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Heart Disease Classification Using Extreme Learning Machine (ELM) Method With Outlier Handling One-Class Support Vector Machine (OCSVM)

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ABSTRACT

Heart disease remains the leading cause of death globally, accounting for approximately 32% of all deaths. Developing countries are particularly affected due to prevalent risk factors such as hypertension, diabetes, and poor lifestyle habits. Accurate and early diagnosis is essential for effective treatment and prevention. Technological advancements have enabled the precise analysis of complex clinical data. This study investigates the application of the Extreme Learning Machine (ELM) algorithm combined with outlier handling using One-Class Support Vector Machine (OCSVM) for heart disease classification. The dataset, obtained from the University of California, Irvine Machine Learning Repository, consists of 1190 clinical records with 12 numerical features. The ELM model was evaluated using the Tanh activation function and 10-fold cross-validation. Among the tested configurations, the best performance was achieved using 450 hidden neurons, yielding a sensitivity of 92,52% with a standard deviation of 4,00%. These results indicate that ELM, when paired with effective outlier handling and properly tuned parameters, can provide reliable and stable performance in heart disease classification.

I. INTRODUCTION

Heart disease is a condition that affects the heart and can manifest in various forms, such as disorders of the heart's blood vessels, changes in heart rate, structural defects in the heart muscle, or genetic factors [1]. One of the common causes of heart vascular problems is the buildup of fat and cholesterol in the coronary arteries, which impede blood flow to the heart [2]. Heart disease is a common type of cardiovascular disease [3]. According to the World Health Organization (WHO), cardiovascular disease caused about 17.9 million deaths worldwide in 2019, or about 32% of total deaths [4]. This mortality rate is expected to continue to increase to 23.6 million by 2030 [5]. The importance of treatment and prevention in reducing the risk and complications of heart disease cannot be underestimated, including lifestyle changes, medical treatment, and surgical intervention if needed [6]. In addition, early detection of heart disease is essential to reduce deaths from heart disease [7]. he introduction of machine learning technology based on Artificial Intelligence (AI) aims to help reduce the possibility of human error in diagnosing or identifying heart disease.

Machine Learning is the ability of a system to learn from data to improve its ability to perform a specific task without explicit programming [8]. Classification techniques are used in machine learning to detect heart disease, and one of them is the Extreme Learning Machine (ELM) method, which is chosen for this study. The main advantage of the ELM method is its fast computation time, which is much faster than other techniques because it has a single hidden layer, and the concept of all processes in ELM uses matrix operations, which makes it faster than having to involve an iterative process [9]. However, the presence of outliers in the dataset can hinder the accuracy and reliability of the ELM model as these aberrant data can cause distortions in the classification pattern [10]. For this reason, outlier handling is important.

One effective method to identify outliers is the One-Class Support Vector Machine (OCSVM). OCSVM functions as an outlier detection tool by building boundaries that separate normal data from deviant data [11]. In the heart disease classification process, the combination of ELM with OCSVM allows the model to first filter outliers so that ELM can work only with more relevant and representative inliers. This improves the accuracy of the model in recognizing significant patterns without being distracted by irrelevant data. As with research that discusses outlier detection of student graduation at Darussalam Gontor University through the use of the SVM method and the One-Class SVM outlier detection technique, the results show that the test produces a percentage value reaching 90.3% [12]. Therefore, this approach is effectively used to detect outliers.

A number of studies have been conducted on the topic of heart disease. As in the case of research that discusses the Application of the K-Nearest Neighbor (KNN) Algorithm in Heart Disease Classification with test results getting an accuracy value of 92% [13]. Then, there is also research that discusses heart disease where the SVM Model can provide better performance in classification with an accuracy of 83% compared to the Neural Network algorithm with an accuracy value of 82% [14]. The research that discusses heart disease cases uses the Artificial Neural Network (ANN) method where it gets an accuracy of 73.77 [15]. Each method used in previous studies has weaknesses. These shortcomings provide an opportunity for the ELM method to compensate for these shortcomings and provide solutions to existing problems.

There is research that discusses the use of the Extreme Learning Machine (ELM) method. Research on the use of ELM methods in software reliability cases where ELM is able to excel from SVM with 84.61% accuracy [16]. Then research on the use of the ELM method in the case of sickle cell anaemia and obtained the ELM method superior to KNN and SVM by 87.73% within 0.0469 seconds [17]. Furthermore, there is research that discusses the comparison of the ELM method with ANN and uses wheat species data. The classification states that ELM excels with an accuracy of 95.85% and a computation time of 0.0069 seconds compared to ANN which only produces an accuracy of 92.51% and a computation time of 0.81 seconds [18]. The ELM method has also been utilised in the context of kidney disease, with 50 hidden neurons giving a maximum performance of 96.7%. This level of accuracy has been considered sufficient to implement the ELM method in the classification of chronic kidney disease Chronic Kidney Disease (CKD) [19]. Meanwhile, research that discusses the use of the ELM method in the diagnosis of brain tumour diseases. It was found that ELM showed a better capacity in the classification of brain tumour diseases. The resulting accuracy rate was 97.3%, which was overall superior to KNN, which showed an accuracy rate of only 81.5% [20].

Thus, based on the previous research described, it can be concluded that ELM, with all its advantages and the addition of outlier handling, can provide optimal classification results. Therefore, the main objective of this research is to develop a heart disease classification model using ELM with the incorporation of OCSVM outlier handling techniques in diagnosing heart disease. The incorporation of outlier handling is expected to improve accuracy so that this system can provide more appropriate recommendations for clinical intervention.

