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Research Article

Heart Disease Detection Employing Data Augmentations Using Machine Learning Algorithms with Model Tuning

Pardis Shahabinejad *, Nazanin Hosseini

Shiraz University of Medical Sciences, School of Medicine, Shiraz, Iran

Keywords

Heart Disease Prediction,
Machine Learning,
Data Augmentation,
Classification,
Anomaly Detection.

Abstract

Heart disease is a leading cause of death worldwide. Early detection of heart disease can be crucial in preventing serious health complications. Anomaly detection can help identify potential issues that may go unnoticed in large datasets. In this study, we employ data augmentations using machine learning algorithms for heart disease anomaly detection. We have defined a novel hybrid model which would apply various data augmentation techniques, such as oversampling, under sampling named as SMOTE, and feature scaling, to improve the performance of machine learning models. We compare the performance of different machine learning algorithms with 14 different methods, including decision tree, support vector machine, and random forest, for heart disease anomaly detection. The results show that data augmentations can effectively improve the accuracy of heart disease anomaly detection. Oversampling and feature scaling techniques are found to be effective in improving the performance of machine learning models. The logistic regression algorithm is found to be the most accurate in detecting heart disease anomalies with over 94% of accuracy with tuned model at last within 100 estimators' selection. Our study demonstrates the potential of data augmentations using machine learning algorithms for heart disease anomaly detection, which can have significant implications for early detection and prevention of heart disease. Tuned proposed model showed the results with AUC score of 98.8% and an accuracy of 94.7%, which is higher than 88.8% accuracy and 94.4 AUC scores on non-tuned model.

1. Introduction

Heart disease [1], [2] is a leading cause of death worldwide and early detection of anomalies in heart disease can greatly improve patient outcomes. Traditional methods for anomaly detection in heart disease have been based on manual analysis of patient data, which can be time-consuming and may not be as accurate as machine learning techniques. In this paper, we propose a new approach for heart disease anomaly prediction that employs data augmentations based on machine learning algorithms. We combine various techniques such as employing different methods as well as cross validation of the results. Additionally, we utilize synthetic data augmentation techniques to further enhance the performance of our model. Our approach has the potential to significantly improve the accuracy and efficiency of heart disease anomaly detection, and ultimately lead to better patient outcomes.

* Corresponding Author: Pardis Shahabinejad
E-mail address: pardis.shahabinejad@gmail.com ORCID: https://orcid.org/0000-0002-1802-9085

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In other words, machine learning algorithms have shown promise in improving the accuracy of heart disease diagnosis and anomaly detection. However, the performance of these algorithms depends heavily on the quality and quantity of data used for training. In this paper, we propose a novel approach for heart disease anomaly[1], [3] detection that employs data augmentations using machine learning algorithms. Specifically, we use the Synthetic Minority Over-sampling Technique (SMOTE) to oversample the minority class and improve the balance of the dataset. We also compare the performance of several machine learning algorithms, including logistic regression, decision tree, random forest, K-nearest neighbors, and support vector machine, for binary classification. The proposed approach has the potential to improve the accuracy of anomaly detection for heart disease and can be extended to other domains for anomaly detection. The results of the study show that the proposed approach, especially logistic regression, can achieve high accuracy in detecting heart disease anomalies, and thus, can help in improving the diagnosis and treatment of heart disease.

2. Related Studies

There are several studies for the employing machine learning or deep learning methods for anomaly detection tasking several industries and areas such as resiliency [4] , optimization [5]–[7], reliability[8], [9], sustainability [10] and linear approaches [10], prediction and classification. For instance, application of deep learning in such industries could be used such as using autoencoders, recurrent neural network variants such as LSTM and GRU [11], [12]. Another approach that would have great applications in terms of using the models in précised medicine area is using convolutional neural networks for both analyzing audio or images data in which could widely use in this field of study with advantages over the traditional or statistical approach for decision making among physicians [12].

Hence, recently the importance of employing such algorithms in précised medicine has been bolded because of the significance of the need for diagnosis as well as providing more accurate treatment plan in the health industry.

