Tuijin Jishu/Journal of Propulsion Technology
ISSN: 1001-4055
Vol. 44 No. 4 (2023)

Heart Disease Feature Extraction Using Machine Learning

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Abstract - In the realm of healthcare, accurate and efficient heart disease diagnosis and prediction are crucial tasks. This abstract introduces a study concentrating on feature extraction from heart disease data using an Enhanced Multi-Layer Perceptron (EMLP) neural network. The method combines deep learning with specialized enhancements such as dropout, batch normalization, and gradient clipping. These enhancements enhance accuracy and robustness in feature extraction. The trained enhanced MLP adeptly captures intricate patterns in heart disease data, generating informative and distinguishing features. These features contribute to precise disease diagnosis and prediction. Experimental results underscore the method's effectiveness, advancing heart disease detection and prognostication within medical data analysis.
Keywords: Heart disease, Enhanced Multi-Layer Perceptron, dropout, batch normalization, feature extraction and gradient clipping

1. Introduction

Cardiovascular diseases, spanning a broad spectrum of conditions, remain a significant contributor to global mortality and health-related issues. Swift and accurate identification of heart diseases holds utmost importance for effective intervention and better patient outcomes. Recent times have witnessed the fusion of machine learning techniques with medical diagnostics, presenting a remarkable potential to heighten diagnostic precision and simplify clinical decision-making procedures. At the core of this amalgamation lies feature extraction, a foundational process that aids in revealing meaningful patterns and correlations within intricate medical data. Machine learning, a subset of artificial intelligence, has showcased exceptional capabilities in automating the analysis of various data modalities such as medical images, electronic health records, and genetic information. Conventional methods for diagnosing heart ailments often hinge on the expert interpretation of medical images and clinical records. Nonetheless, these approaches tend to be subjective and time-intensive, resulting in diagnostic discrepancies and treatment delays. Machine learning, harnessing its proficiency to unveil concealed insights within extensive datasets, emerges as a promising avenue to tackle these issues.

Feature extraction is a crucial component in machine learning algorithms for heart disease diagnosis. It involves distilling pertinent attributes from raw data like ECGs, medical images, and patient records, enabling models to discern intricate patterns that may elude human observation. These patterns can encompass subtle changes in ECG waveforms, alterations in heart chamber dimensions from medical imaging, or combinations of clinical attributes, enhancing the accuracy of heart disease detection.

The choice of features significantly impacts the effectiveness of machine learning models, as irrelevant or redundant attributes can introduce noise and hinder model performance. Feature extraction techniques, from classical statistics to advanced methods like PCA and Wavelet Transform, play a vital role in identifying relevant attributes. Recent research highlights the value of integrating diverse data modalities, such as ECG data, medical images, and genetic markers, to gain a comprehensive understanding of cardiovascular health. However, dealing with different data types presents challenges, emphasizing the need for novel methods that can effectively extract and amalgamate features, capturing each modality's unique traits while leveraging their combined potential. In healthcare, particularly in the context of heart disease, AI-driven feature extraction from big and diverse data offers transformative potential, enhancing disease prediction and diagnosis accuracy by reducing dimensionality.

2. Literature Survey

2.1 Generalized Discriminant Analysis (GDA)

Shahbazi F et.al proposed generalized discriminant analysis for congestive heart failure risk assessment based on long-term heart rate variability. This study has three primary objectives. Firstly, it aims to assess the effectiveness of long-term heart rate variability (HRV) features in distinguishing risk levels among congestive heart failure (CHF) patients. Secondly, it seeks to identify the most powerful HRV features for differentiating low-risk (LRPs) and high-risk (HRPs) patients. Thirdly, it focuses on feature dimension reduction to balance feature count and classification accuracy. Using 12 records from mild CHF patients (LRPs) and 32 records from severe CHF patients (HRPs), a K-nearest neighbor classifier is applied. Generalized discriminant analysis (GDA) helps streamline features, achieving 100% sensitivity and specificity with minimal features. A comparative analysis is conducted to benchmark this approach against similar studies, considering feature selection, classifier performance, and feature magnitude during training.