II. METHOD

A. *Research Stages*

The steps carried out in this study are contained in the form of a flowchart shown in Figure 1.

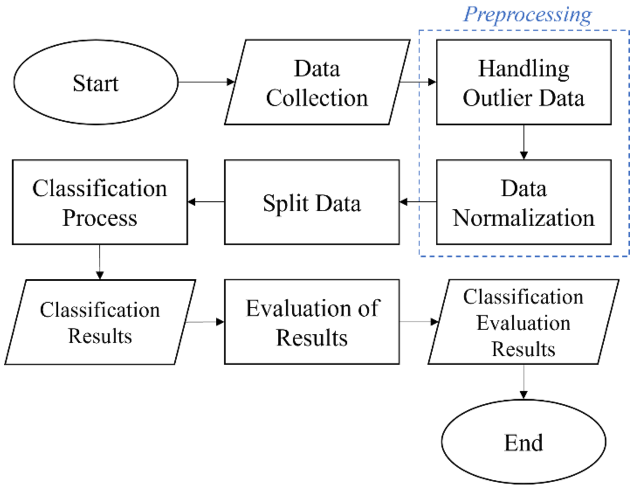

Figure 1. Flowchart of heart disease classification research

The first stage of the process is data input. In the second stage, outlier detection is performed using the One-Class Support Vector Machine (OCSVM). This method is applied before the training process as a pre-filtering step, aiming to identify and remove abnormal data points that could distort the learning process. By eliminating outliers early, the model focuses only on representative data, thereby reducing the risk of bias and overfitting. The third stage is normalization of the remaining (inlier) heart disease feature data using Min-Max scaling. The fourth stage involves training and testing the ELM classification model using K-Fold Cross Validation with values of k = 5 and k = 10. Finally, model performance is evaluated using a Confusion Matrix to compute metrics such as accuracy, sensitivity, and specificity.

B. *Data Collection*

The data used for this study is based on numerical data obtained from GitHub, identified by two different classes of normal and heart disease. The sample data in this study is a type of secondary data consisting of clinical data of patients related to heart disease. This dataset totalled 1190 data where there are 12 feature columns including 11 independent variables and 1 dependent variable which consists of 2 labels [21].

The dataset consists of 629 positive cases (target = 1) and 561 negative cases (target = 0). This information is important for understanding class balance, which significantly influences the training process and the potential bias toward the majority class. With a relatively balanced distribution (53% positive and 47% negative), this study does not require class imbalance handling techniques such as oversampling or undersampling. Therefore, the evaluation results are more likely to reflect the true performance of the model under realistic data conditions.

Since all variables are already in numerical format, no encoding or categorical transformation is required, making them fully compatible with the Extreme Learning Machine (ELM) algorithm, which relies on numerical input. Additionally, the dataset contains no missing values, so no imputation process was necessary. This ensures a clean and consistent dataset, optimized for efficient preprocessing and accurate classification.

Each feature can be explained as follows. Age is patient age, sex is patient gender (1 = male, 0 = female), cp is chest pain type (0-3, indicating the type of pain experienced), resting BP is resting blood pressure in mm/Hg, chol is serum cholesterol level in mg/dl, FBS is fasting blood sugar > 120 mg/dl (1 = yes, 0 = no), restecg is resting electrocardiography result (numeric: 0-2), max HR is the maximum heart rate achieved, exang is exercise-induced angina (binary: 1 = yes, 0 = no), oldpeak is exercise-induced ST depression relative to rest, slope is the peak ST segment slope during exercise (numeric: 1-3), and the target is indicative of the presence of heart disease (1 = heart disease, 0 = normal). As the data can be displayed in Table 1.

TABLE 1
SAMPLE DATA

Nomor	Age	Sex	Cp	Resting BP	Chol	FBS	Restecg	Max HR	Exang	Oldpeak	Slope	Target
1	40	1	2	140	289	0	0	172	0	0	1	0
2	49	0	3	160	180	0	0	156	0	1	2	1
3	37	1	2	130	283	0	1	98	0	1,5	1	0
4	48	0	4	138	214	0	0	108	1	0	2	1
5	54	1	3	150	195	0	0	122	0	0	1	0
6	39	1	3	120	339	0	0	170	0	0	1	0
...	...	...	...	...	...	...	...	...	...	...	...	...
1190	38	1	3	138	175	0	0	173	0	0	1	0

C. Heart Disease

The heart is one of the vital organs in the human body responsible for pumping blood through the circulatory system [22]. Disruptions in heart function can cause disruptions in the body's circulation as a whole, thus the importance of maintaining optimal heart health to prevent various potential diseases. Heart disease, in its various forms, is characterized by damage or disruption to the heart. It often results from the death of heart muscle tissue due to narrowing of the coronary blood vessels [23]. In addition to the narrowing of coronary blood vessels that can cause damage to heart muscle tissue, there are several types of heart disease, each of which has different causative factors. Some common types of heart disease include angina, genetic heart disease, heart failure, arrhythmia (heart rhythm disorder), cardiomyopathy, and myocardial infarction. Each type of heart disease is different in terms of symptoms and causes. Based on the American Heart Association (AHA), the causes of heart disease include hypertension, high cholesterol, obesity, smoking, alcohol, diabetes, lack of physical activity, diet, genetics, age, and gender [24].

