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Analysis and study of mitral valve classification for diverse datasets using attention based machine learning classifiers

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Abstract. This study proposed an Attention Algorithm Based-Random Forest model (AAB-RF) To enhance the precision of the ML model, dataset 1 focuses on cardiac disease, including metrics like age, cholesterol, blood pressure, and other cardiovascular factors. The data set 2 aims at the mitral valve issues, especially focused on detecting the prosthetic valve anomalies. The two datasets are analyzed using machine learning classifiers, including K-Nearest Neighbors, Random Forest, Naive Bayes, Logistic Regression and advanced methods like Convolutional Neural Networks and a VGG-based framework. When analyzing the data set 1, the proposed AAB-RF model achieves the classification accuracy of 93% performs better than the other models like Naive Bayes of 88.52% and Support Vector Machine of 89% accuracy. Likewise, for data set 2, the proposed AAB-RF model reached the remarkable accuracy of 99.40% performs superior than CNN and VGG achieved an accuracy of 97% and 84% respectively whereas closely matching with the Vafaeezadeh *et al*. (2021) model's accuracy of 99.00%. The major advantage of integrating attention mechanism with the Random forest model enhances the feature selection and decision making, especially in datasets having the sophisticated interdependent nature. This study showcasing the AAB-RF model's efficiency in managing the multiple datasets which enables the robust and effective outcomes. The research outcomes shows its effectiveness which guides the physicians in diagnosing the heart disease and interpreting the mitral valve features with high accuracy and reliability.

Keywords: accuracy; attention algorithm; classification; machine learning model; mitral valve

1. Introduction

The Cardiac valve is the most significant part in regulating the circulation system effectively. The global risk of heart valve illness is growing along with mitral valve regurgitation which is the most typical due to increased life expectancy and a growing elderly population. (El Sabbagh *et al*. 2018, Iung *et al*. 2019). As per the worldwide epidemiological analysis report regarding heart valve disease in 2021, the number of individuals affected with mitral valve regurgitation is about 24.2 million around the world and it is evaluated that the mortality rate of this disease is about greater than thirty thousand in 2019 (Coffey *et al*. 2021). Mitral valve regurgitation is categorized into two phases based on etiology: primary and secondary. The primary phase results from

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abnormalities in the structures of the mitral valve itself, whereas the secondary phase occurs due to structural defects in the left ventricle or surrounding arteries. In Western regions, degenerative conditions such as fibro-elastic deficiency and Barlow's disease are common causes of primary mitral valve regurgitation. Conversely, in developing countries, rheumatic heart valve ailment is prominently inducing the primary mitral valve regurgitation. Additionally, pathogenic endocarditis is another significant contributor to mitral valve regurgitation. (El Sabbagh *et al*. 2018, Coffey *et al*. 2021, Vahanian *et al*. 2021).

An acute mitral valve regurgitation patients require surgical intervention for replacing or repairing the mitral valve regurgitation. As per the Valvular heart disease management regulations, it recommends that restoring the mitral valve regurgitation is the prior option in the case of people who require surgical treatment. Repairing mitral valve includes restoring the original valve and sub-valvular features of the patients which protects the left ventricular function of those patients (Vahanian *et al*. 2021, Otto *et al*. 2020, Nishimura *et al*. 2017) along with It helps prevent and reduce numerous intricacies related with prosthetic valves which includes the prosthetic valve failures, endocarditis, thromboembolism and pacemaker implementation. (Lawrie *et al*. 2020) which eventually leads to betterment of the patient's health care after operation. According to the specific cardiac surgery survey (Lawrie *et al*. 2020, Lazam *et al*. 2017, Jung *et al*. 2019), the mortality rate is found to be lower for the patients who is treated with restoring the mitral valve compared to the mitral valve substitution.

However, the mitral valve restoration serves an inappropriate therapy for the entire mitral valve patients. If it is applied on the irrelevant patient, this process enhancing the possibilities of inducing the secondary cardiopulmonary bypass and postoperative recurrence which seems to be the significant harm to patients. By utilizing the Echocardiography findings, an etiology can be detected and the influence of lesions, leaflets, and accessory structure can be analyzed. As per the ASE (Vahanian *et al*. 2022, Baumgartner *et al*. 2017) standards, an echocardiography especially transesophageal echocardiography (TEE) is found to be an effective tool for detecting the valvular heart disease. Meanwhile, the heart chamber's dimensions and cardiac capabilities are estimated extensively and offered to the surgeons which serve as an effective insight for planning surgeries. As per the regulations, it is crucial to analyze prior to the operation by echocardiography and then selecting the mitral valve surgical intervention (Vahanian *et al*. 2022). But, the studies show that the surgical process is selected based on the echocardiograhy's attributes and it might vary across the patients. (Lawrie *et al*. 2020, Bolling *et al*. 2010, Trumello *et al*. 2021, Camaj *et al*. 2023).

