An improved Ensemble Machine Learning Models for Optimized Clinical and Laboratory-Based Prediction of Heart Failure

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Abstract: Heart failure remains a leading cause of both hospitalization and mortality in all countries of the world, and it is important to note the need to develop predictive models that would help physicians to detect and evaluate outcomes early. Kaggle Heart Failure Clinical Records was used, which includes demographic, clinical, and laboratory data. The Chi-square statistics was performed to select features and tests were performed on 13 and 7 feature subsets respectively. Class imbalance was corrected using Synthetic Minority Oversampling Technique (SMOTE). A wide range of classifiers, including Random Forest, Support Vector machine, AdaBoost, Gradient Boosting, and Stochastic Gradient Descent has been used with hyperparameters optimized using Artificial Immune Whale-Particle Swarm Optimization (AIW-PSO), which ensures high performance and efficient optimization of hyperparameters. Random Over Sampling (ROS) was explored to complement SMOTE and ensemble Voting Classifiers using LGBM and AdaBoost were used on the 13-feature and 7-feature sets. eXplainable AI methods, such as Local Interpretable Model-Agnostic Explanations (LIME) and SHapley Additive explanations (SHAP), enhanced model interpretability, whereas deployment preparedness was demonstrated with the help of the Flask framework. According to experiments, the ROS-based 13F Voting Classifier had an accuracy of 99.5, and the 7F Voting Classifier had an accuracy of 99.0, demonstrating the effectiveness of the best ensemble learning in cardiac failure prediction.

"Index Terms: *Cardiovascular diseases, Predictive models, Prediction algorithms, Machine learning algorithms, Accuracy, Machine learning, Computational modeling, Mortality, Adaptation models, Particle swarm optimization".*

1. INTRODUCTION

CVDs constitute an important global health issue, which encompasses coronary artery disease, stroke, and heart failure (HF). According to the reports of the WHO, the leading cause of death in the world is CVDs, which causes approximately 17.9 million deaths annually, about 32 percent of all deaths in the world [1]. HF is also quite alarming, affecting more than 64.3 million individuals around the world and placing a significant financial burden on the health care systems [2]. HF is a chronic and progressive disorder which is marked by reduced efficiency of the heart to pump blood normally, leading to such symptoms as fatigue, dyspnea, and fluid retention. This disease is often related to such underlying factors as high blood pressure, diabetes, overweight, and cardiovascular problems of the past [3].

However, despite the current developments in the field of diagnostic imaging, pharmacological treatment, and surgical methodologies, the prognosis of heart failure is hopeless. It has been shown that more than half of those diagnosed with heart failure die within five years after the diagnosis, which is the severity of this illness and the current challenge in cardiovascular care [4]. This high mortality and morbidity determine the need to develop accurate, timely and individually-tailored prediction tools to assist physicians in tailoring treatments and improving patient outcomes.

The growing availability of electronic health records (EHRs), biological sensors, and large volumes of clinical data has enabled the integration of ML into cardiovascular therapy. ML models have the potential to highlight hidden patterns, associations, and trends in complex data, therefore, they can be a critical tool to make predictions about patient outcomes, risk stratification, and tailor treatment regimens. The ability of ML to predict the progression of heart failure and death has been of great interest due to its ability to enhance clinical decision-making and resource allocation.

However, one of the serious limitations of applying ML to predict heart failure is making sure that it is stable and can generalize to diverse patient populations. Traditional models are often significantly underperformers when applied to heterogeneous data, which is mainly due to the poor hyperparameter optimization and the problem of unbalanced classes [7]. Researchers are also focusing more on optimization algorithms, such as grid search, random search, and evolutionary algorithms, to optimize hyperparameters and improve the accuracy of the predicted results at least by factors of order of magnitude [8]. The combination of these optimization techniques with strong ML codes provides a possible solution to building effective models that can be used in the early prognosis and effective treatment of heart failure patients.