D. One-Class Support Vectors Machine (OCSVM)

One-Class SVM is a variation of Support Vector Machine (SVM) designed to detect and handle outlier data. Outlier handling using One-Class SVM (OCSVM) is a method used to identify anomalous data or data that deviates far [12]. The OCSVM method uses various kernels for outlier identification. These include linear kernels, Radial Basis Function (RBF) kernels, and polynomial kernels. OCSVM often uses kernels to map data to a higher feature space, where data can be separated more effectively. This allows OCSVM to handle non-linear data and detect patterns that cannot be separated by straight lines in the original feature space [25]. The following OCSVM architecture can be seen in Figure 2.

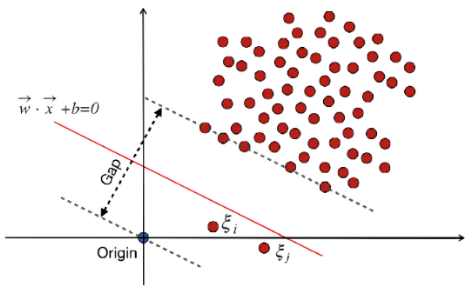

Figure 2. OCSVM illustration [26]

Figure 2 shows an illustration of OCSVM where GAP or support vectors are the distance of the closest data point to the hyperplane, origin is the origin of the coordinates, the red straight line is the determination of the hyperplane or which separates the inlier data from the outliers where there is a choice on the kernel used. Red dots are outlier data or inliers, and ξ is a slack variable or deviation value for specific points that are considered as outliers. The calculations that must be passed in using OCSVM, can be seen in the equation formula as follows [27].

$$\mu = \frac{1}{J \times i} \sum_{L=1}^{J} \sum_{M=1}^{i} A_{LM} \tag{1}$$

$$Var(x) = \frac{1}{J \times i} \sum_{L=1}^{J} \sum_{M=1}^{i} (x_{LM} - \mu)^2 \tag{2}$$

$$\gamma = \frac{1}{i \times Var(x)} \tag{3}$$

$$K(x, x')_{N \times N} = exp(-\gamma ||x - x'||^2) \tag{4}$$

$$min_{\omega,\xi,p} ||\omega||^2 + \frac{1}{vN} \sum_{i=1}^{N} \xi_i - \rho \tag{5}$$

$$F(x) = \sum_{i=1}^{N} a_i K(x, x_i) - \rho \tag{6}$$

OCSVM requires calculations in several steps. In the formula, Equation (1) is used to calculate the average value of all data to find the variance value, where is the average of all data, J is the number of rows, i is the number of columns or features, A_{LM} is the element in the L row and M column. Then Equation (2) is used to calculate the variance value to find the value, where Var is the variance of the elements in the X matrix, and X_{LM} is the X matrix element in the L row and M column. Then Equation (3) calculates the value of γ, where γ is a parameter that controls how far the influence of one data point on other data points. Equation (4) selects a kernel to calculate the inner product between two vectors in feature space where x and x' are feature vectors from two different data points. The kernel used is Radial Basis Function (RBF) because it shows better performance in detecting outliers [12]. In Equation (5), calculating the objective function or quadratic programming is almost impossible to do manually and requires software such as Python due to mathematical and computational complexity [28]. The objective function is used to set a good separation measured by the margin between normal and outlier data, where is how much data is allowed to be deleted, is the weight vector used to determine the direction of separation, and is obtained with the help of software. N is the amount of data analyzed, is the threshold value or bias that determines where the hyperplane that separates the data is located. After the calculation, Equation (6) is used to decide in determining whether the data is considered an outlier or not, where $F(x)$ is the value of the decision function for data x, α is the dual coefficient for each support vector x_i obtained through software and selected based on its contribution to the formation of the decision margin. If the value of $F(x_i)$ is positive, it is normal data, and if $F(x_i)$ is negative, the data is considered outliers. Then data deletion is done as much as .

E. Extreme Learning Machine (ELM)

Extreme Learning Machine (ELM) is a new approach to artificial neural network processing. ELM uses a feedforward neural network consisting of one hidden layer, a configuration commonly referred to as Single Hidden Layer Feedforward Neural Networks (SLFN) [29]. ELMs have random parameters such as input weight and hidden bias, thus speeding up learning and improving generalization performance. ELM is one of the most efficient and easy to implement algorithms with three layers including input layer, hidden layer, and output layer [30]. The following illustrates the ELM architecture in Figure 3.

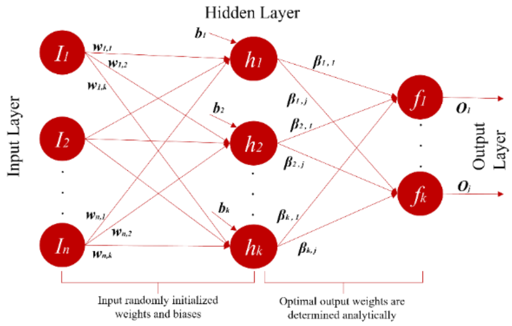

Figure 3. ELM illustration

In Figure 3, the architecture of the ELM consists of I_1, I_2, . . . I_n as normalized input data, n is the amount of data, k is the number of hidden neurons, w is the weight, which amounts to the number of features and k, b is the bias, which amounts to k, H is the hidden layer, h is the hidden neuron, β is the optimal weight value, f is the activation function used in the hidden layer and O (output value). ELM has an easier and more effective mathematical model. The classification process consists of two stages, namely the training process and the testing process. In the training process there are stages with the following formula [31].

