support system combining a genetic algorithm with weighted fuzzy rules, demonstrating significant improvement in heart disease prediction accuracy while enhancing the interpretability of the diagnostic process. Despite its success, the system's reliance on predefined clinical rules can limit its adaptability to new or unusual cases. Jansi et al. [22] developed a smart wearable model integrating machine learning for real-time heart disease prediction and monitoring, achieving over 88% accuracy in cross-validation tests. While this mobile application provides convenience and accessibility, its accuracy and reliability heavily rely on the quality of the input data, which can be affected by user error or device limitations. Naive Bayes, Decision Tree, and Function Simple Logistic Algorithms have also been explored for heart attack prediction. Waberi and Kitiş [23] investigated these methods, achieving 89%, 87%, and 86% accuracy in Heart Attack Prediction. However, Naive Bayes assumes feature independence, which is rarely true in medical data, potentially restricting their predictive power.

Dileep et al. [24] used the C-BiLSTM technique on the UCI Heart Conditions Dataset, incorporating attributes like age, heart rate, and cholesterol levels, resulting in a 94.78% prediction accuracy. Although effective for identifying temporal patterns in sequential clinical data, the model's computational demands limit its practicality in resource-constrained deployment scenarios. Lee et al. [25] proposed a method of mining biosignal data by extracting linear and nonlinear features of heart rate variability (HRV) for coronary artery disease diagnosis, achieving a 90% classification success rate. This method, while effective, is limited by its reliance on specialized HRV signals, which may not be readily available in all clinical settings. Hidayat

et al. [26] compared K-nearest neighbor and decision tree classifiers with principal component analysis for dimensionality reduction in heart disease classification, achieving an accuracy of 91.47%. While both methods are interpretable, their performance is sensitive to feature scaling and the choice of distance metrics.

Artificial neural networks (ANN) based on backpropagation have also shown promise. Suneeta et al. [27] utilized a convolutional neural network with adapted backpropagation to classify cardiovascular disease, achieving an accuracy of 96%, and Nandy et al. [28], a swarm-artificial neural network was used to predict heart disease, achieving 95.78% accuracy. Despite their high accuracy, ANNs are considered black boxes, providing little insight into decision-making processes in medical applications.

Rani et al. [29] the study evaluated support vector machine, naive Bayes, logistic regression, random forest, and AdaBoost classifier, with an accuracy rate of 86.6%. Although SVMs are effective in high-dimensional spaces, they can have a high computational demand and require precise tuning of kernel parameters. Decision trees, on the other hand, are more interpretable but can suffer from overfitting, especially with small datasets.

Further research has explored machine learning models' application to various sources' datasets, improving prediction accuracies, and providing insights into feature selection. For example, Bhatt et al. [30] and Menshavi et al. [31] utilized different datasets and machine learning techniques, achieving accuracies up to 87.28% and 95.6%, respectively. However, the variability in dataset quality and feature selection methods can lead to inconsistent performance across different studies.

Studies on support systems for coronary artery disease classification have also been conducted. Saeedbakhsh et al. [32] employed SVM and ANN to classify coronary heart disease, while Ozcan and Peker [33] utilized a classification and regression tree (CART) algorithm to predict heart attacks, though the method remains sensitive to parameter tuning and carries a risk of overfitting on small datasets. Biswas et al. [34] emphasized the significance of feature selection in machine learning approaches for heart attack prediction. Although the field has advanced, these studies often face challenges related to the generalizability and scalability of the models. Table 1 summarizes the techniques, accomplishments, and limitations of recent works on heart attack prediction.

3 Methodology

In this section, we will explain how we will apply the models to the UCI Heart dataset employed in the study. In Phase 1: data Processing, the raw data is prepared for supervised learning by assigning labels, identifying and addressing any missing values, normalizing the dataset, and then splitting it into training and testing subsets. Phase 2: Feature Selection identifies the most relevant features by feeding labeled data into the feature selection pipeline, ensuring only the most significant attributes are retained. In Phase 3: Model Training, a Convolutional Neural Network (CNN) is trained to learn complex patterns from the selected features. Finally, in Phase 4: Risk Prediction, fuzzy logic is incorporated to enhance prediction accuracy. This involves converting crisp inputs into fuzzy values through a fuzzifier, applying fuzzy inference rules via an inference engine, and then converting the fuzzy output back into a crisp prediction using a defuzzifier. The results are derived from the combination of CNN-based learning and fuzzy logic. Throughout this process, the training data from Phase 1 is used for feature selection and model training, while the test data are applied to evaluate the trained model and generate predictions. The entire methodology is designed to preprocess the data, select key features, train a CNN model, and apply fuzzy logic to improve prediction accuracy. Moreover, the block diagram for the suggested model is shown in Figure 1. The primary objective of this research is to improve and measure predictive models for heart attack risk focusing on deep learning methods, especially CNN and FL. Accurate prediction of heart attacks is crucial for timely intervention and treatment.

