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Comparison of the Adaboost Method and the Extreme Learning Machine Method in Predicting Heart Failure

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ABSTRACT Heart disease, which is classified as a non-communicable disease, is the main cause of death every year. The involvement of experts is considered very necessary in the process of diagnosing heart disease, considering its complex nature and potential severity. Machine Learning Algorithms have emerged as powerful tools capable of effectively predicting and detecting heart diseases, thereby reducing the challenges associated with their diagnosis. Notable examples of such algorithms include Extreme Learning Machine Algorithms and Adaptive Boosting, both of which represent Machine Learning techniques adapted for classification purposes. This research tries to introduce a new approach that relies on the use of one parameter. Through careful optimization of algorithm parameters, there is a marked improvement in the accuracy of machine learning predictions, a phenomenon that underscores the importance of parameter tuning in this domain. In this research, the Heart Failure dataset serves as the focal point, with the aim of demonstrating the optimal level of accuracy that can be achieved through the use of Machine Learning algorithms. The results of this study show an average accuracy of 0.83 for the Extreme Learning Machine Algorithm and 0.87 for Adaptive Boosting, the standard deviation for both methods is "0.83±0.02" for Extreme Machine Learning Algorithm and "0.87±0.03" for Adaptive Boosting thus highlighting the efficacy of these algorithms in the context of heart disease prediction. In particular, entering the Learning Rate parameter into Adaboost provides better results when compared with the previous algorithm. Our research findings underline the supremacy of Extreme Learning Machine Algorithms and Adaptive Improvement, especially when combined with the introduction of a single parameter, it can be seen that the addition of parameters results in increased accuracy performance when compared to previous research using standard methods alone.

INDEX TERMS Adaboost, Extreme Learning Machine, Heart Failure.

I. INTRODUCTION

Heart disease is the main cause of death every year, as described by the World Health Organization (WHO), the annual global death toll exceeds 17.9 million people. The healthcare sector has a significant volume of health data. However, most remain unanalyzed to reveal valuable insights for healthcare providers to make informed decisions. Utilizing appropriate data and information for decision making can lead to rapid disease diagnosis and forecasting, but medical diagnosis of heart disease requires the involvement of medical experts. One effective method for predicting and identifying heart disease is by utilizing Machine Learning algorithms [1].

Machine Learning possesses the capability to simulate data through the process of learning, thereby resembling the cognitive abilities of a human being. This enables it to effectively diagnose the presence or absence of heart disease in a patient [2]. The intricate nature of diagnosing heart disease can be effectively addressed through the application of a

predictive model using Machine Learning techniques. Specifically, the Extreme Learning Machine (ELM) and Adaptive Boosting (Adaboost) algorithms emerge as viable options for performing the classification task.

In the research conducted by Reddy et al, two distinct classification techniques were implemented on the heart failure dataset, which was sourced from Kaggle and served as the primary dataset utilized in their investigation. The performance of these classification methods was rigorously evaluated following the preprocessing of the dataset, during which the attributes pertaining to "age and gender" were deliberately omitted from the analysis. This deliberate omission was justified based on the assessment that these particular attributes were deemed to have negligible impact on the detection of the disease in question. The study meticulously scrutinized the data of 299 individuals extracted from the dataset, with a subset of 200 individuals being allocated for training purposes within educational environments, while the remaining 99 individuals were designated for testing. Subsequent to the implementation of the Gaussian Naive Bayes and Decision Tree classification methodologies, the researchers were able to ascertain success rates of 86.0 percent and 82.0 percent respectively, underscoring the efficacy of these analytical approaches in the realm of disease detection [3].

De Silva and Kumarawadu, along with their colleagues, conducted a comprehensive research study on the Heart Failure Prediction Dataset sourced from Kaggle, wherein they explored the efficacy of seven distinct machine learning methodologies, in his research on analyzing the performance of the ELM algorithm in the case of heart failure prediction which studied the delved into the application of various classification techniques including Logistic Regression, K-Nearest Neighbors (KNN), Support Vector Machine (SVM), Naive Bayes, Decision Trees, Random Forests, and Stochastic Gradient Descent. Remarkably, the researchers refrained from implementing any data preprocessing procedures, opting instead to utilize all attributes present in the dataset for their analysis. Through meticulous examination of the outcomes, the study underscored that the Support Vector Machine (SVM) Algorithm, Naive Bayes, and Random Forests classifiers exhibited superior performance compared to the other classification methodologies under scrutiny. The success rates derived from the study were as follows: Logistic Regression 82.60%, Decision Tree 75.55%, KNN 82.61%, SVM 85.86%, Random Forest 85.32%, Stochastic Gradient Descent 79.98%, and Naive Bayes 58.32%. It is evident from the empirical findings that the highest success rate recorded in this investigation was an impressive 85.86%, achieved by the state-of-the-art Support Vector Machine (SVM) classification algorithm [4].

In a study conducted by Pandiyan and Narayan, deep learning models, including the Extreme Learning Machine (ELM), were employed to make predictions regarding heart disease using established benchmark datasets such as the MIT-BIH Arrhythmia dataset accessible through the PhysioNet database. The process involved the utilization of Principal Component Analysis to extract and determine the most effective features. Ultimately, the proposed model of the Extreme Learning Machine demonstrated successful classification of heart diseases, achieving an impressive accuracy rate of 98.50% [5].

