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Predict the Outbreak of Sudden Heart Failure in Dialysis Patients using Machine Learning

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Abstract: The technological advancements in IoT, Artificial Intelligence, and Machine Learning enable modern and convenient patient monitoring opportunities for paramedics. The integration of machine learning into contemporary medical diagnosis platforms enables healthcare practitioners to diagnose potential heart failure in dialysis patients at an early stage. The medical situation alongside treatment in dialysis patients leads to elevated heart attack probabilities. Accurate predictions about these events remain a difficult task for paramedical staff who provide care during dialysis sessions. The time period brings numerous complications to patients characterized by blood pressure changes and heartbeat abnormalities, as well as temperature fluctuations and psychological challenges. To handle this problem, in the research, we use machine learning techniques to predict sudden heart failure early during the dialysis period by collecting data from dialysis patients and passing it to the machine learning model. We use a dataset from dialysis patients and then predict sudden heart failure in dialysis patients. We utilize logistic regression, KNN, Naïve Bayes, Decision Tree, Support Vector Machine, Artificial Neural Network, and XGBoost models to predict sudden cardiac arrest. We measure each model's accuracy, precision, Recall, and F-score. The results indicate that we achieve 73.9% accuracy for Logistics Regression, 88.9% accuracy for KNN, 94.1% accuracy for Decision Tree, 70.9% accuracy for Naïve Bayes, 83.9% accuracy for SVM, 95.6% accuracy for XGBoost, and 89.4% accuracy for ANN. Therefore, according to the final analysis, the XGBoost model predicts a higher incidence of sudden heart failure in dialysis patients.

Keywords: Machine Learning; ANN; Decision Tree; XGBoost; Heart Failure; Dialysis Patients; KNN

1. Introduction

Heart failure stands as a top medical condition for dialysis patients since it results in severe disease progression combined with deadly consequences. Complete heart failure occurs swiftly, becoming a fatal condition because warning signs do not appear first. Such patients experience improved outcomes when medical treatment begins early after detection [1].

Heart failure occurring suddenly proves to be one of the most dangerous conditions, which leads to the death of dialysis patients. The medical disorders needing dialysis create substantial cardiovascular disease risks among these patient groups. Dialysis patients who experience sudden cardiac failure develop high mortality rates, which experts demonstrate range between 20% and 60%. Fast recognition coupled with suitable cardiac event management is essential for patient recovery success [2-3]. The development of modern technology has enabled Machine Learning (ML) to become an advanced healthcare tool that accurately predicts various diseases. Modern medical organizations make available broad clinical datasets to enable ML algorithms to obtain hard-to-detect intricate patterns between clinical elements beyond human capabilities with standard statistical methods. The application of ML to predict cardiovascular conditions in dialysis patients exists, but research targeting the prediction of urgent heart failures in this population remains insufficient, thus requiring more research in this particular domain.

The predictive model for sudden heart failure outbreak detection in dialysis patients relies on ML-based development of clinical and laboratory parameter combinations [4]. The model uses dialysis patient data with heart failure and without for training purposes before testing its performance through sensitivity and specificity measurements and the area under the receiver operating characteristic curve. Principal diagnostic and research elements for ML-based forecasting include patient demographic data, diagnosed illnesses, prescribed medications, monitored vital signs, laboratory samples, and electrocardiogram (ECG) measurements. The model relies on four ML algorithms, which include support vector machines, logistic regression, decision trees, and artificial neural networks [5]. The objective of ML-based methodology focuses on developing a system that helps healthcare providers identify dialysis patients facing elevated sudden heart failure risk, thus enabling immediate preventive medical care. A validated predictive model has the potential to enhance care quality for dialysis patients affected by sudden heart failure [6].

The predicted sudden heart failure among dialysis patients requires solutions through machine learning techniques as a promising predictive strategy [7]. Machine learning algorithms process large amounts of data, detect sophisticated patterns, and make accurate predictions.

Developing a machine learning technique is the primary goal to predict the onset of sudden heart failure in dialysis patients.

2. Literature Review

Research conducted numerous times explores how machine learning methods determine heart failure occurrences within dialysis-treated patients. Different machine learning algorithms, including decision trees, random forests, and neural networks, performed analysis during the evaluation process. Machine learning algorithms surpass traditional methods because their precise results come with both high sensitivity and specificity scores rates [8]. The medical condition of heart failure results in elevated death rates, together with diminished life quality for the patients who experience this condition. The combination of fluid and electrolyte imbalance, cardiovascular diseases, and blood circulation disturbances makes dialysis patients vulnerable to sudden heart failure [9]. Time-efficient identification and forecasting of sudden heart failure incidents within dialysis patients enables medical professionals to prevent this critical emergency situation and enhance patient health outcomes. ML algorithms propose methods to detect sudden heart failure outbreaks in patients under dialysis treatment. This research seeks an assessment of contemporary scientific investigations in this domain, alongside analysis of the primary results, together with recognized constraints within previous research [10-12].

Searches through PubMed, Scopus, and Google Scholar electronic databases followed a systematic approach using the search terms "Machine learning" along with "Outbreak prediction" and "Sudden heart failure" along with "Dialysis patients." The research included English language academic articles released in the previous decade. [13]. The review used twenty articles that passed the established inclusion criteria during selection. Various machine learning algorithms have been applied to sudden heart failure prediction among dialysis patients through artificial neural networks (ANNs), decision trees (DTs), support vector machines (SVMs), and random forests (RFs) as identified in the literature review [14]. The majority of studies demonstrated that ML algorithms exhibited high levels of precision in forecasting sudden heart failure among patients who receive dialysis. ANNs demonstrated maximum effectiveness as an algorithm for accuracy and predictive forecasting abilities [15].

