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Explainable Heart Failure Outcome Prediction Using TabPFN and Cuckoo Search Optimization for Intelligent Healthcare Prognostic Analytics

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ABSTRACT: Heart Failure (HF) is a serious cardiovascular disease, and challenges in accurate prediction, model optimization and clinical interpretability limit effective decision making. To overcome these issues, this paper proposes a Cuckoo Search Optimization (CSO) optimized TabPFN model (CSO-TabPFN) for reliable and explainable heart failure prediction. The input data set is pre-processed to handle the missing and invalid values and then visualization is done to find important relationships and patterns among the features. Feature scaling and normalization are performed before the dataset is split into training and testing subsets. TabPFN allows fast prediction from tabular clinical data. CSO optimizes the model parameters for improved prediction accuracy and robustness. The proposed model achieved an accuracy, precision, recall and F1-score of 97% and an AUC of 0.9973. SHAP analysis indicates that slope, chest pain and resting blood pressure are important predictive features, increasing model transparency and clinical interpretability.

Keywords: HF, CSO, TabPFN, ML, SHAP Analysis.

1. Introduction

HF, which affects cardiac systolic or diastolic performance, is a critical issue in the global population health and continues to be among the most common causes of cardiovascular deaths [1]. HF limits the ability of the heart to pump adequate blood and oxygen throughout the body, leading to a decrease in physical performance and a low quality of life. Coronary heart disease (CHD) is among many causes of HF, and it is associated with many deaths. People suffering from CHD-induced HF face many difficulties, including physical limitations, slow disease progression, and poor outcomes of care [2-3].

The Long-term management of HF consumes considerable medical resources and places heavy burdens on both economic and social spheres. Therefore, predicting mortality risks becomes an important task to improve patient management and intervention. Identifying the factors that affect the mortality risk prediction becomes another task that help healthcare specialists to create a proper individualized treatment strategy [4-5]. To solve these problems, machine learning and optimization methods are proposed for precise prediction of HF and discovery of influential clinical factors.

Various Machine Learning (ML) are utilized to predict HF outcomes. The Support Vector Machine (SVM) method distinguishes outcome categories deploying an ideal hyper plane and utilizes kernel functions to process non-linear forms; however, the issue of selecting parameters arise. K-Nearest Neighbours (KNN) uses data samples of nearest patients to make predictions, which makes it easy to apply. However, this method's effectiveness depend on data normalization and the size of datasets. Artificial Neural Network (ANN) makes it possible to discover complicated non-linear relations with interconnected neurons; however, it needs careful designing and calibration [6-8]. The TabPFN method is proposed to enhance the prediction results compared to those produced with existing models. Nevertheless, there is still a need to optimize the model to tune the parameters.

Many traditional optimization methods such as Ant Colony Optimization (ACO) and Grey Wolf Optimization (GWO) have been used for optimization of model parameters. The ACO algorithm uses pheromone-based search to find promising solutions, but updating the pheromone repeatedly add an overhead to the computation. GWO gives effective searching capability by imitating hunting behaviour of grey wolves, however, it lead to a loss in population diversity in the later stages [9-10]. CSO is employed to help model parameter optimization techniques.

Research gap

Existing ML methods such as SVM, KNN, and ANN have been used for heart disease prediction, but they may require careful parameter selection and model design. TabPFN is efficient for prediction of tabular clinical data, but the parameter optimization of TabPFN still remains a problem. Optimization methods such as ACO and GWO also have the limitation of computational overhead and search diversity. To address these gaps, this work proposed a CSO-TabPFN model by using CSO to optimize the parameters of TabPFN to improve the prediction performance and using SHAP analysis to improve the interpretability of the model.

2. Recent Works

S. No	Tittle/ author name/year	Methodology used	Advantages	Disadvantages
1.	Petmezas *et al* (2025) [11]	To predict heart failure mortality and identify important clinical factors, hybrid feature selection is integrated with machine learning and explainable AI.	Reduces irrelevant features, improves prediction performance and enhances the interpretability of clinical prediction.	Multiple feature-selection steps increase computational complexity depending on the selected features and prediction model.
2.	Tasnim *et al* (2023) [12]	Combining machine learning and explainable AI with a nature-inspired risk in HF patients.	Selects important clinical features. Reduces redundant information. Improves prediction performance. Provides interpretable results.	Nature based optimization might be more computationally expensive and the performance might be sensitive to the choice of parameters and the quality of feature selection.
3.	Asaad *et al* (2024) [13]	The Artificial Bee Colony (ABC) algorithm is combined with an Artificial Neural Network (ANN)to optimize network parameters for heart disease prediction	Achieves effective classification of heart disease, optimizes the parameters of the model and improves the prediction performance of ANN.	ABC optimization require more iterations and computation time while ANN performance is dependent on selection of proper parameters.
4.	Atimbire *et al* (2024) [14]	Machine Learning integrated with Whale Optimization Algorithm for Feature Selection and Parameter Optimization to predict Heart Disease.	Selects relevant features, improves the classification performance, and provides an effective optimization strategy for heart disease prediction.	WOA might require more iterations to converge and have higher computational complexity for large datasets.