2. LITERATURE REVIEW

Clinical guidelines and technological advances have played an important role in the diagnosis and treatment of HF over the past few decades. Recent guidelines incorporated in the 2021 European Society of Cardiology (ESC) guidelines by McDonagh et al. [9] regarding the diagnosis and management of both acute and chronic heart failure focus on improvements in clinical methods and the incorporation of recent research results of the large trials. These guidelines entailed detailed approaches of risk stratification of patients, pharmacological management and device-based therapy, and this allowed the doctors to provide evidence-based care. The recommendations recognized the potential of AI and ML technology as an addition to standard processes, which would precondition the increased use of predictive analytics in cardiovascular medicine. In the 2016 ESC guidelines, the criteria of heart failure diagnosis and treatment were standardized, which is why Ponikowski et al. [13] introduced significant information on the classification of diseases, subgroups according to ejection fraction, and approaches to treatment. All these guidelines have provided a professional standard of clinical practice and have highlighted the need to have new strategies that are not limited by conventional diagnosis and treatment.

Simultaneously with clinical directions, various researches have focused on improving the prognostic prediction and patient outcomes through advanced analytics. The study conducted by Angraal et al. [10] employed ML technologies to predict death and hospitalization of patients with heart failure of preserved ejection fraction (HFpEF). They found that machine learning model could outperform traditional statistical models in identifying patients at risk with significant potential especially when large volumes of structured and unstructured clinical data are analyzed. This paper addressed the growing problem of HFpEF, a disorder that has limited treatment options, and has shown that predictive analytics can be used to support personalized treatment. Moreover, Ahmad et al. [12] performed a survival analysis of heart failure patients who used clinical records to determine the predictive factors that influenced death. Their results confirmed the significant contribution of age, comorbidities, and clinical characteristics to the survival of patients, as well as demonstrated the effectiveness of statistical and computational models in monitoring patients. The two studies highlighted the need to have predictive methodologies that consider multi-dimensional patient data so as to be able to implement early intervention measures.

The burden of heart failure has been defined with the help of global epidemiological knowledge. Savarese and Lund [11] made an in-depth examination of the public health burden of heart failure, the prevalence, incidence, and socio economic impacts. They also highlighted the fact that heart failure is not just a clinical burden but also a major health issue worldwide, particularly in ageing societies where the health care facilities are scarce. Their study has highlighted the importance of prevention, early diagnosis and cost-effective treatment plans, which can be enhanced using predictive modeling and personalized medicine. Similarly, Ahmad et al. [12] highlighted the global crisis by focusing on patient-level analysis of survival by demonstrating the differences in the development of the disease in diverse demographic and clinical groups.

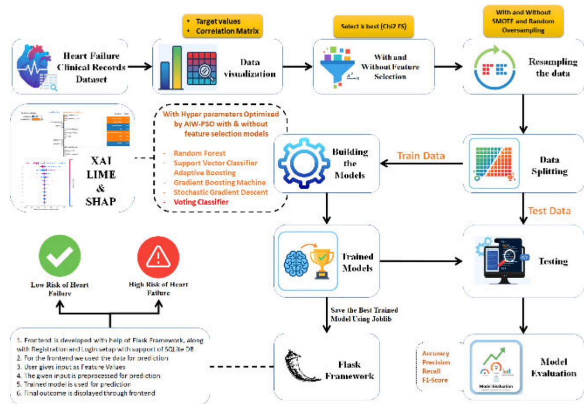
Because of the shortcomings of the conventional regression-based statistical approaches to deal with the complex, high-dimensional healthcare data, scientists have proposed adopting the concept of machine learning. Goldstein, Navar and Carter [14] suggested going beyond the previous strategies of regression when evaluating cardiovascular risks by focusing on the ability of ML to discover non-linear relationships, interactions, and heterogeneity in patient data. They demonstrated that machine learning methods could be used to address challenges such as overfitting, missing data, and model interpretability and provide more flexible and resilient predictions compared to traditional approaches. They played a critical role in promoting the shift to ML-based predictive analytics in cardiovascular care, bridging clinical epidemiology and computational sciences.