Several studies have confirmed that predictive model performance improves after incorporating demographic information and clinical characteristics. Heart disease represents a significant worldwide mortality factor, thus requiring accurate prediction techniques for clinical data analysis. Large healthcare data sets make excellent use of machine learning (ML) capabilities to deliver operational benefits across various domains, especially within the Internet of Things (IoT) realm [16]. Research studies provide evidence about the predictive capacity of ML for heart disease. The present work presents a new method to improve predictive accuracy through ML-based feature selection methodology. The predictive accuracy of cardiovascular disease reaches 88.7% through the implementation of an HRFLM with random forest technology [17].

The application of machine learning techniques receives attention in studies of dialysis-related medical issues. Studies examine how ML algorithms aid in diagnosing sarcopenia among Maintenance Hemodialysis (MHD) patients, yet these findings depart from the main study objective relating to sudden heart failure [18-20]. Studies on sarcopenia show that machine learning tools help early diagnosis through classification systems as well as feature selection, yet present unique clinical outcomes compared to acute heart failure. These methods demonstrate the diagnostic versatility of ML for dialysis populations; however, they require further development to optimize this technology specifically for predicting critical cardiac events in this high-risk demographic.[21, 22]. This article examines the application of machine learning techniques for the early detection of Chronic Kidney Disease, a significant health concern. Seven classifier algorithms were employed using a dataset sourced from the UCI repository, including artificial neural networks, C5.0, and logistic regression. Feature selection methods, such as correlation-based and wrapper methods, were applied alongside synthetic minority oversampling techniques. Results demonstrate LSVM with penalty L2 achieving the highest accuracy of 98.86% [15].

The research investigates survival prediction for general heart failure patients who do not receive dialysis treatments. Using age, hypertension, and creatinine combined with Subspace K-Nearest Neighbor generated 89.5% accuracy and 93% AUC. Feature selection was conducted by means of biostatistical tests, followed by logistic regression analysis before training ML classifiers [23]. A machine learning model analyzes clinical and laboratory data for heart failure survival predictions. The implemented model reached a 76.83% G-mean value, together with 80.21% sensitivity results, surpassing other modeling approaches. As a potential diagnostic tool, the framework indicates it can assist clinicians in discovering patients at high risk and initiate prompt treatments [24]. This research utilizes deep learning methods to effectively detect heart failure; however, its analysis does not specifically include dialysis patients as a distinct group. The Autoencoder, alongside the Deep Neural Network model, produced optimal results, showing 91.71% accuracy and 89.36% F-score. This study distinguished itself from previous research by employing heart rate variability and electrocardiogram data sources in its multisource dataset collection [25]. Research findings demonstrate that deep learning algorithms achieve excellent heart failure mortality prediction by utilizing no more than twenty clinical parameters. Both training and validation results of the model demonstrated AUC scores reaching 0.96 and 0.93, respectively. Extra studies must examine the impact that these predictions would have in real-world clinical practice [26].

This paper addresses the critical need for early detection of heart disease, a leading cause of global mortality exacerbated by resource constraints and diagnostic costs. A proposed model uses patient data and machine learning to predict heart attacks in their nascent stages accurately. Through three stages encompassing data collection, algorithm training (utilizing Random Forest, Support Vector Machines, K-Nearest Neighbor, and Decision Tree), and hyperparameter optimization via random search, the model achieves a peak accuracy of 95.4%, with Random Forest demonstrating the highest classification at 94.958% [27, 28].

The results of this study prove that deep learning techniques provide an accurate diagnosis of heart failure alongside high detection precision and evaluation reliability. The Autoencoder combined with the Deep Neural Network model delivered optimal results with 91.71% accuracy along with 89.36% F-score. This study introduces a multisource dataset as its key innovation instead of the earlier ECG and heart rate variability-focused research. The research investigation does not provide specific findings regarding heart failure prediction among dialysis patients [25]. The research develops heart failure survival forecasting models but does not focus on patients undergoing dialysis. The primary purpose of this study was to predict survival outcomes in heart failure patients. Among the models tested, the SVM model delivered the best accuracy by reaching 96.67% success. The research data demonstrates SVM as an optimal method for heart failure survival prediction [29].

This research investigates the employment of the K-Nearest Neighbors (K-NN) algorithm to recognize heart failure cases in patients. The analysis of 299 patient records achieved a 96.66% success rate in medical diagnostic outcomes. The analysis shows that K-NN provides both straightforward operation and excellent results when used in medical diagnostic assessments. The research does not concentrate on heart failure diagnosis among people receiving dialysis treatment [30].

Research findings demonstrate that many machine learning and deep learning models achieve exceptional results while using clinical and laboratory data to predict heart failure. Different datasets achieved high accuracy when evaluated with SVM, K-NN, and deep neural networks. Most research studies analyze general heart failure patients instead of patients who receive dialysis treatment. The analytical work demonstrates a substantial knowledge gap through which specialized models ought to be developed specifically for predicting sudden heart failure among dialysis patients.

