Prediction of Cardiovascular Diseases Using Convolutional Neural Network and Fuzzy Logic

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Abstract: Heart diseases are among the most significant factors that threaten public health. Accurate and early recognition of these diseases enhances the chances of timely intervention, increases survival rates, and reduces the risk of long-term disability. In recent years, with the advancement of technology and the development of electronic medical systems, the use of ECG signals as a non-destructive and non-invasive method for diagnosing heart diseases has increased. In this article, the combination of a convolutional neural network (CNN) and fuzzy logic (FL) is used to automatically detect heart disease from ECG signals. The purpose of combining CNN and FL is that to enable the system to handle cognitive uncertainties in a human-like manner and process ambiguous or imprecise information effectively. The proposed model was tested on the MIT-BIH arrhythmia dataset, and the results demonstrate that it achieves a 97.54% accuracy, outperforming other existing methods.

Keywords: *Heart disease, Electrocardiogram (*ECG) *signals, Convolutional neural network (CNN), Fuzzy logic (FL), Wavelet transform.*

1- Introduction

Today, one of the most important concerns in the field of medicine is data collection. Data sources in the field of health contain a large amount of clinical data, which has become more important due to the emergence of an integrated information system and the development of information technology. It is noteworthy that the amount of collected data is very high and in order to obtain the desired patterns and results from this massive amount of data, artificial intelligence techniques must be used. Artificial intelligence and then data mining are among the technological advances in the direction of data management, and the widespread use of information systems and databases, its integration with traditional methods has become a requirement [1].

Today, one of the most important concerns in the field of medicine is how to effectively collect and manage medical data. Health-related data sources contain a large amount of clinical information. This data has gained importance due to the rise of integrated information systems and advances in information technology. The volume of collected data is extremely high. To extract useful patterns and insights, artificial intelligence techniques are required. Artificial intelligence, followed by data mining, represents a key technological advancement for managing medical data. The widespread use of information systems and databases has made their integration with traditional analytical methods essential [1].

In recent years, the high rate of cardiovascular disease and the large number of heart disease-related deaths worldwide have made this issue a major concern in the healthcare industry. Each year, heart disease claims the lives of many people or severely impacts their quality of life. Since the heart is one of the most important organs of the human body, any disorder in its function significantly affects the overall performance of the body. This is because the circulatory system supplies the energy required by all organs, including the heart itself [2].

Conditions that affect the functioning of the heart are called cardiovascular diseases. In 2020, more than 17 million people died from cardiovascular diseases, representing more than 40% of deaths worldwide [2]. The same study showed that more than 70% of deaths occur in low- and middle-income countries. Mortality due to heart disease in Iran, which is the most significant challenge facing the country's health system, accounts for over one third of all deaths. Accidents and cancer are the second and third leading causes of death in Iran [1]. It is predicted that cardiovascular diseases will remain the leading cause of death worldwide [3].On the other hand, since the end of 2018, we have witnessed the widespread spread of COVID-19. According to recent studies and surveys, the highest death rate among infected people is related to underlying diseases such as high blood pressure and heart problems [4]. In fact, people with cardiovascular disease are highly vulnerable to other illnesses as well. Therefore, it is necessary to screen the population, especially high-risk groups, to control the rate of heart disease or prevent the disease from worsening. This approach can reduce mortality rates. Effective monitoring of physical conditions and the use of necessary measures based on clinical and medical data can enable early diagnosis — even before symptoms appear. Such early detection can reduce the prevalence of cardiovascular diseases [5].

This is where AI technologies are used in healthcare systems to predict heart disease [6]. In this regard, the aim of this article is to use artificial intelligence methods, followed by deep learning, to predict heart diseases caused by cardiac arrhythmia. This will enable doctors and healthcare centers to develop solutions for early diagnosis. Unlike medical devices such as heart monitors, which examine a person's vital signs, artificial intelligence can collect information from these devices and, after analysis, detect more complex conditions. These include risks that may threaten the patient in the future.

The proposed model in this article uses a combination of a convolutional neural network (CNN) and fuzzy logic (FL). This approach involves adding a fuzzy layer to the neural network to improve pattern recognition and capture complex relationships within the data. In the proposed model, the fuzzy method enhances the accuracy of features between the integration layer and the fully connected layer. This method improves classification accuracy. Unlike classical classification methods, the fuzzy method can detect adjacent classes with continuous boundaries and overlapping regions. The purpose of combining convolutional and FL neural networks is to enable the system to process uncertain and inaccurate information and achieve a high detection rate despite diagnostic uncertainties [7, 8].