3.1 Dataset Description and Rationale for Selection

3.1.1 Dataset Description

The **Heart Disease dataset** from the UCI Machine Learning Repository contains **303 records** and **14 features**, including both continuous (e.g., **age**, **serum cholesterol**) and categorical (e.g., **sex**, **chest pain type**) variables. It is widely used in heart disease prediction research, making it a suitable choice for testing machine learning models in medical applications.

3.1.2 Feature Distribution

The dataset includes a mix of continuous and categorical variables. The **age** range is between 29 and 77 years, with the **sex** distribution being imbalanced (68.3% male, 31.7% female). **Chest pain type** is fairly balanced, while **serum cholesterol** is skewed, with

Table 1. Summary of related work on heart attack prediction.

References	Techniques	Achievements	Limitations
Dileep et al. [24]	Cluster-based Bi-directional LSTM (C-BiLSTM)	94.78% prediction accuracy on UCI Heart dataset	Computational complexity higher than simpler sequential models
Hidayat et al. [26]	K-nearest neighbor and decision tree with PCA	Achieved 91.47% classification accuracy	Sensitive to feature scaling and distance metric selection
Suneetha et al. [27]	CNN with adapted backpropagation	Achieved 96% classification accuracy	Prone to overfitting; interpretability limited for clinical use
Lee et al. [25]	Mining HRV biosignal features (linear and nonlinear) for coronary artery disease diagnosis	90% success rate in classification	Limited to specialized HRV signal acquisition, which may not be available in all clinical settings
Nandy et al. [28]	Swarm-artificial neural network	95.78% accuracy rate	High computational demands, requires careful tuning
Rani et al. [29]	SVM, Naive Bayes, Logistic Regression, Random Forest, AdaBoost	86.6% classification accuracy	Considered a "black box"; low interpretability
Bhatt et al. [30]	Multiple ML techniques (ANN, SVM, etc.)	High accuracy for cardiovascular classification	Prone to overfitting, hard to interpret
Menshawi et al. [31]	Hybrid ML framework comparison	95.6% accuracy	SVMs need precise tuning, computationally heavy
Saeedbakhsh et al. [32]	SVM, ANN, Random Forest	Up to 87.69% accuracy	Highly dependent on dataset quality
Ozcan and Peker [33]	Classification and regression tree (CART)	Predicts heart attacks	Sensitive to parameter tuning, risk of overfitting
Biswas et al. [34]	Feature selection with ML classifiers	Shows feature importance in predictions	Requires diverse, high-quality datasets

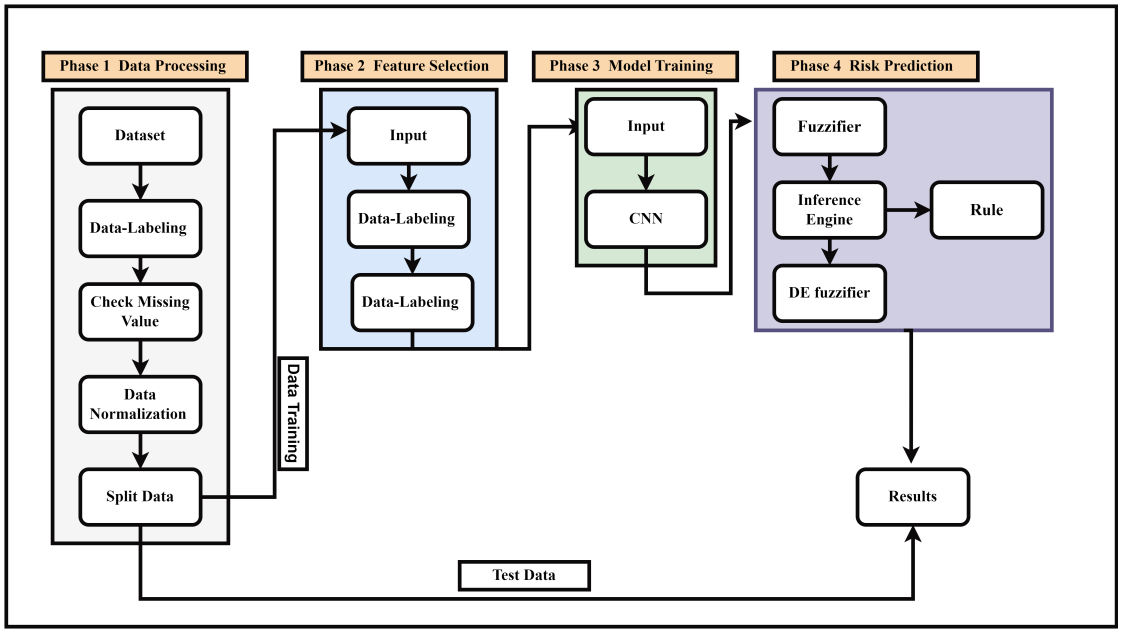

Figure 1. Framework of proposed solution.

most values below 350 mg/dl.