A.K. Yadav, G.K. Pal, and S. Gangwar conducted thorough research on enhancing heart disease prediction using machine learning techniques like Random Forest, AdaBoost, Decision Tree, and Multilayer Perception. Results of the trial indicated predictive improvements. AdaBoost achieved high scores in accuracy, precision, recall, F1 score, and roc during training on 80% data samples. AdaBoost outperformed other classifier methods in accuracy, precision, recall, F1 score, and ROC during testing on 20% sample data. [6].

In a study conducted by P. K. Mall et al., the Extreme Learning Machine algorithm is noted for its high efficiency in the realm of neural networks, particularly for its proficiency in managing extensive datasets. The algorithm's method of noniterative training involves simultaneous parameter adjustment, leading to rapid training. These algorithms are especially valued for their user-friendly nature and their capability to tackle intricate issues. The suggested model demonstrates an archival accuracy of 96.77%, surpassing other models with accuracies of 90.16%, 90.16%, 88.52%, and 81.97%. There is potential for the application of this technique in various medical fields in the future [7].

Based on the explanation given previously Pandiyan and Narayan who successfully used ELM without additional parameters with benchmark data set classification produced a promising accuracy of 98.50% and the explanation given by AK. Yadav, G.K. Pal, and S. Gangwar, predicted heart disease using Adaboost technique without additional parameters outperformed other classifier methods in terms of accuracy, precision, recall, F1 score, and ROC during testing on 20% of data samples and found that the AdaBoost classifier model performed better in terms of accuracy, precision, recall, F1 score, and ROC, with scores of 94.51, 48.33, 39.52, 41.78 and 66.71 respectively.

This research seeks to assess the predictive effectiveness of heart failure categorization through the use of Adaptive Boosting (Adaboost) and Extreme Learning Machine (ELM) methodologies by introducing additional parameters without external assistance. These parameters include additional elements such as n_neurons for ELM, as well as learning_rate, n_estimator, and maximum depth for Adaboost. This analysis provides insight into the capability and efficiency of the ELM and Adaboost algorithms in managing heart failure prognosis. Additionally, this investigation promises to have a significant impact on broader heart failure prognosis by demonstrating the reliability of ELM and Adaboost-powered prognostic models through the addition of a single parameter, thereby potentially enhancing the development of predictive techniques in the healthcare domain. This study contributes to the advancement of understanding and application of the Adaboost and ELM algorithms in the specific domain of heart

failure prognosis classification by introducing additional parameters, thereby enriching the knowledge pool in health-related research, especially in the context of heart failure.

II. METHODS

This research methodology delineates the utilized datasets, the preprocessing techniques, the Adaptive Boosting classification algorithm, and the Extreme Learning Machine. Moreover, it employs a validation test through cross validation with evaluation measurements focusing on accuracy. The research procedure is expounded upon as follows. FIGURE 1 visually represents the flow of this study.

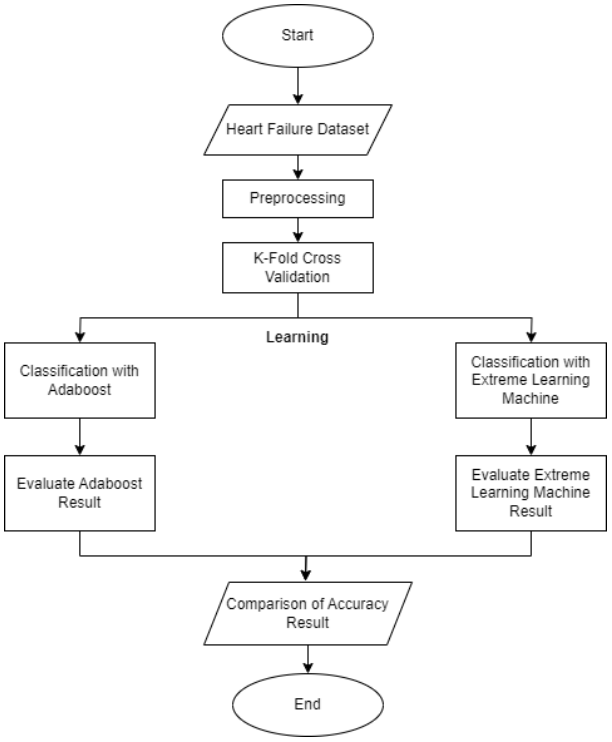

FIGURE 1. Research Flow

Throughout this investigative study, the initial stage involved the utilization of the Heart Failure Prediction dataset. This dataset was subsequently subjected to preprocessing through the application of Min-Max Normalization, a technique widely used in data preparation processes. Following this preprocessing step, the sharing of data was carried out through the implementation of K-Fold Cross Validation, a robust method for assessing the performance of machine learning models. The validation technique adopted in this particular study entailed 10-fold validation, which involves dividing the dataset into 10 subsets or folds. Each of these folds is then used once as a validation while the remaining folds act as training data, ensuring comprehensive model evaluation.