The proposed model was tested on the MIT-BIH dataset, and the results showed that it outperformed conventional methods in diagnosing heart disease. The remainder of this article is organized as follows. Section 2 presents related work. Section 3 describes the proposed method. Section 4 details the experiments and results. Section 5 provides the conclusions and outlines directions for future work.

2. Related Works

Human life depends on the proper functioning of the heart, as it directly affects the performance of other organs in the body [1]. Early detection of cardiovascular risks or diseases enables physicians to take preventive measures and reduce complications [9]. Numerous studies have focused on predicting and analyzing heart diseases using various data mining techniques. Some of these works are reviewed below. In [10], heart disease prediction and diagnosis were conducted using available data and the k-means classification technique with Clementine software. The disease was diagnosed, and the system's performance was evaluated using test data, achieving an error rate of 13%. In [11], a learnable bioelectrical system was designed and simulated for diagnosing cardiac arrhythmia diseases using a multilayer perceptron (MLP) neural network. Accurate disease diagnosis, which is critical for improving patient outcomes, was emphasized. The system was designed to store all training data, eliminating the need for retraining at each testing stage.

In [12], heart disease prediction and diagnosis were performed using fuzzy logic methods. In [13], electrocardiogram (ECG) signal modeling was proposed using a spline interpolation method to diagnose heart diseases. As the heart is one of the most vital organs in the human body, various mathematical approaches have been applied to simulate cardiac signals. The study introduced a new ECG simulation method compared to traditional techniques such as Wavelet, Fourier, and neural networks, each having its own strengths and limitations. In [14], cardiac arrhythmia diagnosis was carried out using principal component analysis (PCA) and an MLP neural network. Arrhythmias are abnormal heartbeats that cause the heart to beat excessively fast (tachycardia) or slow (bradycardia), leading to ineffective pumping. ECG, a painless procedure that records the electrical activity of the heart, was analyzed. In this study, the first principal component was used as input to a neural network with two hidden layers, each containing 100 neurons. The system achieved 93.40% accuracy for binary classification and 78% for multiclass classification using the UCI arrhythmia dataset.

In [15], disease prediction and diagnosis were examined through iridology based on an error back-propagation neural network. The aim was to detect diseases by analyzing iris structures and matching them with known iridology patterns. The proposed model consisted of four main modules—receiving, processing, matching, and decision-making—that identified disease symptoms based on iris patterns. In [16], the performance and accuracy of data mining algorithms for early diagnosis of heart diseases were evaluated. Classification algorithms such as nearest neighbor, neural network (NN), logistic regression, a hybrid support vector machine–particle swarm optimization model, and random forest were tested. The highest accuracy was achieved by the random forest algorithm, with 97.61% in testing and 71.29% in training, followed by logistic regression with 91.87% in training and 78.48% in testing.

In [17], pattern recognition technology was applied for the diagnosis and analysis of heart diseases. ECG was identified as an essential diagnostic tool for assessing heart function and pathology. The study emphasized the importance of pattern recognition in characterizing and classifying ECG signals. In [18], an automatic diagnostic system for heart diseases was developed using features from the chaos domain and LMAN neural networks. Owing to the chaotic nature of heart signals, features such as the correlation dimension and standard deviation from the Poincaré diagram were used as system inputs. The Marquardt–Levenberg back-propagation algorithm was adopted for training due to its faster convergence, with a stopping error threshold set at 0.001. In [19], an intelligent heart disease prediction system called *Smart Heart* was developed using data mining techniques such as decision tree, Bayes network, and neural networks. The system, designed to answer complex medical questions in an if–then structure, is web-based, user-friendly, scalable, and reliable. It predicts the likelihood of heart disease based on medical parameters such as age, gender, blood pressure, and blood sugar levels. In [20], data mining methods including the J48, Bayesian network, and neural network algorithms were used for heart disease prediction. The pruned J48 algorithm achieved the best performance with an accuracy of 95.56%. In [21], a heart disease prediction model was developed using data mining techniques, achieving an accuracy rate of 84.1% through the decision tree algorithm. In [22], a classification-based prediction system for heart disease was proposed. The system predicted heart attacks with 99% accuracy using parameters such as gender, age, chest pain type, heart rate, cholesterol, smoking habits, blood sugar, blood pressure, ECG readings, diet, and alcohol consumption. In [23], a predictive model for arrhythmia classification was developed using the random forest clustering algorithm. Experimental results showed that the multilayer perceptron (MLP) classifier outperformed other models with an accuracy of 78.26%.