Awan et al. [15] evaluated the readiness of ML in heart failure management, which provides a critical evaluation of the use of ML in diagnostic, prognosis, and optimization of therapy. They argued that ML has shown a lot of promise in improving heart failure outcomes, but its application into clinical practice is still in its infancy, requiring extensive validation, interpretability and integration into clinical workflow. They highlighted specific ML algorithms, such as decision trees, support vectors and ensemble models which have produced promising results in predicting activities. Their study provided a lot of valuable information about the potentials and limitations of ML research translation into clinical care, and the need to balance precision of algorithms and their transparency and usability by healthcare professionals.

Panahiazar et al. [16] also contributed to the use of ML by exploring the use of electronic health records (EHRs) to suggest heart failure treatment through multidimensional patient similarity analytics. Their study offered a new approach to patient-centered decision support comparing new patients with past cases according to the multidimensional clinical characteristics, which helped to make specific therapy prescriptions. This method used the vast EHR data to enhance precision and outcome of therapy as compared to the traditional models that relied heavily on generic treatment pathways. This research showed the potential of ML to align population-wide instructions with the needs of the individual patient, which is a significant step in the direction of precision medicine in the management of heart failure.

3. MATERIALS AND METHODS

The suggested methodology creates the best ML model to predict heart failure using the Heart Failure Clinical Records data on Kaggle. Preprocessing of data is used to solve the missing data, encode the categorical variables and normalize features. Class imbalance is overcome by applying SMOTE and ROS. The Chi-square (Chi 2) test is applied to select the relevant predictors. The different classifiers (RF, SVM, AdaBoost, GBM and SGD) are trained and optimised using Artificial Immune Whale-Particle Swarm Optimisation (AIW-PSO) to effectively tune-hyper-parameters. Also, Explainable AI (LIME) is used to explain important features, and the trained models are deployed via a Flask-based web application that supports real-time clinical decision support.



"Fig.1 Proposed Architecture"

The proposed system architecture outlines a ML pipeline of clinical prediction of heart failure. This process starts with the acquisition of the dataset, followed by preprocessing operations such as the handling of missing values, the encoding of categorical variables, feature normalization, and SMOTE balance. The selection of features based on chi-squared is used and the data is split into training and testing sets using resampling techniques. Various models are trained and evaluated with the use of performance measures such as as accuracy, precision, recall, and F1-score. The model is finally deployed with Flask and explainable AI (XAI) to explain prediction and give results to users.

a) Dataset Collection:

The Heart Failure Clinical Records collection is a patient record of 299 patients with 13 clinical attributes as they include demographic, laboratory, and lifestyle factors including age, anaemia, diabetes, smoking status, blood pressure, biochemical markers. The objective variable, DEATH_EVENT which represents patient survival has 203 survivors and 96 deaths, which demonstrate the imbalance in classes. All documents are detailed, and none of the records has missing values, including both categorical and continuous data types. This data provides a solid foundation on predictive modeling and survival analysis in heart failure prognosis.

	age	anaemia	creatinine_phosphokinase	diabetes	ejection_fraction	high_blood_pressure	platelets	serum_creatinine	serum_sodium	sex	smoking	time	DEATH_EVENT
0	75.0	0	582	0	20	1	265000.00	1.9	130	1	0	4	1
1	55.0	0	7861	0	38	0	263358.03	1.1	136	1	0	6	1
2	65.0	0	146	0	20	0	162000.00	1.3	129	1	1	7	1
3	50.0	1	111	0	20	0	210000.00	1.9	137	1	0	7	1
4	65.0	1	160	1	20	0	327000.00	2.7	116	0	0	8	1

"Fig.2 Heart Failure Clinical Records Dataset"

b) Exploratory Data Analysis:

It conducted an Exploratory Data Analysis (EDA) to have a full picture of the data before modeling. The statistics of the target variable were presented in the form of pie charts with the focus on the difference between survival and non-survival cases. Moreover, heatmaps were generated to analyze the correlation between features, which made it possible to find strongly related clinical factors. This step helped clarify the interactions of features, patterns and possible redundancies, which informed the later preprocessing, feature selection, and resampling steps, ensuring that the models were trained on well understood and organized data.

c) Data Processing:

