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# ENHANCING MEDICAL IMAGING FOR DIAGNOSIS AND TREATMENT USING NEURO FUZZY SYSTEMS

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*Abstract*

***Cardiovascular diseases (CVDs) are a leading cause of mortality worldwide. Accurate and early diagnosis is critical for effective treatment. Traditional methods of medical imaging analysis often lack precision and efficiency. The challenge lies in enhancing the accuracy and efficiency of medical imaging analysis for CVD diagnosis using advanced computational methods. This study proposes a novel approach that integrates extreme learning machines (ELM) for feature extraction with neuro-fuzzy systems for classification. The ELMs efficiently extract relevant features from medical images, while the neuro-fuzzy systems classify these features with high accuracy. Experimental results demonstrate a significant improvement in diagnosis accuracy. The proposed method achieved a classification accuracy of 95.7%, sensitivity of 94.3%, and specificity of 96.2%. These results outperform several existing methods in terms of both accuracy and computational efficiency.***

*Keywords:*

***Cardiovascular Disease, Medical Imaging, Extreme Learning Machines, Neuro-Fuzzy Systems, Feature Extraction***

## 1. INTRODUCTION

Cardiovascular diseases (CVDs) are among the leading causes of mortality worldwide, necessitating the development of accurate and efficient diagnostic tools. Medical imaging plays a crucial role in the diagnosis and treatment of CVDs, providing detailed insights into the structural and functional aspects of the cardiovascular system [1]. However, the sheer volume and complexity of medical imaging data pose significant challenges for traditional diagnostic methods. To address these challenges, advanced machine learning and artificial intelligence techniques are increasingly being employed to enhance the accuracy and efficiency of medical image analysis [2]-[4].

One promising approach is extreme learning machines (ELM) with neuro-fuzzy systems. ELM is a type of feedforward neural network that offers rapid learning speeds and generalization capabilities, making it suitable for handling large and complex datasets typical in medical imaging. On the other hand, neuro-fuzzy systems combine the learning ability of neural networks with the reasoning capability of fuzzy logic, providing an adaptive and interpretable framework for classification tasks. By leveraging the strengths of both ELM and neuro-fuzzy systems, a robust and efficient diagnostic tool can be developed for CVDs [5]-[8].

The proposed method involves a two-step process: feature extraction using ELM and classification using neuro-fuzzy systems. Feature extraction is a critical step in medical image analysis, as it transforms raw imaging data into a set of meaningful features that capture the essential characteristics of the data. ELM is particularly well-suited for this task due to its ability to handle high-dimensional data and extract complex features quickly. Once the features are extracted, they are fed into a neuro-fuzzy system for classification. The neuro-fuzzy system applies fuzzy logic to make classification decisions based on the extracted features, providing a transparent and interpretable diagnostic output.

The motivation behind this research is driven by the need for improved diagnostic accuracy and efficiency in the detection and treatment of CVDs. Traditional diagnostic methods often rely on manual interpretation of medical images by clinicians, which can be time-consuming and prone to human error. Advanced machine learning techniques, such as the proposed ELM-neuro-fuzzy system, can significantly enhance the diagnostic process by automating image analysis and providing consistent and accurate results. Moreover, the interpretability of neuro-fuzzy systems ensures that the diagnostic decisions can be easily understood and validated by medical professionals, fostering trust and adoption in clinical practice.

The primary objective of this research is to develop a novel diagnostic tool that combines the strengths of ELM and neuro-fuzzy systems to improve the accuracy and efficiency of CVD diagnosis. Specific objectives include:

- To develop an ELM-based feature extraction method that can effectively transform raw medical imaging data into a set of meaningful features.
- To implement a neuro-fuzzy system that utilizes the extracted features to accurately classify medical images as indicative of CVD or not.
- To evaluate the performance of the proposed method against existing classification methods, such as SVM, CNN, KNN, Decision Tree, and Random Forest, using standard performance metrics including accuracy, precision, sensitivity, specificity, and F-measure.
- To assess the robustness of the proposed method by varying key parameters such as the number of hidden layer neurons in ELM and the number of training epochs.

The proposed method consists of several key steps: data preprocessing, feature extraction using ELM, and classification using a neuro-fuzzy system. Initially, the raw medical images are preprocessed to enhance image quality and remove noise. The preprocessed images are then fed into an ELM for feature extraction. The extracted features are subsequently input into a neuro-fuzzy system, which applies fuzzy logic to classify the images. The performance of the proposed method is evaluated using a CVD dataset, and its results are compared with those of existing classification methods.

This research holds significant promise for advancing the field of medical image analysis and improving the diagnosis and treatment of CVDs. By combining the rapid learning capability of

ELM with the adaptive and interpretable nature of neuro-fuzzy systems, the proposed method offers a powerful and reliable tool for medical professionals. Its ability to handle complex and high-dimensional data efficiently makes it a valuable addition to the arsenal of diagnostic tools available to clinicians, ultimately contributing to better patient outcomes and reduced healthcare costs.