$$w = \begin{bmatrix} w_{1,1} & \cdots & w_{i,k} \\ \vdots & \ddots & \vdots \\ w_{i,1} & \cdots & w_{i,k} \end{bmatrix}_{i \times k} \tag{7}$$

$$b = [b_1\, b_2\, b_3 \cdots b_k]_{1 \times k} \tag{8}$$

$$H = f(I \times w + b) \tag{9}$$

$$H^{\dagger} = (H^t \times H)^{-1} \times H^t \tag{10}$$

$$\beta = (H^{\dagger} \times O) \tag{11}$$

In the training process, there are several stages in the calculation to get classification results. Equations (7) and (8) are the size of the matrix used to initialize the weight (w) and bias (b) values, where the values of w and b range from -1 to 1. The weight value (w_{ik}) is randomly generated proportional to the size of the weight matrix, where the number of features (i) is multiplied by the number of hidden neurons (k). The size of the bias matrix is 1 the number of hidden neurons (k). Then, Equation (9) is used to calculate the value of the hidden layer output matrix (H) using the activation function. After calculating the hidden layer using the activation function, the optimal weights (β) are calculated by applying the Moore Penrose generalized inverse formula as in Equations (10) and (11). After the β value obtained from ELM training data, several steps can be made in the following ELM testing data as can be seen in Equation (12).

$$O_{test} = H_{test} \times \beta \tag{12}$$

Equation (12) is used to calculate the value of the hidden layer output matrix from the testing data using the activation function, hidden neurons, weights, and bias initialized in the training process using Equations (7) - (9) and Table (2). This value determines how much the model can be classified according to the target on the original data. As for the activation function used, it can be seen in Table 2.

TABLE 2
ACTIVATION FUNCTIONS

Activation Function	Formula
Sigmoid	$f(x) = \dfrac{1}{1 + e^{-x}}$
Tanh	$f(x) = \dfrac{e^x - e^{-x}}{e^x + e^{-x}}$
Linear	$f(x) = (x)$

III. RESULTS AND DISCUSSION

The amount of data processed in this study is 1190 data with data samples shown in Table (1). Data with variables Age, sex, cp, resting, chol, FBS, restecg, max HR, exang, oldpeak, slope, and target as parameters for classifying heart disease. Heart disease data obtained from Github has some deviant data or called outliers.

A. *Outlier Handling*

Handling outliers is a crucial preprocessing step to improve model performance in classification tasks. By addressing outliers, the ELM method can better recognize patterns in the data, reducing misclassification and enhancing its generalization ability. Therefore, preprocessing is needed, starting from handling outliers to help the ELM method learn data patterns better, so that the model can distinguish relevant data and minimize misclassification. This process enhances the model's ability to generalize and improves overall classification performance.

The outlier handling applied in the research is one-class SVM (OCSVM). Where the *v* value is set at 0.1 which means only 10% of the data is removed. A total of 1072 data were retained as inliers, which means that these data are considered to have characteristics that match the general or normal pattern that the model has learned. Meanwhile, 118 data were identified as outliers and then deleted. After removing the data, the data distribution of the original data and the retained data (inliers) can be seen. It can be seen in Figure 4 that only some features with numeric data types are presented.

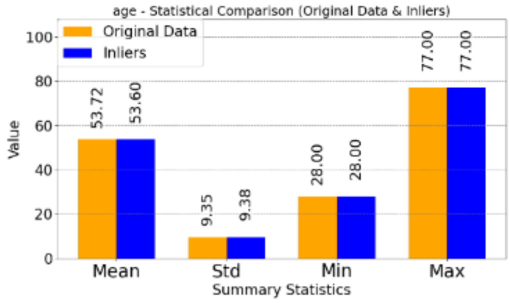

Figure 4. Data Distribution on Age features

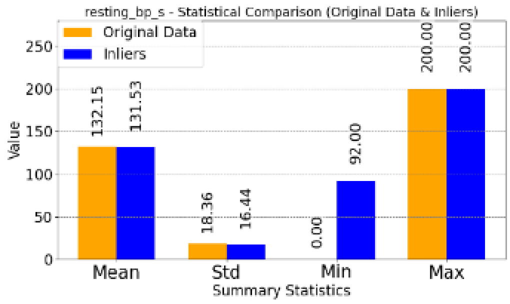

Figure 5. Data Distribution on Resting BP features

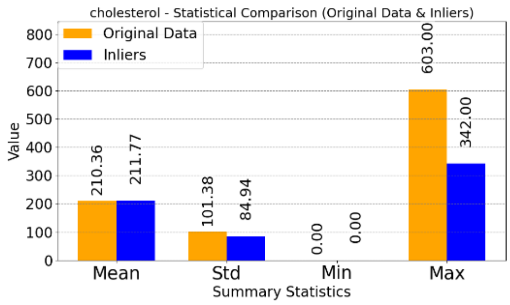

Figure 6. Data Distribution on Cholesterol features

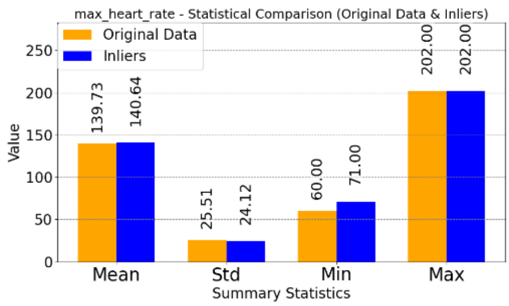

Figure 7. Data Distribution on Max Heart features

Overall, in Figure (4-7) of the data distribution, the changes although not very significant in each feature before and after being handled using OCSVM have an impact on each feature.