3.1.3 *Potential Biases*

There is **class imbalance** (45.5% with heart disease), and **gender imbalance**, with more males than females. The dataset also lacks extreme age groups, limiting its applicability to younger or older individuals.

3.1.4 *Rationale for Dataset Choice*

This dataset was chosen due to its relevance to heart disease prediction and its wide use in research. It offers a manageable size (303 records) and diverse features for model testing and comparison.

3.1.5 *Representativeness of Diverse Populations*

The dataset is not fully representative of global populations, with biases in gender, age, and geographical diversity. Future research could include more diverse data to improve model generalization.

Table 2 provides an overview of these attributes. The dataset is available for access online through the UCI machine learning repository: https://archive.ics.uci.edu/ml

/datasets/Heart+Disease.

3.2 Data Pre-processing

3.2.1 Data Cleaning

The dataset was cleaned to address missing values and uphold consistency across attributes. Missing values were imputed using mean or median values as appropriate.

3.2.2 Normalization of Data

Continuous variables were normalized to achieve a zero mean and unit variance and to facilitate efficient model training.

$$x' = \frac{x - \mu}{\sigma} \tag{1}$$

where x represents the original value, μ is the variable's mean, and σ is the standard deviation.

3.2.3 Data Labeling

Each data instance was labeled with clinically relevant information, including age, gender, and health history. Accurate labeling is crucial for developing reliable predictive models and for subsequent analysis.

3.3 Feature Selection

3.3.1 LASSO Method

LASSO is a feature selection method utilizing L1 regularization to simplify the model by removing irrelevant features. The LassoCV class from the linear model library was used with 5-fold cross-validation to automatically tune the regularization parameter. The LASSO method minimizes the objective function:

$$\mathcal{L}(\beta) = \frac{1}{2N} \sum_{i=1}^{N} (y_i - \mathbf{x}_i^T \beta)^2 + \lambda \sum_{j=1}^{p} |\beta_j| \tag{2}$$

where N is the number of observations, x_i is the target variable, $\mathbf{x}_i$ is the input vector for the 1-th observation, β represents vector of coefficients, p represents features counting, and λ represents the regularization parameter.

3.3.2 1D-CNN Architecture

The proposed 1D-CNN model is designed to process one-dimensional data, making it particularly well-suited for tasks involving time-series or sequential data. Unlike conventional 2D CNNs, which are applied to two-dimensional inputs such as images, our 1D-CNN focuses on learning patterns from a single dimension (e.g., time or sequence). This is achieved through convolution operations along one axis, enabling the model to efficiently capture local temporal dependencies.

Mathematically, the convolution operation for a 1D-CNN can be expressed as:

$$y(t) = (x * w)(t) = \sum_{i=0}^{K-1} x(t+i) \cdot w(i) \tag{3}$$

where $x(t)$ is the input sequence at time t, $w(i)$ is the filter or kernel of size K, and $*$ denotes the convolution operation. This operation is applied across the input sequence to extract local features.

The architecture of the 1D-CNN typically includes several 1D convolutional layers followed by pooling layers. The pooling operation can be represented as:

$$y_{\text{pool}}(t) = \max_{i \in [t, t+k-1]} x(i) \tag{4}$$

where k is the window size for pooling, and the max function selects the most dominant feature in the local neighborhood. These layers are followed by fully connected layers that generate the final prediction.

One significant advantage of the 1D-CNN over conventional 2D CNNs is its computational efficiency. Traditional 2D CNNs apply convolutions over both spatial dimensions (width and height) of an image, which requires larger filters and higher computational cost. In contrast, 1D-CNNs operate over a single dimension, which reduces the number of parameters and operations, making it faster to train and less computationally expensive. For example, the number of parameters in a 2D convolution is:

$$K \times K \times C_{\text{in}} \times C_{\text{out}} \tag{5}$$

where K is the filter size, C_{in} is the number of input channels, and C_{out} is the number of output channels. In a 1D-CNN, the number of parameters is:

$$K \times C_{\text{in}} \times C_{\text{out}} \tag{6}$$

leading to a reduction in the total number of computations.

Table 2. Overview of dataset attributes.