Moreover, to achieve this rigorous validation process, each Heart Failure Dataset dataset was divided into 10 segments. Within these segments, 9 were allocated for training purposes, allowing the model to learn from the data, while the remaining segment was utilized for testing the model's performance. Moving on to the modeling phase, this stage will be bifurcated into 2 distinct experiments. The first experiment will focus on classification tasks utilizing the Adaboost algorithm, a popular ensemble learning technique known for its ability to improve classification accuracy. On the other hand, the second experiment will involve classification tasks employing Extreme Learning Machines, a type of neural network that offers fast learning capabilities and high generalization performance.

Furthermore, at this critical juncture of the study, the evaluation process will be conducted through the utilization of the Confusion Matrix. This evaluation metric provides detailed insights into the performance of the classification models, specifically focusing on metrics such as Accuracy, which is crucial for assessing the overall effectiveness of the models in making correct predictions. Through this comprehensive approach, the study aims to provide a thorough analysis of the predictive models developed and their performance in predicting heart failure, contributing to the existing body of knowledge in the field of healthcare analytics.

A. DATA COLLECTION

The dataset utilized in this study is the heart failure dataset available on the Kaggle website under the title "Heart Failure Prediction." This dataset can be downloaded at the following website: https://www.kaggle.com/code/karnikakapoor/heart-failure-prediction-ann. TABLE 1 displays 299 rows of data and 13 attributes, with 12 attributes serving as features and 1 attribute as the goal (Death_Event).

TABLE 1
Heart Dataset

Age	Anaemia	Creatinine_phosphokinase	Diabetes	Ejection_fraction	...	Death_event
75	0	582	0	20	...	1
55	0	7861	0	38	...	1
65	0	146	0	20	...	1
50	1	111	0	20	...	1
65	1	160	1	20	...	1
90	1	47	0	40	...	1
75	1	246	0	15	...	1
60	1	315	1	60	...	1
65	0	157	0	65	...	1
80	1	123	0	35	...	1
75	1	81	0	38	...	1
62	0	231	0	25	...	1
...	...	...	...	...	...	...
50	0	196	0	45	...	0

B. PREPROCESSING

Before data division, the data will be adjusted according to the algorithm's requirements. The preprocessing procedure aims at tailoring the data to accommodate classification algorithms, thereby improving the effectiveness of classification models [8]. The preprocessing to be conducted involves data normalization to standardize the data scale within the range of

0-1 [9]. MinMax Normalization is a normalization method that transforms the range of data values to be between 0 and 1 is a technique for normalizing data through linear transformations to ensure a harmonized comparison of values both pre- and post-processing [10], [11]. The process of data normalization encompasses the adjustment of feature values to adhere to a standard normal distribution, consequently promoting consistency in the input dataset [12]. The equation for calculating MinMax Normalization can be found in Equation (1) [13], [14].

$$x^1 = \frac{x_i - min(x)}{max(x) - min(x)} \quad (1)$$

where x^1 is a specific value to be normalized, x^1 is the normalized result, minx(x) is the minimum value of an attribute, and max(x) is the maximum value of an attribute.

C. K-FOLD CROSS VALIDATION

Cross Validation technique is used as a performance evaluation to ensure the reliability of prediction results [15]. Cross Validation divides the original data into training and testing data. Ten-fold is a term used to describe a value of K where K = 10. The data will be divided into a specified number, K, which is 10, resulting in 10 data sets [16]. One dataset will be used as testing data and the rest will be used as training data, following this sequence for each set alternately. **FIGURE 2** illustrates data partitioning using 10-fold cross-validation [17]

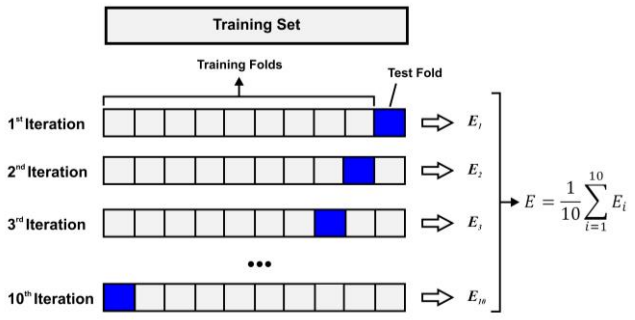

FIGURE 2. Data Sharing witch Cross Validation

A schematic representation of ten-fold cross-validation is displayed. The dataset underwent partitioning into ten segments, with nine serving as training data iteratively, and one as test data for evaluation purposes. The mean value E of the outcomes from the ten segments is computed to approximate the model's accuracy and serves as a metric for assessing the current K-fold cross-validation model. Here, Ei denotes the cross-validation error of the ith segment [18]. The limitation of K-Fold Cross Validation lies in the unequal distribution of data, resulting in a risk of data loss, particularly evident when dealing with imbalanced datasets [19].