Preprocessing prepares the input data to be analyzed by ensuring consistency and quality. Since there are no missing values in the data, categorical variables are converted into numerical formats to ensure their compatibility with ML algorithms, whereas continuous variables are normalized with the help of StandardScaler and others to give normalized scales. This alleviates the risk of bias due to unequal features ranges, enhances the effectiveness of the algorithms, and makes the data ready to be sampled and trained on the model in a fair manner.

d) Feature Selection:

The Chi 2 test is used in feature selection to statistically evaluate and retain clinical variables that are most relevant in heart failure prediction outcomes. It also removes redundant or less important predictors by identifying strong relationships among the features and the target variable. Not only does this reduce complexity and computing costs but also increases the interpretability of the model so that classifiers can focus on the most salient variables thereby improving the accuracy of the prediction and clinical relevance.

e) Data Resampling:

The data is characterized by the imbalance of classes, as there are more survival cases than instances of death. In this regard, resampling algorithms like SMOTE and ROS are applied. SMOTE creates synthetic sample of the minority category, but ROS randomly replicates the existing sample, thereby creating a balance in the dataset. These methods reduce biased predictions that prefer the majority group so that ML models can learn effectively and be reliable in both survival and non-survival classes.

f) Training & Testing:

The balanced dataset is separated into training and testing subgroups, which may have a ratio of 80-20. The training set is used to learn the model and the test set is used to evaluate performance on new data. This split ensures that the model does not merely memorize patterns but generalizes well, which can be used to assess accuracy, precision, recall, and F1-score accurately. Proper division will help in reducing data leakage and creating an objective criterion where predictive models are evaluated during heart failure research.

g) Algorithms

Random Forest: RF makes use of a large number of decision trees in order to classify the outcomes of heart failure using 13-feature and 7-feature sets. Predicting accuracy and generalization is enhanced by refining hyperparameters with the help of Artificial Immune Whale-Particle Swarm Optimization (AIW-PSO). Training of models will be done under conditions with and without the SMOTE to eliminate the issue of class imbalance. This approach summarizes the complex interactions between clinical features, it reduces overfitting through ensemble averaging, and ensures robust survival prediction. RF provides interpretable feature importance scores, which makes it easy to discover essential clinical markers, as well as provides stability across different datasets and settings.

$$Gini = 1 - \sum_{i=1}^{c} (Pi)^2 \qquad (1)$$

Support Vector Classifier (SVC): SVM constructs suitable hyperplanes in order to distinguish patient outcomes through 13 and 7 features sets. AIW-PSO is a method that maximizes the selection of kernels, regularization and margin parameters to enhance generalization. The models are evaluated with and without SMOTE to overcome the problem of class imbalance and improve the minority class detection. The SVM are good with high-dimensional clinical data, explain non-linear correlation through kernel adjustments and can be used to effectively distinguish between survival and non-survival cases. Its methodology of maximizing margins is systematic and ensures low misclassification plus giving a comprehensive basis on risk segmentation. SVM offers reliable and computationally efficient predictions when it is used with feature selection.

$$minimize \ \frac{1}{2} ||W||^2 + C \sum_{i=1}^{n} \xi_i \qquad (2)$$

AdaBoost: An ensemble method, Adaptive Boosting (also known as AdaBoost or AB) is a combination of many weak classifiers, typically decision stumps, into one more powerful model through the sequential focus on misclassified instances. Every classifier has weight and the models that follow it are more focused on the more difficult examples to classify. Utilization also involves sequential learning whereby mistakes are used to better the boosting process and therefore, enhancing performance even in the case of rudimentary learners. The aim is to improve the accuracy of the forecasts and maintain efficiency and interpretability. AdaBoost improves poor predictors of heart failure, boosts minority classes, and provides strong predictions hence ensuring reliable support of clinical decisions of heart failure in imbalanced data.

$$H(x) = sign\left(\sum_{t=1}^{T} \alpha_t \, h_t(x)\right) \qquad (3)$$

Gradient Boosting Machine (GBM): Gradient Boosting Machine is used to construct additive decision trees using both 13 and 7-feature sets and is used to successively minimize errors in prediction. AIW-PSO maximizes the learning rate, depth of the tree, and estimators in order to improve generalization. Training of models with and without SMOTE is used to correct skewed patient outcome data. GBM determines complex non-linear relationships between variables, reduces bias and increases predictive accuracy. Iterative boosting corrects past errors, therefore, enhancing the performance on the minority classes. This method will ensure the accuracy of survival outcome prediction with the economy of computation and interpretability. GBM is competent in determining significant clinical variables that affect the prognosis of heart failure.