No.	Attribute	Explanation
01	Age	Age of the individual in years
02	Gender	1 = Male, 0 = Female
03	CP	Category of chest pain experienced
04	Trestbps	Blood pressure measurement at rest, expressed in mm Hg
05	Chol	Concentration of serum cholesterol in mg/dl
06	FBS	Fasting blood glucose level greater than 120mg/dl (1 = Yes, 0 = No)
07	Restecg	Electrocardiogram results taken at rest
08	Thalach	Highest heart rate recorded during testing
09	Exang	Presence of exercise-induced angina (1 = Yes, 0 = No)
10	Oldpeak	ST segment depression during exercise relative to rest
11	Slope	Gradient of the ST segment during peak exercise
12	CA	Count of major blood vessels visualized via fluoroscopy
13	Thal	Thalassemia type (3 = Normal, 6 = Fixed defect, 7 = Reversible defect)
14	Target	Presence of heart disease (0 = No, 1 = Yes)

3.4 Model Training

CNNs were chosen for their capability to deal in complex and high-dimensional data. The CNN architecture was designed to identify key attributes from the provided data, followed by fully connected layers for classification.

3.4.1 Convolutional Layers

The CNN model includes convolutional, pooling, and fully connected layers convolutional layers perform a convolution operation on the input:

$$(\mathbf{W} * \mathbf{x})_{ij} = \sum_m \sum_n \mathbf{W}_{mn} \mathbf{x}_{i+m,j+n} \tag{7}$$

where $\mathbf{W}$ denotes the filter matrix, $\mathbf{x}$ is the input matrix, and i, j are the indices used in the output matrix.

3.4.2 Activation Function

The convolutional layer's output is passed through a non-linear activation function, typically the RELU (Rectified Linear Unit):

$$\text{ReLU}(x) = \max(0, x) \tag{8}$$

3.4.3 Model Training Process

The data was partitioned into two sets in a way that 80% was used in the training set and 20% in the validation set. The models were trained with the training dataset and the process of hyperparameter tuning as well was performed over the data splits of the validation set. The Adam optimizer was utilized to train the CNN, with early stopping applied to avoid overfitting. The Adam optimizer updates the weights using the following equations:

$$m_t = \beta_1 m_{t-1} + (1 - \beta_1) g_t \tag{9}$$

$$v_t = \beta_2 v_{t-1} + (1 - \beta_2) g_t^2 \tag{10}$$

$$\hat{m}_t = \frac{m_t}{1 - \beta_1^t} \tag{11}$$

$$\hat{v}_t = \frac{v_t}{1 - \beta_2^t} \tag{12}$$

$$\theta_t = \theta_{t-1} - \eta \frac{\hat{m}_t}{\sqrt{\hat{v}_t} + \epsilon} \tag{13}$$

where m_t and v_t represent the first and second moment estimates, β_1 and β_2 are the decay rates, g_t is the gradient, η is the learning rate, and ϵ is a small constant.

3.4.4 Hyperparameter Configuration

The hyperparameters used in the proposed 1D-CNN model are summarized in Table 3. These values were determined through a grid-search procedure over the validation set.

Table 3. Hyperparameter configuration of the proposed 1D-CNN model.

Hyperparameter	Value
Number of Conv1D layers	3
Filters per layer	64, 128, 256
Kernel size	3
Pooling window size	2
Dropout rate	0.3
Fully connected units	128
Optimizer	Adam
Learning rate (η)	0.001
β_1	0.9
β_2	0.999
ϵ	1×10^{-7}
Batch size	32
Maximum epochs	100
Early stopping patience	10
LassoCV folds	5

3.5 Fuzzy Logic Integration in CNN

FL is integrated into the CNN model to enhance decision-making under uncertainty by incorporating linguistic variables and fuzzy membership functions. Instead of relying solely on crisp decision boundaries, the proposed model uses fuzzy set to handle ambiguous or imprecise input data. The fuzzy system consists of three key components: fuzzification, inference, and defuzzification.

3.5.1 Fuzzification

The input features of the CNN, denoted as $X = \{x_1, x_2, ..., x_n\}$, are transformed into fuzzy values using membership functions $\mu(x)$, which map crisp inputs into fuzzy sets:

$$\mu_A(x) = \frac{1}{1 + e^{-\alpha(x-c)}} \tag{14}$$

where α is the shape parameter, and c is the center of the fuzzy set. This allows input values to belong to multiple categories with varying degrees of membership.

3.5.2 Fuzzy Inference System (FIS)

FIS is integrated into the CNN layers to modify feature maps based on fuzzy rules. A set of fuzzy IF-THEN rules is applied:

$$\text{IF} x_1 \text{ is } A \text{ AND } x_2 \text{ is } B, \text{ THEN } y \text{ is } C \tag{15}$$

where A, B, and C are fuzzy sets. The rule strength is computed using the T-norm operator, typically a product operation:

$$w_r = \mu_A(x_1) \cdot \mu_B(x_2) \tag{16}$$

This weight is then applied to modify the activation maps in the CNN layers, enhancing feature extraction under uncertain conditions.