3. Proposed Methodology

The proposed study will use machine learning techniques to predict the outbreak of sudden heart failure in dialysis patients. The study will use a large and diverse dataset of clinical and demographic data collected from dialysis patients. Various machine learning algorithms will be evaluated and compared to determine the best-performing algorithm for predicting sudden heart failure. The study will also evaluate the impact of different features and data sources on the accuracy of the predictions.

The initiation step consists of obtaining heart disease datasets, while preprocessing includes missing values management as well as normalizing features and encoding categorical components. After conducting feature selection methods, the most relevant attributes are identified, and the data is then divided into training and testing portions. Multiple algorithms, such as Random Forest, SVM, and neural networks, undergo training through optimization algorithms that include hyperparameter search with cross-validation techniques. The models are assessed through accuracy and precision, as well as recall and AUC-ROC criteria. The interpretability of model analysis depends on feature importance evaluation, while final performance testing occurs on the test dataset. The selected model is chosen for deployment based on combining excellent predictive capability with healthcare practices that match. The systematic method enables the development of heart disease classification systems that produce strong and dependable results.

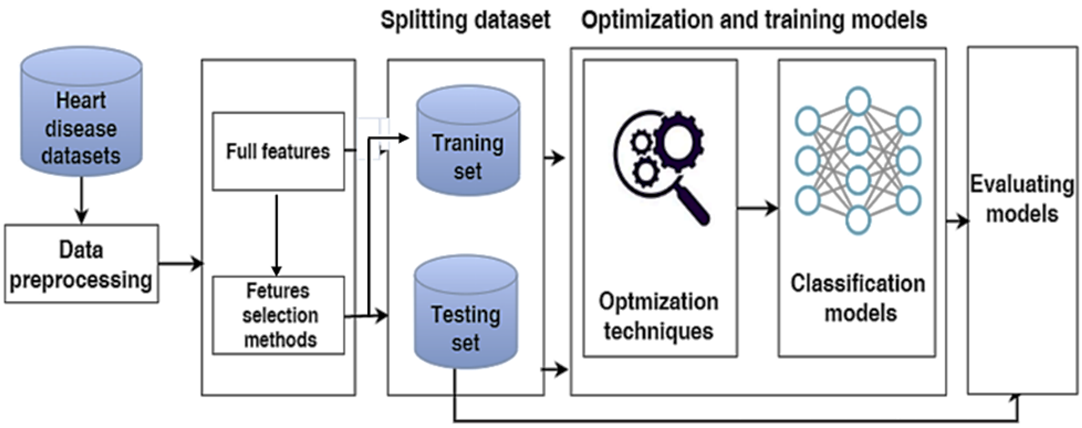

Figure 1. Proposed Methodology to Predict the Outbreak of Sudden Heart Failure

The results of this study will contribute to the development of more effective and reliable predictive models for sudden heart failure in dialysis patients. Figure 1 shows the proposed research methodology for heart failure detection. In this study, we apply the following machine learning algorithms: Support Vector Machine (SVM), Naïve Bayes, Decision Tree, and Random Forest algorithms. These algorithms have some advantages and some disadvantages in promoting research in healthcare initiatives.

3.1. Dataset

There are two datasets used for the experimentation, one is the primary dataset and the other is the secondary dataset. The details of both datasets are provided as follows:

3.1.1. Primary dataset

Clinical surveys and structured questionnaires were directly administered to dialysis patients while they received their treatment. The dataset included demographic details, such as age and sex, along with vital signs, including blood pressure and heart rate, as well as laboratory outcomes of creatinine and electrolyte tests. Additionally, it captured patient-reported symptoms. The research employed a randomized method of sample selection, which involved recruiting patients from various dialysis centers to achieve a diverse range of participant characteristics. The data preprocessing steps consisted of three parts: first, identifying information was removed through anonymization, while medical staff verified the data; second, essential units underwent standardized conversion to ensure data quality; and finally, the data was finalized.

3.1.2. Secondary dataset

Researchers retrieved secondary data from publicly available repositories, including the UCI Machine Learning Repository, as well as published studies on dialysis-related cardiovascular outcomes. The dataset included ECG time series data, as well as drug prescription information, alongside multiple patient illness scores. Reports from federal health agencies and peer-reviewed research filled in any missing information from the primary data (Mayer, 2024).