3. The Proposed Model

The heart and circulatory system are the most important organs of the human body. Any disorder in these organs significantly affects the functioning of the entire body because the circulatory system provides energy to all organs, including the heart itself. Every year, heart diseases kill many people worldwide or impair their performance. Electrocardiography (ECG) is the primary method for monitoring heart activity. The ECG waveform consists of several characteristic waves: P, Q, R, S, and T. Features such as signal peaks, durations, and intervals between waves provide key information for detecting cardiac disturbances. In [23], a convolutional neural network (CNN) consisting of a convolutional layer, integration layer, and fully connected layer was used. CNN reduces errors in medical signal processing. To improve feature accuracy, a fuzzy layer is placed between the integration and fully connected layers. The general schematic of the proposed model's steps is shown in Figure 1.

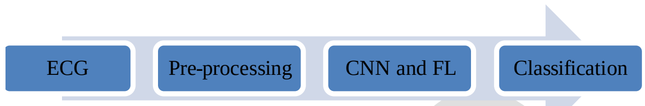

Figure 1. Steps of the proposed model

The model proposed in this article consists of two main parts. Next, each section is explained separately.

3.1. First Step: Pre-processing

The dataset that will be used in this study is the MIT/BIH arrhythmia database. This dataset consists of 48 records collected by the BIH Arrhythmia Laboratory. Each record contains a 30-minute two-channel ECG signal selected from each patient's 24-hour recording. The frequency of ECG signal is 360 Hz. The database not only provides ECG signal, but also the heart rate time and class information verified by the cardiologist. From the MIT/BIH arrhythmia database, 44 records will be selected for use. These records include different categories of heart rate, such as normal rate, ventricular and atrial arrhythmias. In the preprocessing step, four records containing fast heart rate will be removed for use in this study. In the following, only lead-1 ECG signal is used as raw data. Due to the presence of external noises among ECG signals, denoising method will be used to obtain clean data. Wavelet transform is a denoising method that uses a wavelet function to convolve the signal. This method will also be used in the proposed model, because it can maintain the accurate time-frequency components of ECG signal. Also, wavelet transform can extract wavelet coefficients with an appropriately wavelet $\psi(t)$ and reconstruct the signal. The k and j are integer values, related to the scale and shift parameters a and b, respectively. To make it easier to work with wavelet transformation, its discretization is usually done in binary form. In this way, the scale and location are in perfect powers of 2. With these definitions, the discrete wavelet is created in the form of equation (1).

$$\begin{cases} a = 2^j \ , j \in Z \\ b = ka, \quad k \in Z \end{cases} , \Psi_{j,k}(t)=(2^{1/2}\Psi(2^{-j}t-k)) \qquad (1)$$

According to equation (1) and the definition of continuous wavelet transformation, the discrete wavelet transformation of time series *f*(n) is written according to equation (2).

$$C(j,k) = \sum_{n\in Z} f(n)\psi_{j,k}(n) \tag{2}$$

Signal reconstruction calculated from equation (3).

$$f(t) = \sum_{j\in Z}\sum_{k\in Z} C(j,k)\psi_{j,k}(t) \tag{3}$$

Where *t* is denotes mentioning that in the process of signal reconstruction, it is possible to reconstruct only certain parts of it as needed, so you can delete a part of the signal at will. This feature is used in applications such as signal noise reduction according to equation (4).

$$f_j(n) = \sum_{k\in Z} C(j,k)\psi_{j,k}(n) \tag{4}$$

Therefore, the signal decomposed into components related to each scale. As shown in Figure 2, the red signal is the raw data and the green signal is the noise-free signal. Compared to the signal before denoising, the processed signal is smoother and oscillates around the 0-level curve, which indicates that the wavelet transform is effective. Therefore, the noise-free signal avoids noise interference.

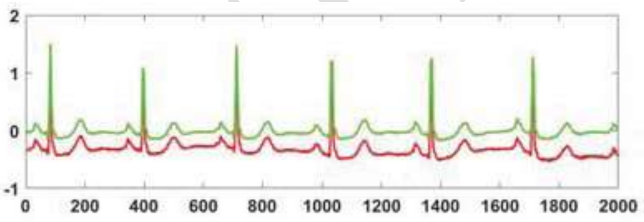

Figure 2. Raw ECG signal and noise-free signal using wavelet transform

3.2. Second step: Improved CNN network

CNN is a special type of neural network with multiple layers. Its main advantage is that it removes the need for many traditional image processing steps. In the convolutional layer, a kernel moves across the image to filter it by multiplying and adding pixel values in overlapping areas. In the proposed model, a fuzzy layer is placed between the integration layer and the fully connected layer. This layer classifies the input distribution into a set number of clusters. The fuzzy fully connected layer outputs membership functions representing the degree of belonging of each input to the clusters. It acts as the data classifier and determines the output class. Figure 3 shows a schematic of the proposed model. The network has nine layers: four convolutional layers, two subsampling layers, one fuzzy layer, one fully connected layer, and one Softmax layer. The activation function is ReLU, and the convolution kernel sizes are 5 and 3.