2.1 Objectives

- To pre-process the HF dataset by treating missing values and invalid data entries.
- To visualize and analyse the dataset to find out the important patterns and relationship between features.
- To design and normalize useful features for proper training of models.
- To develop a CSO optimized TABPFN model for accurate heart failure prediction.
- To interpret prediction results using SHAP to find the contribution of important features.

3. Proposed Work Explanation

The proposed framework begins with the input dataset, which is first processed to handle missing values and to identify invalid string entries. After cleaning, the data is visualized to investigate relationships and patterns in the dataset. Next, feature engineering is carried out thru feature scaling and normalization to bring the input variables into a suitable range for model development.

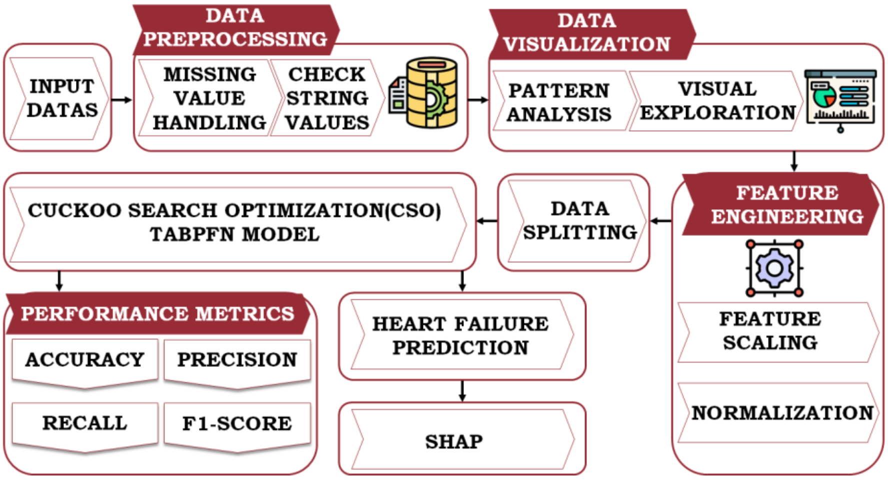

Figure 1: *Proposed System Architecture*

The processed dataset is then split through data splitting into suitable training and testing subsets. Then, the CSO-TABPFN model is used to predict heart failure. In the CSO model, the model parameters are optimized to improve the predictive performance. The model is assessed based on accuracy, precision, recall, and F1-score.Finally, SHAP is employed to explain the model predictions and to determine the contribution of individual features for heart failure prediction.

4. Proposed system modelling

4.1 Data Pre-processing

In the initial stage, the input heart failure dataset is inspected to detect missing values and invalid entries. Missing values are handled properly so that no incomplete information is used in model training. Non-numeric or wrong string entries are identified and corrected to make sure that all features are in a suitable format for analysis. After data cleaning, the processed features are scaled and normalized to bring the variables into a consistent numerical range. This step reduces feature magnitude differences and facilitates stable model training.

4.2 Data Visualization

The HF dataset that has undergone cleaning is presented visually to observe important patterns, distribution of the features, and associations between clinical features. The visual analysis enables the detection of trends, variations as well as possible outliers and provides a better understanding of the data before feature engineering and model construction.

4.3 Feature Engineering

The HF data is pre-processed before being subjected to feature scaling and normalization so that the clinical variables fall within a uniform range of values, reducing the variances of feature values and ensuring the stability of the models. The dataset is subsequently split into two parts, that is, a training dataset contributes towards the model development and the testing dataset serves to evaluate the model on given unseen cases. The CSO-TABPFN approach should be implemented for parameter optimization and improved heart failure forecasting.