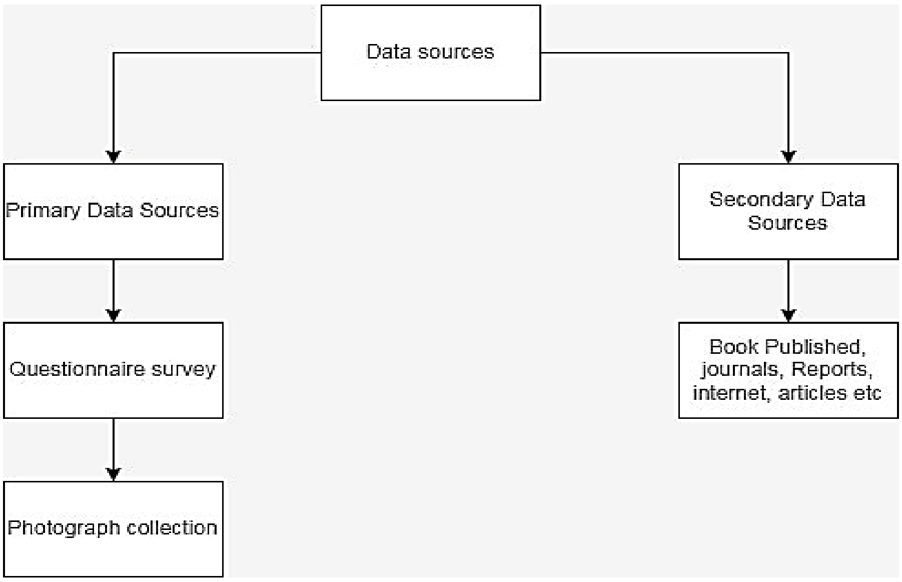

Figure 2. Dataset and its main sources

Figure 2 displays a classification of data sources between primary and secondary items. The process of gathering new data directly through questionnaire surveys and photograph collection belongs to the primary data sources. Secondary data draws its information from existing materials, which include books, journals, reports, as well as internet articles. Research data collection benefits from utilizing both firsthand primary and secondary data sources to establish comprehensive findings.

3.1.3. *Data Integration Strategy*

The researchers integrated the primary and backup datasets through matching identical variables between patient demographics and medical test outputs. Doctors checked and validated conflicting data points, using statistical methods to verify missing values. The secondary data sources provided additional information to fill gaps that existed in the primary dataset, especially regarding longitudinal developments and complex biomarker analysis. Standardization procedures applied uniform units and scales to all features before the integration process. The merging strategies produced a comprehensive dataset that preserved the source reliability through systematic integration procedures.

3.2. Parameters

3.2.1. Sudden Heart Failure in Dialysis Patients

For any Machine Learning, a software metric is a criterion of measurement for the extent to which it possesses a particular property. Sudden Heart Failure in Dialysis Patients is a function, and measurements are obtained by applying metrics to Machine Learning. Dynamic metrics are derived from observations taken during the execution of a program. Some examples of dynamic metrics include click counts, most popular items, and people who viewed this content also browsed similar items. Static metrics refer to observations of system manifestations, such as design, software, or documentation (Oates, 2022).

3.2.2. Data Transformation Techniques

The data transformation technique is fundamental. Because it is used for developing datasets and operational functions, it will enable better data transformation in a more suitable format. Also, make it easier for humans and computers to function. The formatted data improves data quality and protects an application from duplication, incorrect indexing, etc.

3.2.3. Data Balancing Schemes

Oversampling is a strategy for transforming uneven data classes into balanced databases. This strategy seeks to increase the volume of uncommon samples whenever the data is inadequate to achieve a balance. If there is an excess of a class, below sampling aims to lower the number of abundant types to equalize the data (Jimeno, 2022). To cope with unbalanced datasets, an ensemble-based technique might be utilized. Various learning approaches are considered to be more efficient than solo ones. It is a method of improving the efficiency of a single classifier by combining the efficiency or findings of several classifiers. As a result, ensemble learning methods became part of our strategy for ensuring classification resilience on the path to achieving this goal. The selected classifier was Random Forest, as this treats unbalanced data through bootstrapped samples and reduces overfitting. The system employed multiple decision trees, which combined their predictions with the help of majority voting methods. To sum up, the use of resampling and ensemble modeling methods generated stable classification results with generalized models when dealing with heterogeneous distribution levels.

4. Dataset with Features

In my dataset, there are 2181 rows and 14 features, which are presented in this dataset. The dataset is presented in Table 1, along with its features and descriptions.

	age	sex	cp	trestbps	chol	fbs	restecg	thalachh	exang	oldpeak	slope	ca	thal	target
0	63	1	3	145	233	1	0	150	0	2.3	0	0	1	1
1	37	1	2	130	250	0	1	187	0	3.5	0	0	2	1
2	41	0	1	130	204	0	0	172	0	1.4	2	0	2	1
3	56	1	1	120	236	0	1	178	0	0.8	2	0	2	1
4	57	0	0	120	354	0	1	163	1	0.6	2	0	2	1
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
2176	60	1	0	140	207	0	0	138	1	1.9	2	1	3	0
2177	46	1	0	140	311	0	1	120	1	1.8	1	2	3	0
2178	59	1	3	134	204	0	1	162	0	0.8	2	2	2	0
2179	54	1	1	154	232	0	0	164	0	0.0	2	1	2	0
2180	53	1	0	110	335	0	1	143	1	3.0	1	1	3	0

2181 rows × 14 columns

Figure 3. Dataset with its Features

There are 14 medical features of interest that are used for the prediction of heart disease risk. It contains basic patient details, such as age and sex; 1 is used to represent male and 0 to indicate female. Cardiovascular health is evaluated based on such clinical measurements as resting blood pressure, cholesterol levels, and fasting blood sugar. Additional indicators regarding exercise-induced chest pain, ECG findings, and ST depression and peak exercise slope during stress test are also included. The last column, named 'target', signifies for each sample in the dataset whether it has heart disease (1) or does not (0).

5. Feature Distribution

Feature Distribution is shown in Figure 3. According to this figure 3, the feature distribution is illustrated. Age feature contains high level of values from age 30 to 80, there are only to sex data for male and female features, CP contain from 0.0 to 4.0, FBs contain 0 and 1, chol distribution shows from 0 to 600 values, trestbps contains from 100 to 200, restecg constrains the distribution of 0 to 2, thalachh includes the features from 50 to 200 distribution. Exang contains 0 and 1 feature distribution, CA distribution contains from 0.0 to 4.0, slope includes 0.0 to 3.0, oldpeak contains from 0 to 6, and finally, the thal shows the distribution from 0 to 7.