In order to authenticate the developed machine learning model and evaluate its capacity to generalize to unseen data, a cross-validation approach was implemented, specifically employing the k-fold cross-validation method. This particular technique involves partitioning the original dataset into multiple subsets, in this scenario 10 subsets, where each subset is alternatively designated as testing data while the other subset serves as training data. Through 10 iterations, it is ensured that each data point is utilized as testing data once and as training data nine times, thereby diminishing the risk of overfitting and furnishing a more dependable assessment of model efficacy. The k-fold cross-validation technique furnishes the mean value of the predictive outcomes for all subsets, serving as a benchmark to gauge the comprehensive accuracy of the model. This methodology is notably advantageous in guaranteeing that the model not only memorizes the data but also exhibits proficiency in predicting unseen data. Nevertheless, this technique does present constraints, particularly in scenarios where there is a discernible pattern in the data distribution, thereby potentially introducing bias in the evaluation outcomes. Consequently, to address the issue of class imbalance in the heart failure dataset, various strategies may be employed, notwithstanding the absence of elaboration on these strategies in this discourse. Furthermore, meticulous attention to feature engineering is imperative to ensure that the model can effectively discern pertinent patterns from diverse medical data sources, encompassing the scaling and normalization of data to mitigate any scale-related biases. Consequently, machine learning models devised utilizing AdaBoost and ELM can be meticulously validated, affirming their precision and reliability in real-world clinical contexts, though comprehensive validation with independent datasets is indispensable to ascertain the model's generalizability.

D. LEARNING

The AdaBoost algorithm, also known as adaptive boosting, was introduced in the year 1995 by Yoav Freund and Robert Shapire with the aim of providing a universal approach to constructing a robust classifier from a collection of classifiers with limited predictive power [20], [21]. AdaBoost operates effectively even in scenarios where the classifiers originate from a spectrum of possible classifiers, encompassing neural networks, linear discriminants, among others. Yet, to facilitate comprehension, we will posit that the group of experts is restricted, comprising L classifiers, and is presented as input to AdaBoost. An illustration of this scenario is evident in the renowned facial recognition technique pioneered by Viola and Jones [22]. Adaptive Boosting (Adaboost) is the most common and widely used ensemble learning algorithm, namely from the boosting family of ensemble learning methods. The AdaBoost algorithm generates a series of subpar learners through the management of a set of weights across the training dataset, and then dynamically adjusts these weights following each iteration of weak learning [23]. The weights assigned to training instances that are misclassified by the current weak learner will undergo an increment, whereas the weights of the correctly classified samples will experience a reduction [24]. AdaBoost is characterized by using initial training data to generate weak learners, then adjusting the training data distribution according to the performance prediction for the next round of training weak learners [25]. AdaBoost works by initially constructing a weak learner model, such as a tree, with equal weights assigned to each

observation. The obtained tree is then evaluated to assess its predictive ability [26]. This procedure is carried out repeatedly so that tens to hundreds of weak learners are obtained. The final model is obtained by combining various trees obtained with a certain weighting mechanism [27].

AdaBoost implementation can be easily performed. Generally, there are four stages: (1) Data collection through experiments; (2) Development of resilient learners; (3) Testing or validation of students; (4) Application of students to technical problems. The second stage is the core of AdaBoost. As discussed above, this involves two levels: a framework to integrate weak learners into strong learners and regression learning algorithms to train weak learners using training data. The Decision Tree algorithm, specifically the Classification and Regression Tree (CART) [28], is utilized to create weak learners, which are then integrated through the median of weak learners weighted accordingly. The AdaBoost parameter consists of two levels: one for the AdaBoost framework and another for the weak learner algorithm, which is CART. This framework only has two parameters: the number (or maximum iteration number) N of weak learners and the regularization factor (or learning rate) m. CART is more complex and has several parameters. The steps for implementing the Adaboost algorithm can be found in FIGURE 3 below[25].

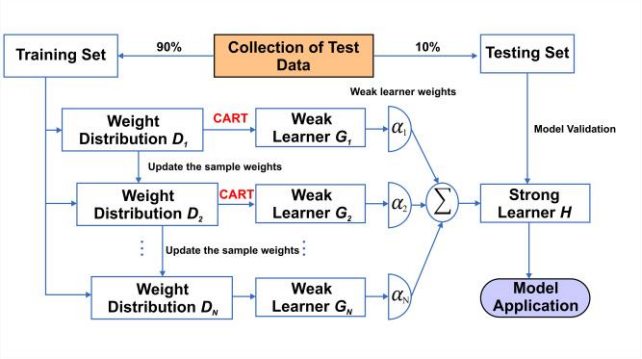

FIGURE 3. Implementation of the Adaboost algorithm

The steps in the Adaboost algorithm are as follows [29], Firstly, commence by inputting the research collection denoted with the label in Equation (2) specifically pertaining to an algorithmic learning component and the quantity of rotations denoted as T. nextly, proceed to Equation (3) to initialize the training sample Weights for all i = 1. .., executing this for t= 1, ... , T. Following this, compute the active training error as outlined in Equation (4). Proceed to establish the weight for the classifier using components specified in Equation (5) employed by the algorithmic learning component for training a classification component on the training weight sample, then proceed to update the research sample weight according to Equation (6), and finally, generate the formula presented in Equation (7).