5. TABPFN

TabPFN is a foundation model based on Transformers for tabular data prediction. In the proposed framework for prediction of HF, the processed clinical dataset is fed into TabPFN to learn the relationships between patient features and HF outcomes. Given a training data set $D = \{(x_i, y_i)\}_{i=1}^{N}$ and a test sample x^* , the prediction is expressed as

$$P(y^*|x^*, D) \qquad (1)$$

Where x_i are the clinical features, y_i are the corresponding HF outcomes, and x is the test sample. TabPFN employs the attention mechanism of Transformer to model complex interactions between tabular features and samples. The attention mechanism is explained as

$$Attention(Q, K, V) = softmax\left(\frac{QK^T}{\sqrt{d_k}}\right) \qquad (2)$$

Where Q, K and v are query, key and value matrices respectively, and d_k is the key dimension. It predicts probability of the predicted outcome for each patient and classifies heart failure efficiently. Optimization is needed to fine-tune the TabPFN model parameters and find the best configuration, so that the prediction accuracy and model performance improved.

5.1 Cuckoo Search Optimization

To improve performance of TabPFN, the best model parameters are obtained using CSO. CSO is a nature inspired global optimization algorithm based on the behaviour of cuckoos. Each nest corresponds to a candidate parameter configuration of TabPFN and its fitness value is the prediction performance.

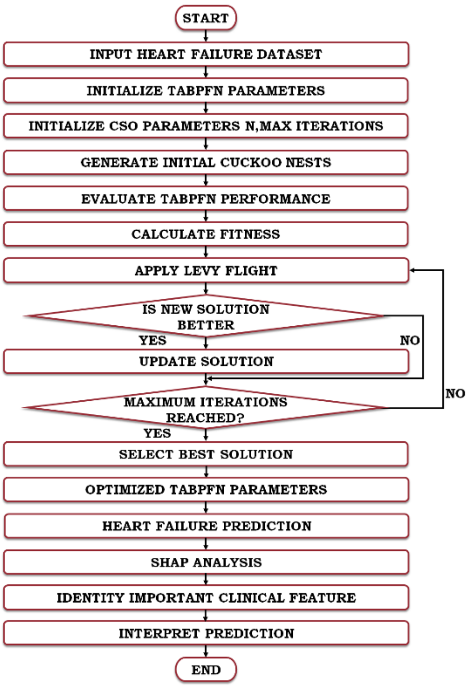

Figure 2: *Flowchart of CSO*

The first cuckoo nests are randomly generated in pre-defined search boundaries as

$$X_{i,j} = LB_j + r(UB_j - LB_j), \quad i=1,2,\ldots,N \qquad (3)$$

Where $X_{i,j}$ is the j^{th} parameter of the i^{th} cuckoo. The fitness of each candidate configuration is evaluated using the prediction performance of TabPFN:

$$F(X_i) = Accuracy(X_i) \qquad (4)$$

The Levy flight strategy searches for new candidate solutions as

$$X_i^{t+1} = X_i^t + \alpha L(\lambda) \qquad (5)$$

Where X_i^t and X_i^{t+1} represent the current and updated solutions, alpha is the step size and $L(\lambda)$ is the Levy flight distribution. This strategy allows to explore different parameter combinations and eliminates premature convergence.

Then a biased random-walk mechanism is applied to generate further solutions:

$$X_i^{t+1} = X_i^t + r\left(X_j^t - X_k^t\right) \quad (6)$$

Where X_j^t and X_k^t are random solutions and r is a random number in the range of [0, 1]. The better solution is kept based on its fitness value. The CSO process continues until the stopping criterion is satisfied and the best solution is selected as optimal TabPFN configuration. Finally, SHAP analysis is applied to analyse contribution of each clinical feature to optimized TabPFN predictions, thus improving the interpretability and transparency of the model.

6. Results and Discussion

This section evaluates proposed TabPFN-CSO model for the prediction of HF outcome. Results show strong predictive performance and interpretability over existing methods.

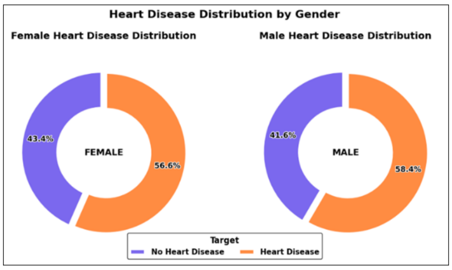

Figure 3: *Heart Disease distribution by gender*

Figure 3 shows the distribution of heart disease cases among female and male patients. Heart disease is present in 56.6% of females and 58.4% of males with the rest of the patients free of heart disease.