3.5.3 Defuzzification and Uncertainty Management

To make final predictions, defuzzification is performed using the centroid method, which converts fuzzy outputs into crisp values:

$$y^* = \frac{\sum w_r \cdot c_r}{\sum w_r} \tag{17}$$

where c_r is the centroid of the fuzzy region associated with rule r. This step ensures that the CNN model outputs precise classifications even with uncertain or noisy inputs.

3.5.4 Fuzzy System Configuration

The fuzzy membership functions are parameterized as follows. For age-based fuzzification, three sigmoid-based functions are defined with center parameters $c \in \{35, 50, 65\}$ years and shape parameter $\alpha = 0.2$ for Young, Middle, and Old Age categories, respectively. For risk-score fuzzification, two membership functions with $c \in \{0.3, 0.7\}$ and $\alpha = 5.0$ represent Low Risk and High Risk categories. The complete fuzzy rule base consists of three IF-THEN rules governing age- and risk-score-based membership combinations, with the T-norm product operator applied for rule strength computation and the centroid defuzzification method used for final risk score derivation. The fuzzy system is implemented using the `scikit-fuzzy` library (version 0.4.2) in Python 3.9.

3.6 Performance Evaluation Metrics

We evaluated the model's accuracy, precision, recall, and F1-score. By using these metrics, you can evaluate a model's classification abilities and overall effectiveness based on the dataset.

3.6.1 Accuracy

The proportion of correctly predicted instances by the total instances as shown in equation (18):

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN} \tag{18}$$

3.6.2 Precision

Precision shows the fraction of positive identifications that are truly correct. It can be found out through the following equation (19):

$$\text{Precision} = \frac{TP}{TP + FP} \tag{19}$$

where False Positives are represented by FP and True Positives by TP .

3.6.3 Recall

Recall (sensitivity) evaluates how well the method identifies the real positive instances. It can be measured through the following equation (20):

$$\text{Recall} = \frac{TP}{TP + FN} \tag{20}$$

where FN stands for False Negatives and TP for True Positives.

3.6.4 F-Measure

F-Measure, also known as the F1 Score, combines both Recall and Precision into a single metric. The formula for calculating it:

$$\text{F-Measure} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \tag{21}$$

3.7 Model Training and Validation

The loss function is essential in training a deep learning model, as it quantifies the difference between the model's predictions and the actual outcomes. Two primary types of loss are monitored during the training process: training loss and validation loss.

3.7.1 Training Loss

Training loss evaluates the error in the training data over each training process. It reflects how well the model adjusts its weights and biases to fit the training data. The training loss is computed after each epoch (complete pass over the training dataset) and offers an indication to measure how well the model is learning from the training data. Mathematically, the training loss L_{train} at epoch i can be defined as equation (22):

$$L^i_{train} = \frac{1}{N} \sum_{j=1}^{N} \ell(y_j, \hat{y}_j) \tag{22}$$

where N represents the number of training samples, ℓ is represents the loss function, y_j represents the true label, and $\hat{y}_j$ denotes the predicted label.

3.7.2 Validation Loss

Validation loss quantifies the error on a distinct validation dataset that is not involved in the training process. It serves as a measure of how well to predict outcomes to previously unseen data. Analyzing the validation loss helps uncover overfitting issues, where the model achieves high accuracy on the training data but fails to generalize on the validation data. Mathematically, the validation loss L_{val} at epoch i can be defined as:

$$L^i_{val} = \frac{1}{M} \sum_{k=1}^{M} \ell(y_k, \hat{y}_k) \tag{23}$$

where M indicates number of validation samples, ℓ Indicates loss function, y_k Indicates true label, and $\hat{y}_k$ denoted the predicted label.

4 Results and Analysis

In this section, we discuss the evaluation outcomes of our devised CNN, FL deep learning model, and compare its performance with varied benchmarks. The results are compared based on accuracy, precision, recall, and F-score metrics, such as are useful for understanding the learning process of the models and how they perform on new test data. The CNN and FL outperform all other models in terms of accuracy shown in Table 4. While comparing the model in terms of Precision, recall, and F-measure are shown in Table 5, which shows the proposed model capabilities.