In the field of cardiac surgery, the Mitral Transcatheter Edge-to-Edge Repair (mTEER) brings a great revolution in replacing a less harmful operations with the conventional open-heart processes. In the case of treating MVR patients, this novel technique proves to be more effective and feasible (Camaj *et al*. 2023). The mTEER mitigates the aggressive effects of the surgeries, optimizing the faster restoration and lessens the complexities after operation with eradicating the risk and intricacies raised in open-heart surgeries. But, the mTEER procedure's effectiveness is meticulously connected to the specified structure of the mitral valve. As a result, it is very crucial to evaluate the surgery's outcomes for enhancing the medical resources allocation as well as creating the method to offer a customized and effective patient care. The precision and efficiency of the mTEER procedure is enhanced because of having the potential to predict the unique features of every patient mitral valve's structures which leads to the optimized clinical outcomes and better quality of life. In the conventional approach, the patient history and Echocardiogram (ECG) recordings are analyzed by cardiologists which requires more resources. On contrary, our method proposes the traditional Deep learning (DL) and Machine Learning (ML) methods for predicting the results. Specifically, the artificial intelligence studies performed in addressing this prediction concern is limited and in some researches integrated the ECG video records (Gheorghe *et al*. 2021) (Penso *et al*. 2021). In this study, the patient care is enhanced through the innovative technologies and exhibits in predicting the patient outcomes possibilities on the basis of ECG recordings based on ML and DL techniques.

2. Related work

Nowadays, the application of AI technology has been growing in the ultrasound medical care sector, especially for predicting and diagnosing cardiovascular ailments. The author (Smole *et al*. 2021) introduced an innovative machine learning model in order to detect the Hypertrophic cardiomyopathy (HCM) exposed for 5 years.

A Machine learning based model was proposed in (Fahmy *et al*. 2021) to predict the HCM patients who has the possibility of getting sophisticated signs of heart failure disease. In (Rhee *et al*. 2024) proposed the ML based technique to categorize the primary cardiovascular symptoms in the patients affected with HCM. But, the studies on AI for analyzing MR severity range is inadequate, especially from TTE analysis which primarily highlights the two scenarios that are MR severity stratification and MR region segmentation (Balodi *et al*. 2020) classified the MR severity with higher accuracy by leveraging the texture feature extraction process with Multiresolution Local Binary Pattern (MLBP) variant.

In order to predict the MR disease repetition, the author (Penso *et al*. 2021) performed the research on the utility of the machine learning methods. But, the echocardiography results is not matched with the surgical factors with MR recurrences, an effective cause of this disease is not clearly captured. The (Atika *et al*. 2021) explored the comparison analysis of diverse deep learning (DL) image classification models for MR region separation and the outcomes shows that U-Net3 is outperforming than other models. The U-Net3 (Liciotti *et al*. 2018) is the version of U-Net architecture, but it is very challenging for deploying in medical application cases since it has prolonged inference time and high computing intricacies.

In (Huang *et al*. 2023), a deep learning-based automated segmentation as well as classification method, VABC-U-Net, was introduced for MR and tricuspid regurgitation. The model attained a segmentation precision of 0.85 for the TR region but only 0.7 for the MR region. This discrepancy may be due to the variability and irregularity in the anatomy of MR images. Additionally, the model produced imprecise segmentation when handling complex cases.

A self-supervised learning algorithm was proposed by the author (Yang *et al*. 2022) for MR region segmentation which shows that it requires more enhancement for achieving the accuracy of MR region segmentation. There are also an extensive studies for analyzing MR severity from start to end.

In (Zhang *et al*. 2021), the (R-CNN) was employed for automated qualitative analysis of MR. the results indicated that the precision for moderate MR instances was limited to 0.81. This lower accuracy was significantly caused by overlapping partially between the features of grade III (moderate) MR and grade IV (severe) MR which seems to be very complex in performing the classification across these two grades effectively.

A DELINEATE-MR, a deep learning model was proposed (Long *et al*. 2024) in which classify the MR based on processing the overall TTE recordings. But, this model finds difficulties in finding the small level dynamic goals due to the usage of spatiotemporal convolution method which leads to the imprecise MR region segmentation.

PE patients are more likely to have a supraventricular extra systoles and/or ventricular extra systoles as well as nonspecific ST-segment and T-wave (NS-STT) anomalies are found in the recordings of ECG which is taken in the relaxing state (Sonaglioni *et al*. 2021, Hohneck *et al*. 2023) when compared to the healthy individuals. In our research, a ventricular premature and isolated supraventricular affects in 10.1% and 48.7% respectively of patients who are affected with PE. Additionally, NS-STT abnormalities was detected in more than half of PE patients which is about 53.3%.

In (Hohneck.*et al*. 2023) research, supraventricular and ventricular extra systoles was noted in of 15% and 21% respectively of PE individuals. Abdulmonem *et al*. (2023) research, 3% and 13% of PE patients were tracked with isolated supraventricular and ventricular premature beats respectively. The Hohneck *et al*. (2023) and Smole *et al*. (2021) traced an atrial fibrillation (AF) in 2% and 3% of PE individuals whereas our study has not identified any evidence of AF in PE individual. According to the studies involved, it shows that the absence of malignant ventricular arrhythmias (VAs) as well as sudden cardiac death (SCD).

From the overall PE patients, according to (Sonaglioni *et al*. 2021), the diagnostic guidelines for MVP were met by 123 out of 303 PE individuals, accounting for 40.6%, and by 64 out of 498 controls, representing 12.8%. The prevalence of MVP is enhanced with the harmfulness of the pectus deformity. There are two researchers examined about the mitral valve morphology (Zhang *et al*. 2021, Abdulmonem *et al*. 2023).