2.2 Audicor Device Measurements

Hendrick, Z. et.al proposed Feature Extraction of the VSD Heart Disease based on Audicor Device Measurement. This study aims to create an automated diagnostic system for Ventricular Septal Defect (VSD) using Heart Sounds (HS) obtained from the Audicor device. It extracts key features like Electro-Mechanical Activation Time, Left Ventricular Systolic Time, heart sounds, heart rate, and ECG. Ultrasound confirms VSD diagnosis. The system, involving data collection, segmentation, FFT, and PCA-based feature extraction, successfully distinguishes normal and VSD heart sounds. This work will expand to employ machine learning for preliminary VSD screening, streamlining medical assessments and reducing costs. Data was collected at Chang Gung Memorial Hospital, involving 29 VSD cases and healthy subjects.

2.3 Empirical Mode Decomposition (EMD)

Mondal A et.al proposed a novel feature extraction technique for pulmonary sound analysis based on EMD. This paper introduces an innovative automated diagnostic approach for identifying pulmonary dysfunctions through the analysis of chest sounds. By extracting disease-specific features from lung sound signals and employing statistical parameters (mean, variance, skewness, and kurtosis) via empirical mode decomposition, the method effectively differentiates various dysfunction classes. Experimental validation with supervised and unsupervised classifiers, alongside physician validation, underscores the importance of these features in precise disease discrimination, particularly in noisy environments, surpassing baseline features.

2.4 Probabilistic Principal component analysis (PPCA)

Shah SM et.al proposed Feature extraction through parallel probabilistic principal component analysis for heart disease diagnosis. This study introduces a novel approach to diagnose heart disease using Probabilistic Principal Component Analysis (PPCA) to handle missing data and reduce feature dimensions. The method incorporates Parallel Analysis (PA) for projection vector selection and employs Support Vector Machines (SVM) with radial basis function kernels to classify heart patients and normal subjects. The approach achieved impressive accuracy, surpassing existing methods with rates of 82.18% (Cleveland), 85.82% (Hungarian), and 91.30% (Switzerland) on UCI datasets.

2.5 Pan- Tompkins real time QRS detection algorithm

Patel AM et.al proposed Real time ECG feature extraction and arrhythmia detection on a mobile platform. This paper introduces a reliable ECG arrhythmia detection algorithm for early identification via smartphones. It covers various conditions and utilizes the Pan-Tompkins algorithm to pinpoint key ECG positions. Testing on the MIT-BIH arrhythmia database yielded impressive 97.3% accuracy in classifying arrhythmic beats. This algorithm shows great promise for clinical arrhythmia diagnosis with its precision and efficiency.

3. Proposed Methodology

The study introduces the Enhanced Multi-Layer Perceptron (EMLP) method, which focuses on extracting key features from heart disease datasets to improve disease diagnosis. This approach aims to enhance prediction accuracy by eliminating irrelevant features, addressing a challenge in feature extraction. The research contributes to the advancement of crucial feature selection in medical dataset analysis.

3.1 Multi-Layer Perceptron (MLP)

The Multi-Layer Perceptron (MLP) is a feedforward Neural Network with input, hidden, and output layers, each serving distinct roles. Neurons in these layers employ activation functions to capture complex nonlinear relationships. Constructing effective neural network architecture requires thoughtful selection of activation functions and the number of hidden layers/neurons. There's no universal method for determining optimal structure, so it often involves empirical experimentation or insights from similar problems to find the best configuration.

The Multi-Layer Perceptron (MLP) is a type of Artificial Neural Network (ANN) characterized by three layers: input, hidden, and output layers [47]. Neurons in each layer are interconnected. Neurons in the hidden and output layers establish connections with all neurons in the preceding layer via weight vectors. The weighted sum of inputs along with a bias term undergoes non-linear activation, producing outputs for the subsequent layer. Fig 1 illustrates an instance of an MLP with three input neurons(x_1, x_2, x_3), two hidden neurons, and one output neuron. The input layer incorporates the mentioned neurons and a bias term (b1). After applying a learned non-linear transformation (activation function g (w)), inputs move to the hidden layer where research become linearly separable. Outputs of two hidden neurons rely on input and a bias neuron (b2) within the same layer. The output layer features a single neuron, taking hidden layer inputs with the activation function denoted as f(x), generating the feed-forward prediction value for input vector x.