In Figure (4-7), the mean values for the original data and the inliers data are almost the same. This shows that the removal of outliers does not affect the average of each feature, so the inliers data still represents the average pattern present in the original data. The standard deviation values for the original data and the inliers data are also similar, showing no significant difference. This shows that the spread of the data around the mean remains stable after removing the outliers, so the variability in the original data and the inliers data is almost the same. The minimum values in the original data and the inliers data are not significantly different, indicating that the inliers data retained after handling outliers have a range of values that still includes the minimum value of the original data. The maximum values in the original data and the inliers data are also very similar, indicating that the removed outliers do not significantly affect the upper limit of the data distribution. This comparison shows that the process of handling outliers in each feature does not significantly affect the distribution of the main statistics of the data, so the inliers data still represents the characteristics of the original data in general.

B. Data Normalization

After the outlier handling process is complete, preprocessing is done by normalizing the data. The following can show the results of data normalization in Table (4). The data normalization applied in this research is min-maxs scaler normalization. This method is used to convert data that has a very long value interval into a range between 0 and 1 [29]. The purpose of this normalization is to ensure that each parameter has a consistent scale, because a range difference between parameters that is too large can make it difficult for the process to reach convergence [30]. The results of data normalization can be shown in Table 3.

TABLE 3
DATA NORMALIZATION RESULTS

Nomor	**Age**	**Sex**	**Cp**	**Resting BP**	**Chol**	**FBS**	**Restecg**	**Max HR**	**Exang**	**Oldpeak**	**Slope**	**Target**
1	0,244	1	0,333	0,444	0,845	0	0	0,770	0	0,243	0,333	0
2	0,428	0	0,666	0,629	0,526	0	0	0,648	0	0,365	0,666	1
3	0,183	1	0,666	0,351	0,827	0	0	0,206	0	0,243	0,333	0
4	0,408	0	1	0,425	0,625	0	0,5	0,282	1	0,426	0,666	1
5	0,530	1	0,666	0,537	0,570	0	0	0,389	0	0,243	0,333	0
6	0,346	0	0,333	0,351	0,692	0	0	0,755	0	0,243	0,333	0
…	…		…	…	…	…	…	…	…	…	…	…
1072	0,204	1	0,666	0,425	0,511	0	0	0,778	0	0,243	0,333	0

C. Hyperparameter Tuning Results

After data normalization, the next stage is data division. The data division process is based on training and testing data. In the data division process, the data used is the normalized data in Table 4 which amounts to 1,072 data points. The data division used is 10-fold Cross Validation, where the data is split into training and testing sets in each iteration. The results from this validation are used to ensure the reliability of the evaluation and determine the most optimal model configuration. Next, the classification stage is performed.

The classification process was conducted using the Extreme Learning Machine (ELM) algorithm, which includes both training and testing stages. To obtain optimal model performance, hyperparameter tuning was carried out manually through a trial and error approach, rather than automated optimization methods like grid search or random search. Two main hyperparameters were tuned: the number of hidden neurons and the type of activation function. The number of hidden neurons influences the model's capacity to learn complex patterns, while the activation function determines how neuron outputs are calculated. In this study, only the Tanh activation function was tested in combination with three different hidden neuron sizes: 300, 450, and 600. Each combination was evaluated using 10-fold cross-validation, with sensitivity used as the primary evaluation metric to reflect the model's ability to detect heart disease cases. In addition, the standard deviation of sensitivity was also considered to assess the consistency and stability of the model across folds. The best-performing configuration was selected by considering both high average sensitivity and low variation.

D. Data Without Outlier Handling

This evaluation examines the performance of the ELM model using the Tanh activation function under a 10-fold cross-validation scheme without applying any outlier handling. The focus is on comparing different hidden neuron configurations—specifically 300, 450, and 600 neurons—to identify the most effective setting. Sensitivity is selected as the primary metric, as it indicates the model's ability to accurately detect heart disease cases. The analysis also includes the calculation of the standard deviation of sensitivity scores across folds to assess the stability of each configuration. A smaller standard deviation suggests more consistent performance and stronger generalization capability. Using 300 hidden neurons, the model achieved a mean sensitivity of 81.59% with a standard deviation of 9.20%, indicating moderate detection ability but low stability across folds. These results are summarized in Table 4.

TABLE 4
PERFORMANCE OF ELM MODEL USING TANH ACTIVATION WITH 300 HIDDEN NEURONS (K-FOLD = 10, WITHOUT OUTLIER HANDLING)

Hidden Neuron	Fold	Accuracy	Sensitivity	Specificity
300	1	84,87 %	83,72 %	85,53 %
	2	85,71 %	78,05 %	89,74 %
	3	71,43 %	67,95 %	78,05 %
	4	82,35 %	88,12 %	50,00 %
	5	81,51 %	86,81 %	64,29 %
	6	80,67 %	81,03 %	80,33 %
	7	93,28 %	94,44 %	92,31 %
	8	80,67 %	73,08 %	86,57 %
	9	89,08 %	92,59 %	86,15 %
	10	81,51 %	70,18 %	91,94 %
	Mean	83,10 %	81,59 %	80,49 %
	Std. Deviation	5,80	9,20	13,53

Building on the previous configuration, the model was then tested using 450 hidden neurons to examine whether increasing the number of neurons could enhance both sensitivity and performance stability. Using the Tanh activation function and 10-fold cross-validation without outlier handling, the model achieved a mean sensitivity of 85.86% with a standard deviation of 7.85%. This result shows a noticeable improvement in detection capability and a slight reduction in variability compared to the 300-neuron configuration. Nevertheless, fluctuations across folds remain evident. The complete results for this setting are presented in Table 5.