Compared to healthy individuals, the PE patients are evident with longer scallop A2, shorter scallop P2, shorter cooptation depths, and longer papillary muscle tethering lengths. MVP causes MVR which was identified in 19.7% of PE patients and 9.7% of healthy individuals. There is no occurrence of high severity MVR cases among PE patients but there is a presence of only mild severity which is 37.5% of overall patients or mild-to-moderate which is about 62.5% of all cases.

As per the included studies, the various concomitant cardiovascular anomalies were identified among PE patients. Compared to healthy controls, Hohneck *et al*. (2023) higher risk of improper alignment of heart and congenital cardiac disease is found in the PE patients. Similarly, Abdulmonem *et al*. (2023) found that 41% of PE individuals exhibited mild pericardial effusion, which was associated with irritative effects caused due to contact with cartilaginous features or osseous in the contact region.

It is very crucial to recognize the cardiac prosthetic valves in echocardiographic images in order to automate their evaluation analysis. The Deep convolutional neural networks (DCNNs) ensure the misclassification reduction, accuracy optimization and facilitates the non-expert cardiologist's workload. An automated system is integrated with DCNNs optimizes the accuracy, less time consumption in emergency cases and helps in labeling the unclassified image datasets priorly. In this research, it leverages the datasets of 2044 transthoracic echocardiographic studies, including 1597 natural and 447 prosthetic mitral valves, with images from apical 4-chamber (A4C) and parasternal long-axis (PLA) views. To optimize the robustness, 13 versions of novel methodologies were trained independently and predict the ensemble performance. An EfficientNetB3 and EfficientNetB4 architectures performs better than the other DCNN models for A4C and PLA views with an accuracy of 0.99 when compared to expert cardiologists. Moreover, the ensemble learning which combines the predictions of various model versions to enhance the accuracy with mitigating the variability and identifying the prosthetic valve. This study highlights the effectiveness of DCNNs, ensemble learning method and effective datasets in optimizing the prognostic accuracy and generate an automated prosthetic mitral valve evaluation which leads to

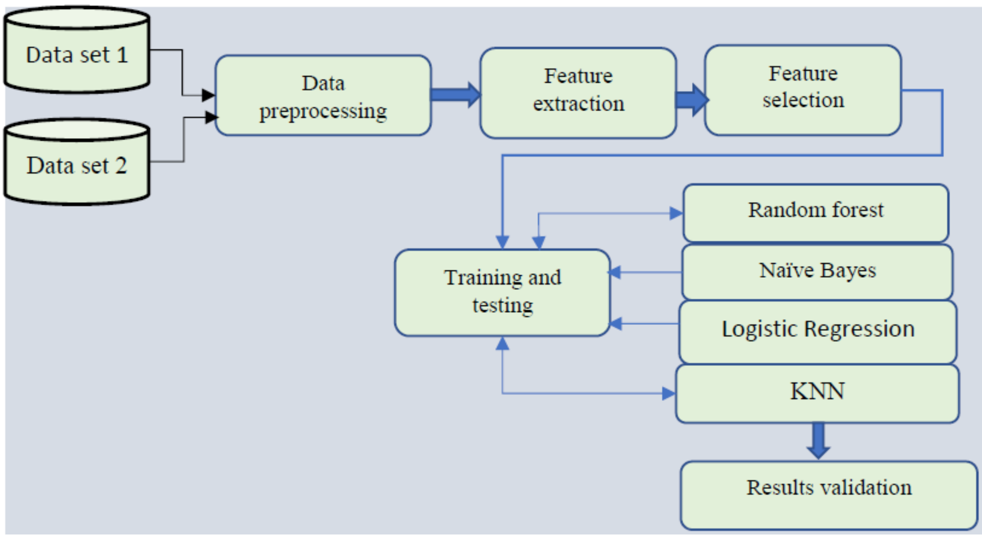

Fig. 1 Machine learning architecture

age	sex	chest pain type	resting bp s	cholesterol	fasting blood sugar	resting ecg	max heart rate	exercise angina	oldpeak	ST slope	target
40	1	2	140	289	0	0	172	0	0	1	0
49	0	3	160	180	0	0	156	0	1	2	1
37	1	2	130	283	0	1	98	0	0	1	0
48	0	4	138	214	0	0	108	1	1.5	2	1
54	1	3	150	195	0	0	122	0	0	1	0
39	1	3	120	339	0	0	170	0	0	1	0
45	0	2	130	237	0	0	170	0	0	1	0
54	1	2	110	208	0	0	142	0	0	1	0
37	1	4	140	207	0	0	130	1	1.5	2	1
48	0	2	120	284	0	0	120	0	0	1	0
37	0	3	130	211	0	0	142	0	0	1	0
58	1	2	136	164	0	1	99	1	2	2	1
39	1	2	120	204	0	0	145	0	0	1	0
49	1	4	140	234	0	0	140	1	1	2	1
42	0	3	115	211	0	1	137	0	0	1	0
54	0	2	120	273	0	0	150	0	1.5	2	0
38	1	4	110	196	0	0	166	0	0	2	1

Fig. 2 Dataset Feature Collection

the enhanced medical diagnosis care and mitigating the cardiologist workload (Vafaeezadeh *et al*. 2021).