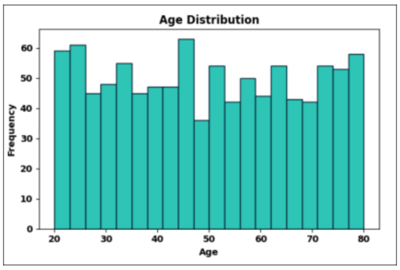

Figure 4: *Age distribution of heart disease dataset*

Figure 4 shows the distribution of patients' age ranging from about 20 to 80 years with different frequencies in different age groups.

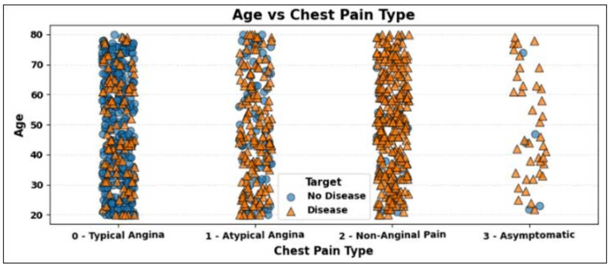

Figure 5: *Age distribution by chest pain type*

Figure 5 shows the age variations in the different chest pain categories for heart disease and non-heart disease cases.

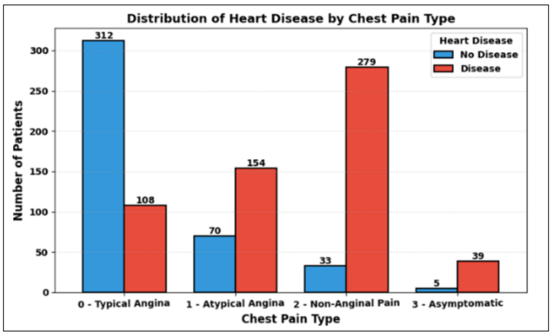

Figure 6: *Heart disease distribution*

Figure 6 indicates that the Non-anginal pain has the highest number of heart disease cases and typical angina has the highest number of non-heart disease cases.

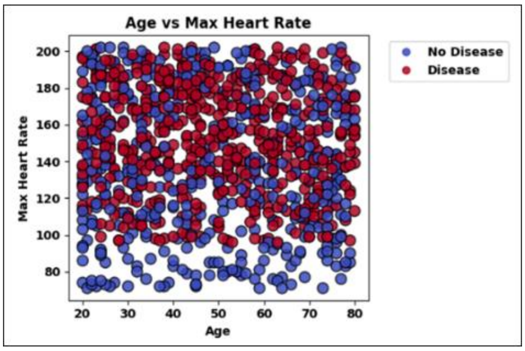

Figure 7: *Maximum heart rate variation with age*

Figure 7 shows the age and maximum heart rate for patients with and without heart disease. There is nothing clear in the separation of heart disease cases by age and both groups are well distributed.

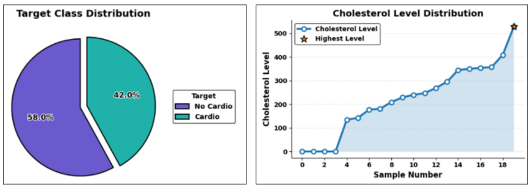

Figure 8: *class and cholesterol distribution*

Figure 8 represents 58% of the cases are identified as heart disease and 42% are non-heart disease. Cholesterol levels varied between samples, with the highest value around 520.

Table 1: *Assessment metrics of proposed model*

Evaluation metrics	
Accuracy	97%
Precision	97%
Recall	97%
F1 score	97%

Table 1 shows that model it achieves 97% accuracy, precision, recall and f1 score indicating reliable heart disease classification performance.

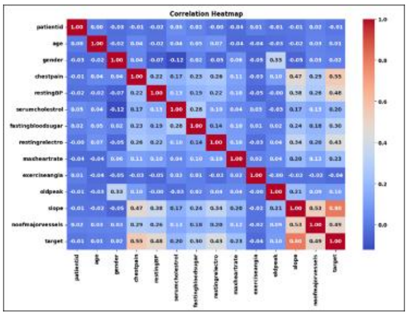

Figure 9: *Correlation heat map of heart disease features*

Figure 9 indicates the Heatmap of correlations between patient characteristics and clinical features. Oldpeak has the strongest positive correlation with the target, followed by chest pain type, slope, and number of major vessels.