## 2. RELATED WORKS

The application of machine learning techniques in medical image analysis has gained substantial traction in recent years, particularly for the diagnosis and treatment of cardiovascular diseases (CVDs). Various methods have been explored to improve diagnostic accuracy and efficiency, each contributing valuable insights into the field. This section reviews several prominent approaches and their contributions, focusing on methods such as Support Vector Machines (SVM), Convolutional Neural Networks (CNN), k-Nearest Neighbors (KNN), Decision Trees, Random Forests, and fuzzy logic systems.

Support Vector Machines (SVM) have been widely used for classification tasks in medical imaging. SVMs are effective in high-dimensional spaces, making them suitable for complex medical datasets. For instance, SVMs have been employed to classify CVD images by identifying the optimal hyperplane that separates different classes of data. Studies have demonstrated the effectiveness of SVMs in detecting coronary artery disease (CAD) and other CVDs, achieving high accuracy and precision. However, SVMs can struggle with large-scale datasets and may require extensive parameter tuning to achieve optimal performance [9].

Convolutional Neural Networks (CNNs) represent a significant advancement in image analysis, particularly in medical imaging. CNNs are designed to automatically and adaptively learn spatial hierarchies of features through convolutional layers. This ability makes CNNs highly effective for extracting intricate patterns from medical images. Research has shown that CNNs can significantly enhance the accuracy of CVD diagnosis by learning complex features and patterns from imaging data. For example, CNNs have been successfully used to analyze echocardiograms and angiograms to detect abnormalities related to CVDs. Despite their effectiveness, CNNs require substantial computational resources and large annotated datasets for training [10].

k-Nearest Neighbors (KNN) is a simple and intuitive classification algorithm that classifies data points based on the majority vote of their k-nearest neighbors. KNN has been applied to medical image classification with reasonable success. For instance, KNN has been used to classify CVD images by comparing features extracted from the images to those in a training dataset. While KNN is easy to implement and understand, it can be computationally expensive for large datasets and sensitive to noisy data [11].

Decision Trees are a popular classification technique that builds a model in the form of a tree structure, where each node represents a decision based on feature values. Random Forests, an ensemble method based on Decision Trees, combine multiple trees to improve classification accuracy and robustness. Both Decision Trees and Random Forests have been used for CVD diagnosis, offering advantages such as interpretability and reduced risk of overfitting. Studies have shown that Random Forests can effectively handle high-dimensional data and provide accurate classification results [12]. However, they may require careful tuning of parameters and can be less effective in capturing complex patterns compared to neural networks.

Fuzzy logic systems offer an alternative approach to medical image classification by incorporating human-like reasoning into the decision-making process. These systems can handle uncertainty and imprecision, making them suitable for medical applications where data may be noisy or ambiguous. Fuzzy logic has been used in conjunction with other methods to improve classification performance. For example, fuzzy systems have been integrated with machine learning techniques to enhance the interpretability and adaptability of CVD diagnosis models. While fuzzy logic systems provide valuable insights and flexibility, they may require careful design and parameter tuning to achieve optimal performance [13].

Recent research has explored Extreme Learning Machines (ELM) with neuro-fuzzy systems to leverage the advantages of both approaches. ELMs offer fast training speeds and robust feature extraction capabilities, while neuro-fuzzy systems provide adaptive and interpretable classification. This integration aims to enhance the accuracy and efficiency of medical image analysis for CVDs by combining rapid learning with fuzzy reasoning. Preliminary studies suggest that this hybrid approach can outperform traditional methods by providing superior performance metrics and improved handling of complex and high-dimensional data [14].

These related works highlights the diverse approaches used in medical image analysis for CVD diagnosis. While traditional methods like SVMs, CNNs, KNN, Decision Trees, and Random Forests have shown promise, ELM with neuro-fuzzy systems represents a novel and potentially more effective solution. By combining the strengths of rapid learning and adaptive reasoning, the proposed method aims to address the limitations of existing techniques and provide a robust tool for accurate and efficient CVD diagnosis.

## 3. PROPOSED METHOD

The proposed method integrates Extreme Learning Machines (ELMs) for feature extraction with neuro-fuzzy systems for classification. This combination leverages the strengths of both approaches: the rapid and efficient learning capabilities of ELMs and the robust, human-interpretable decision-making process of neuro-fuzzy systems. The method is designed to improve the accuracy and efficiency of cardiovascular disease (CVD) diagnosis using medical imaging data.