TABLE 5
PERFORMANCE OF ELM MODEL USING TANH ACTIVATION WITH 450 HIDDEN NEURONS (K-FOLD = 10, WITHOUT OUTLIER HANDLING)

Hidden Neuron	Fold	Accuracy	Sensitivity	Specificity
450	1	80,67 %	81,40 %	80,26 %
	2	83,19 %	85,37 %	82,05 %
	3	73,11 %	69,23 %	80,49 %
	4	78,15 %	84,16 %	44,44 %
	5	79,83 %	86,81 %	57,14 %
	6	87,39 %	87,93 %	86,89 %
	7	96,64 %	94,44 %	98,46 %
	8	87,39 %	92,31 %	83,58 %
	9	93,28 %	96,30 %	90,77 %
	10	86,55 %	80,70 %	91,94 %
	Mean	**84,62 %**	**85,86 %**	**79,60 %**
	Std. Deviation	**7,09**	**7,85**	**16,49**

To further investigate the effect of increasing model complexity, the number of hidden neurons was raised to 600 under the same configuration. While several folds yielded high detection rates, the overall sensitivity decreased to 79.35%, accompanied by a higher standard deviation of 11.52%. This indicates that, despite the larger network capacity, the model became less stable and less effective in consistently detecting heart disease cases. These findings suggest diminishing returns beyond a certain number of neurons. The detailed performance metrics for this configuration are provided in Table 6.

TABLE 6
PERFORMANCE OF ELM MODEL USING TANH ACTIVATION WITH 600 HIDDEN NEURONS (K-FOLD = 10, WITHOUT OUTLIER HANDLING)

Hidden Neuron	Fold	Accuracy	Sensitivity	Specificity
600	1	73,95 %	72,09 %	75,00 %
	2	74,79 %	70,73 %	76,92 %
	3	72,27 %	69,23 %	78,05 %
	4	63,03 %	63,37 %	61,11 %
	5	77,31 %	79,12 %	71,43 %
	6	89,08 %	84,48 %	93,44 %
	7	97,48 %	96,30 %	98,46 %
	8	87,39 %	84,62 %	89,55 %
	9	96,64 %	98,15 %	95,38 %
	10	82,35 %	75,44 %	88,71 %
	Mean	81,42 %	79,35 %	82,80 %
	Std. Deviation	11,17	11,52	12,08

E. Data With Outlier Handling

Outlier handling was applied using the One-Class Support Vector Machine (OCSVM) method to improve data quality and minimize potential bias during model training. Approximately 10% of the original dataset was identified as outliers and excluded, resulting in a refined dataset of 1072 entries. The remaining data was normalized using Min-Max scaling to ensure consistent feature ranges. This preprocessing step allowed the ELM model to be trained on cleaner and more representative data, reducing the influence of extreme values and enhancing generalization. The model was evaluated using the same hyperparameter configuration as in the previous experiment, employing the Tanh activation function, 300 hidden neurons, and 10-fold cross-validation.

As shown in Table 7, the model achieved a mean sensitivity of 85,22% with a standard deviation of 6,52%, indicating a reasonably strong detection capability. Although the sensitivity improved compared to the same configuration without outlier handling, the moderate standard deviation suggests that some variability across folds remains. Nevertheless, the use of outlier handling contributed to a more stable and accurate classification performance under this configuration.

TABLE 7
PERFORMANCE OF ELM MODEL WITH TANH ACTIVATION AND 300 HIDDEN NEURONS (K-FOLD 10, WITH OUTLIER HANDLING)

Hidden Neuron	Fold	Accuracy	Sensitivity	Specificity
300	1	81,48 %	83,78 %	80,28 %
	2	84,26 %	82,35 %	85,14 %
	3	86,92 %	92,98 %	80,00 %
	4	77,57 %	83,53 %	54,55 %
	5	77,57 %	84,62 %	58,62 %
	6	87,85 %	85,42 %	89,83 %
	7	93,46 %	95,65 %	91,80 %
	8	78,50 %	76,47 %	80,36 %
	9	85,05 %	91,49 %	80,00 %
	10	83,18 %	76,00 %	89,47 %
	Mean	83,58 %	85,22 %	79,00 %
	Std. Deviation	5,07	6,52	12,68

The ELM model was further evaluated using 450 hidden neurons under the same conditions: Tanh activation function, 10-fold cross-validation, and prior outlier handling using OCSVM. The results showed a mean sensitivity of 92,52% with a standard deviation of 4,00%, indicating a strong and consistent ability to detect heart disease cases. In addition, the model achieved an average specificity of 90,04%, showing reliable performance in correctly identifying negative cases. This configuration demonstrated improved overall performance and lower variability compared to the 300-neuron setting, as summarized in Table 8.