$$h_i = g(W_{il}^1 x_1 + W_{i2}^1 x_2 + W_{i3}^1 x_3)$$

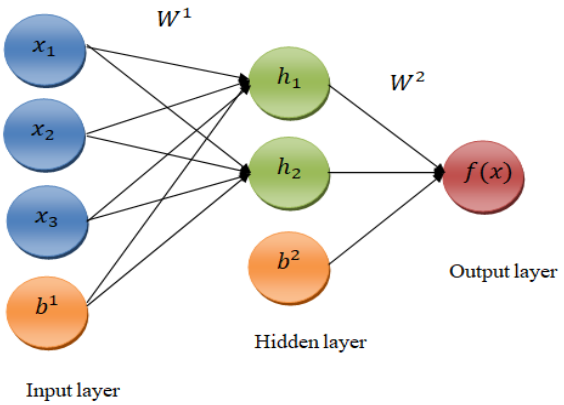

Fig 1: Instance of an MLP

The backpropagation algorithm is employed to train the network, utilizing activation features for its preparation and learning. The activation features for backpropagation are detailed below. The ultimate layer of research model is structured as a linear regression model, which can be denoted by the following equation:

$$f(x) = w^T x + b \quad (2)$$

Where

x – input

w – weighted matrix

b – bias that gets trained to reduce the activation function

Activation Function: In the study, two distinct activation functions are employed for training purposes. The initial activation function is a hyperbolic tangent, characterized by values ranging from -1 to 1. The formulation of this function is as follows:

$$y(v_i) = \tanh(v_i)$$

Secondly, the study uses a logistic function with its evaluation ranges between 0 and 1 it is described as below:

$$y(v_i) = (1 + e^{-v_i})^{-1}$$

Where

y_i -output of i^{th} neuron

Backpropagation Learning: Following data analysis for individual neurons, an MLP network undergoes training through weight adjustments of its connections. The research employs supervised learning, irrespective of output errors compared to the predicted results. In the study the errors e are quantified in a node of n^{th} row of the training data as below:

$$error_j(n) = d_j(n) - y(n)$$

Where

d − Expected value

y − Target value

The model makes suitable corrections in order to reduce the probability of errors on the MLP output as below:

$$e(n) = 0.5 \sum_i error_j^2\,(n)$$

The change in weight after the application of gradient descent is represented as below:

$$\Delta w_{ji}(n) = -\eta \frac{\partial e(n)}{\partial v_j(n)} y_i(n)$$

Where

y − Previous layer output

y − Learning rate or momentum

With several induced local fields, the study tends to define a derivative for the overall output node and it is defined as below:

$$-\frac{\partial e(n)}{\partial v_j(n)} = error_i(n)\emptyset'(v_j(n))$$

Where

$\emptyset'$ − activation function derivative with constant rate.

In cases where alterations occur in the weights within the hidden layers, the analytical process becomes intricate. Therefore, it becomes imperative to furnish the relevant derivative expression. This step ensures the facilitation of a smoother and more comprehensible analysis.

$$-\frac{\partial e(n)}{\partial v_j(n)} = \emptyset'\left(v_j(n)\right) \sum_k -\frac{\partial e(n)}{\partial v_k(n)} w_{kj}(n)$$

Node weight variations in the output layer influence the derivative. Adjusting hidden layer weights requires prior modification of output layer weights based on the activation function's derivative, embodying an activation function-driven backpropagation. This aligns output layer weights with the activation function's derivative, enabling changes in hidden layer weights.

3.2 Enhanced Multi-Layer Perceptron (EMLP)

This research concentrates on improving feature extraction in heart disease data using an advanced Multi-Layer Perceptron (MLP) neural network. It integrates deep learning principles and techniques like dropout, batch normalization, and gradient clipping to enhance accuracy and robustness. The process begins with defining network architecture, specifying neurons, and initializing weights and biases. Activation functions like hyperbolic tangent or sigmoid introduce nonlinearity, and training unfolds over epochs with forward propagation during each instance. These enhancements aim to boost the MLP's performance in heart disease data analysis. This involves computing the weighted sum (z) for neurons in hidden layers, followed by batch normalization ($z_{normalized}$) to standardize the sum. The chosen activation function (a) is then applied. To counter overfitting, dropout is employed on hidden layers, randomly deactivating a portion of neuron activations:

$for\ epoch = 1\ to\ Number\ of\ epochs\ do$
$Shuffle\ the\ tranning\ data\ (X_{train}, Y_{train})$
$for\ each\ training\ sample\ (X, d)$
$in\ shuffled\ dataset\ do$
$Perform\ forward\ propagation$
$: weighted\ sum: z = W * X + b$
$z_{normalized} = (z - \mu)/\sigma$
$a = activation_{fuction(z_{normalized})}$