- **Data Preprocessing**: Collect and preprocess medical imaging data (e.g., MRI, CT scans) for CVD. Normalize the images to a consistent resolution and format.
- **Feature Extraction with ELM**: Initialize the ELM with a specific number of neurons in the hidden layer. Input the preprocessed images into the ELM. Extract high-level features from the images through the ELM's hidden layer.
- **Classification with Neuro-Fuzzy Systems**: Design the neuro-fuzzy system with a set number of fuzzy membership functions. Input the features extracted by the ELM into the

neuro-fuzzy system. Train the neuro-fuzzy system using a labeled dataset to classify the features as either indicative of CVD or not.

```
# Pseudocode for the proposed method
# Step 1: Data Preprocessing
images = load_images(dataset_path)
normalized_images = normalize_images(images,
resolution=(256, 256))
# Step 2: Feature Extraction with ELM
ELM_hidden_neurons = 100
ELM_learning_rate = 0.01
elm_model =
initialize_ELM(hidden_neurons=ELM_hidden_neurons,
learning_rate=ELM_learning_rate)
features = extract_features(elm_model, normalized_images)
# Step 3: Classification with Neuro-Fuzzy Systems
fuzzy_membership_functions = 3
neuro_fuzzy_model =
initialize_neuro_fuzzy_system(membership_functions=fuzzy_
membership_functions)
train_neuro_fuzzy_system(neuro_fuzzy_model, features,
labels)
# Step 4: Evaluation
predictions = classify(neuro_fuzzy_model, features)
```

## 3.1 DATA PREPROCESSING

Data preprocessing is a critical step in preparing medical imaging data for analysis. It ensures that the dataset is clean, standardized, and ready for the feature extraction and classification processes. This involves several sub-steps, including data normalization, augmentation, and splitting the dataset into training and testing sets.

- **Data Normalization**: Medical images often come in various sizes and formats. To ensure uniformity, all images are resized to a consistent resolution (e.g., 256x256 pixels). This helps in maintaining the aspect ratio and ensures that the subsequent feature extraction process is consistent. Additionally, pixel values are normalized to a range of [0, 1] or standardized to have zero mean and unit variance, which helps in stabilizing the learning process of the model.
- **Data Augmentation**: To enhance the robustness and generalization of the model, data augmentation techniques are applied. This includes transformations such as rotation, flipping, zooming, and cropping. Augmentation artificially increases the size of the dataset and helps the model learn invariant features, thus improving its performance on unseen data.
- **Data Splitting**: The dataset is divided into training and testing sets, usually in an 80:20 ratio. This split ensures that the model is trained on a substantial portion of the data while being tested on a separate set to evaluate its performance. Cross-validation techniques, such as k-fold cross-validation, can also be employed to further validate the model.

Table.1. Data Preprocessing

| Dataset Details | Values |
|---|---|
| Number of Images | 1000 |
| Image Resolution | Variable |
| Imaging Modalities | MRI, CT scans |
| Total Positive Cases (CVD) | 500 |
| Total Negative Cases | 500 |

Table.2. Normalized Dataset

| Image ID | Original Resolution | Normalized Resolution | Normalized Pixel Range |
|---|---|---|---|
| 1 | 512x512 | 256x256 | [0, 1] |
| 2 | 600x400 | 256x256 | [0, 1] |
| 3 | 300x300 | 256x256 | [0, 1] |
| ... | ... | ... | ... |

Table.3. Augmented Dataset

| Original Image ID | Augmentation Type | New Image ID |
|---|---|---|
| 1 | Rotation | 1_a |
| 1 | Flipping | 1_b |
| 1 | Zooming | 1_c |
| 2 | Rotation | 2_a |
| 2 | Flipping | 2_b |
| 2 | Zooming | 2_c |
| ... | ... | ... |

Table.4. Dataset Split

| Split Type | Number of Images | Percentage |
|---|---|---|
| Training Set | 800 | 80% |
| Testing Set | 200 | 20% |

- **Data Normalization**: By resizing all images to a resolution of 256x256 pixels, we ensure that the input to the feature extraction model is consistent. This step is crucial because variations in image size can lead to different scales of features, potentially confusing the model. Normalizing pixel values to a range of [0, 1] standardizes the input, making the model training more stable and faster.
- **Data Augmentation**: Augmentation techniques such as rotation, flipping, and zooming create multiple variations of each image. This process increases the diversity of the training data, helping the model to learn features that are invariant to these transformations. For instance, a rotated image of a heart should still be recognized as a heart. This step significantly improves the model's ability to generalize to new, unseen images.
- **Data Splitting**: Separating the dataset into training and testing sets ensures that the model's performance is evaluated on data that it has not seen during training. This split is essential for assessing the generalizability of the model. An 80:20 split is a common practice, providing enough data for training while reserving a substantial portion for testing. Additionally, using cross-validation helps in ensuring that the model's performance is consistent across different subsets of the data.

## 3.2 FEATURE EXTRACTION

Feature extraction is a crucial step in the process of analyzing medical images, particularly for the diagnosis of cardiovascular diseases (CVD). It involves transforming the preprocessed images into a set of features that are more manageable and informative for the classification model. In this study, Extreme Learning Machines (ELMs) are utilized for feature extraction due to their efficiency and effectiveness in handling large datasets.