TABLE 8
PERFORMANCE OF ELM MODEL WITH TANH ACTIVATION AND 450 HIDDEN NEURONS (K-FOLD 10, WITH OUTLIER HANDLING)

Hidden Neuron	Fold	Accuracy	Sensitivity	Specificity
450	1	87,85 %	89,83 %	85,42 %
	2	93,28 %	94,44 %	92,31 %
	3	87,39 %	92,31 %	83,58 %
	4	86,92 %	92,98 %	80,00 %
	5	95,33 %	97,83 %	93,44 %
	6	95,33 %	93,75 %	96,61 %
	7	97,20 %	95,65 %	98,36 %
	8	85,98 %	88,24 %	83,93 %
	9	94,39 %	95,74 %	93,33 %
	10	89,08 %	84,48 %	93,44 %
	Mean	**91,27 %**	**92,52 %**	**90,04 %**
	Std. Deviation	**4,22**	**4,00**	**6,26**

The final configuration tested used 600 hidden neurons with the Tanh activation function and 10-fold cross-validation after outlier handling. The model achieved a mean sensitivity of 88,35% with a relatively high standard deviation of 12,30%, suggesting inconsistent detection performance across folds. Although certain folds produced excellent results, including a perfect sensitivity of 100% and high specificity, other folds showed significantly lower performance. This variation affected the overall reliability of the model. The summary of results for this configuration is presented in Table 9.

TABLE 9
PERFORMANCE OF ELM MODEL WITH TANH ACTIVATION AND 600 HIDDEN NEURONS (K-FOLD 10, WITH OUTLIER HANDLING)

Hidden Neuron	Fold	Accuracy	Sensitivity	Specificity
600	1	97,20 %	95,65 %	98,36 %
	2	72,22 %	58,82 %	78,38 %
	3	87,39 %	89,55 %	84,62 %
	4	87,85 %	89,83 %	85,42 %
	5	95,33 %	97,83 %	93,44 %
	6	95,33 %	91,67 %	98,31 %
	7	98,13 %	100 %	96,72 %
	8	81,31 %	82,35 %	80,36 %
	9	97,20 %	97,87 %	96,67 %
	10	86,92 %	80,00 %	92,98 %
	Mean	89,88 %	88,35 %	90,52 %
	Std. Deviation	8,42	12,30	7,63

F. *Effect of Outlier Handling on Model Performance*

Handling outliers is crucial in machine learning to enhance model robustness and improve classification accuracy. The implementation of One-Class Support Vector Machine (OCSVM) for outlier handling is expected to refine the model's ability to distinguish between heart disease patients and healthy individuals. The following figure compares model performance with and without outlier handling, focusing on sensitivity, accuracy, and specificity. The values presented represent the best average results obtained from various configurations, with particular emphasis placed on sensitivity as the primary metric for evaluating the model's ability to detect heart disease cases.

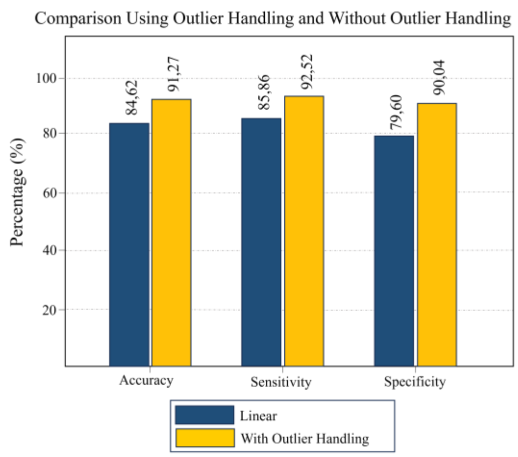

Figure 8. Comparison of Best Mean using Outlier Handling and without Outlier Handling

Figure 8 presents a comparison of the best average performance results of the classification model with and without outlier handling, measured by accuracy, sensitivity, and specificity. Sensitivity is highlighted as the primary evaluation metric due to its importance in identifying heart disease cases. The chart shows that applying outlier handling using One-Class Support Vector Machine (OCSVM) improved the model's performance across all metrics. Sensitivity increased from approximately 86,52% to 92,52%, indicating better capability in detecting positive cases and reducing false negatives. Similarly, accuracy improved from 88.09% to 91,27%, and specificity rose from 89,87% to 90,04%. These improvements demonstrate the positive impact of outlier handling on the model's reliability and classification effectiveness. These improvements not only demonstrate the positive impact of outlier handling on classification performance but also reflect increased model stability, which is further supported by the comparison of standard deviation values shown in Figure 9.

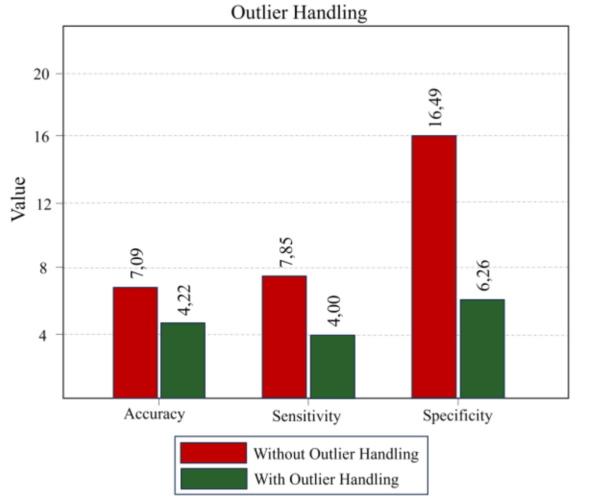

Figure 9. Comparison of Standard Deviation with Outlier Handling and without Outlier Handling

Figure 9 illustrates the comparison of standard deviation values for accuracy, sensitivity, and specificity before and after outlier handling. The graph clearly shows that after applying OCSVM, the standard deviations decreased across all metrics. Sensitivity experienced a notable reduction from 6,52% to 4,00%, suggesting more consistent detection of positive cases. Accuracy also became more stable, with standard deviation decreasing from 5,07% to 4,22%, while specificity showed the most significant drop, from 12,68% to 6,26%. These reductions indicate that outlier handling contributes not only to better performance but also to enhanced model stability and reliability across different folds.