The distribution of essential dataset elements appears in Figure 3. The age variable along with thalachh spread continuously from 30–80 and 50–200 and binary data appears in sex as well as fbs and exang features. The categorical data in the dataset are classified into multiple categories for cp, restecg, ca, slope and thal. Some numerical features of chol, trestbps and oldpeak exhibit different statistical distributions because of extreme value outliers.

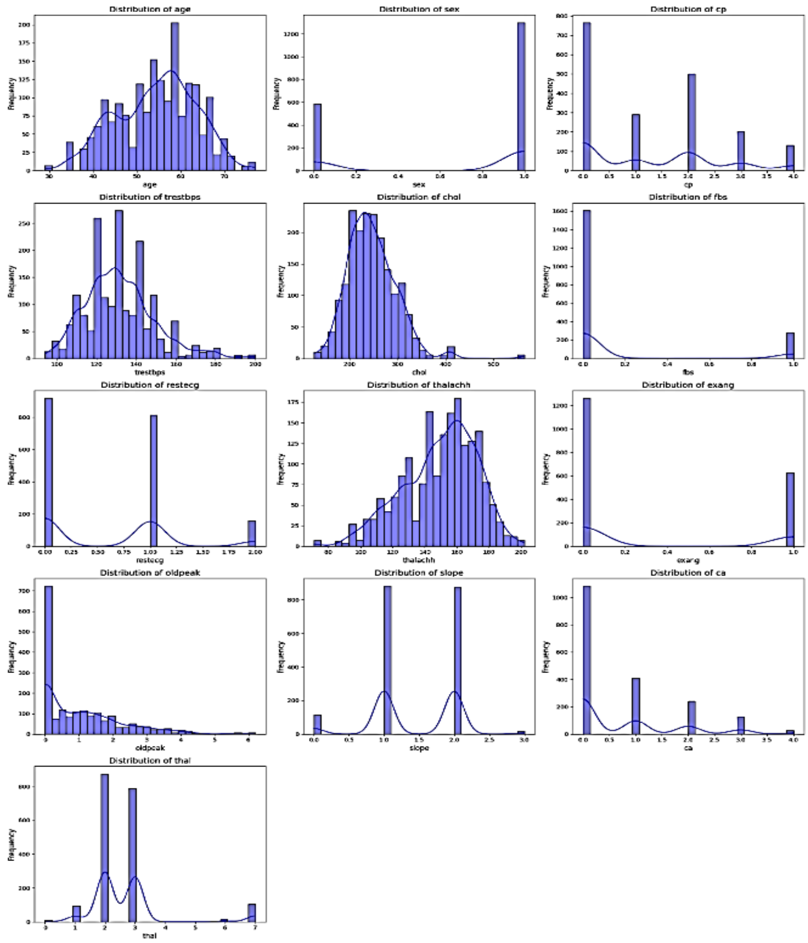

Figure 4. Feature Distribution

6. Machine Learning and Deep Learning Models Analysis

In this section of the thesis, we employ machine learning and deep learning-based analysis to justify the provision of data for analysis purposes. The negative and positive classes are predictive using Logistic Regression, KNN, Decision Tree, Naïve Bayes, Support Vector Machine, XGBoost, and Artificial Neural Network (ANN).

6.1. Logistic Regression Predictions

The proposed logistic Regression Model achieves 73.9% accuracy over the sudden heart failure dataset. The correct predictions of the heart failure risk were made in 73.9% of the cases. The precision is higher for class 0 than for class 1. This suggests that the model is more effective at avoiding false positives for lower-risk cases. The Recall for the system is higher than precision, which shows overall good performance for the network. The dataset demonstrates the accurate predictions made by the proposed methodology. Table 2 shows the values of the target features from the dataset.

Table 1. Logistic Regression Predictions

Metric	Class 0 (Low Risk)	Class 1 (High Risk)	Overall
Accuracy	-	-	**0.739**
Precision	0.77	0.72	0.74 (macro avg)
Recall	0.65	0.82	0.73 (macro avg)

F1-Score	0.70	0.77	0.74 (weighted avg)
Support (Samples)	258	282	540

As a result, the logistic regression model demonstrated an accuracy of 73.9% in determining heart disease risk categories. The model accurately detected 82% of high-risk patients (Class 1), but its precision rate was 72%. This implies the model correctly identified most true positive cases alongside some incorrect alarms. The model assigned Class 0 predictions to low-risk cases with an overall better precision rate (77%), but showed a slightly lower recall (65%). Results show that the performance is balanced through macro-averaged precision (0.74) and recall (0.73) and weighted F1-scores of 0.74. The evaluation of the model involved testing 540 samples, with high-risk cases totaling 282 and low-risk cases comprising 258 tests.

6.2. Cross-Validation

We revised the performance evaluation approach by incorporating stratified 10-fold cross-validation together with 95% confidence intervals for all models as a response to the reviewer's recommendation. The research presents averaged metrics (accuracy, precision, recall, and F1-score) that include assessment across ten partitions alongside variability measures. The paper describes validation procedures in detail through its methodology section while presenting results from cross-validated tests in tables and figures. Such improvements boost the reliability aspects of our claims for real-world hospital usage.