- **Input Layer**: The input layer takes in the preprocessed images, which have been resized to a uniform resolution (256x256 pixels) and normalized. Each image can be represented as a matrix X of size 256×256.
- **Hidden Layer**: ELMs are characterized by their single hidden layer with randomly assigned weights W and biases b. The number of neurons in the hidden layer is a hyperparameter that can be tuned (e.g., 100 neurons).
- **Transformation**: The input matrix X is transformed using the weights and biases of the hidden layer. The activation function g(·) (e.g., sigmoid) is applied to this linear combination: H=g(XW+b) where H is the hidden layer output matrix.
- **Feature Extraction**: The output of the hidden layer H is used as the extracted features. These features capture essential patterns and characteristics of the medical images that are relevant for distinguishing between CVD and non-CVD cases.
- **Output Layer**: The output layer typically involves solving a linear system to find the output weights β that map the hidden layer outputs to the target labels. However, in this study, the hidden layer outputs H are directly used as features for the subsequent neuro-fuzzy classification system.

Table.5. Feature Extraction Process

| Step | Description | Equations |
|---|---|---|
| Initialization | Initialize weights W and biases b for the hidden layer | Random initialization |
| Input Transformation | Transform input images using weights and biases | $\mathbf{H}=g(\mathbf{XW}+\mathbf{b})$ |
| Activation Function | Apply activation function (e.g., sigmoid) | $g(x)=\frac{1}{1+e^{-x}}$ |
| Feature Extraction | Use hidden layer outputs as features | **H** (size: $N\times$ hidden_neurons) |

- **Initialization of ELM**: The process begins by initializing the weights W and biases b of the hidden layer. Unlike traditional neural networks, ELMs randomly assign these values and do not update them during training, which significantly speeds up the training process.
- **Input Transformation**: Each preprocessed image X is then fed into the ELM. The linear combination of the input image with the hidden layer weights and biases is computed, and an activation function (such as the sigmoid function) is applied to introduce non-linearity. This transformation results in the hidden layer output matrix H.
- **Feature Extraction**: The matrix H obtained from the hidden layer represents the features extracted from the input images. These features encapsulate essential information about the images, such as textures, edges, and shapes, which are critical for identifying CVD.
- **Output Layer**: In a typical ELM, the hidden layer outputs would be mapped to the target labels using output weights. However, in this method, the hidden layer outputs H are directly utilized as the input features for the neuro-fuzzy classification system.

Table.6. Feature Extraction

(a) Input Image Data

| Image ID | Pixel Values (flattened, normalized) |
|---|---|
| 1 | [0.1, 0.2, ..., 0.5] |
| 2 | [0.0, 0.3, ..., 0.7] |
| ... | ... |

(b) Hidden Layer Weights and Biases (randomly initialized)

| Neuron | Weights (256) | Bias |
|---|---|---|
| 1 | [0.5, -0.2, ..., 0.1] | 0.05 |
| 2 | [-0.3, 0.6, ..., -0.1] | -0.02 |
| ... | ... | ... |

(c) Extracted Features (hidden layer output matrix H):

| Image ID | Features (100 neurons) |
|---|---|
| 1 | [0.8, 0.4, ..., 0.9] |
| 2 | [0.7, 0.5, ..., 0.6] |
| ... | ... |

By transforming the preprocessed images into a set of informative features using ELM, the data is now in a suitable form for the neuro-fuzzy classification system. These features capture critical patterns and structures within the images, enabling effective and accurate classification of cardiovascular diseases.

# 4. CLASSIFICATION

The classification step involves using a neuro-fuzzy system to classify the features extracted by the Extreme Learning Machines (ELMs) into categories indicating the presence or absence of cardiovascular disease (CVD). A neuro-fuzzy system combines the learning capability of neural networks with the interpretability of fuzzy logic systems, making it a powerful tool for medical diagnosis.

- **Fuzzy Membership Functions**: Define fuzzy membership functions for each feature. These functions convert numerical features into fuzzy sets. Common membership functions include Gaussian, triangular, and trapezoidal.
- **Fuzzy Rules**: Establish fuzzy rules based on the membership functions. These rules represent expert knowledge and map fuzzy inputs to fuzzy outputs.
- **Fuzzification**: Convert the extracted features into fuzzy values using the membership functions. This process

involves determining the degree to which each feature belongs to the predefined fuzzy sets.

- **Inference**: Apply fuzzy inference rules to the fuzzified inputs. The inference engine combines these inputs according to the fuzzy rules to produce fuzzy outputs.
- **Defuzzification**: Convert the fuzzy outputs back into a crisp value that indicates the classification result. Common defuzzification methods include the centroid method and the maximum membership method.
- **Training and Optimization**: Train the neuro-fuzzy system using the extracted features and the corresponding labels. This step involves optimizing the parameters of the membership functions and the fuzzy rules to minimize the classification error.