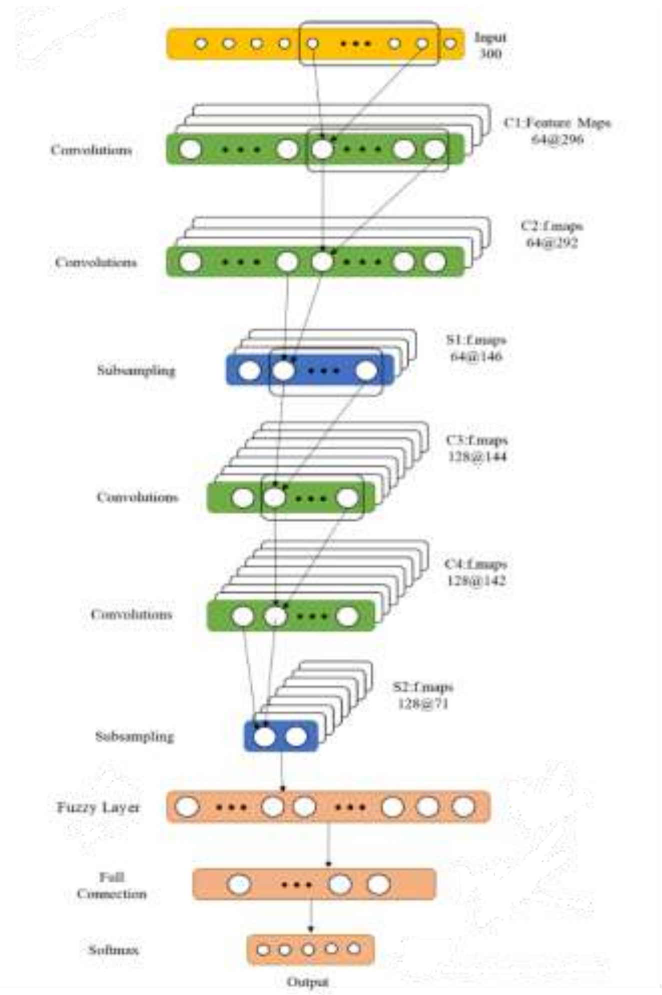

Figure 3. General structure of the proposed model

In this article, the number of neurons in the fuzzy layer is considered the same as the number of clusters. In equation (5), it shows the fuzzy membership function, which models the membership of the input vector *x* in each of the *L* clusters.

$$f(x) = \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{(x-m)^2}{2\sigma^2}} \tag{5}$$

In equation 1, the center m represents the center of a cluster and the surface of the cluster boundaries. The way it works is that if the vector $X=[x_1, x_2, x_3,\ldots,x_n]$ is given as input to a network, the fuzzy layer creates a vector that shows how much X belongs to a particular opinion cluster has $\mu(x)=[\mu_1(x), \mu_2(x), \mu_3(x), \ldots \mu_n(x)]$. Here, $\mu(X)$ is calculated using equations (6) and (7) to determine the normalization conditions and each training sample.

$$\mu l\left(X^{(k)}\right) = f(s) = f\left(\sum_{j=1}^{n} x_j^{(k)}\right) \quad (6)$$

$$\sum_{l=1}^{L} \mu l\left(X^{(k)}\right) = 1 \quad (7)$$

Here, the number of training sample vectors is denoted by k and the classification is fully calculated by the relation between fuzzy and fully connected layer. The fuzzy output is considered as the input of the fully connected layer. As it is known, the process of the proposed model is done in three steps. In the first step, the image related to the brain is obtained as different input on the input matrix of features from the image. In the phase, the fuzzy layer performs the initial generation of the inputs in the form of fuzzy clusters and finally gives the last fully connected layers and the final result.

4. Experiments

4.1. Datasets

The MIT-BIH arrhythmia dataset consists of 48 records, each approximately 30 min, from a two-channel ambulatory system collected [24]. The data for this dataset is publicly available for download. Also, these samples have all been normalized and all their noises have been removed by transformation and the important features have remained. Table 1 shows the number of samples in 10 disease categories with dataset characteristics.