G. Comparison of Model Performance Across Different Methods

To demonstrate the superiority of the proposed method, this study includes a baseline comparison with three commonly used machine learning algorithms for medical classification: K-Nearest Neighbors (KNN), Support Vector Machine (SVM), and Artificial Neural Network (ANN), both with and without outlier handling using One-Class Support Vector Machine (OCSVM). For fairness, all baseline models were implemented using their default hyperparameter settings as provided by standard libraries.

The comparison is specifically based on the best average sensitivity values obtained using 10-fold cross-validation, as sensitivity plays a crucial role in evaluating the model's ability to correctly detect heart disease cases. Under this criterion, the proposed ELM method with outlier handling consistently produced superior results. A visual comparison of the sensitivity outcomes is presented in Figure 10.

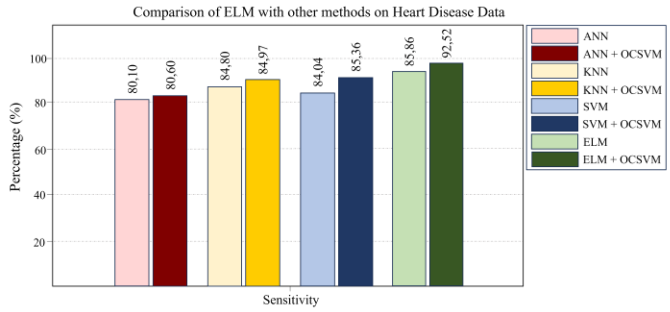

Figure 10. ELM comparison chart with other methods

From the graph in Figure 10, the ANN method without outlier handling has the lowest sensitivity compared to the KNN, SVM, and ELM methods because ANN is very susceptible to overfitting on small datasets. The KNN method has a higher sensitivity than ANN but also lower than SVM and ELM. This is because KNN is sensitive to outlier data, such as extreme cholesterol values. SVM shows lower sensitivity than both ELM methods, indicating that it is less effective in detecting true positive cases in this dataset. ELM without outlier handling still performs better than SVM, while ELM with outlier handling achieves the highest sensitivity overall. This is because ELM is sensitive to outlier data, so it is necessary to handle outliers using OCSVM to get maximum sensitivity. However, there is a weakness in ELM, namely, there are unstable results on running parameters. Therefore, another method is suggested, namely the KELM method, which uses a kernel function that may be able to correct the instability of the ELM activation function. This explanation is further supported by the test results presented in Table 11.

TABLE 10
COMPARISON WITH OTHER METHODS

Method	Akurasi (%)	Sensitivitas (%)	Spesifisitas (%)
KNN	84,98	84,80	82,06
SVM	84,71	84,04	81,57
ANN	81,85	80,10	76,64
ELM	84,62	85,86	79,60
KNN + OCSVM	84,12	84,97	78,71
SVM + OCSVM	85,06	85,36	81,56
ANN + OCSVM	82,74	80,60	78,51
ELM + OCSVM	**91,27**	**92,52**	**90,04**

H. Limitations and Future Work

Although this study demonstrates promising results in heart disease classification, several limitations must be acknowledged. First, the dataset used in this research comprises only 1190 records, which may limit the model's generalizability. Despite the application of K-Fold Cross Validation to mitigate overfitting, a small sample size inherently increases the risk of performance variance and model instability. Second, although the dataset is relatively balanced in terms of class distribution, there remains a potential for bias due to the absence of control over demographic diversity such as age range, gender, and ethnicity which may not be evenly distributed across classes. Third, the dataset originates from a single, publicly available source and has not undergone external validation. As such, the model’s robustness and practical applicability in real-world clinical settings remain uncertain. External validation using independent clinical datasets is essential to confirm the model’s performance in broader, more diverse populations. Furthermore, while Extreme Learning Machine (ELM) provides computational efficiency and good predictive accuracy, it is known to be sensitive to hyperparameter choices particularly the number of hidden neurons which may lead to inconsistency across different runs. Future research is recommended to incorporate more robust methods, such as Kernel-based ELM (KELM), and to test the model’s integration within clinical decision support systems for real-time application and validation.

IV. CONCLUSIONS

In this study, outlier handling using the One-Class Support Vector Machine (OCSVM) method successfully detected and removed outlying data up to 10%. The mean values of the two datasets are similar, which indicates that the trend or center value of the data has not changed. However, the standard deviation values were lower for the dataset after outlier treatment, indicating a reduction in variability after outlier removal. The maximum values observed in certain features have decreased but not significantly, indicating the effectiveness of the outlier handling process in removing extreme values from the dataset. In addition, the minimum values of the features remain relatively unchanged, indicating that the lower bound of the data distribution remains consistent. It can be concluded that the removal of these outliers contributes to improving the quality of the data used for model training, resulting in more accurate classification.

The implementation of the Extreme Learning Machine (ELM) algorithm with outlier handling demonstrates that the model is capable of classifying heart disease with high sensitivity and consistent performance, depending on the parameters used. The best configuration using 450 hidden neurons, the Tanh activation function, and 10-fold cross-validation achieved a sensitivity of 92,52% with a standard deviation of 4,00%, indicating that the model performs reliably across different data folds. The application of One-Class Support Vector Machine (OCSVM) for outlier detection contributed significantly to enhancing the model’s robustness by reducing the influence of abnormal or irrelevant data. These results confirm that the ELM method, when supported by effective outlier handling, is a reliable and powerful tool for heart disease classification, particularly in datasets with complex structures and potential deviations.

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