Subsequently, the algorithm computes the error of the output layer by contrasting the projected output against the desired output. Through backpropagation, adjustments are made to the network's weights and biases. The process commences with determining the error gradient concerning the weighted sum in the output layer. This gradient facilitates the modification of output layer weights and biases, considering the learning rate. This gradient is subsequently propagated through the hidden layers, enabling the adaptation of hidden layer weights and biases. Compute the error between predicted output (y_j) and expected output (d_j):

$$error_j = d_j - y_j$$

Calculate the gradient of the error with respect to the output layer's weighted sum:

$$\delta_{output} = error_j * activation_{function}{}_{derivate(z_{output})}$$

Update output layer weights and biases using the gradient and learning rate:

$$\Delta W_{ouput} = \eta * \delta_{output} * a_{previous-layer,} \triangle b_{ouput} = \eta * \delta_{output}$$

Calculate the gradient of the error with respect to the hidden layer's weighted sum:

$$\delta_{hidden} = (W_{output} * \delta_{output}) * activation_{function}{}_{derivate(z_{hidden})}$$

Update hidden layer weights and biases using the gradient and learning rate:

$$\Delta W_{hidden} = \eta * \delta_{hidden} * X, \triangle b_{hidden} = \eta * \delta_{hidden}$$

Weight and bias updates are performed for both output and hidden layers, incorporating the calculated weight changes.

$$(\Delta W_{ouput}, \Delta W_{hidden}, \triangle b_{ouput}, \triangle b_{hidden})$$

Upon reaching the predetermined epoch count, the MLP model concludes training and becomes operational. This refined model gains the capability to predict outcomes and derive significant insights from input data, rendering it appropriate for tasks like classification or regression across various domains like healthcare and finance. The incorporation of techniques like dropout and batch normalization bolsters the model's resilience, empowering it to effectively adapt to novel, unfamiliar data.

3.3 Proposed Enhancements

The diagram illustrates the improvements brought about by the suggested approach, working together to enhance the training process of the MLP. Batch normalization enhances convergence, dropout mitigates overfitting, and gradient clipping stabilizes learning. Throughout epochs, the algorithm refines weights and biases to minimize errors, integrating these enhancements simultaneously.

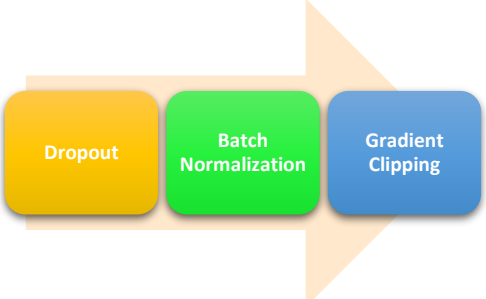

Fig 2: Enhancements of the proposed method

3.3.1 Dropout:

Dropout is a technique involving the random deactivation of a fraction (p) of neuron activations during training. This is achieved by element-wise multiplication of activations with a binary mask, generated with a probability of p.

3.3.2 Batch Normalization:

Batch normalization addresses the weighted sum (z) of each hidden layer by normalizing it using the mean (μ) and standard deviation (σ) computed over the mini-batch. This crucial step enhances training stability and mitigates the risks of vanishing or exploding gradients.

3.3.3 Gradient Clipping:

After calculating gradients (δ_{output} and δ_{hidden}), gradient clipping can be employed. This involves scaling down gradients that exceed a defined threshold. By doing so, the training process becomes more stable, effectively preventing the occurrence of gradient explosions.

Algorithm for Enhanced MLP

Step 1: Initialize weights (W) and biases (b) using random values or initialization techniques.
Step 2: Choose activation functions for hidden layers and output layer (e.g., tanh, sigmoid).
Step 3: Shuffle the training data (input features and expected outputs) for each epoch.
Step 4: Calculate the weighted sum for each neuron (z = W * x + b).
Step 5: Apply batch normalization to the weighted sum, then activate and introduce dropout
Step 6: Compute the error between predicted output and expected output.
Step 7: Determine the gradient of the error concerning the output layer's weighted sum.
Step 8: Update output layer weights and biases based on the gradient and learning rate.
Step 9: Calculate the gradient of the error with respect to the hidden layer's weighted sum.
Step 10: Update hidden layer weights and biases based on the gradient and learning rate.
Step 11: Update weights and biases for both output and hidden layers using the computed changes.
Step 12: The trained MLP is now prepared for predictions.