Table 1. Number of samples in each class

Normal Rhythm	80921
Arterial Rhythm	2745
Ventricular Rhythm	8538
Arrhythmia	335
Cannot analysis	7187
Noise	586
Block	193
Abnormal A	1241
Abnormal B	982
Sum	102548

The number of samples of each class is different and in each category, there is a category of heart diseases. Table 2 gives the number of examples of the collection selected in this article .In this paper, we have selected five classes which include normal rhythm, left bundle branch block (LBBB), right bundle branch block (RBBB), premature ventricular contraction (PVC) and premature atrial beat (APB) .The main reason for choosing these five classes is that they constitute the largest number of samples among 102,548 heartbeats. Since if the number of samples of each has a huge difference, it will make the classification class completely useless, to solve this problem, in this research, we ignore the small classes and choose the large classes. This has two main reasons. First, it is easier and easier to train the proposed model with a large dataset to small datasets. Hence, classes with the best samples are selected to ensure that the proposed model trained. Second, the effect of unbalanced classes can reduce.

Table 2. Number of samples in each selected class

Class	Train data	Test data
Normal Beat	48755	20895
Left Bundle branch block beat	2576	1104
Right bundle branch block beat	5092	2182
Premature ventricular contraction beat	4867	2086
Atrial premature beat	1782	764
total number	63072	27031

4.2. Evaluation Criteria

In order to evaluate the proposed model, the accuracy, correctness and recall criteria and the F-score are used and are calculated according to the equation (8), (9), (10) and (11):

$$Accuracy=(TP+TN)/N \quad (8)$$

$$Precision=TP/(TP+FP) \quad (9)$$

$$Recall=TP/(TP+FN) \quad (10)$$

$$F-measure = \frac{2 \times Precision \times Recall}{Precision + Recall} \quad (11)$$

In the above relationships, TP and TN are respectively positive and negative examples that are correctly classified. FP and FN are the misclassified positive and negative samples, respectively, and N is the total number of samples.

4.3. Experimental Results

Deep learning requires processing millions of data points, which a normal processor cannot efficiently handle. Therefore, hardware with higher speed and greater computational power is necessary. The proposed method is implemented using Python, which facilitates designing and implementing machine learning and deep learning algorithms.

Table 3. Hyperparameters used to adjust the proposed model

Learning rate	0.001
Epochs	500
Optimizer	Adam
Batch size	2
Activation	ReLU
Subdivision	12
Weight Decay	0.0005

In summary, all the implementations of this article have been done with the help of Python 3 and TensorFlow 0.1.2 library on the system with GH Intel Xeon 2 E5-2620 2.0 processor and 8 GB of RAM in Linux environment. It should be noted that based on the proposed model, a combination of CNN and FL is used for classification. The hyperparameters used to adjust the proposed model are shown in Table 3.

In the medical world, the diagnosis of heart disease is considered as one of the most important and primary diagnostics for the heart and blood vessels. ECG features are usually used to diagnose heart disease. The results of ECG evaluations, including the analysis and evaluation of the heart's electrical signals, can help doctors diagnose various types of heart failure, arrhythmias, and other heart disorders.

These results can be the most important reference for the interpretation and diagnosis of heart disease in patients and based on that, treatment decisions can made. After providing the hardware and software platforms, the process of preprocessing and feature extraction and modeling is applied to the data.

In this section, a comparison is made with the aim of evaluating the efficiency of the proposed model in comparison with other traditional models. The results of applying the proposed model on the educational data samples of all five classes are shown in Figure 4 and Table 4. All the tests of this article are implemented and the accuracy test is done by K-Fold (K= 10) cross validation. In order to check the performance of the proposed model, this model has been compared with competing models.

As seen in Figure 4, the best accuracy is related to the proposed model with rate of 97.8%. Meanwhile, one-dimensional CNN had the lowest accuracy rate with 88.25%. Table 5 shows the comparison of competing models.

As seen in Table 5, Che et al [25] proposed a deep end-to-end environment based on (CNN) for ECG analysis evaluation and arrhythmia classification. The ECG data used in this study were obtained from a heart and body challenge, for which a total of 6877 subjects were collected. The proposed method has been able to obtain an F1-score of 81.7% for the detection of normal beats. In [26], the authors presented an idea using a training model for a 14-layer consisting of a one-dimensional CNN that displays features and long-term short-term memory (LSTM), which features temporal sequences. Finally, it is transferred to the dense. F1-score in this proposed model is reported as 81%.