4.1 Analysis of Training and Validation Loss

The training and validation loss is shown in Figure 2. Depicts the training and validation loss curves for training and validation over 50 epochs for the model. Both the training loss depicted in blue alongside validation loss in orange show a general downward trend, indicating that the model is progressively learning and enhancing its performance over time. Initially, both losses are relatively high, but as training progresses, the losses decrease significantly, suggesting that the model is gradually fitting the training data and optimizing its predictions on the validation set. There are minor fluctuations in both curves, which can be attributed to the stochastic nature of the training process, but the overall loss reduction is consistent. Importantly, there is no significant divergence between the training and validation losses, which implies that the model generalizing well and not overfitting the training data and is generalizing well to unseen data. This indicates a balanced learning process, as both losses decrease in tandem, showing the model's proficiency to generalize without losing predictive performance on the validation dataset.

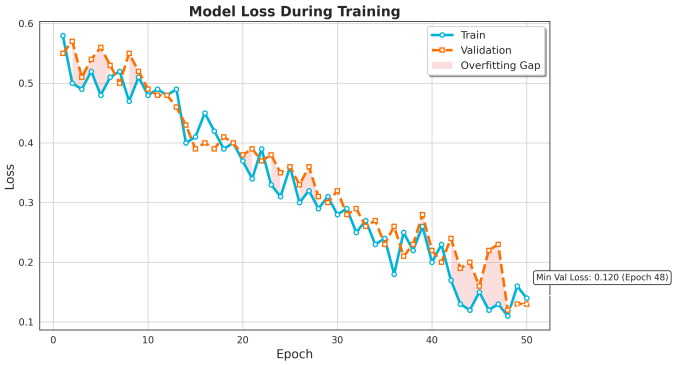

Figure 2. Training and validation loss.

Table 4. Accuracy-based comparison between proposed methods with existing methods.

References	Methods	Accuracy
[44]	Multi-task neural network	90.09%
[45]	Adaptive Boosting	85.28%
[45]	Bagging	86.37%
[45]	Stacking	87.24%
[46]	Random-Forest	86.93%
[47]	Stacking	89.86%
[48]	K-nearest neighbor + ICA	88.25%
[35]	Fuzzy-based expert system for coronary artery disease diagnosis	94.55%
[36]	Machine learning classifiers (Naive Bayes, KNN, SVM, Random Forest) for survival prediction among heart patients	Up to 86.2%
[37]	Self-attention-based Transformer model	96.51%
[38]	Logistic Regression with ensemble and hyperparameter tuning	88.16%
[43]	ensemble learning approach	98%
Proposed Method	**CNN, FL**	**98.5%**

Table 5. Contrasting existing models with the proposed model.

Reference	Methods	Accuracy	Recall	Precision	F-Measure
[39]	Logistic Regression	92%	97%	88%	92%
[40]	Deep learning	82.49%	77.08%	87.24%	84.41%
[29]	Adaboost	86.59%	83.53%	88.96%	86.16%
[41]	lightweight CNN	94.09%	91.71%	91.82%	-
[42]	MLP-EBMDA	94.28%	96%	96%	96%
Proposed Method	**CNN, FL**	**98.50%**	**97%**	**100%**	**98.50%**

4.2 Convolutional Neural Networks (CNN) and Fuzzy Logic (FL) compare the accuracy of various existing techniques

The proposed method, which combines Convolutional Neural Networks (CNN) and Fuzzy Logic (FL), achieves the highest accuracy of 98.5%, as shown in Figure 3, surpassing other techniques. The next best approach employs a self-attention-based Transformer model by Rahman et al. [37], achieving 96.51%. Other methods, such as the multi-task neural network by García-Ordás et al. [44] and stacking techniques by Liu et al. [47], reported accuracies of 90.09% and 89.86%, respectively. In contrast, traditional machine learning methods like Adaptive Boosting 85.28% and Random Forest 86.93% showed lower performance. The fuzzy-based expert system by Muhammad and Algehyne [35] reached a high accuracy of 94.55% but still falls short compared to the proposed method. Table 4, demonstrates that deep learning-based methods, particularly the proposed CNN-FL approach, significantly improve predictive accuracy compared to classical techniques.

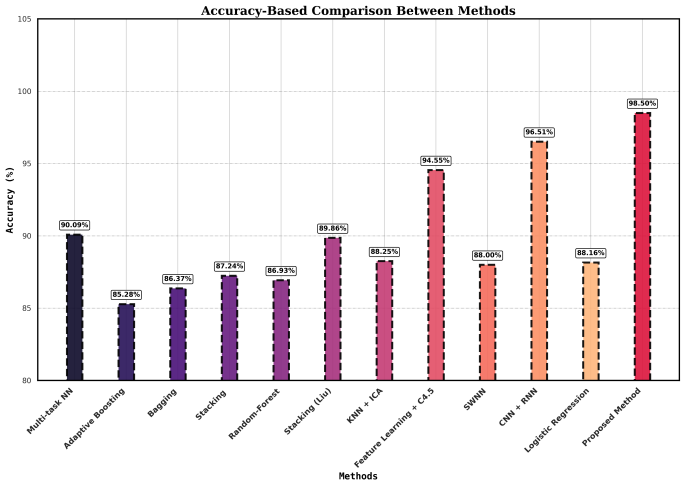

Figure 3. Comparison of methods in terms of accuracy.