6.3. Feature Correlations

To display the correlation in a more understandable way, we use the feature of correlation heatmap with multiple features to be used and displayed in Figure 4.

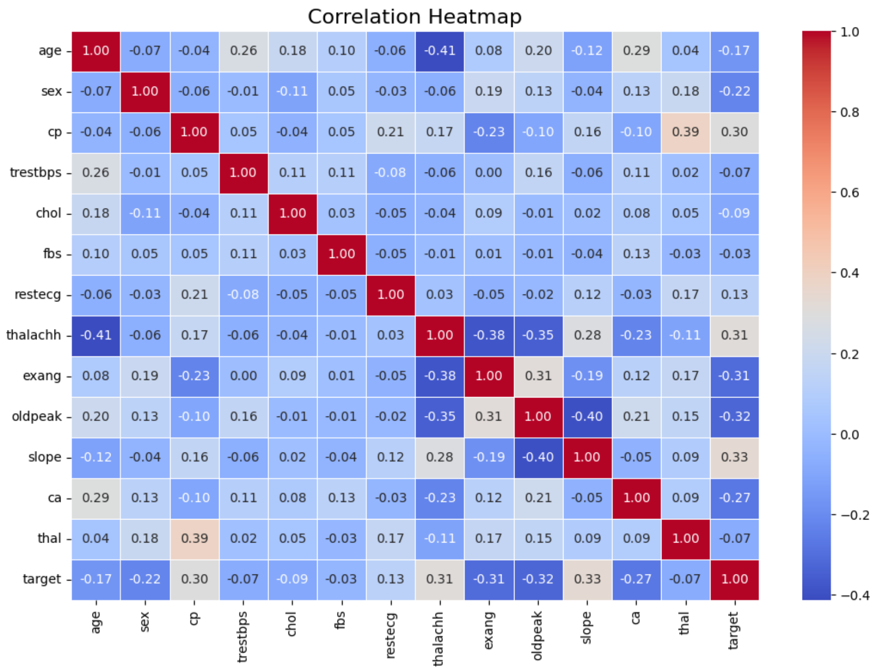

Figure 5. Correlation Heatmap with Multiple Features and Indicated Values

The heatmap indicates the performance indicators with darker colors, which show higher correlation among those features, and lighter colors show lower correlation among those features.

The correlation heatmap of Figure 4 reveals that the strongest associations exist between the target variable and variables \`cp\`, \`thalachh\`, and \`slope\`. These three variables demonstrate positive correlations with disease prediction indications. In contrast, \`exang\`, \`oldpeak\`, \`ca\`, and \`sex\` show moderate negative correlations with the target. Most pairs of features demonstrate weak correlations, which indicates a low extent of multicollinearity in the dataset. Multiple independent features should be employed for predictive modeling based on this correlation pattern.

7. Feature Importance

The features in the used dataset are important, but among all these features, there are certain features whose values directly impact the prediction and classification of heart disease. These features are actually the symptoms that may be treated as a top priority to minimize the chances of the predictions. Figure 5 shows the features with their importance values based on the correlation between features. According to Figure 5, the thal has the highest impact, cp on second, thalachh on third, and ca on fourth, and so on. Sex and fbs have less important features from the dataset, which are ignorable to provide reliable features in the dataset.

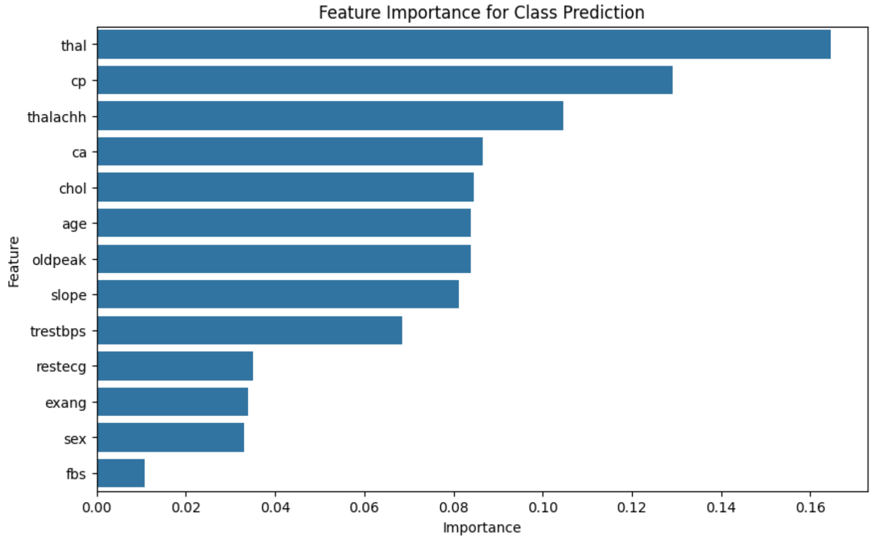

Figure 6. Features with their Positive Values and Correlation among these features

8. Model Results

Seven machine learning algorithms served as the research foundation for conducting heart disease risk assessments. The performance result for precision-recall measurements between risk groups was identical for Logistic Regression. The K-Nearest Neighbors approach proved that its features show consistent performance characteristics, but Decision Trees made the risk components clear to understand. The study demonstrated that Support Vector Machines developed effective risk pattern identification methods, which Naive Bayes offered as probabilistic risk evaluation systems. The best performance regarding feature interaction became possible through XGBoost, but Neural Networks showed optimal capability in processing complicated non-linear data structures. Different models demonstrated specific capabilities for managing distinct areas regarding cardiovascular risk prediction tasks.