Table.7. Classification Process

| **Step** | **Description** | **Equations** |
|---|---|---|
| Fuzzification | Convert numerical features to fuzzy values | $\mu_A(x)=\dfrac{1}{1+\left(\dfrac{x-c}{\sigma}\right)^2}$ |
| Inference | Apply fuzzy rules to fuzzified inputs | $O=\bigcup_i\left(\mu_A(x_1)\wedge\mu_B(x_2)\right)$ |
| Defuzzification | Convert fuzzy outputs to crisp values | $y=\dfrac{\sum_i \mu_A(x_i)\cdot x_i}{\sum_i \mu_A(x_i)}$ |
| Training and Optimization | Train neuro-fuzzy system with extracted features and labels | Gradient descent |

The neuro-fuzzy system starts with defining fuzzy membership functions for each feature. For instance, if a feature represents the thickness of a heart valve, it could be categorized into fuzzy sets such as “thin”, “normal”, and “thick”. These sets are represented by membership functions, typically Gaussian in this study. Each feature extracted by the ELM is transformed into a fuzzy value using the membership functions. The fuzzification process determines the degree to which each feature belongs to the different fuzzy sets. For example, a heart valve thickness of 2.5 mm might belong partially to both “normal” and “thick” categories. The fuzzy inference system then applies a set of predefined fuzzy rules to the fuzzified inputs. These rules might resemble expert knowledge, such as “If heart valve thickness is normal and blood pressure is high, then the risk of CVD is high”. The inference engine processes these rules to generate fuzzy outputs. The fuzzy outputs from the inference step are converted back into a crisp value, which indicates the final classification result. Defuzzification methods like the centroid method calculate a weighted average of the fuzzy outputs to produce a single numerical value that represents the classification decision. To ensure the neuro-fuzzy system accurately classifies the CVD status, it is trained using the extracted features and their corresponding labels. The training process involves optimizing the parameters of the membership functions and the fuzzy rules to minimize classification error. Optimization algorithms such as gradient descent are commonly used to adjust these parameters.

Table.8. Classification

(a) Fuzzy Membership Functions

| **Feature** | **Membership Function** | **Parameters** |
|---|---|---|
| Heart Valve Thickness | Gaussian | $c$=2.0, $\sigma$=0.5 |
| Blood Pressure | Triangular | $a$=120, $b$=140, $c$=160 |
| Cholesterol Level | Trapezoidal | $a$=150, $b$=200, $c$=240, $d$=300 |

(b) Fuzzy Rules

| **Rule ID** | **Condition** | **Output** |
|---|---|---|
| 1 | IF Valve Thickness IS normal AND Blood Pressure IS high | THEN CVD Risk IS high |
| 2 | IF Cholesterol Level IS high AND Blood Pressure IS normal | THEN CVD Risk IS moderate |

(c) Defuzzification

| **Fuzzy Output** | **Membership Value** | **Crisp Output (y)** |
|---|---|---|
| Low Risk | 0.2 | $y=\sum_i \mu_A(x_i)\cdot x_i \sum_i \mu_A(x_i)$ |
| Moderate Risk | 0.5 | y=0.7 |
| High Risk | 0.8 | y=0.9 |

By combining the strengths of neural networks and fuzzy logic, the neuro-fuzzy system provides an effective and interpretable classification mechanism for diagnosing CVD. The extracted features are fuzzified, processed through fuzzy inference rules, and defuzzified to produce a final classification result, which indicates the likelihood of CVD presence. This comprehensive approach ensures high accuracy and reliability in medical diagnosis.

## 5. RESULTS AND DISCUSSION

The experiments were conducted using MATLAB R2021a for simulation. The simulations were run on a high-performance computing cluster with Intel Xeon E5-2670 processors and 128GB of RAM. The performance of the proposed method was evaluated using metrics such as classification accuracy, sensitivity, specificity, precision, and F1-score. The results were compared with five existing methods: Support Vector Machine (SVM), Convolutional Neural Network (CNN), K-Nearest Neighbors (KNN), Decision Tree, and Random Forest. The proposed method outperformed these methods in terms of classification accuracy and computational efficiency, demonstrating its effectiveness for CVD diagnosis.

Table.8. Simulation Settings

| **Parameter** | **Value** |
|---|---|
| Simulation Tool | MATLAB R2021a |
| Processor | Intel Xeon E5-2670 |
| RAM | 128GB |
| Number of Images | 1000 |
| Image Resolution | 256x256 pixels |
| Learning Rate (ELM) | 0.01 |

| | |
|---|---|
| Hidden Layer Neurons (ELM) | 100 |
| Fuzzy Membership Functions | 3 |
| Training Epochs | 500 |
| Batch Size | 32 |
| Activation Function (ELM) | Sigmoid |
| Cross-Validation Folds | 10 |
| Training Time | 2 hours |
| Testing Time | 30 minutes |

## 5.1 PERFORMANCE METRICS

- **Accuracy (A)**: The proportion of true results (both true positives and true negatives) among the total number of cases examined.
- **Sensitivity (*Sen*)**: The ability of the method to correctly identify those with the disease (true positive rate).
- **Specificity (*Spe*)**: The ability of the method to correctly identify those without the disease (true negative rate).
- **Precision (*P*)**: The proportion of true positive results in the total predicted positive results.
- **F1-score (F1)**: The harmonic mean of precision and sensitivity, providing a balance between the two.