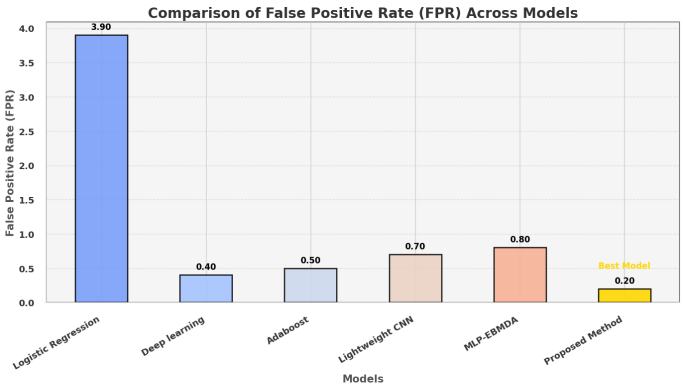

Figure 4. False positive rate (FPR) comparison.

Figure 4 illustrates the FPR values for various models compared to the proposed method. This plot helps to illustrate and contrast the evaluation of different models based on their false positive rates, providing a clear view of which models are more or less prone to false positive errors.

4.3 Results Comparison with existing methods

The proposed CNN-based approach, combined with Fuzzy logic (FL), achieves the highest accuracy of

98.5%, surpassing several well-established models. The logistic regression model from Berdinanth et al. [39], achieved a notable accuracy of 92%, with a strong recall of 97% but slightly lower precision at 88%, leading to an F-measure of 92%. Almazroi et al. [40] employed a deep learning approach, yielding an accuracy of 82.49% and a high precision of 87.24%, although the recall was lower at 77.08% and F-measure of 84.41%. Rani et al. [29] used an Adaboost model, attaining an accuracy of 86.59%, balanced recall and precision 83.53% and 88.96%, respectively, and an F-measure of 86.16%. Malibari et al. [41] applied a lightweight CNN, delivering an impressive accuracy of 94.09% and near-identical recall and precision values around 91.71%,91.82%. Another model, MLP-EBMDA by Deepika et al. [42] demonstrated high accuracy 94.28% and balanced recall and precision 96%, reflected in an F-measure of 96%. In contrast, the proposed method integrating CNN and fuzzy logic significantly outperforms these models with a remarkable accuracy of 98.50%, recall 97% with perfect precision at 100%, and a high F-measure of 98.50%. This demonstrates the superiority of the proposed hybrid approach in enhancing heart attack risk prediction. Moreover, the plot shown in Figure 5 effectively demonstrates the superior results of the proposed CNN-FL model outperform other models, making it a strong candidate for applications where high Recall, Precision, and F-Measure are critical.

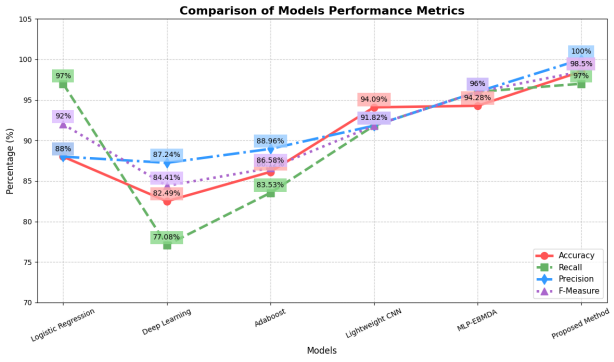

Figure 5. Line plot comparing recall, precision, and F-Measure across different models.

4.4 Confusion Matrix

The confusion matrix provides a comprehensive evaluation of the binary classifier by comparing predicted labels against actual ground-truth labels across the test set. It reports four outcomes: True Positives (TP), where heart disease cases are correctly identified; True Negatives (TN), where healthy cases are correctly identified; False Positives (FP), where healthy cases are incorrectly classified as diseased; and False Negatives (FN), where disease cases are missed. Analyzing the distribution of these outcomes allows researchers to identify specific weaknesses in the model and guide targeted improvements. Figure 6 presents the confusion matrix obtained by the proposed CNN-FL model on the test set.