Table 4. The results of the implementation of the proposed model

Category	Accuracy	Precision	Recall	F-Measure
Normal Beat	97.50	97.65	96.77	97.01
Left Bundle branch block beat	97.60	96.75	98.00	97.02
Right bundle branch block beat	97.01	97.23	97.02	97.43
Premature ventricular contraction beat	97.30	97.02	97.00	97.22
premature beat Atrial	97.32	97.01	97.25	97.92

Average/Total number	97.54	97.06	97.66	97.76

Table 5. Comparison of competing models based on F1-Score on educational data samples

Che et al [25]	81.7%
Banerjee et al [26]	81%
Rahman et al [27]	95.2%
Warrick et al [28]	82.0%
Warrick et al [29]	83.10 %

Rahman et al [27] presented classifications based on five model class classifications of ECG arrhythmia indices from the MIT-BIH Physionet arrhythmia dataset. In this paper, the proposed CNN structure consisting of 4 convolution layers, three integration layers after a fully connected layer and a Softmax is used. By checking their results, they have reached 95.2% F1-score. Varik et al. [28] have proposed CNN and combined it with a sequence of short-term memory units to detect cardiac arrhythmias and noise in ECG signals. In this method, ECG features are automatically extracted for each of these inputs using a single-layer CNN. In this article, F1 –score is reported as 82%. In [29], the authors addressed the automatic identification and classification of cardiac arrhythmias using ECG and CNN methods and a sequence of short-term memory units. The results obtained from their proposed model were 83.10% ± 0.015.

In this article, in order to check the performance of the proposed model and select the correct dataset, the UCI database has also been used in this article [30]. The data in this dataset includes 452 records with 279 features for each record. The comparison results of these two datasets are shown in Table 6.

Table 6. Diagnosis rate of cardiac patients using the proposed model on MIT_BIH and UCI datasets

Evaluation criteria	MIT-BIH Dataset	UCI Dataset
Accuracy	97.54 %	93.35 %
Precision	97.06 %	94.33 %
Recall	97.66 %	92.53 %
F-Measure	97.76 %	95.30 %

Table 6 shows the diagnosis rate of heart patients using the proposed model and different criteria such as accuracy, precision, recall and F-measure on MIT-BIH and UCI datasets. As it is known, the proposed model has higher classification accuracy than the basic methods on MIT-BIH dataset. It should be noted that in this comparison, the entire dataset introduced in has been used for implementation.

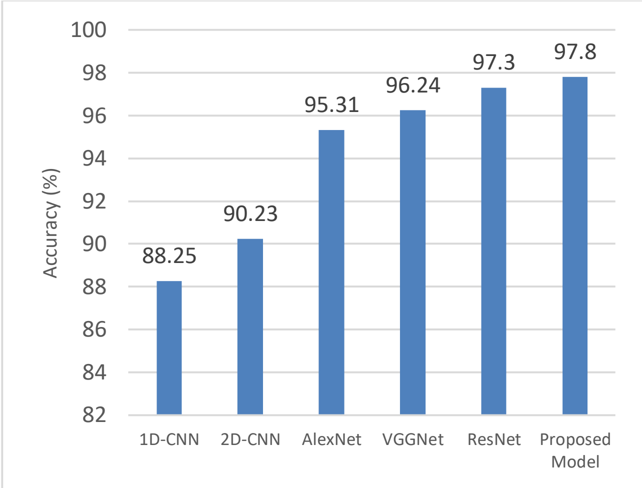

Figure 4. Comparison of the proposed model with other basic models

The results in Table 4 show that the proposed CNN + fuzzy layer model performs consistently across all classes, reaching a mean accuracy of 97.54% with a peak accuracy of 97.8%. These figures indicate a clear improvement over competing baselines and suggest that integrating fuzzy reasoning into the CNN feature pipeline reduces errors and enhances class separability on ECG data. This trend is consistent with recent reports in the Persian journal Soft Computing, where deep learning methods combined with fuzzy concepts or applied to medical signal/image analysis have achieved competitive performance across various healthcare tasks [31–33]. Overall, the findings in this section confirm that introducing a mid-stream fuzzy layer within a CNN is an effective strategy for arrhythmia detection from ECG and provides a solid basis for continued research on deep–fuzzy integration.

5. Conclusion

Heart diseases are among the leading causes of death worldwide. Currently, their diagnosis and prognosis rely on clinical signs, symptoms, medical history, and specialized tests. However, with the rapid advancement of artificial intelligence (AI), it is now possible to use this technology to predict heart conditions more effectively.

AI has emerged as a powerful tool in medical sciences, especially in diagnosing heart diseases. By using algorithms, neural networks, and machine learning systems, AI can develop diagnostic patterns from patient data and identify individuals at higher risk. One key application of AI is diagnosing heart disease from electrocardiograms (ECGs). This method involves automatic analysis of ECG signals to detect signs of heart issues and extract detailed information. AI can learn complex algorithms to analyze ECGs and deliver fast, accurate diagnostic results. To achieve this, machine learning and deep learning algorithms must be trained on ECG datasets.