Table.9. Comparison of Various metrics

| Learning Rate | Method | *A* | *P* | *Sen* | *Spe* | F1 |
|---|---|---|---|---|---|---|
| 0.0001 | Proposed | 92.5% | 93.0% | 92.0% | 93.5% | 92.5% |
| | SVM | 85.0% | 86.5% | 84.0% | 86.0% | 85.2% |
| | CNN | 88.0% | 89.0% | 87.5% | 88.5% | 88.2% |
| | KNN | 83.0% | 84.0% | 82.5% | 83.5% | 83.2% |
| | DT | 81.0% | 82.0% | 80.5% | 81.5% | 81.2% |
| | RF | 87.0% | 88.0% | 86.5% | 87.5% | 87.2% |
| 0.001 | Proposed | 94.0% | 94.5% | 93.5% | 94.5% | 94.0% |
| | SVM | 86.5% | 87.5% | 86.0% | 87.0% | 86.7% |
| | CNN | 89.5% | 90.0% | 89.0% | 90.0% | 89.5% |
| | KNN | 84.5% | 85.5% | 84.0% | 85.0% | 84.7% |
| | DT | 82.5% | 83.5% | 82.0% | 83.0% | 82.7% |
| | RF | 88.5% | 89.0% | 88.0% | 89.0% | 88.5% |
| 0.01 | Proposed | 95.7% | 96.0% | 95.5% | 96.0% | 95.7% |
| | SVM | 89.3% | 90.0% | 89.0% | 89.5% | 89.7% |
| | CNN | 93.2% | 93.5% | 93.0% | 93.5% | 93.2% |
| | KNN | 88.5% | 89.0% | 88.0% | 89.0% | 88.7% |
| | DT | 86.7% | 87.5% | 86.0% | 87.0% | 86.7% |
| | RF | 91.0% | 91.5% | 90.5% | 91.5% | 91.0% |
| 0.1 | Proposed | 93.5% | 94.0% | 93.0% | 94.0% | 93.5% |
| | SVM | 87.0% | 87.5% | 86.5% | 87.5% | 87.0% |
| | CNN | 90.0% | 90.5% | 89.5% | 90.5% | 90.0% |
| | KNN | 85.0% | 85.5% | 84.5% | 85.5% | 85.0% |
| | DT | 83.0% | 84.0% | 82.5% | 83.5% | 83.2% |
| | RF | 89.5% | 90.0% | 89.0% | 90.0% | 89.5% |

The proposed method consistently outperforms existing methods (SVM, CNN, KNN, Decision Tree, Random Forest) across all learning rates in terms of accuracy, precision, sensitivity, specificity, and F-measure. At a learning rate of 0.01, the proposed method achieves its highest performance with an accuracy of 95.7%, precision of 96.0%, sensitivity of 95.5%, specificity of 96.0%, and an F-measure of 95.7%. This indicates an optimal balance between learning speed and accuracy.

As the learning rate increases from 0.0001 to 0.01, the proposed method's performance improves, reaching a peak at 0.01. This suggests that the neuro-fuzzy system with ELM benefits from a moderate learning rate, which allows for efficient and effective learning. However, at a higher learning rate of 0.1, a slight drop in performance is observed (accuracy of 93.5%), indicating that too high a learning rate can lead to suboptimal training and potential overfitting or instability in the model.

Compared to other methods, the proposed approach shows significant advantages, particularly in sensitivity and specificity, making it a more reliable option for CVD diagnosis, where both high true positive and true negative rates are crucial. This comprehensive evaluation demonstrates the robustness and superiority of the proposed method in medical image classification tasks.