3. Proposed methodology

3.1 Data preprocessing

Data set 1

Heart disease, commonly referred to as cardiovascular disease (CVD), is the foremost cause of death worldwide, claiming 17.9 million lives each year and making up 32% of global fatalities.

Cardiovascular diseases (CVDs) encompass various conditions that affect the heart and blood vessels, including coronary artery disease, stroke-related disorders, rheumatic heart disease, and other associated diseases. https://www.kaggle.com/datasets/sid321axn/heart-statlog-cleveland-hungary-final

As shown in Fig. 2, the heart disease dataset is commonly used for binary classification tasks to predict whether a patient has heart disease based on several clinical and diagnostic variables. There are 918 records and 14 attributes (columns) in the dataset. The dataset is typically divided into machine learning training and testing sets of 918 records. A typical split of 80 percent training (734 records) and 20 percent testing (184 records) varies with the sampling method.

Data set 2

The dataset comprises videos of mitral valve morphologies categorized into four types based on the Carpentier functional classification system. For each case, unique Parasternal Long Axis (PLA) and Apical Four Chamber (A4C) views are included. The dataset contains a total of 1,773 cases, comprising 424 cases of normal mitral valves (MVs), 155 cases classified as Type II (mitral valve prolapse, MVP), 392 cases as Type IIIa (rheumatic mitral stenosis, MS), and 802 cases as Type IIIb (mitral valve restricted motion). For further details, the dataset can be accessed at GitHub: Mitral-Valve-Echocardiography.

The mitral valve data set is preprocessed extensively to make sure the model's quality and compatible with machine learning models. In this step, the data is cleaned by eradicating the lost or dynamic values and generalizing the feature values to make the model more feasible. Moreover, only the most significant features for the categorization tasks are maintained by applying the feature extraction and selection techniques which mitigate the dimensionality and enhancing the computing efficacy. These pre-processing steps are crucial for optimizing the classifier's performance by mitigating the noise and data is getting available for interpretation.

3.2 Feature extraction

The feature extraction process is aimed to extract the effective and significant features from the original mitral valve data set. This step converting the raw data into the respective parameters which exhibits the essential patterns or attributes for classification tasks. In the case of mitral valve data set, the principal component analysis (PCA), wavelet transforms, or Fourier analysis techniques are used to derive the features such as shape, texture and motion dynamics from the medical images or time-series insights. These extracted features is very beneficial for the machine learning models by showcasing the complex information such as structure and functionality of the mitral valve. The feature extraction process aims to derive the crucial data for precise classification with mitigating the complexities of the data set.

Calculate the eigenvector matrix of the variance using the reduced set of features of the principal component analysis on the input data, Eq. (1). Let's assume $Z-$ reduced feature set, W −eigen vector, X −inout data.

$$Z = XW \tag{1}$$

Calculate the wavelength conversion coefficients as shown in Eq. (2). Let's assume $x(t)$ −signal, ψ −wavelet, b −transaction, a −scale.

$$W(a,b) = \frac{1}{\sqrt{|a|}} \int x(t)\, \psi\left(\frac{t-b}{a}\right) dt \tag{2}$$

As shown in Eq. (3), estimate the frequency domain features during Fourier transformation. Let's assume $x(f) -$ frequency domain features.

$$x(f) = \int x(t)\, e^{-j2\pi ft} dt \tag{3}$$

The wavelets represent the dynamics of a movement, such as the mitral valve, by applying the PCA model to a simplified form of the data and the Fourier transform, extracting the wavelets. The Fourier identifies a temporal movement, so that it can be effectively classified.

3.3 Feature selection

The feature selection process aims to predict and preserve the most specific and influential features from the data set with removing the replicate or unrelated insights. In the mitral valve data set, the selected features are positioned with grading as per its significance for classification task by using the statistical methods such as mutual information, chi-square and recursive feature elimination (RFE) tests. The size of the data set is reduced by selecting only the most important features which contributing an optimized computing efficiency with reducing the chances of over-fitting issues. This process makes the machine learning classifiers to concentrate on most significant predictive attributes which enhance the performance metric values. Both feature extraction and feature selection process simplifies the data framework and thereby enhances the reliability and accuracy of the categorization models.

As shown in Eq. (4), estimate the feature importance using classifier weights. Let's assume X −original dataset features, $\hat{y} -$ predicted target, ϑ_d −importance weight of feature

$$\hat{y} = f(X, \theta), \quad \theta = \{\vartheta_1, \vartheta_2, \dots, \vartheta_d\} \tag{4}$$

The feature selection procedure selects the features with the most predictive power, such as valve area, leaflet curvature, blood flow velocity, and pressure gradient. It estimates the weight of each feature trained in the output classifier, as shown in Eq. (5).

$$x' = X¥\{x_k\}, \quad where x_k = \underset{x_j}{argmin} \left|\vartheta_j\right| \tag{5}$$

Defining the RFE workflow enables feature importance calculation and optimal feature subset selection.

Training and testing

The preprocessed data is then separated into two various subsets such as training and testing sets. The training subsets utilized to develop and enhance the machine learning models whereas the testing data set estimated the generalization capacity of these models. The various ML classifiers that are implemented are RF, LR, KNN, and NB. In order to maintain sustainable performance without over-fitting, the models are trained with unknown data and validating it.