In this study, we introduce a model based on the combination of Convolutional Neural Networks (CNN) and Federated Learning (FL). The model is implemented using the MIT/BIH Arrhythmia Database, which contains 48 records collected by the BIH Arrhythmia Laboratory. Experimental results show that the proposed model outperforms basic methods in terms of accuracy. It is important to note that deep learning models perform well when trained on large datasets. However, in many real-world applications, such datasets are not available. To address this, domain adaptation and transfer learning techniques are recommended. These approaches allow knowledge from other datasets—possibly from different domains—to be used for training models in the target application. In the proposed model, the number of network layers was increased, and its impact was observed. Since each deep learning model has its own strengths and limitations, combining different models can be beneficial.

For future work, there are still unexplored topics in multi-label feature selection that require further investigation. Additionally, evaluating and comparing multi-label datasets with varying sample distributions in deep learning classifiers is a promising direction for research

References

[1] M.M. Ahsan and Z. Siddique, *Machine learning-based heart disease diagnosis: A systematic literature review.* Artificial Intelligence in Medicine, 2022: p. 102289. 10.1016/j.artmed.2022.102289

[2] I.S. Brites, et al. *Machine learning and iot applied to cardiovascular diseases identification through heart sounds: A literature review.* in *International Conference on Information Technology & Systems*. 2022. Springer. 10.3390/informatics8040073

[3] M. Diwakar, et al., *Latest trends on heart disease prediction using machine learning and image fusion.* Materials Today: Proceedings, 2021. 37: p. 3213-3218. 10.1016/j.matpr.2020.09.078

[4] M. Elhoseny, et al., *A new multi-agent feature wrapper machine learning approach for heart disease diagnosis.* Comput. Mater. Contin, 2021. 67: p. 51-71. 10.32604/cmc.2021.012632

[5] P. Elias, et al., *Deep learning electrocardiographic analysis for detection of left-sided valvular heart disease.* Journal of the American College of Cardiology, 2022. 80(6): p. 613-626. 10.1016/j.jacc.2022.05.029

[6] Z. Liu, Y. Chen, Y. Zhang, S. Ran, C. Cheng, G. Yang, *Diagnosis of arrhythmias with few abnormal ECG samples using metric-based meta learning*. Computational Biology and Medicine, 2023.https://doi.org/10.1016/j.compbiomed.2022.106465 . 10.1016/j.compbiomed.2022.106465

[7] G. Napoles, I. Grau, L. Concepcion, L. Koumeri, J. Papa, *Modeling implicit bias with fuzzy cognitive maps. Neurocomputing.* 2022;481:33-45. 10.1016/j.neucom.2022.01.070

[8] L. Concepcion, G. Napoles, R. Falcon, K. Vanhoof, R. Bello, Unveiling the dynamic behavior of fuzzy cognitive maps. *IEEE Transactions on Fuzzy Systems.* 2020;29(5):1252-1261. 10.1109/TFUZZ.2020.2973853

[9] M. Kavitha, et al., *Heart Disease Prediction using Hybrid machine Learning Model.* 2021 6th International Conference on Inventive Computation Technologies (ICICT), 2021: p. 1329-1333. 10.1109/ICICT50816.2021.9358597

[10] A. Amiri, H. Jafarzadeh, Zh, Pervartbar. *diagnosis of heart disease using artificial intelligence and data mining techniques*. The first regional conference on information technology of electricity refining. 2013. (Persian).

[11] M. Feridouni, W. Ishtakhrian, *design and simulation of bioelectrical system that can be trained in the diagnosis of heart arrhythmia diseases using neural network*. The first national conference of electrical engineering of young and elite researchers club. 2015. (Persian).

[12] L. Rajab, I. Melayan, F. Yaghmai, *diagnosis of heart disease in fuzzy logic*. The second national conference on mathematics and its applications in engineering sciences. 2014. (Persian).

[13] M. Mokhtari, S. H. Peshgar, *ECG signal modeling by spline interpolation method to diagnose heart diseases.* The third international conference on recent innovations in electrical and computer engineering. 2015. (Persian).

[14] A. Naroi, W. Zamani, *diagnosis of cardiac arrhythmia using PCA and MLP neural network*. The second conference of new researches in science and technology. 2014. (Persian).