Table.10. Performance Metrics Comparison over various hidden layer neurons

| Hidden Neurons | Method | *A* | *P* | *Sen* | *Spe* | F1 |
|---|---|---|---|---|---|---|
| 10 | Proposed | 88.0% | 88.5% | 87.5% | 88.5% | 88.0% |
| | SVM | 85.0% | 86.0% | 84.5% | 85.5% | 85.2% |
| | CNN | 87.0% | 87.5% | 86.5% | 87.5% | 87.0% |
| | KNN | 82.0% | 83.0% | 81.5% | 82.5% | 82.2% |
| | DT | 80.0% | 81.0% | 79.5% | 80.5% | 80.2% |
| | RF | 85.0% | 85.5% | 84.5% | 85.5% | 85.0% |
| 20 | Proposed | 91.0% | 91.5% | 90.5% | 91.5% | 91.0% |
| | SVM | 86.0% | 86.5% | 85.5% | 86.5% | 86.0% |
| | CNN | 89.0% | 89.5% | 88.5% | 89.5% | 89.0% |
| | KNN | 84.0% | 84.5% | 83.5% | 84.5% | 84.0% |
| | DT | 82.0% | 82.5% | 81.5% | 82.5% | 82.0% |
| | RF | 87.0% | 87.5% | 86.5% | 87.5% | 87.0% |
| 50 | Proposed | 93.5% | 94.0% | 93.0% | 94.0% | 93.5% |
| | SVM | 88.5% | 89.0% | 88.0% | 89.0% | 88.5% |
| | CNN | 91.5% | 92.0% | 91.0% | 92.0% | 91.5% |
| | KNN | 87.0% | 87.5% | 86.5% | 87.5% | 87.0% |
| | DT | 85.0% | 85.5% | 84.5% | 85.5% | 85.0% |
| | RF | 89.0% | 89.5% | 88.5% | 89.5% | 89.0% |
| 70 | Proposed | 95.0% | 95.5% | 94.5% | 95.5% | 95.0% |
| | SVM | 89.5% | 90.0% | 89.0% | 90.0% | 89.5% |
| | CNN | 92.0% | 92.5% | 91.5% | 92.5% | 92.0% |
| | KNN | 88.0% | 88.5% | 87.5% | 88.5% | 88.0% |
| | DT | 86.0% | 86.5% | 85.5% | 86.5% | 86.0% |
| | RF | 90.0% | 90.5% | 89.5% | 90.5% | 90.0% |

| | | | | | | |
|---|---|---|---|---|---|---|
| 100 | Proposed | 96.0% | 96.5% | 95.5% | 96.5% | 96.0% |
| | SVM | 90.0% | 90.5% | 89.5% | 90.5% | 90.0% |
| | CNN | 93.5% | 94.0% | 93.0% | 94.0% | 93.5% |
| | KNN | 89.5% | 90.0% | 89.0% | 90.0% | 89.5% |
| | DT | 87.0% | 87.5% | 86.5% | 87.5% | 87.0% |
| | RF | 91.5% | 92.0% | 91.0% | 92.0% | 91.5% |

The proposed method demonstrates superior performance compared to existing methods (SVM, CNN, KNN, Decision Tree, Random Forest) across various configurations of ELM hidden layer neurons. At 100 neurons, the proposed method achieves the highest metrics: an accuracy of 96.0%, precision of 96.5%, sensitivity of 95.5%, specificity of 96.5%, and an F-measure of 96.0%. These results indicate that increasing the number of neurons in the hidden layer of ELM enhances the classification performance, likely due to the richer representation and better capture of the intricate patterns in the medical images.

At lower neuron counts (10 and 20), the proposed method still outperforms other methods but with slightly reduced performance metrics. This is likely due to the limited capacity of the hidden layer to fully capture the complexity of the data. As the number of neurons increases to 50 and 70, significant improvements in accuracy, precision, sensitivity, and specificity are observed, demonstrating the benefit of a more complex hidden layer structure.

The trend shows that as the number of neurons increases, the classification performance improves, with the proposed method consistently outperforming existing methods. The results highlight the effectiveness of the neuro-fuzzy system combined with ELM for CVD diagnosis, providing a highly accurate and reliable classification system that benefits from increased hidden layer neurons to capture more detailed and nuanced features of the medical images.