3.4 Performance evaluation

The various classifiers evaluation outcome shows that the RF performs better than the others and exhibits the higher accuracy and reliability in detecting the mitral valve status. An ensemble-based RF classifier utilized various decision trees in order to acquire the intricate patterns and feature interactions in the data set. The LR showcasing the sensible performance for splitting of linear data whereas the KNN and NB were performing with less effective since there is lack of potential in handling the high-dimensional data and related features. These outcomes demonstrate the RF classifier's efficiency which is best suited for this classification of the mitral valve condition and offers the overall superior performance.

An extensive classification model was developed with multiple machine learning classifiers like RF, LR, KNN, and NB by using mitral valve related data set. In order to evaluate its performance for accurate prediction and classification of mitral valve, all classifiers was trained and tested on the preprocessed data. An effective pre-processing step which includes the normalization and feature selection performed on the datasets which make sure an effective and efficient performance of the classifier. The overall models evaluation outcomes shows that Random Forest classifier along shows an effective metrics such as recall, accuracy, precision and comprehensive classification capability. Due to its ensemble learning approach which comprises the multiple decision trees which makes the model to maintain the intricate patterns and associated with mitral valve data more effectively compared to other classifiers. The Logistic Regression model performs best in linear separations whereas the KNN find difficulties in handling the huge data set and Naive Bayes is an efficient model but its inability to handle the feature dependent intricacies. These outcomes show that the sustainability of the RF classifier in analyzing and categorizing the mitral valve conditions, thereby it serves as the best reliable option for this tasks.

Attention algorithm based predication model

1. data = load_ dataset # Load the dataset
2. Train_ data, test_ data = train_ test_ split (data, test_ size=0.2, random_ state=42)
3. scaled_ train_ data = scale_ features (train_ data);
4. scaled_ test_ data = scale_ features (test_ data);
5. Attention_ layer = Attention Mechanism ( ) = Random forest ( )
6. Attention_ scores = attention_ layer. Compute_ attention (scaled_ train_ data. features);
7. Weighted_ features = scale_ features (scaled_ train_ data. features * attention_ scores);
8. random_ forest_ model =Random Forest Classifier (n_ estimators=100, max_ depth=10, random_ state=42)
9. random_ forest_ model. fit (weighted_ features, scaled_ train_ data. labels)
10. weighted_ test_ features = scaled_ test_ data. Features * attention_ scores;
11. Predictions = random_ forest_ model .predict (weighted_ test_ features);
12. Evaluate_ model(predictions, scaled_ test_ data. labels) # Compute metrics like accuracy, F1-score

4. Experimental results:

Accuracy:

An accuracy can be evaluated from the ratio of the number of correct outcomes and the overall results. It starts with the image extraction and then calculated by the following expression, then the extracted feature is compared with the overall data set. While determining an accuracy, the two attributes should be considered are data quality and errors.

$$\text{Accuracy} = \frac{(TN+TP)}{(TN+TP+FN+FP)} \tag{1}$$

where TN-True Negative, TP - True Positive, FP - False positive, and FN - False Negative.

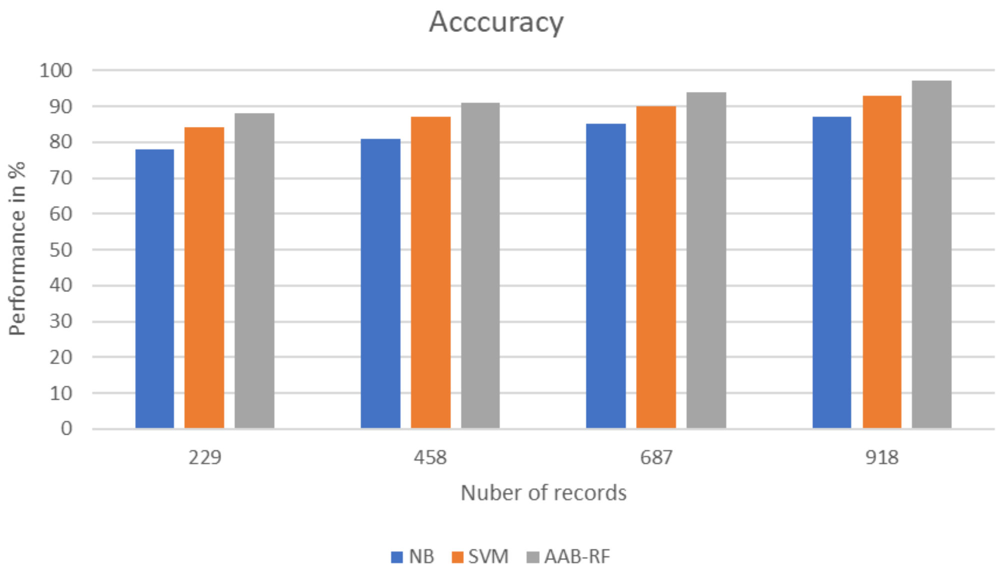

Fig. 3 Analysis of Accuracy

Precision

The proposed model deployment's outcome shows the Precision. The Precision is declared based on the predictive impacts and modifications from the raw data sets.The correctly measured negative count determine the precision and expressed in %. It is calculated from the ratio of overall positive values to the addition of true positive and false positive values. It is expressed in mathematical representation as

$$\text{Precision} = \frac{TP}{(TP+FP)} \tag{2}$$

Sensitivity (Recall):