$$\{(xi, yi), \ldots, (xN, yN)\}, \quad (2)$$

$$W_i^1 = \frac{1}{N} \text{ for all i = 1,2,3, …, N. For t= 1, ..., T} \quad (3)$$

$$h_t : \varepsilon_t = \sum_{i=1}^{N} W \frac{t}{i}, y_i \neq h_t(x_i) \quad (4)$$

$$h_t = \alpha_t = \frac{1}{2} ln\left(\frac{1-\varepsilon_t}{\varepsilon_t}\right) \quad (5)$$

$$W_i^{t+1} = \frac{W_i^t \exp\{-\alpha_t y_{ih_t}(x_i)\}}{C_t} \quad (6)$$

$$f(x) = \text{sign}\left(\sum_t^T \alpha_t h_t(x)\right) \quad (7)$$

The Extreme Learning Machine (ELM) is a classification method published in 2006, but was first introduced in 2004 by Huang [30]. This method consists of 3 neural network layers using an activation function in the calculation process. Compared to gradient-based methods, ELM has many advantages such as being able to minimize the number of iterations, a very fast learning (training) process, being able to optimize the learning rate value, being suitable for many nonlinear activation functions and having better classification results than backpropagation in many cases [31].

The ELM approach utilizes a distinct mathematical framework compared to feedforward artificial neural networks. The mathematical framework employed by ELM is characterized by its simplicity and enhanced efficiency. The mathematical representation associated with ELM, adjusted for N varying samples (Xi, ti) is shown in the Equation (8) .

$$Xi = [\, Xi_1, Xi_2 \ldots., Xi_n \,]_T \in R_n$$
$$Xt = [\, Xt_1, Xt_2 \ldots., Xt_n \,]_T \in R_n, \quad (8)$$

ELM is an artificial neural network (ANN) with a feedforward structure that consists of a single hidden layer, also known as Single Hidden Layer Feedforward Neural Networks (SLFNs). The ELM learning method was developed to address issues caused by feedforward artificial neural networks, particularly in terms of learning speed. Huang et al. The single hidden layer feed-forward network (SLFN) is utilized as a network structure for classification and prediction tasks, possessing learning capabilities and error tolerance skills. The parameters are adjusted for numerous iterative procedures to obtain a local minimum, which might be relatively slow [32]. There are numerous new rapid learning algorithms that enhance accuracy and minimize overall computational time in the framework. Loss and learning rate are used to adjust control parameters. ELM can be implemented for prediction processes without the need for repetitive tuning procedures The efficiency of its learning process is also faster compared to other traditional methods. The learning parameter is adjusted by considering the input weight vector and bias of the hidden node [31].

A standard SLFN can be defined mathematically as a network with N hidden nodes and the activation function g(x) can be seen in Equation (9),

(10) .

$$\sum_{i=1}^{n} \beta i \, gi(xi) = \sum_{i=1}^{N} \beta i g(wi, xbi) = 0i \quad (9)$$

$$\beta = H * T \quad (10)$$

where w represents a vector of weights that establish connections between the i-th hidden nodes and input nodes. The parameter βi denotes the weight vector responsible for linking the i-th hidden nodes with the output nodes. Moreover, bi signifies the threshold associated with the i-th hidden nodes. The expression w i x j corresponds to the inner product of w i and x. FIGURE 4 ilustrates the internal structure of the ELM base network.

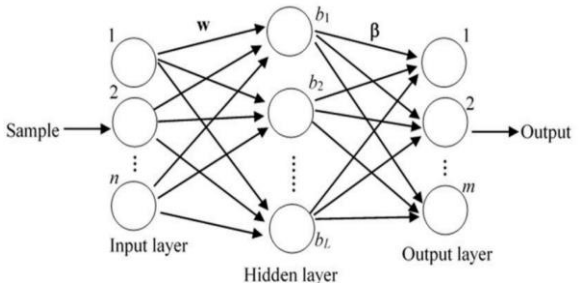

FIGURE 4. Structure of ELM

The utilization of the AdaBoost and Extreme Learning Machine (ELM) algorithms for the prediction of heart failure was predicated upon their respective strengths in enhancing classification efficacy. AdaBoost transforms a collection of feeble classifiers into robust classifiers through the adjustment of misclassified data weights in each iteration, proving highly efficacious in managing intricate and diverse medical data. Conversely, ELM employs a feedforward artificial neural network configuration with a single hidden layer, offering the benefit of reducing the iteration count, expediting the training process, and optimizing the learning rate parameter. ELM is renowned for its mathematical straightforwardness and efficiency, along with its superior performance compared to backpropagation techniques in numerous scenarios. Within the domain of feature engineering, the selection of pertinent features like medical records, laboratory test outcomes, and vital signs, in addition to scaling and normalization procedures, contributed to enhancing the efficacy of both algorithms. Accuracy serves as the predominant assessment criterion for gauging the overall model performance. Nevertheless, both algorithms possess constraints; AdaBoost assumes independent errors and is susceptible to noise, whereas ELM might necessitate meticulous parameter calibration to attain optimal efficacy. Nevertheless, through adept feature engineering methodologies, the amalgamation of AdaBoost and ELM could potentially enhance accuracy and clinical applicability in heart failure prognosis, although rigorous validation with autonomous data is imperative to ensure model generalizability.