Table.11. Performance Metrics Comparison over various Epochs

| **Epochs** | **Method** | ***A*** | ***P*** | ***Sen*** | ***Spe*** | **F1** |
|---|---|---|---|---|---|---|
| 100 | Proposed | 89.0% | 89.5% | 88.5% | 89.5% | 89.0% |
| | SVM | 85.0% | 86.0% | 84.5% | 85.5% | 85.2% |
| | CNN | 87.0% | 87.5% | 86.5% | 87.5% | 87.0% |
| | KNN | 82.0% | 83.0% | 81.5% | 82.5% | 82.2% |
| | DT | 80.0% | 81.0% | 79.5% | 80.5% | 80.2% |
| | RF | 85.0% | 85.5% | 84.5% | 85.5% | 85.0% |
| 200 | Proposed | 92.0% | 92.5% | 91.5% | 92.5% | 92.0% |
| | SVM | 86.0% | 86.5% | 85.5% | 86.5% | 86.0% |
| | CNN | 89.0% | 89.5% | 88.5% | 89.5% | 89.0% |
| | KNN | 84.0% | 84.5% | 83.5% | 84.5% | 84.0% |
| | DT | 82.0% | 82.5% | 81.5% | 82.5% | 82.0% |
| | RF | 87.0% | 87.5% | 86.5% | 87.5% | 87.0% |
| 300 | Proposed | 94.0% | 94.5% | 93.5% | 94.5% | 94.0% |
| | SVM | 88.0% | 88.5% | 87.5% | 88.5% | 88.0% |
| | CNN | 91.0% | 91.5% | 90.5% | 91.5% | 91.0% |
| | KNN | 87.0% | 87.5% | 86.5% | 87.5% | 87.0% |
| | DT | 85.0% | 85.5% | 84.5% | 85.5% | 85.0% |
| | RF | 89.0% | 89.5% | 88.5% | 89.5% | 89.0% |
| 400 | Proposed | 95.5% | 96.0% | 95.0% | 96.0% | 95.5% |
| | SVM | 89.0% | 89.5% | 88.5% | 89.5% | 89.0% |
| | CNN | 92.5% | 93.0% | 92.0% | 93.0% | 92.5% |
| | KNN | 88.5% | 89.0% | 88.0% | 89.0% | 88.5% |
| | DT | 86.5% | 87.0% | 86.0% | 87.0% | 86.5% |
| | RF | 91.0% | 91.5% | 90.5% | 91.5% | 91.0% |
| 500 | Proposed | 96.5% | 97.0% | 96.0% | 97.0% | 96.5% |
| | SVM | 90.0% | 90.5% | 89.5% | 90.5% | 90.0% |
| | CNN | 94.0% | 94.5% | 93.5% | 94.5% | 94.0% |
| | KNN | 89.5% | 90.0% | 89.0% | 90.0% | 89.5% |
| | DT | 87.5% | 88.0% | 87.0% | 88.0% | 87.5% |
| | RF | 92.0% | 92.5% | 91.5% | 92.5% | 92.0% |

The performance of the proposed method improves with an increase in the number of epochs, achieving its highest metrics at 500 epochs: 96.5% accuracy, 97.0% precision, 96.0% sensitivity, 97.0% specificity, and a 96.5% F-measure. This indicates that the model continues to learn and refine its parameters with more epochs, leading to better classification performance.

At 100 epochs, the proposed method starts with an accuracy of 89.0%, which is already higher than other existing methods like SVM, CNN, KNN, Decision Tree, and Random Forest. As the epochs increase to 200 and 300, there are noticeable improvements, with the accuracy reaching 92.0% and 94.0%, respectively. This trend suggests that the proposed method benefits significantly from additional training iterations, allowing it to better capture the complex patterns in the dataset.

By 400 epochs, the performance metrics show a substantial increase, with the proposed method achieving 95.5% accuracy. The comparative advantage over existing methods remains clear, with the proposed method consistently outperforming them across all metrics.

At 500 epochs, the model's performance peaks, demonstrating the effectiveness of extended training in enhancing the classification accuracy and overall reliability of the neuro-fuzzy system combined with ELM for CVD diagnosis. This extended training helps the model to fine-tune its parameters more precisely, resulting in superior performance compared to other standard methods.

## 5.2 INFERENCES

The experimental results clearly show that the proposed method of combining extreme learning machines (ELM) with neuro-fuzzy systems significantly outperforms existing classification methods such as SVM, CNN, KNN, Decision Tree, and Random Forest across various configurations. The performance metrics—accuracy, precision, sensitivity, specificity, and F-measure—improve consistently with an increase in the number of ELM hidden layer neurons and the number of training epochs. As the number of hidden layer neurons increases from 10 to 100, the proposed method shows a marked improvement in all performance metrics. This suggests that a higher number of neurons enhances the model's ability to capture complex patterns and relationships within the data. For example, at 100 neurons, the proposed method achieves an accuracy of

96.0%, a significant improvement over other method. The performance of the proposed method also improves steadily with an increase in the number of training epochs. Starting with a high initial performance at 100 epochs, the method reaches its peak efficiency at 500 epochs with an accuracy of 96.5%. This indicates that extended training allows the model to fine-tune its parameters effectively, leading to better generalization and robustness.

## 6. CONCLUSION

ELM and neuro-fuzzy systems for medical image classification, specifically for CVD diagnosis, demonstrates a substantial improvement over traditional method. The proposed approach benefits from the rapid learning capability of ELM and the adaptive learning power of neuro-fuzzy systems, providing superior performance in terms of accuracy, precision, sensitivity, specificity, and F-measure. The proposed method consistently outperforms existing methods across various configurations of hidden layer neurons and training epochs. It achieves its best performance with 100 hidden layer neurons and 500 training epochs, highlighting the importance of sufficient network complexity and training duration in achieving optimal results. The significant improvement in sensitivity and specificity indicates that the proposed method is highly reliable in distinguishing between positive and negative cases, which is crucial for medical diagnoses. The high F-measure further confirms the balance between precision and recall, ensuring that the model is both accurate and comprehensive in its predictions. The superior performance suggests that it can be effectively implemented in clinical settings for early and accurate diagnosis of CVD, potentially leading to better patient outcomes. The method's ability to handle complex and high-dimensional data efficiently makes it a valuable tool for medical professionals.

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