4. Experimental Results

4.1 Accuracy

Accuracy is the degree of closeness between a measurement and its true value. The formula for accuracy is:

$$\boldsymbol{Accuracy} = \frac{(\boldsymbol{true\ value} - \boldsymbol{measured\ value})}{\boldsymbol{true\ value}} * \mathbf{100}$$

Table 1: Comparison table of Accuracy

Dataset	GDA	PPCA	Proposed EMLP
100	68	75	88
200	72	73	93
300	77	68	85
400	83	71	97
500	86	62	95

The Comparison table 1 of Accuracy demonstrates the different values of existing GDA, PPCA and Proposed EMLP. While comparing the Existing algorithm and Proposed EMLP, provides the better results. The existing algorithm values start from 68 to 86, 62 to 75 and Proposed EMLP values starts from 85 to 95. The proposed method provides the great results.

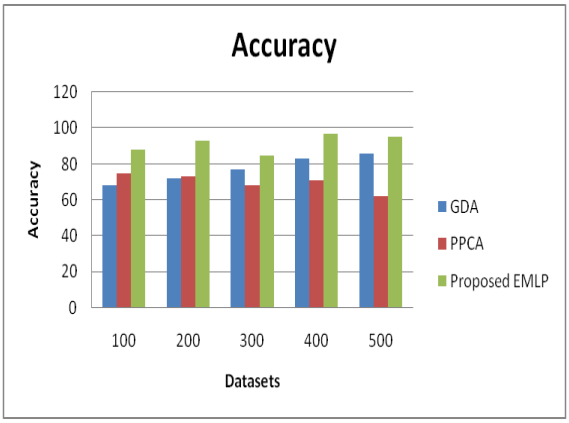

Fig 3: Comparison chart of Accuracy

The Figure 3 Shows the comparison chart of Accuracy demonstrates the existing GDA, PPCA and Proposed EMLP. X axis denote the Dataset and y axis denotes the Accuracy. The Proposed EMLP values are better than the existing algorithm. The existing algorithm values start from 68 to 86, 62 to 75 and Proposed EMLP values starts from 85 to 95. The proposed method provides the great results.

4.2 Precision

Precision is a measure of how well a model can predict a value based on a given input.

$$\boldsymbol{Precision} = \frac{\boldsymbol{true\ positive}}{(\boldsymbol{true\ positive}\ +\ \boldsymbol{false\ positive})}$$

Table 2: Comparison tale of Precision

Dataset	GDA	PPCA	Proposed EMLP
100	85.12	81.37	97.67
200	80.69	85.82	94.26
300	76.62	83.54	98.21
400	73.55	79.63	95.58
500	75.94	77.72	90.87

The Comparison table 2 of Precision demonstrates the different values of existing GDA, PPCA and Proposed EMLP. While comparing the Existing algorithm and Proposed EMLP, provides the better results. The existing algorithm values start from 73.55 to 85.12, 77.72 to 81.37 and Proposed EMLP values starts from 90.87 to 97.67. The proposed method provides the great results.

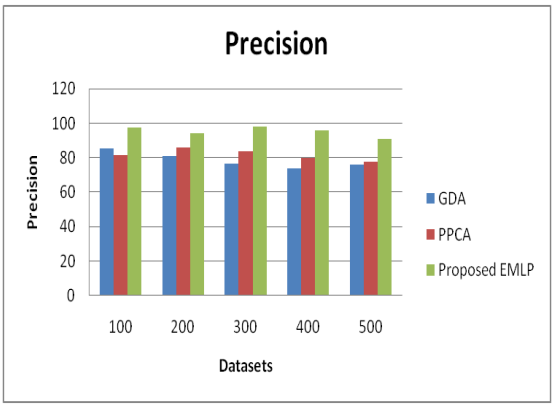

Fig 4: Comparison chart of Precision

The Figure 4 Shows the comparison chart of Precision demonstrates the existing GDA, PPCA and Proposed EMLP. X axis denote the Dataset and y axis denotes the Precision ratio. The Proposed EMLP values are better than the existing algorithm. The existing algorithm values start from 73.55 to 85.12, 77.72 to 81.37 and Proposed EMLP values starts from 90.87 to 97.67. The proposed method provides the great results.