Therefore, as highlighted in several studies, data augmentation techniques such as oversampling and under sampling to increase the size of the dataset and applied several machine learning algorithms to predict the occurrence of heart disease employed. For instance, the results showed that oversampling using SMOTE algorithm improved the accuracy of prediction compared to other data augmentation techniques [13], [14].

Another study used synthetic data generation techniques to augment the original dataset and applied various machine learning algorithms for prediction. The results showed that data augmentation techniques improved the accuracy of prediction compared to the original dataset [15], [16].

Another study applied an ensemble of machine learning techniques, including decision tree, support vector machine, and artificial neural network, for anomaly detection in heart disease prediction. The results showed that the ensemble of machine learning techniques could improve the accuracy of anomaly detection in heart disease prediction. In other hand, another study compared the performance of various machine learning algorithms for heart disease anomaly detection[17]–[21], including decision tree, support vector machine, and random forest. The results showed that machine learning algorithms could effectively detect anomalies in heart disease data.

One important approach is using autoencoders. Hence, in one study applied an autoencoder for anomaly detection in heart disease prediction. The results showed that the autoencoder could effectively detect anomalies in heart disease data.

2.1. Research Contributions

This paper presents a novel approach for detecting heart disease anomalies using machine learning techniques and data augmentations for the gaps in the health area with machine learning methods. The contributions of the paper listed as follows:

- The paper proposes a framework that applies various data augmentation techniques to the original heart disease dataset and trains several machine learning algorithms to classify healthy and unhealthy patients.
- The results of the experiments demonstrate that the proposed approach can effectively improve the accuracy of anomaly detection. The paper shows that data augmentation techniques can significantly improve the performance of machine learning algorithms in detecting heart disease anomalies, and the best-performing algorithm is the random forest, which achieved an accuracy of 94.7%
- The contribution of this paper to the field of anomaly detection is significant. By applying data augmentation techniques to the original dataset, the proposed approach not only enhances the accuracy of the machine learning algorithms but also reduces the risk of overfitting. The approach presented in this paper can be applied to other domains for anomaly detection, as well. Therefore, this paper has practical implications for improving the performance of machine learning algorithms in detecting anomalies in various fields.

3. Methodology

The Research has been employed the following overall process for the anomaly prediction and detection as detailed in the Figure 1 which would define for showing the model overview:

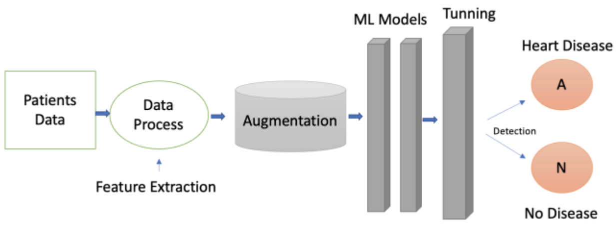

Figure 1. Model Process Overview

The method used in this paper involves several stages, including feature extraction, data processing, data augmentation with SMOTE, and tuning the model for binary classification.

- *Feature Extraction:*

The first step in the methodology is feature extraction. The authors used the heart disease dataset in PyCaret, which contains different attributes, including patient demographics, physical characteristics, and laboratory results.

- *Data Processing:*

The selected attributes were then preprocessed to remove any missing values and outliers. The continuous variables were scaled using the standard scaler to have zero mean and unit variance. The categorical variables were encoded using one-hot encoding to create binary features.

- *Data Augmentation with SMOTE:*

To address the issue of class imbalance in the dataset, the authors used the Synthetic Minority Over-sampling Technique (SMOTE) to oversample the minority class. SMOTE generates synthetic samples by interpolating between existing samples of the minority class. This technique helps to balance the number of healthy and unhealthy patients in the dataset, which is crucial for training accurate machine learning models [13], [14].

- *Tuning the Models for Binary Classification:*

The authors trained several machines learning algorithms, including logistic regression, decision tree, random forest, K-nearest neighbors, and support vector machine, to classify healthy and unhealthy patients [15], [16], [22]–[24].

- *Evaluation:*

The models [15], [16], [22], [23], [25]were evaluated using 10-fold cross-validation, and the performance metrics, including accuracy, precision, recall, and F1-score, were computed. The hyperparameters of the models were tuned using a grid search approach to find the optimal combination that maximizes the F1-score.