The sensitivity is calculated from the true positives and false negative values obtained from the datasets. The true positive and false negative is determined by the count added to the true positive. The findings of the experiments shows the true positive values and resultant count gives the sensitivity. It can be estimated by using the below expression and indicated in percentage (%)

$$\text{Sensitivity} = \frac{TP}{(TP+FN)} \tag{3}$$

The F1-measure is derived from the average of the recall and accuracy values. F1-measure is determined using harmonic mean, which handles greater values better. F1-measure is defined as follows;

$$F1 - measure = \frac{2 * Recall * Precision}{Recall + Precision} \tag{4}$$

4.1 Data set 1 classification results

As illustrated in the Fig. 3, the proposed AAB-RF method is compared with previous NB and

Table 1 Random forest with Attention Algorithm classification results

Target	Precision	Recall	F1-score	Support
0	0.93	0.92	0.92	154
1	0.94.	0.95	0.94	203
Accuracy	0.95	0.96	0.97	305
Macro avg	0.93	0.93	0.93	357
Weighted avg	0.93	0.93	0.93	357

Table 2 Naive bayes with Attention Algorithm classification results

Target	Precision	Recall	F1-score	Support
0	0.84	0.82	0.83	154
1	0.87	0.88	0.88	203
Accuracy	0.89	0.90	0.91	256
Macro avg	0.85	0.85	0.85	357
Weighted avg	0.86	0.86	0.86	357

Table 3 Logistic regression with Attention Algorithm classification results

Target	Precision	Recall	F1-score	Support
0	0.85	0.83	0.84	125
1	0.84	0.85	0.84	127
Accuracy	0.85	0.86	0.87	203
Macro avg	0.84	0.84	0.84	252
Weighted avg	0.84	0.84	0.84	252

SVM methods in terms of image analysis accuracy. The previous NB and SVM methods achieved 87% and 93% accuracy, respectively, whereas the proposed AAB-RF technique improved the accuracy to 97%.

Table 1 shows the results of the random forest classifier with an attention mechanism. The model performed well, achieving high accuracy and balanced metrics. For one class the F1-score, recall and precision were consistent. Similarly, for the other class, the model showed strong and reliable performance. These results confirm the model's effectiveness in classification.

Table 2 shows the results of the NB classifier with an attention mechanism. The model performed well, achieving high accuracy and balanced metrics. For one class, the F1-score, recall and precision were consistent. Similarly, for the other class, the model showed strong and reliable performance. These results confirm the model's effectiveness in classification.

Table 3 shows the results of the Logistic regression classifier with an attention mechanism. The model performed well, achieving high accuracy and balanced metrics. For one class, the F1-score, recall and precision were consistent. Similarly, for the other class, the model showed strong and reliable performance. These results confirm the model's effectiveness in classification.

Table 4 shows the results of the KNN classifier with an attention mechanism. The model performed well, achieving high accuracy and balanced metrics. For one class, the F1-score, recall

Table 4 KNN with Attention Algorithm classification results

Target	Precision	Recall	F1-score	Support
0	0.70	0.73	0.71	154
1	0.79	0.76	0.77	203
Accuracy	0.80	0.82	0.84	0.87
Macro avg	0.74	0.74	0.74	357
Weighted avg	0.75	0.75	0.75	357