4.3 Recall

Recall is a measure of a model's ability to correctly identify positive examples from the test set:

$$\boldsymbol{Recall} = \frac{\boldsymbol{True\ Positives}}{(\boldsymbol{True\ Positives} + \boldsymbol{False\ Negatives})}$$

Table 3: Comparison tale of Recall

Dataset	GDA	PPCA	Proposed EMLP
100	0.73	0.81	0.83
200	0.75	0.77	0.90
300	0.82	0.67	0.94
400	0.84	0.74	0.93
500	0.87	0.71	0.96

The Comparison table 3 of Recall demonstrates the different values of existing GDA, PPCA and Proposed EMLP. While comparing the Existing algorithm and Proposed EMLP, provides the better results. The existing algorithm values start from 0.73 to 0.87, 0.71 to 0.81 and Proposed EMLP values starts from 0.83 to 0.96. The proposed method provides the great results.

Fig 5: Comparison chart of Recall

The Figure 5 Shows the comparison chart of Recall demonstrates the existing GDA, PPCA and Proposed EMLP. X axis denote the Dataset and y axis denotes the Recall ratio. The Proposed EMLP values are better than the existing algorithm. The existing algorithm values start from 0.73 to 0.87, 0.71 to 0.81 and Proposed EMLP values starts from 0.83 to 0.96. The proposed method provides the great results.

4.4 F -Measure

F1-measure is a test's accuracy that combines precision and recall. It is calculated by taking the harmonic mean of precision and recall.

$$\boldsymbol{F1 - Measure} = \frac{(\boldsymbol{2 * Precision * Recall})}{(\boldsymbol{Precision} + \boldsymbol{Recall})}$$

Table 4: Comparison tale of F -Measure

Dataset	GDA	PPCA	Proposed EMLP
100	0.86	0.75	0.94
200	0.88	0.73	0.95
300	0.82	0.66	0.93
400	0.80	0.64	0.92
500	0.78	0.65	0.90

The Comparison table 4 of F -Measure Values explains the different values of existing GDA, PPCA and Proposed EMLP. While comparing the Existing algorithm and Proposed EMLP, provides the better results. The existing algorithm values start from 0.78 to 0.86, 0.64 to 0.75 and Proposed EMLP values starts from 0.90 to 0.94. The proposed method provides the great results.

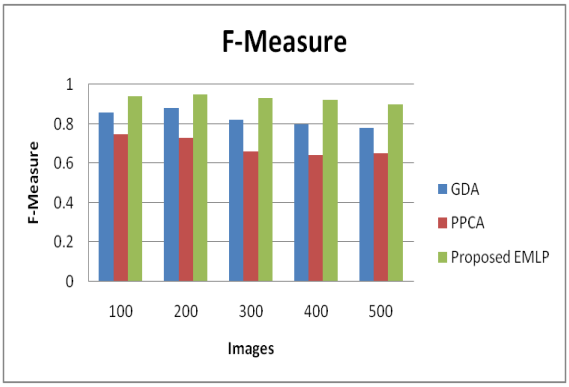

Fig 6: Comparison chart of F –Measure

The Figure 6 Shows the comparison chart of F -Measure demonstrates the existing GDA, PPCA and Proposed EMLP. X axis denote the Dataset and y axis denotes the F -Measure ratio. The Proposed EMLP values are better than the existing algorithm. The existing algorithm values start from 0.78 to 0.86, 0.64 to 0.75 and Proposed EMLP values starts from 0.90 to 0.94. The proposed method provides the great results.

5. Conclusion

In this paper, we present an Enhanced Multi-Layer Perceptron (EMLP) method for heart disease data feature extraction. This innovation enhances cardiovascular understanding, diagnostic accuracy, and predictive models. By incorporating dropout, batch normalization, and gradient clipping, the EMLP excels at revealing intricate features in complex heart disease data. The model captures subtle patterns and generalizes effectively to new instances, holding promise for diagnosis and risk assessment. Extracted features provide insights into heart disease factors, aiding early detection and personalized treatments. The EMLP's versatility extends to varied medical scenarios, from prognosis to treatment evaluation. As research refines these methods, more sophisticated models are expected to revolutionize medical data analysis and diagnosis.

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