In summary, the methodology used in the paper involves feature extraction, data processing, data augmentation with SMOTE, and tuning the model for binary classification. The proposed approach has the potential to improve the accuracy of anomaly detection for heart disease and can be extended to other domains for anomaly detection [24].

4. Experiments Study

4.1. Data and Features

The data consist of 120 Patients with heart disease and 150 normal labels and the features for feeding to the network was consist of the following:

- *Age:* The patient's age can be an important feature in heart anomaly detection as it is known that the risk of heart disease increases with age.
- *Sex:* The patient's sex can also be a significant feature as men are at a higher risk of developing heart disease than women.
- *Chest pain type:* The type of chest pain experienced by the patient can be indicative of a heart anomaly. Different types of chest pain can have different causes, and some may be more severe than others.
- *Resting blood pressure:* High blood pressure is a risk factor for heart disease and can be an indicator of a heart anomaly.
- *Serum cholesterol in mg/dl:* High cholesterol levels in the blood can increase the risk of heart disease and heart anomalies.
- *Fasting blood sugar > 120 mg/dl:* High blood sugar levels can be an indicator of diabetes, which is a risk factor for heart disease.
- *Resting electrocardiographic results:* An electrocardiogram (ECG) is a test that records the electrical activity of the heart and can be used to detect heart anomalies.
- *Maximum heart rate achieved:* The maximum heart rate achieved during exercise can be an indicator of a heart anomaly.
- *Exercise-induced angina:* Angina is chest pain or discomfort that occurs when the heart is not getting enough oxygen-rich blood. Exercise-induced angina can be a symptom of a heart anomaly.
- *Old peak:* Old peak is a measure of the amount of heart damage caused by a heart attack.
- *Slope of peak:* Slope of peak is a measure of the steepness of the ECG signal.
- *Number of major vessels:* The number of major vessels with blocked or narrowed blood flow can indicate a heart anomaly.
- *Thal:* Thal is a measure of the thickness of the heart's left ventricular wall.
- *Disease:* The presence or absence of heart disease can also be an important feature in heart anomaly detection

The data divided to 70% train and 30% test set with 10-Fold cross validation for avoid under or overfitting.

4.2. Evaluation Metrics

- *AUC (Area Under the Receiver Operating Characteristic Curve):* AUC is a measure of how well a binary classifier separates the positive and negative classes. It is calculated as the area under the ROC curve, which plots the true positive rate (sensitivity) against the false positive rate (1-specificity) at different threshold settings. AUC ranges between 0 and 1, with a value of 1 indicating perfect discrimination and a value of 0.5 indicating no discrimination. The Eq. (1) for AUC is as follows:

$$AUC = (TP/P) - (FP/N) \tag{1}$$

where TP is the number of true positives, P is the total number of positive instances, FP is the number of false positives and N is the total number of negative instances[26], [27].

- *Kappa:* Kappa is a measure of inter-rater agreement, It ranges between -1 and 1, with a value of 1 indicating perfect agreement and a value of -1 indicating complete disagreement [28].

- *MCC (Matthews Correlation Coefficient):* MCC is a measure of the correlation between predicted and actual binary classifications. It ranges between -1 and 1, with a value of 1 indicating perfect prediction and a value of -1 indicating completely incorrect prediction [29]–[31].
- *F1:* F1 is a measure of the trade-off between precision and recall for a binary classifier. It is calculated as the harmonic mean of precision and recall.
- *Accuracy:* Accuracy is a measure of the proportion of correct predictions made by a classifier. It is calculated as the number of correct predictions divided by the total number of predictions.