E. EVALUATION

A confusion matrix is a table commonly used to describe the performance of a machine learning model. Confusion Matrix represents the predicted and actual conditions of data generated by machine learning algorithms, specifically classification models. In data mining there is a method called Confusion Matrix which is used to measure the accuracy of data so that it can be used in decision support systems. There are 4 terms in the confusion matrix that describe the classification of performance measurement results, namely True Negative (TN), False Positive (FP), True Positive (TP), and False Negative (FN), for more details can be seen in TABLE 2 [32] , [33].

TABLE 2
Confusion Matrix

		True Values	
		True	**False**
Prediction	**True**	TP Correst Result	FP Unexpected result
	False	FN Missing result	TN Correct absence of result

III. RESULT

These results underwent a Min-Max normalization process which is carefully displayed in TABLE 3, which shows the results of procedural normalization.

TABLE 3
Min-Max Normalization Result

No	Age	Creatinine_phosphokinase	Diabetes	Ejection_fraction	High_blood_pressure	…	Death_event
1	0.636	0.636	0.071	0	0.091	…	1
2	0.273	0	1	0	0.364	…	1
…	..	…	…	…	…	…	…
296	0.273	0	0.229	0	0.364	…	0
297	0.091	0	0.260	1	0.697	…	0
298	0.091	0	0.305	0	0.364	…	0
299	0.182	0	0.022	0	0.470	…	0

TABLE 4 serves as a crucial tool within the framework of this research endeavor, facilitating the exploration and identification of key parameters essential for the comprehensive analysis conducted in this study.e in the research outcomes and findings.

TABLE 4
Parameter Range

Model	Parameter	Description	Range	
ELM	n_neuron	regulates the number of neurons	10	300
Adaboost	n_estimator	determines the number of models in the Adaboost ensemble	10	300
	learning Rate	controls how much learning occurs at each training step	0.01	0.9

	max depth	depth of Tree	5	50

The experimentation and search conducted using ELM and Adaboost yielded performance results in terms of accuracy for each model. The evaluation results of the Heart Failure Detection dataset by the ELM model may be observed in TABLE 5.

TABLE 5
Search Results Using Parameters and Neurons

Experiment	Neuron parameters							
	10	20	…	230	240	…	290	300
1	0.833	0.833	…	0.833	0.8	…	0.833	0.833
2	0.8	0.8	…	0.833	0.833	…	0.833	0.833
3	0.8	0.8	…	0.833	0.833	…	0.833	0.833
4	0.733	0.8	…	0.833	0.833	…	0.8	0.833
5	0.833	0.8	…	0.833	0.833	…	0.833	0.833
6	0.733	0.833	…	0.8	0.8	…	0.833	0.833
7	0.767	0.833	…	0.833	0.7	…	0.8	0.833
8	0.833	0.833	…	0.833	0.833	…	0.833	0.8
9	0.7	0.767	…	0.833	0.833	…	0.8	0.833
10	0.833	0.833	…	0.833	0.833	…	0.833	0.833
Average	0.787	0.817	…	**0.830**	0.8267	…	0.823	**0.830**

The accuracy results of the Adaboost model with the parameter n_estimator ranging from 10 to 300 are displayed in TABLE 6.

TABLE 6
Search Result Using the n_estimator Parameter

Experiment	Accuracy
10	0.767
20	0.8
30	**0.833**
40	0.767
50	0.767
60	0.767
70	0.733
80	0.733
90	0.733
100	0.733
200	0.767
300	0.767

The accuracy results of the Adaboost model with the Learning Rate parameter ranging from 0.01 to 0.9 are shown in

TABLE 7.

TABLE 7
Learning Rate Parameter Accuracy Results

Experiment	Accuracy
0.01	0.8
0.1	**0.87**
0.2	0.83
0.3	0.8
0.4	0.83
0.5	0.8
0.6	0.8
0.7	0.8
0.8	0.8
0.9	0.767

The accuracy results of the Adaboost Model using the parameter max depth ranging from 5 to 50 are displayed in TABLE 8.

TABLE 8
Max depth parameter accuracy results

No	Max depth parameters									
	5	10	15	20	25	30	35	40	45	50
1	0.83	0.8	0.83	0.80	0.83	0.8	0.8	0.83	0.8	0.77
2	0.83	0.86	0.8	0.86	0.8	0.83	0.8	0.86	0.8	0.83
3	0.83	0.86	0.83	0.80	0.8	0.83	0.83	0.86	0.87	0.83
4	0.833	0.83	0.86	0.86	0.76	0.83	0.8	0.86	0.83	0.83
5	0.83	0.83	0.8	0.8	0.83	0.83	0.83	0.8	0.87	0.8
6	0.83	0.8	0.86	0.8	0.83	0.83	0.83	0.8	0.87	0.8
7	0.83	0.83	0.83	0.83	0.76	0.76	0.86	0.83	0.9	0.83
8	0.83	0.83	0.8	0.8	0.8	0.86	0.86	0.83	0.73	0.8
9	0.83	0.83	0.9	0.83	0.86	0.8	0.8	0.83	0.8	0.87
10	0.83	0.8	0.86	0.83	0.8	0.83	0.83	0.83	0.8	0.83
Av	0.83	0.83	**0.84**	0.82	0.80	0.82	0.82	0.84	0.84	0.82