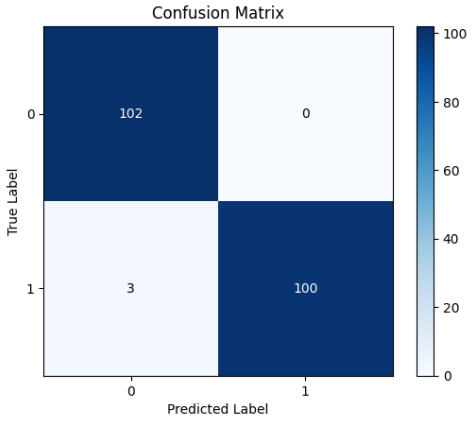

Figure 6. Confusion matrix.

4.5 FL-Based Model for Risk Evaluation

This section describes the implementation of an FL system to assess risk levels based on age implementing with visualization of the results. FL allows for handling the imprecision and uncertainty inherent in real-world data by defining membership functions and rules that mimic human reasoning. We define three age-based membership functions:

- **Young Age:** Provides a membership value indicating how much age is categorized as youthful.
- **Middle Age:** Provides a membership value indicating how much an age is categorized as intermediate.
- **Old Age:** Provides a membership value indicating how much an age is categorized as advanced.

similarly, two risk score-based membership functions are defined:

- **Low Risk:** Provides a membership value indicating the extent to which a risk score is classified as minimal.
- **High Risk:** Provides a membership value indicating the extent to which a risk score is classified as elevated.

The membership values for age are calculated for each

individual in the test dataset. For risk scores, the numerical values from the predicted risk scores are used to calculate their membership values. We then define three fuzzy rules:

- **Rule 1:** When the age is classified as young or the risk score is assessed as low, the risk level is categorized as low.
- **Rule 2:** When the age falls into the middle-aged category or the risk score is evaluated as low, the risk level is categorized as low.
- **Rule 3:** When the age is considered old or the risk score is rated as high, the risk level is categorized as high.

The final risk score for each individual is determined by taking the maximum value among the three rules. This approach ensures that the most significant factor among age and risk score determines the risk level.

5 False Positive Rate (FPR) Analysis

It is a critical measure for determining the performance of classification models, particularly when the cost of false positives carries a high cost. The FPR tracks how many negative cases are incorrectly classified as positive. It is computed using the following equation:

$$\text{FPR} = \frac{FP}{FP + TN} \tag{24}$$

A certain number of false positives (FP) and true negatives (TN) are present. FPR provides insight into the likelihood that a model will incorrectly classify a negative instance as positive, which is particularly important in applications such as the detection of fraud or medical assessments, where erroneous positive findings could cause major ramifications.

6 Conclusion

Heart attacks are still among the top causes of mortality worldwide, making early and accurate risk prediction essential for successful prevention and prompt intervention. The paper provides a novel method for estimating the risk of heart attacks by using CNNs and FL. The UCI Heart Disease dataset (Cleveland subset) contains 14 features, from which LassoCV identified the most significant predictors to aid in feature selection. A specialized 1D-CNN model was developed, achieving exceptional results with a 98.5% accuracy, 100% precision, 97% recall, and 98.5% F1 score. Incorporating FL allowed for handling uncertainties in the data, enhancing the model's forecasting accuracy and reliability. The design model and rule-based decision-making provided a nuanced risk assessment based on the patient's age and risk profile, offering a practical tool for healthcare professionals.

This study emphasizes the effectiveness of coupling deep learning with FL to develop highly accurate and reliable heart attack risk prediction models. By integrating feature selection, advanced modeling techniques, and uncertainty handling, the research presents a comprehensive approach to heart attack risk assessment. Continued advancements in this field have the potential to completely transform cardiovascular medicine, improving patient outcomes and healthcare delivery. To improve model performance, interpretability, and ethical deployment in clinical settings, current research and development efforts must be pursued.

6.1 Limitations

The proposed model shows remarkable performance in predicting heart attack risk, several challenges and limitations must be acknowledged. These include the computational cost of training deep learning models, potential biases in the dataset, and the critical importance of data quality and availability. Additionally, the model's lack of interpretability, the risk of overfitting, and the complexities of integrating fuzzy logic with CNNs present further hurdles. Moreover, real-world deployment could face challenges related to data inconsistencies and system integration. Addressing these issues is essential for improving the model's robustness, generalizability, and applicability in practical healthcare environment.

6.2 Future Work

Future work could delve into incorporating sophisticated deep learning methods, including LSTM and recurrent neural networks, to improve predictive accuracy. Establishing a real-time data collection environment using IoT sensors would enable comprehensive evaluation and validation of the proposed method. Incorporating explainable AI methods will facilitate clarity and trust in the model's predictions, facilitating clinical decisions. Additionally, addressing ethical considerations and ensuring model impartiality through rigorous data evaluation and ethical rules will be crucially reliable for use in healthcare.

Data Availability Statement

Data will be made available on request.

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Conflicts of Interest

The authors declare no conflicts of interest.

Ethical Approval and Consent to Participate

Not applicable.

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