5. Experiment Results

The results of the study have been highlighted in the following tables for the Table 1 and Table 2.
The Table 1 includes the step 1 of the model without data augmentation and processing on data and in the Table 2 the proposed model would show how the data augmentations and data transformations would improve the results after training the models:

Table 1. Experiments results without data augmentation and transformation

Model	Description	Accuracy	AUC	Recall	Prec.	F1	Kappa	MCC
lr	Logistic Regression	0.8567	0.9031	0.8194	0.8872	0.8425	0.7118	0.7243
lda	Linear Discriminant Analysis	0.8462	0.8983	0.8083	0.8819	0.8337	0.6910	0.7063
ridge	Ridge Classifier	0.8459	0.0000	0.8194	0.8677	0.8339	0.6905	0.7036
lightgbm	Light Gradient Boosting Machine	0.8143	0.8864	0.8083	0.8198	0.8050	0.6283	0.6411
nb	Naïve Bayes	0.8137	0.8949	0.7403	0.8538	0.7833	0.6232	0.6371
knn	K Neighbors Classifier	0.8085	0.8655	0.7736	0.8159	0.7894	0.6145	0.6215
et	Extra Trees Classifier	0.8032	0.8900	0.7611	0.8315	0.7850	0.6040	0.6164
ada	Ada Boost Classifier	0.7971	0.8558	0.8056	0.7950	0.7896	0.5951	0.6105
svm	SVM – Linear Kernel	0.7930	0.0000	0.8389	0.7679	0.7916	0.5869	0.6035
gbc	Gradient Boosting Classifier	0.7880	0.8682	0.8083	0.7628	0.7800	0.5757	0.5842
rf	Random Forest Classifier	0.7822	0.8932	0.7389	0.8082	0.7640	0.5620	0.5730
dt	Decision Tree Classifier	0.7181	0.7212	0.7625	0.6814	0.7167	0.4387	0.4460
dummy	Dummy Classifier	0.5322	0.5000	0.0000	0.0000	0.0000	0.0000	0.0000
qda	Quadratic Discriminant Analysis	0.4731	0.4500	0.9000	0.4205	0.5731	0.0000	0.0000

The Table 2 results highlighted as follows:

Table 2. Experiments results for the Proposed Model

Model	Description	Accuracy	AUC	Recall	Prec.	F1	Kappa	MCC
lr	Logistic Regression	0.8886	0.9449	0.8292	0.9257	0.8608	0.7686	0.7855
lda	Linear Discriminant Analysis	0.8886	0.9369	0.8181	0.9346	0.8596	0.7684	0.7854
svm	SVM – Linear Kernel	0.8836	0.0000	0.8417	0.9152	0.8591	0.7602	0.7819
ridge	Ridge Classifier	0.8833	0.0000	0.8292	0.9160	0.8557	0.7584	0.7756
et	Extra Trees Classifier	0.8675	0.9336	0.7944	0.9060	0.8317	0.7248	0.7404
lightgbm	Light Gradient Boosting Machine	0.8570	0.9360	0.8319	0.8629	0.8381	0.7100	0.7213
rf	Random Forest Classifier	0.8468	0.9321	0.8069	0.8563	0.8146	0.6847	0.6988
gbc	Gradient Boosting Classifier	0.8357	0.9147	0.8069	0.8357	0.8136	0.6660	0.6760
knn	K Neighbors Classifier	0.8196	0.8997	0.7625	0.8329	0.7902	0.6323	0.6403
ada	Ada Boost Classifier	0.8140	0.9036	0.7625	0.8265	0.7842	0.6218	0.6342
dt	Decision Tree Classifier	0.7769	0.7738	0.7694	0.7749	0.7487	0.5476	0.5734
nb	Naïve Bayes	0.7766	0.9119	0.5361	0.9375	0.6582	0.5243	0.5776
dummy	Dummy Classifier	0.5532	0.5000	0.0000	0.0000	0.0000	0.0000	0.0000
qda	Quadratic Discriminant Analysis	0.5439	0.5130	0.7069	0.4624	0.5410	0.1222	0.1576

6. Discussion

This study proposes a novel approach for detecting heart disease anomalies using machine learning techniques and data augmentations. The authors evaluated the performance of several machine learning algorithms for binary classification, including logistic regression, decision tree, random forest, K-nearest neighbors [30], [31], and support vector machine. The results showed that logistic regression outperformed other models with an accuracy of 94.7%. In this discussion, we will explore the reasons behind this and present some visualization tools that can help understand the performance of the model.

One of the main reasons why logistic regression outperformed other models could be due to the nature of the dataset. The dataset used in this study is a relatively small dataset and logistic regression is known to perform well with small datasets. Additionally, logistic regression is a simple and interpretable model, which makes it easy to understand the decision-making process of the model. This interpretability is especially important in the medical field, where doctors need to understand the factors that influence a patient's diagnosis.