$$F_m(x) = F_{m-1}(x) + \gamma_m h_m(x) \qquad (4)$$

Stochastic Gradient Descent (SGD): SGD Classifier uses incremental updates to improve the linear classifiers with 13-features and 7- features datasets. AIW-PSO is used to optimize hyperparameters in order to enhance convergence, generalization and stability. Models are trained on SMOTE and without it to deal with the imbalance of the classes and improve the detection of not very frequent outcomes. SGD can process large datasets efficiently without incurring large computing costs and memory requirements. It identifies major characteristics whilst retaining a linear predictive model, which allows it to train quickly and scale to larger datasets. It is a reliable survival prediction method, it can be used to classify risks in clinical data, and it improves ensemble and non-linear algorithms because it is simple and fast.

Voting Classifier (LGBM + AdaBoost) with Random Oversampling (ROS): Voting classifiers use a combination of LGBM and AdaBoost with 13 and 7 feature sets, respectively, combining the prediction of multiple models in order to enhance robustness. ROS balances the classes of minorities and the majority and improves sensitivity to rare events. Each base learner has hyperparameters that are highly tuned to ensure that the performance is optimal. This joint method takes the benefits of gradient boosting and adaptive boosting, which effectively represents complex interactions between features without making predictions inconsistent. ROS ensures that there is fair representation of survival and non-survival cases. The combined method provides accurate and reliable classification, which allows for practical clinical application and provides a clear and interpretable framework of decision-making.

$$\hat{y} = argmax_c \left(\sum_{i=1}^{n} II \ (\hat{y}_i = c) \right) \qquad (5)$$

h) Integration of XAI and Flask Framework:

The combination of XAI systems with the Flask platform will enable an open and interactive environment to predict heart failure. The machine learning models based on both 13- and 7-feature sets are examined through the information of LIME and SHAP that explain the influence of various clinical variables on the estimated outcomes. LIME generates localized explanations of individual cases based on intuitive visuals such as waterfall plots but SHAP offers global and feature-specific explanations, which help physicians understand how models behave and make decisions.

The application of interpretable models via Flask framework allows access with a web interface, which allows real-time predictions and interactive analysis of feature relevance. Patient data, predicted probability, and XAI visualization can be easily provided by users and analyzed, thus making the automated decision support systems applicable in practice and more trusted by users.

4. EXPERIMENTAL RESULTS

Accuracy: Accuracy of a test is the ability of a test to differentiate patient and a healthy case correctly. In order to determine the accuracy of a test, it is important to divide the number of true positives and true negatives with all the cases that are assessed. This can be mathematically stated as:

$$Accuracy = \frac{\mathrm{TP} + \mathrm{TN}}{\mathrm{TP} + \mathrm{FP} + \mathrm{TN} + \mathrm{FN}} \quad (6)$$

Precision: Precision measures the percentage of correctly classified cases of those diagnosed to be positive. This leads to the formula of finding the precision as follows:

$$Precision = \frac{\text{True Positive}}{\text{True Positive} + \text{False Positive}} \quad (7)$$

Recall: Recall is a ML metric that can be used to evaluate the ability of a model to identify every relevant instance of a particular class. It is the ratio of correctly predicted positive data to the total actual positives, which provides information about the effectiveness of a model that identifies the occurrence of a particular class.

$$Recall = \frac{\mathrm{TP}}{\mathrm{TP} + \mathrm{FN}} \quad (8)$$

F1-Score: F1 score is used to measure the accuracy of a ML model. It combines precision and recall measures of a model. The accuracy measure is used to measure the frequency of the correct predictions made by a model during the whole dataset.

$$F1\ Score = 2 * \frac{Recall\ X\ Precision}{Recall + Precision} * 100 \quad (9)$$