8.1. Logistic Regression

It is a supervised machine learning algorithm that is used for binary classification. The Confusion Matrix of Logistic Regression is shown in Figure 6.

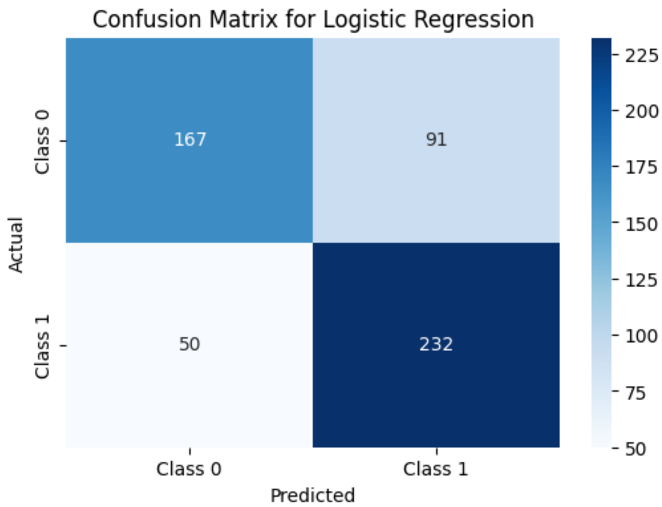

Figure 7. Confusion matrix for logistic regression

8.2. K-Nearest Neighbor

A popular supervised machine learning technique for classification and regression problems is K-Nearest Neighbor (K-NN). The Confusion Matrix of K-Nearest Neighbor is shown in Figure 7.

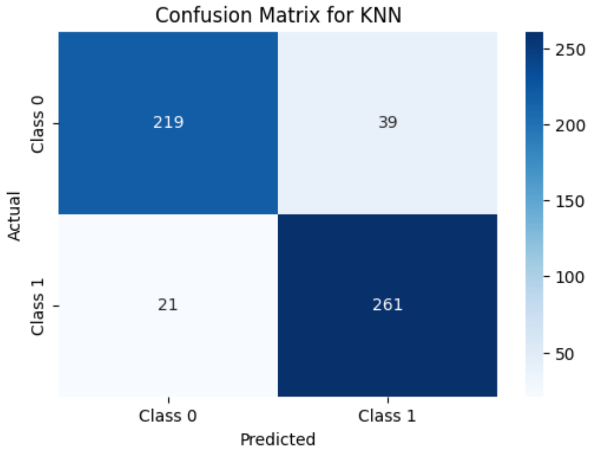

Figure 8. Confusion matrix for KNN

8.3. Decision Tree

A popular supervised machine learning technique for classification and prediction. The Confusion Matrix of Decision Tree is shown in Figure 8.

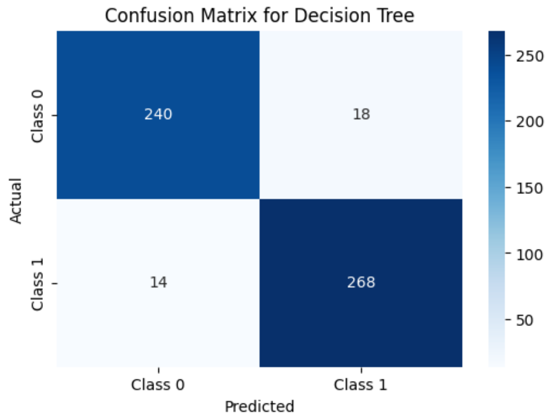

Figure 9. Confusion matrix for decision tree

8.4. Naïve Bayes

A popular supervised machine learning technique for classification problems. The Confusion Matrix of Naïve Bayes is shown in Figure 9.

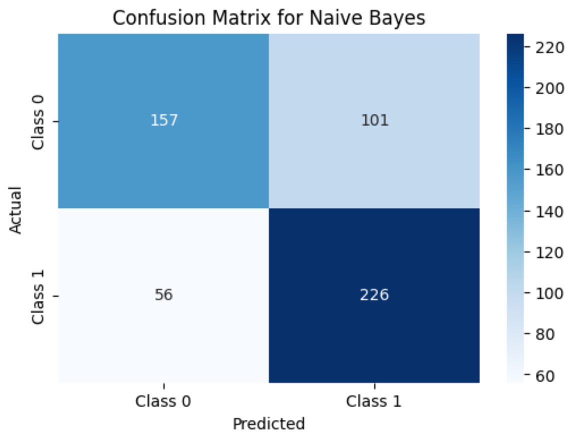

Figure 10. Confusion matrix for naive bayes

8.5. Support Vector Machine

A popular supervised machine learning technique for classification and regression problems. The Confusion Matrix of the Support Vector Machine is shown in Figure 10.