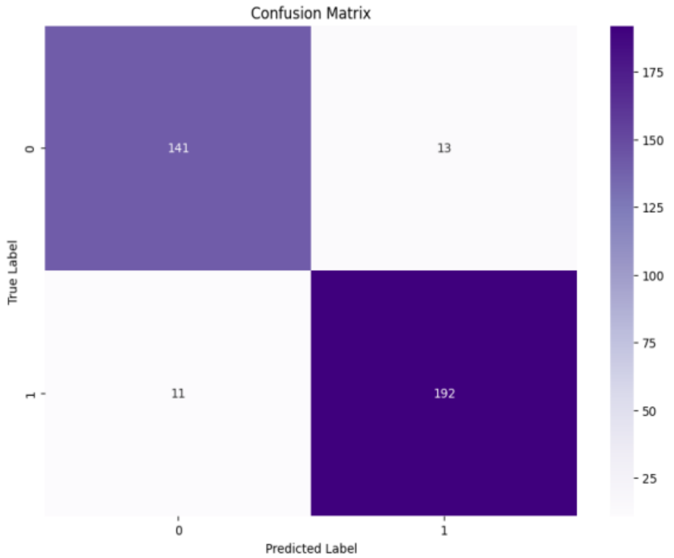

Fig. 4 Random forest

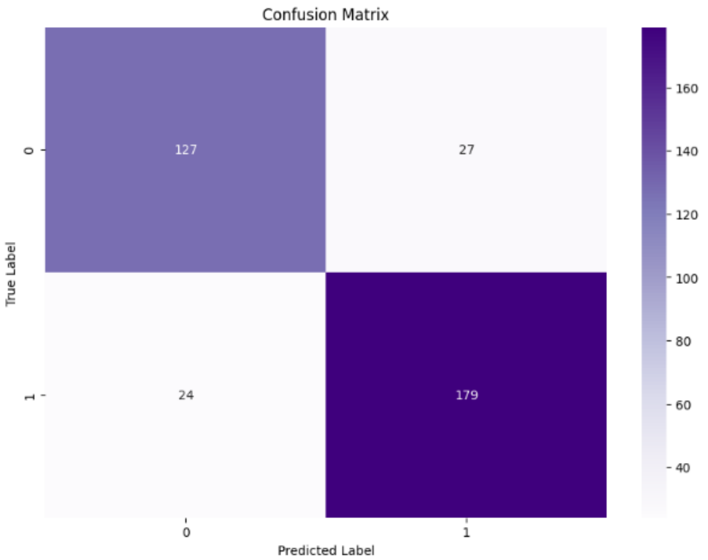

Fig. 5 Naïve bayes

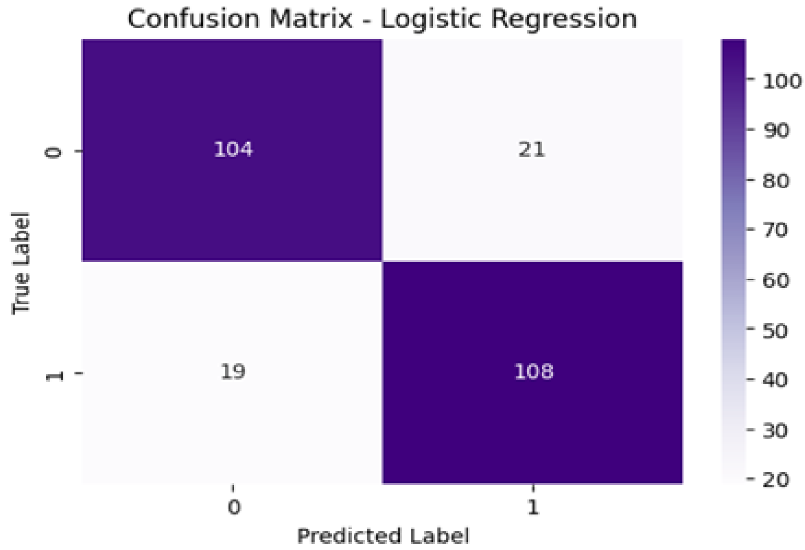

Fig. 6 Logistic regression

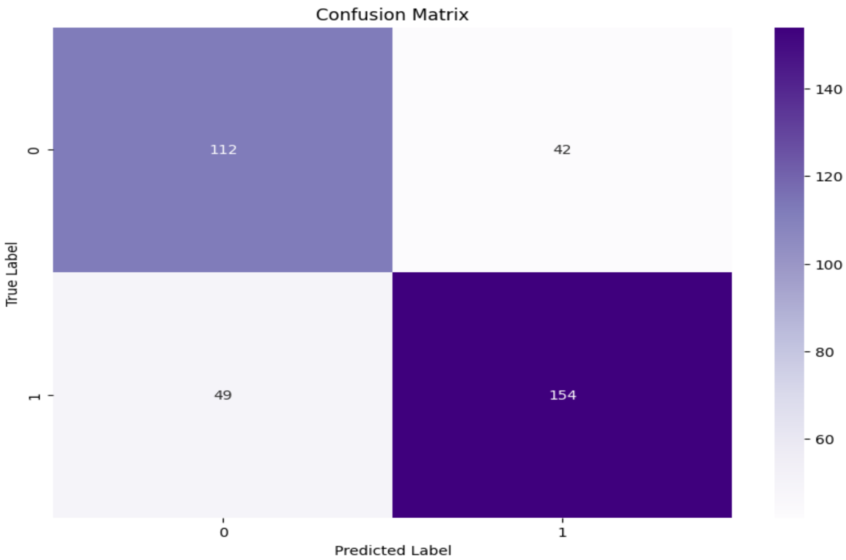

Fig. 7 KNN

and precision were consistent. Similarly, for the other class, the model showed strong and reliable performance. These results confirm the model's effectiveness in classification.

Confusion Matrix

The overall comparison accuracy of multiple classifiers is represented in Table 5. The KNN classifier exhibits poor performance with achieved an accuracy of 75% whereas the Naïve Bayes and logistic regression shows a mediocre performance of about 86% and 84% respectively. The Random Forest classifier with attention algorithm outperforms the other models by achieving the

Table 5 Overall classification comparison results

Classifier with Attention Algorithm	Accuracy
KNN	75 %
Naïve Bayess	86 %
Logistic Regression	84 %
Random forest [687]	93 %

Table 6 comparison between existing and proposed architecture

NB (Singh *et al*. 2020)	88.52%
SVM (Dubey *et al*. 2021)	89%
Proposed AAB-RF	93%
NB (Singh *et al*. 2020)	88.52%