IV. DISCUSSION

This first stage is dedicated to presenting research findings that have been obtained through the use of normalization procedures with min-max preprocessing techniques. Before sharing data, the data must undergo necessary adjustments according to the requirements of the algorithm used. The pre-processing stage to be carried out requires data normalization which aims to standardize the data scale within a defined range from 0 to 1. MinMax normalization stands out as a leading normalization method that facilitates the transformation of data ranges. data values are in the interval 0 to 1. The mathematical equation used to calculate MinMax Normalization can be observed in great detail. Before the data sharing process, data adjustments will be made according to

the algorithm specifications. The preprocessing stage involves data normalization to ensure standardization of the data scale within a certain range from 0 to 1. MinMax Normalization emerged as an important technique for normalization, enabling the transformation of data values in the range 0 to 1. A detailed depiction of the equation governing MinMax Normalization can be seen in Equation (1) The data that underwent the Min-Max process are carefully displayed in TABLE 3 which displays the results of the normalization procedure.

The second stage is the Heart Failure Prediction Dataset which is divided using cross validation with the test data split following the 10 k fold cross validation rule. Next, classification is carried out. At this stage, classification is carried out using the ELM and Adaboost methods using the n_neuron parameters for ELM and n_estimator, learning rate, and max depth for Adaboost as shown in TABLE 4 which displays the range of parameters to be searched.

Inspection of the results obtained from the predefined parameters specified in Table 4 reveals that the experimental ELM model, characterized by the n_neuron parameter, achieves a commendable accuracy metric of 0.83. Similarly, the Adaboost model, configured with n_estimator parameters, displays an accuracy rate of 0.83, a learning rate of 0.87, and a maximum depth of 0.84. It is noteworthy that a thorough analysis of the average performance of the model can be observed through the visualization presented in FIGURE 5.

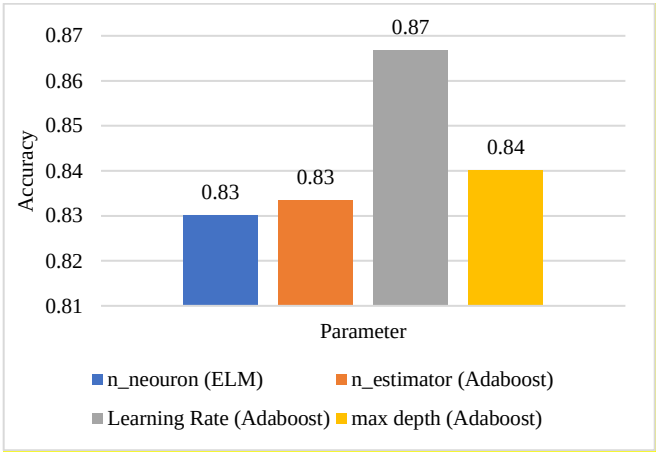

FIGURE 5. Accuracy Results of All Models

In previous areas of academic investigation, the classification process was carried out using various algorithms without any additional parameter configuration, resulting in an accuracy of 82% in the case of Decision Tree and 86% for Naïve Bayes [3]. Within the framework of current scientific research, the classification procedure involves the use of Extreme Learning Machine (ELM) and Adaboost, with specific parameters depicted explicitly in TABLE 4. Noteworthy is the fact that the Adaboost model shows superior performance compared to the ELM model, especially when evaluating average accuracy metrics in the context of the Heart Failure Prediction dataset. The investigation results show that ELM succeeded in achieving an average accuracy score of 0.83. In contrast, Adaboost, after utilizing the n_estimator parameter, was able to achieve a numerical value of 0.83, with a maximum depth of 0.84. Additionally, there was a substantial increase in the average accuracy rate observed after the incorporation of the Learning Rate parameter, culminating in an average accuracy reading of 0.87, thus showing a marked improvement when compared to previous researchers' findings. The detailed alignment of accuracy values can be appreciated visually through the graphical representation provided in **FIGURE 6.**