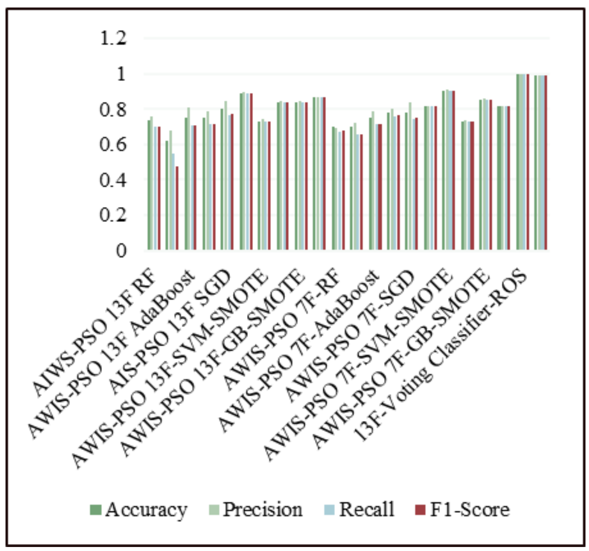
Table.1 Performance Evaluation

ML Model	Accuracy	Precision	Recall	F1-Score
AIWS-PSO 13F RandomForest	0.733	0.756	0.697	0.700
AWIS-PSO 13F SVM	0.617	0.679	0.546	0.477
AWIS-PSO 13F AdaBoost	0.750	0.812	0.706	0.707
AWIS-PSO 13F GradientBoost	0.750	0.787	0.711	0.715
AIS-PSO 13F SGDClassifier	0.800	0.844	0.766	0.775
AWIS-PSO 13F-RandomForest-SMOTE	0.890	0.892	0.890	0.890
AWIS-PSO 13F-SVM-SMOTE	0.732	0.741	0.732	0.729
AWIS-PSO 13F-AdaBoost-SMOTE	0.841	0.843	0.841	0.841
AWIS-PSO 13F-GradientBoost-SMOTE	0.841	0.842	0.841	0.841
AWIS-PSO 13F-SGDClassifier-SMOTE	0.866	0.868	0.866	0.866
AWIS-PSO 7F-RandomFore	0.700	0.696	0.674	0.677

st				
AWIS-PSO 7F-SVM	0.700	0.725	0.657	0.653
AWIS-PSO 7F-AdaBoost	0.750	0.787	0.711	0.715
AWIS-PSO 7F-GradientBoost	0.783	0.798	0.757	0.764
AWIS-PSO 7F-SGDClassifier	0.783	0.834	0.746	0.753
AWIS-PSO 7F-RandomForest-SMOTE	0.817	0.817	0.817	0.817
AWIS-PSO 7F-SVM-SMOTE	0.902	0.911	0.902	0.902
AWIS-SPO 7F-AdaBoost-SMOTE	0.732	0.737	0.732	0.730
AWIS-PSO 7F-GradientBoost-SMOTE	0.854	0.861	0.854	0.853
AWIS-PSO 7F-SGDClassifier-SMOTE	0.817	0.817	0.817	0.817
13F-Voting Classifier-Random Oversampling	**0.995**	**0.995**	**0.995**	**0.995**
7F-Voting Classifier-Random Oversampling	0.990	0.990	0.990	0.990

Table 1 provides a performance analysis, which also contains comparative results of different ML models, indicating the accuracy, precision, recall, and F1-score with resampled and non-resampled settings. Importantly, Voting Classifiers based on ROS demonstrated better predictive efficacy.

Fig 3. Comparison graph



To provide a comparative graph that can show the performance of various ML models regarding accuracy, precision, recall, and F1-score, Figure 3 has been drawn, which shows that ROS-based Voting Classifiers outperform all the other methodologies.