[15] N. Dashtinejad, K. Mirzaei, *diagnosis of liver and heart disease through iridology based on error back propagation network*, International Conference on New Research Findings in Electrical Engineering and Computer Science. 2014. (Persian).

[16] A. Nazari, *Evaluation of performance and accuracy of data mining techniques in timely diagnosis of heart diseases*, Fourth International Conference on New Researches in Engineering Sciences and Technology. 2014. (Persian).

[17] J. Hadadania, A. Mahdavi, *The use of pattern recognition technology in the diagnosis and analysis of heart diseases*. The third national conference and the first international conference on applied research

in electrical, mechanical and mechatronic engineering. 2014. (Persian).

[18] A. Dolatabadi, W. Hajipour, *Diagnosing heart diseases with the help of chaos domain features and LMAN neural networks*. 7th National Conference of Electrical and Electronic Engineering of Iran. 2014. (Persian).

[19] S. Palaniappan, and R. Awang. *Intelligent heart disease prediction system using data mining techniques*. in *2008 IEEE/ACS international conference on computer systems and applications*. 2008. IEEE. 10.1109/AICCSA.2008.4493524

[20] A. Taneja, *Heart disease prediction system using data mining techniques*. Oriental Journal of Computer science and technology, 2013. **6**(4): p. 457-466.

[21] M.S. Lakshmi, D. Haritha, and V. SRKIT, *Heart disease diagnosis using predictive data mining*. International Journal of Computer Science and Information Security, 2016.

[22] H.D. Masethe, and M.A. Masethe. *Prediction of heart disease using classification algorithms*. in *Proceedings of the world Congress on Engineering and computer Science*. 2014.

[23] S.K. Dhara, N. Bhanja, P. Khampariya, *An adaptive heart disease diagnosis via ECG signal analysis with deep feature extraction and enhanced radial basis function*. Comput. Methods Biomech. Biomed. Eng. Imaging Vis. 2023, 1–23. 10.1080/21681163.2023.2245927

[24] S. Alinsaif, *Unraveling Arrhythmias with Graph-Based Analysis: A Survey of the MIT-BIH Database*. Computation. 2024, 12, 21. https://doi.org/10.3390/computation12020021. 10.3390/computation12020021

[25] C. Che, P. Zhang, M. Zhu, Y. Qu, B. Jin, *Constrained transformer network for ECG signal processing and arrhythmia classification. BMC Med. Inf. Decis. Making*, 2021; **21**: 184. 10.1186/s12911-021-01546-2

[26] S. Banerjee, A. Paul, S. K. Jindal, *Real time arrhythmia detecting wearable using a novel deep learning model*. Proceedings of the 2020 International Conference on Interdisciplinary Cyber Physical Systems (ICPS). IEEE, Chennai, India2020, 14-19 (December). 10.1109/ICPS51508.2020.00009

[27] M. Rahman Khan, B. Siddique, A. Md, S. Sakib, A. Aziz, A. K. Tanzeem, Z. Hossain, *Electrocardiogram heartbeat classification using convolutional neural networks for the detection of cardiac arrhythmia*. Proceedings of the 2020 Fourth International Conference on I-SMAC (IoT in Social, Mobile, Analytics and Cloud) (I-SMAC). IEEE: Palladam, India, October 7 2020: 915-920. 10.48550/arXiv.2010.04086

[28] P. A. Warrick, M. Nabhan Homsi, *Ensembling convolutional and long short-term memory networks for electrocardiogram arrhythmia detection*.Physiol. Meas. 2018; **39**114002. 10.1088/1361-6579/aad386

[29] M. Warrick, N. Homsi, *Cardiac Arrhythmia Detection from ECG Combining Convolutional and Long Short-Term Memory Networks*. Computing in cardiology. September 2017. 10.22489/CinC.2017.161-460

[30] https://www.kaggle.com/datasets/redwankarimsony/heart-disease-data

[31] M. Sarchahi, E. Mahdipour, *Using ensemble deep learning to improve the accuracy of CT-Scan lung image detection of COVID-19 patients*. Soft Computing, 13(1): 20–39, 2024. (Persian). 10.22052/scj.2023.253142.1158

[32] Z. Sharifi-Mehrjerd, H. Momeni, H. Adabi-Ardakani, *A review of machine learning algorithms for autism detection using EEG signals*. Soft Computing, 13(1): 2–19, 2024. (Persian). 10.22052/scj.2023.248522.1110

[33] M. Eftekharian, A. Nodehi, *Breast cancer diagnosis and classification improvement based on deep learning and image processing*. Soft Computing, 12(1): 22–26, 2023. (Persian). 10.22052/scj.2023.246416.1067