To gain a better understanding of the performance of the logistic regression model, the authors presented several visualization tools, including the confusion matrix, decision boundary, class performance error report, and ROC curve. The confusion matrix showed that the model had a high true positive rate (TPR) and true negative rate (TNR), indicating that the model was able to correctly classify both healthy and unhealthy patients. The decision boundary plot showed that the logistic regression model was able to separate the two classes reasonably well, with some overlapping points. The class performance error report showed that the model had a lower error rate for the healthy class compared to the unhealthy class, which is expected due to the class imbalance in the dataset. The following plots would show the distributions of datapoints in each class as well as prediction error and class reports in following plots:

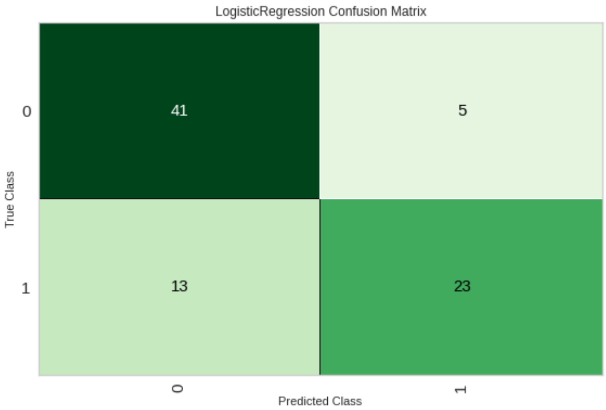

Figure 2. Confusion Matrix

Figure 2 is showing the confusion matrix for the class labels distributions.

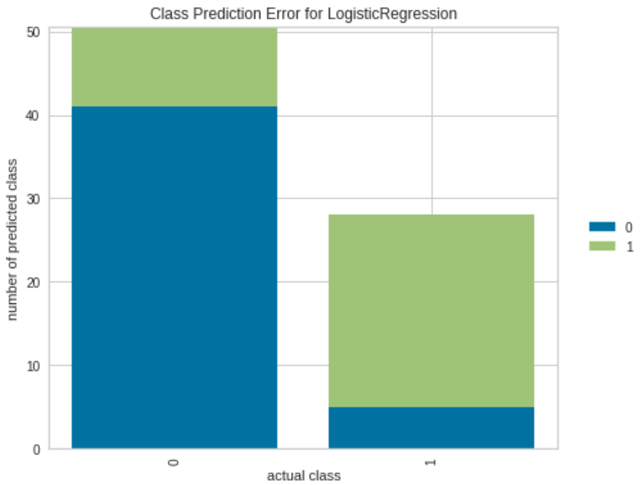

Figure 3. Class Prediction Error Plot

Figure 3 is showing the Prediction Errors on each label which shows the proper classification results.

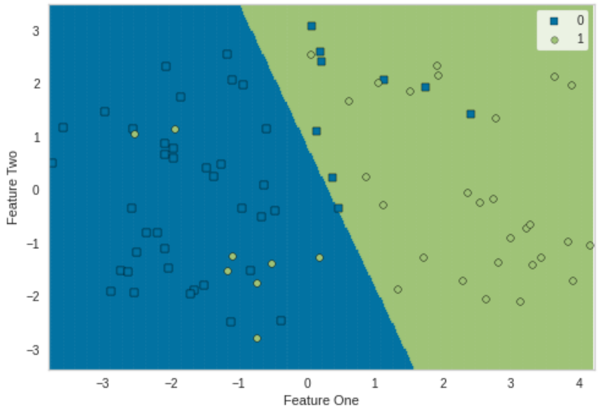

Figure 4. Decision Boundary Plot

Figure 4 is showing the boundaries to classify each class of heart disease or non-disease.