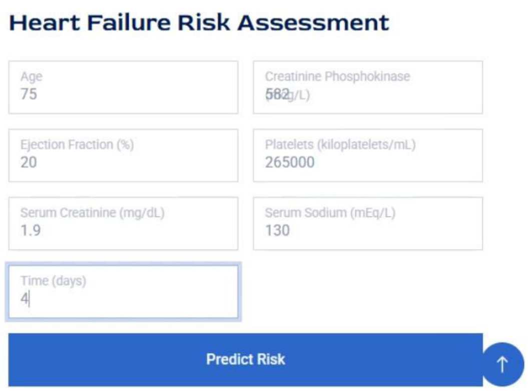


Fig.4 Upload Input Data

Figure 4 shows the upload input interface that allows the user to input patient clinical and demographic data in a structured format, thereby guaranteeing accurate data entry to be used in future prediction and analysis using the trained model.

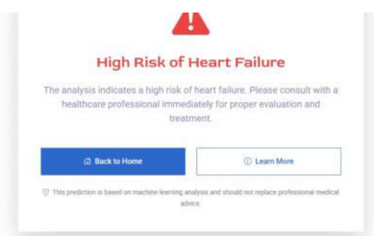


Fig.5 Predicted Results – High Risk of Heart Failure

Figure 5 shows the expected outcome that will be generated in the model process, which shows a High Risk of Heart Failure.

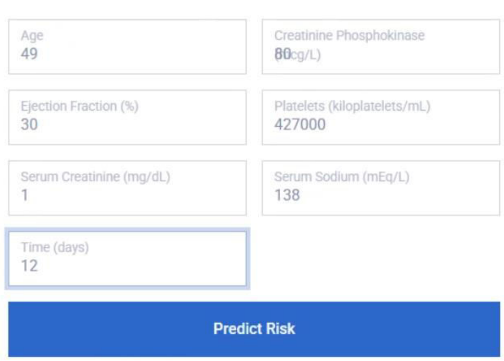


Fig.6 Upload Input Data

Figure 6 is the input interface that enables the user to key in tabulated patient data, therefore, guaranteeing accurate data preparation to make predictions.

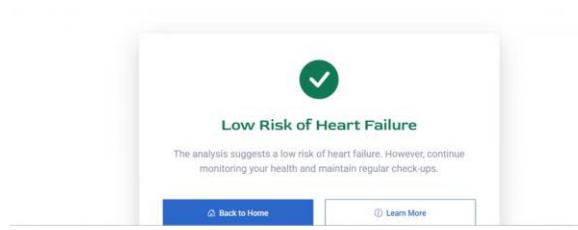


Fig.7 Predicted Results – Low Risk of Heart Failure

One can see the processed prediction result displayed in figure 7, stating that there is a Low Risk of Heart Failure.

5. CONCLUSION

To sum up, ML techniques combined with advanced ML methods and clinical data are able to make accurate and understandable predictions of the outcomes of heart failure. Kaggle Heart Failure Clinical Records dataset was analyzed using the full set of 13 features and a subset of 7 features, and the feature selection was based on Chi-square statistics to increase the predictive accuracy. SMOTE was used to eliminate class imbalance on individual models and ROS on ensemble settings. Several classifiers, including RF, SVM, AdaBoost, Gradient Boosting and Stochastic Gradient Descent, were trained where hyperparameters were optimized using AIW-PSO to enhance accuracy, precision, recall and F1-score. Ensemble Voting Classifiers that combined LGBM and AdaBoost with ROS were more robust and sensitive, whereas explainable AI methods, such as LIME and SHAP, provided transparency in decision-making. The actual implementation of clinical decision support was made through the Flask framework. The ROS-based Voting Classifier (13-feature version) demonstrated a 99.5 per cent accuracy and the 7-feature version (ROS-based Voting Classifier) achieved a 99.0 per cent accuracy, which is indicative of the effectiveness of enhanced ensemble and resampling methods in predicting patient survival with high accuracy.

Future studies can focus on enriching the dataset with larger and more diverse clinical data to increase the model applicability to other populations. More complex DL architectures such as CNNs and RNNs can be applied to learn interactions between features and time in patient records. Predictive accuracy may be improved by integrating multimodal data, like medical imaging, electrocardiograms, and genetic data. Research on ensemble solutions combining optimized classical models and DL methods. Also, decentralized model training through federated learning frameworks will offer safe patient privacy protection in decentralized hospital databases, which will increase the usefulness of the system in real-world health care.

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