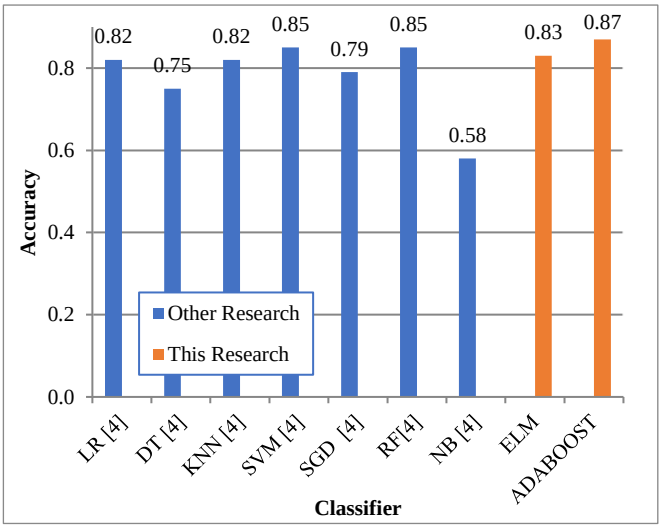

FIGURE 6. Comparison of Accuracy Same Dataset Values for All Models

In various other research efforts using various methodologies and data sources, the success rates obtained from these investigations are as follows: Logistic Regression (LR) shows an accuracy rate of 82.60%, Decision Tree (DT) shows a success rate of 75.55%, K-Nearest Neighbor (KNN) shows a performance level of 82.61%, Support Vector Machine (SVM) achieved a success rate of 85.86%, Random Forest (RF) achieved an accuracy rate of 85.32%, Stochastic Gradient Descent (SGD) achieved a success rate of 79.98%, and Naive Bayes (NB) showed an accuracy rate of 58.32% [4]. After reviewing the results of previous studies, it is clear that the superiority achieved in our research, especially the Adaboost algorithm, exceeds the findings of previous studies. The graphical representation of Accuracy Values is visually depicted in FIGURE 7. In this study, the research is constrained by the utilization of a single parameter in each classification procedure. For instance, the ELM algorithm employs n_neuron parameters, where each node is a multiple of 10, and undergoes 10 iterations of trials before calculating the average outcome. Similarly, the Adaboost algorithm utilizes n_estimator parameters within the range of 10-300, learning rates between 0.01 and 0.9, and a consistent max_depth of 50.

The implications of this study enhance the academic sphere by delineating the efficacy outcomes of the Extreme Learning Machine (ELM) and Adaboost algorithms through the inclusion of their respective parameters in the classification of heart failure. The discernible outcome of this experimentation reveals that the learning_rate parameter

exerts the most significant impact within our analysis, surpassing the influence of the n_estimator and max_Depth parameters in Adaboost, as well as overshadowing the role of the n_neouron parameter in the ELM algorithm.

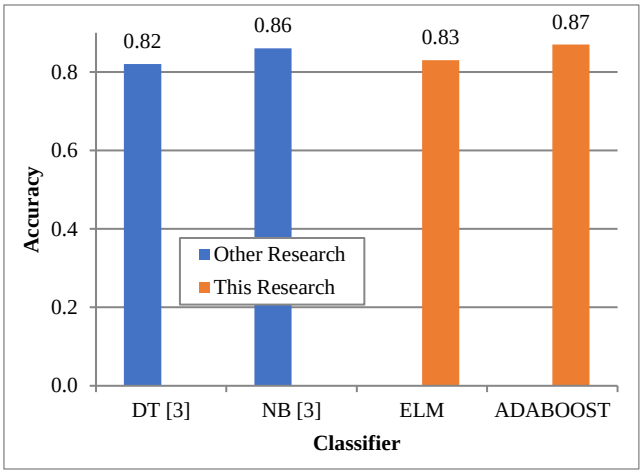

FIGURE 7. Comparison of Accuracy Different Dataset Values for All Models

This study identifies limitations that should be acknowledged for accurate interpretation and generalization. Data bias can affect model performance, especially with unbalanced or underrepresentative data. Assumptions of AdaBoost and ELM models may not fully capture the complexity of medical data. Methodological constraints like parameter selection and overfitting should be considered, with k-fold cross-validation used to reduce overfitting. Results highlight learning_rate as the most significant parameter, affecting AdaBoost more than n_estimator and max_Depth, and ruling out n_neuron's role in ELM. Future research should address limitations by collecting diverse data and exploring alternative algorithms and refinements. External validation studies using independent data are crucial for model generalization. The study shows the effectiveness of ELM and AdaBoost in heart failure classification, but further steps are needed to improve reliability in clinical practice.

V. CONCLUSIONS

This research tries to predict the occurrence of heart failure by utilizing the Heart Failure Prediction Dataset through the application of a classification approach involving Extreme Learning Machine (ELM) and Adaboost techniques. This process also involves the integration of additional parameters such as n_neurons for ELM and learning_rate, n_estimator, and maximum depth for Adaboost. The efficacy of this model shows variability, a fact that is proven by the comparative results observed during the testing phase. It can be seen that adding parameters to the Adaboost algorithm results in increased accuracy performance when compared to previous research which used Logistic Regression (LR), Decision Tree (DT), K-Nearest Neighbor (KNN), Support Vector Machine (SVM), Random Forest (RF) , Stochastic Gradient Descent (SGD) and Naive Bayes (NB) with standard parameters which can be seen in figures 6 and 7.

The outcomes of this study reveal that the application of the ELM technique alongside additional parameters set at the upper limits of n_neuron (230, 250, 260, and 300) results in an average accuracy of 0.83 across ten experimental runs. Furthermore, Adaboost, when infused with the supplemental parameter Learning rate set at 0.1, attains the highest accuracy score of 0.87 on the Heart Failure Prediction dataset.

Future investigations could potentially derive benefits from amalgamating the ELM and Adaboost methodologies with other algorithms. The primary objective of such an endeavor would be to ascertain the level of performance yielded by the fusion of these two approaches and to attain an enhanced performance metric.

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