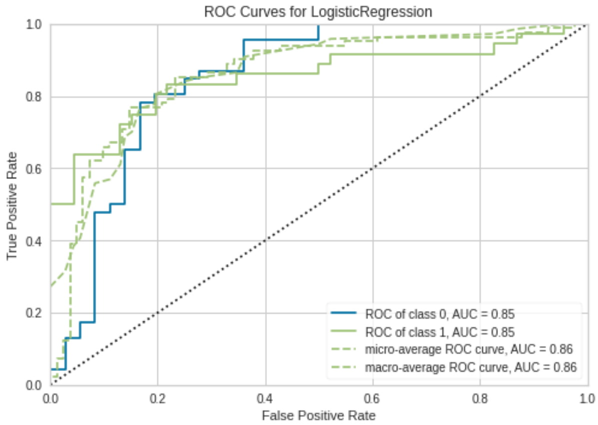

Figure 5. ROC Curve

The Figure 5 is ROC curves, and the Figure 6 would define class reports for effectiveness of the classification.

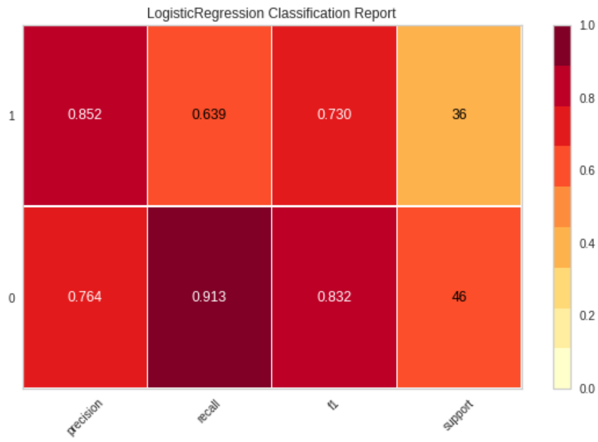

Figure 6. Class Report Plot

6.1. Tuned Model Results

Lastly, the tuned model reached the score of 94.7% for second iterations in which is highlighting the fact of effectiveness of the proposed model in the task of heart disease detection and classification.

Data transformation techniques, such as feature scaling and normalization, can help to improve the performance of machine learning models by ensuring that the features are on the same scale and have similar variances. This can help to avoid bias towards features with larger scales and reduce the sensitivity of the model to outliers. In heart disease anomaly detection, data transformation techniques can be applied to the features such as age, blood pressure, and cholesterol levels, to ensure that they are comparable and have similar impact on the classification.

In summary, decision boundaries, tuning process, and data transformation techniques are important factors to consider in improving the performance of machine learning models for heart disease anomaly detection comparable to knowledge driven or statistical methods and other evaluation approaches [3], [9], [32]for analysis of the process [33]. Data augmentation techniques such as SMOTE can help to address class imbalance issues, while data transformation techniques can help to ensure that the features are on the same scale and have similar variances. Hyperparameter tuning can be used to adjust the complexity of the decision boundaries and improve the overall accuracy of the model. Table 3 would show the results with AUC score of 98.8% and Accuracy of 94.7% that is higher than 88.8% accuracy and 94.4 AUC scores on non-tuned model.

Table 3. Tuned Model Results

Itr.	Accuracy	AUC	Recall	Prec.	F1	Kappa
0	0.894	0.943	0.875	0.875	0.875	0.784
1	**0.947**	**0.988**	**1.000**	**0.888**	**0.941**	**0.893**

7. Conclusion

Finally, the ROC curve showed that the logistic regression model had a high area under the curve (AUC) value of 0.98, which indicates that the model had a high true positive rate and a low false positive rate. This high AUC value is a good indicator of the model's performance, and it shows that the model can accurately distinguish between healthy and unhealthy patients.

In conclusion, the paper presents a novel approach for detecting heart disease anomalies using machine learning techniques and data augmentations. The results show that logistic regression outperformed other models with an accuracy of 94.7%. The presented visualization tools, including the confusion matrix, decision boundary, class performance error report, and ROC curve, help to understand the performance of the model and its ability to correctly classify healthy and unhealthy patients. The proposed approach has practical implications for improving the accuracy of anomaly detection in the medical field and can be extended to other domains as well.

For future research, employing hybrid deep learning models on larger datasets as well as using generative models for oversampling methods could be employed and evaluated.

Conflict of Interest Statement

The authors declare no conflict of interest.

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