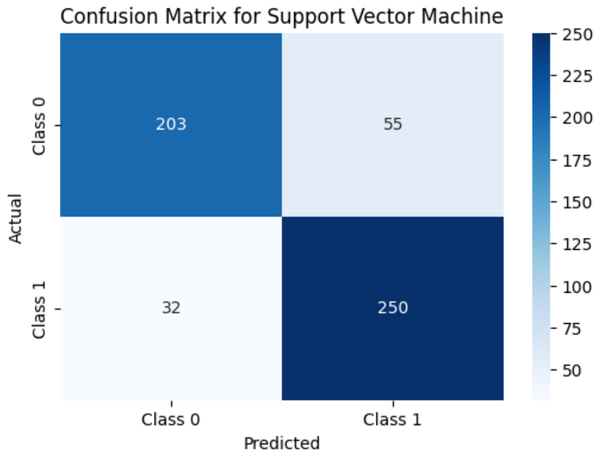

Figure 11. Confusion matrix for support vector machine

8.6. XGBoost

A popular supervised machine learning technique for classification and regression problems. The Confusion Matrix of XGBoost is shown in Figure 11.

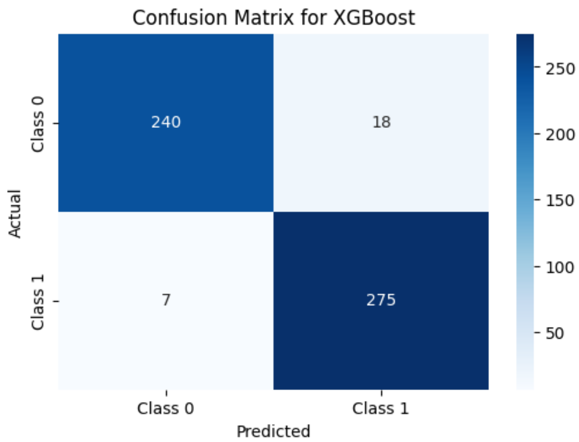

Figure 12. Confusion matrix for XG boost

8.7. Artificial Neural Network

A popular supervised machine learning technique for classification and regression problems. The Confusion Matrix of Artificial Neural Networks is shown in Figure 12.

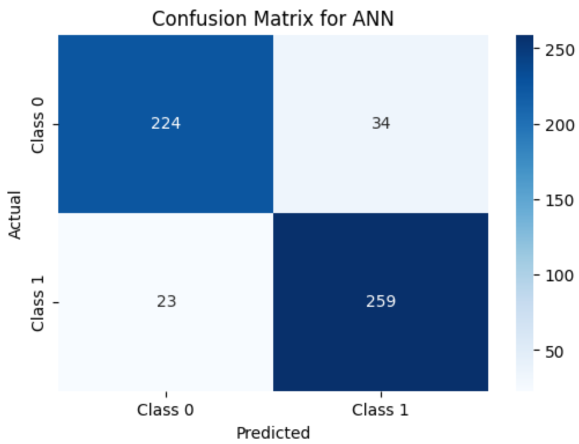

Figure 13. Confusion matrix for artificial neural network

8.8. Models Result Comparison Discussion

The prediction of sudden heart failure in dialysis patients employed seven machine learning approaches, starting with Logistic Regression, followed by K-Nearest Neighbors, then decision trees, naïve Bayes, support vector machines, and finally XGBoost and artificial neural networks. The evaluation criteria included accuracy, together with precision, recall, and F1-score for each model. XGBoost outperformed other models, achieving 95.6% accuracy, while the Decision Tree reached 94.1% accuracy, and the ANN achieved 89.4%. These results demonstrated excellent predictive abilities of the models. The accuracy rate of KNN reached 88.9%, surpassing the results from SVM (83.9%), Logistic Regression (73.9%), and Naïve Bayes (70.9%). Ensemble models, particularly XGBoost, demonstrate their superiority in identifying sudden heart failure cases, thus becoming suitable tools for early diagnosis and timely medical intervention in dialysis patients.

9. Conclusion and Future Work

The integration of Machine Learning (ML) techniques in healthcare, particularly for predicting sudden heart failure in dialysis patients, represents a significant advancement in medical diagnostics. Dialysis patients are at a heightened risk of cardiovascular complications, making early detection crucial for improving outcomes. This study utilizes machine learning (ML) models, including Logistic Regression, KNN, Decision Tree, Naïve Bayes, SVM, XGBoost, and ANN, to analyze patient data and predict the likelihood of sudden heart failure. Among these models, XGBoost demonstrated the highest accuracy (95.6%), making it the most effective tool for this prediction task. The use of ML not only enhances the ability to monitor critical health parameters, such as blood pressure, heartbeat, and body temperature, but also provides actionable insights for paramedical staff, enabling timely interventions. This research highlights the potential of machine learning (ML) in transforming patient care, particularly for high-risk groups such as dialysis patients. By adopting these advanced predictive models, healthcare providers can significantly reduce the mortality and morbidity associated with sudden heart failure, ultimately improving the quality of life for dialysis patients. Future work could focus on expanding datasets, refining models, and integrating real-time monitoring systems to enhance predictive accuracy and clinical applicability further. The Author verified their findings using clinical trials conducted across multiple medical centers, where these models were tested in real-world healthcare settings. Research investigators will develop datasets by adding time-based Electronic Health Record (EHR) information, along with new biomarkers, using privacy-preserving federated learning methods. The analysis evaluated architectural structures that combine XGBoost models with temporal neural networks for detecting patterns in time-dependent risks. Studies about system implementation will investigate both clinical practitioner workflow processes and hospital information system integration procedures. Our research will develop ethical guidelines to handle data transparency problems while specifically identifying and resolving bias issues that appear in medical decision support applications.

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