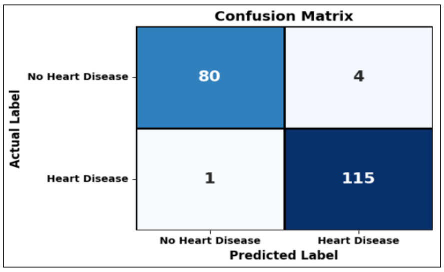

Figure 10: *Confusion matrix*

Figure 10 shows 80 and 115 correctly classified samples and only 4 and 1 misclassified samples, respectively. These results indicate that the proposed model achieves accurate classification with very few errors in prediction.

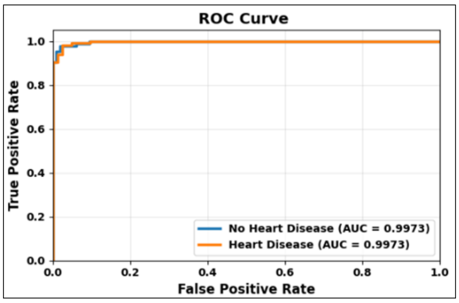

Figure 11: *ROC curve*

Figure 11 shows the AUC for both classes is 0.9973, which is a good classification ability with high true-positive and low false-positive rates.

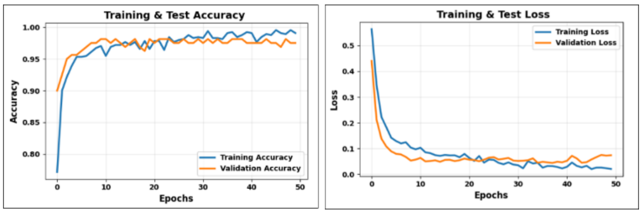

Figure 12: *Training and validation performance*

Figure 12 indicates that the accuracy increases and stabilizes at around 98–99%, and the losses decrease steadily and converge at low values, indicating actual learning of the model.

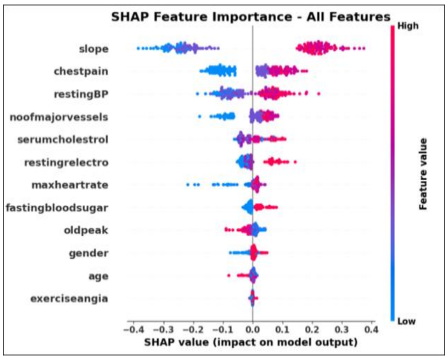

Figure 13: *SHAP feature importance analysis*

Figure 13. represents The SHAP analysis indicates that slope, chest pain and resting blood pressure are the most important features while age and exercise angina have lower contributions to the model output.

Table 2: Accuracy *comparison of Heart disease classification methods*

Accuracy	
Method	Value
KNN [7]	85%
ANN[8]	81%
Proposed	97%

Table.2.presents that the proposed method has achieved the highest accuracy of 97% in the heart disease classification as compared to KNN (85%) [7] and ANN (81%) [8].

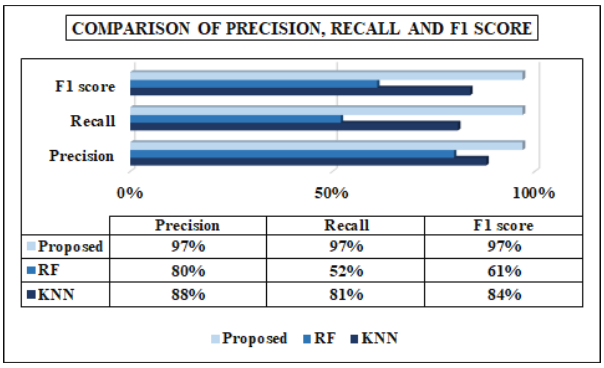

Figure 14: *comparative analysis of precision, recall and F1 score*

Figure.14s.shows that the proposed model achieves 97% precision, recall and F1-score, which are better than KNN [7] and RF [11] in all three metrics. The model has exhibited high accuracy and balanced performance in heart disease classification.

7. Conclusion

The Explainable HF Outcome Prediction using TabPFN and CSO is proposed for an accurate and interpretable framework for intelligent healthcare prognostic analytics. TabPFN enables effective prediction from clinical tabular data and CSO optimizes the model to improve performance and robustness. The proposed CSO-TabPFN model achieved 97% accuracy, precision, recall and F1-score and AUC of 0.9973. SHAP analysis showed slope, chest pain and resting blood pressure as important features with effective and interpretable prediction. The proposed method achieved accuracy of (97%) outperforming KNN (85%) and ANN (81%), showing reliable and explainable predictions of healthcare outcomes. Future work include larger datasets, additional patient features, real-world validation, and other applications in the area of cardiovascular diseases.

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