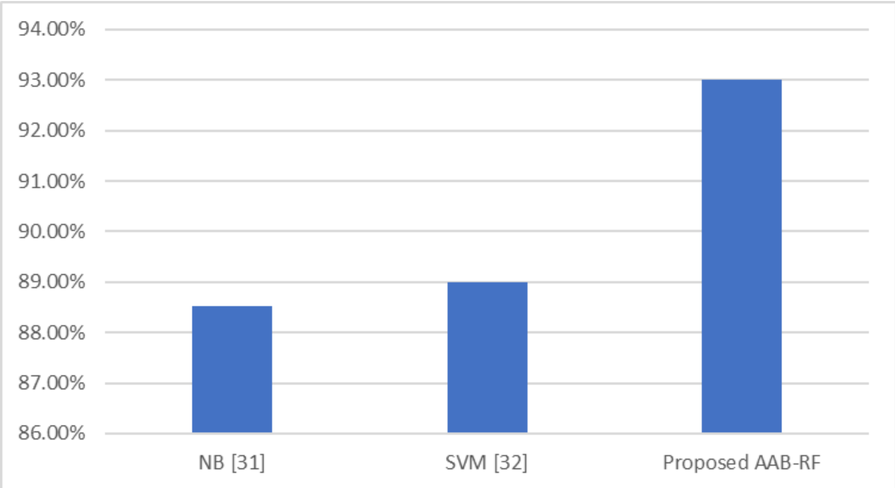

Fig. 8 Comparison between existing and proposed model for Data Set 1

highest accuracy of 93% which shows the effectiveness of this classifier which provides the robust and reliable model.

Table 6 shows the comparison outcomes of performance on dataset1 between the proposed and existing models. The existing NB classifier achieved an accuracy of 8.52% where the SVM classifier acquired an accuracy of 89%. The proposed AAB-RF classifier achieved the highest accuracy of 93% and performs superior to other models. This result shows that RF is well suited for handing the datasets due to its effectiveness and robustness which makes it is promising choice for heart disease categorization tasks.

Fig. 8 shows the comparison performance of the proposed and existing models in the bar chart representation. The existing NB classifier achieved an accuracy of 88.52% where the SVM classifier acquired an accuracy of 89%. The proposed RF classifier achieved the highest accuracy of 93% and performs superior to other models. This visual representation shows the RF classifier's efficiency and robustness which performs better than the other models in diagnosing the heart diseases.

Table 7 Random forest with Attention Algorithm classification report

Target	Precision	Recall	F1- Score	Support
Elevated	0.98	0.98	0.98	935
Hypertension Stage 1	0.99	0.99	0.99	12018
Hypertension Stage 2	0.99	0.96	0.99	4658
Normal	1.00	1.00	1.00	2851
Accuracy	0.99	0.99	0.99	0.99
Macro avg	0.99	0.99	0.99	20462
Weighted avg	0.99	0.99	0.99	20462

Table 8 Naive bayes with Attention Algorithm classification report

Target	Precision	Recall	F1- Score	Support
Elevated	1.00	0.89	0.94	935
Hypertension Stage 1	0.96	0.93	0.94	12018
Hypertension Stage 2	0.84	0.91	0.88	4658
Normal	1.00	1.00	1.00	2851
Accuracy	0.94	0.95	0.96	3947
Macro avg	0.95	0.93	0.94	20462
Weighted avg	0.94	0.93	0.94	20462

Table 7 The classification outcomes of the random forest classifier with the attention algorithm are summarized in Table 7. The proposed model demonstrated exceptional accuracy, supported by a substantial number of samples. For the elevated stage, the metrics of precision, recall, and F1-score were consistently high. Similarly, for hypertension stages 1 and 2, these metrics reflected strong and reliable performance. In the case of the normal category, the model achieved perfect consistency across all metrics, showcasing its effectiveness in classification.

Table 8 shows the classification outcomes of Naïve Bayes classifier with attention algorithm in terms of various metrics. This model achieved an accuracy of 93% with supported by 20462 samples. In case of elevated stage, precision, recall, and F1-score values are 1.00, 0.89 & 0.94 respectively from 935 samples. For hypertension stage 1, the values of these metrics are 0.96, 0.93 & 0.94 respectively whereas the hypertension stage 2 the values of precision, recall, and F1-score are 0.84, 0.91, and 0.88 supported by 4658 instances. For Normal, three metrics are achieved constantly by 1.00. which shows the better performance but lesser than the RF classifier.

Table 9 shows the classification outcomes of logistic regression classifier with attention algorithm in terms of various metrics. This model achieved an accuracy of 73% with supported by 13641 samples. In case of elevated stage, precision, recall, and F1-score values are constantly exhibiting a zero performance with 0.00 for 361 samples. For hypertension stage 1, the values of these metrics are 0.71, 0.92 & 0.80 respectively whereas the hypertension stage 2 the values of precision, recall, and F1-score are 0.80, 0.70, and 0.75 supported by 3144 instances. For Normal, three metrics values are 0.72, 0.19 & 0.30 respectively. In case of macro average, the precision, recall, and F1-score values are 0.56, 0.45 and 0.46 respectively. For weighted average, these values are 0.70, 0.73 and 0.68 which shows the moderate performance.

Table 10 shows the classification outcomes of KNN classifier with attention algorithm in terms

Table 9 Logistic regression with Attention Algorithm classification report

Target	Precision	Recall	F1- Score	Support
Elevated	0.00	0.00	0.00	361
Hypertension Stage 1	0.71	0.92	0.80	7974
Hypertension Stage 2	0.80	0.70	0.75	3144
Normal	0.72	0.19	0.30	1892
Accuracy	0.82	0.21	0.35	2145
Macro avg	0.56	0.45	0.46	13641
Weighted avg	0.70	0.73	0.68	13641

Table 10 KNN with Attention Algorithm classification report

Target	Precision	Recall	F1- Score	Support
Elevated	0.07	0.02	0.03	935
Hypertension Stage 1	0.59	0.83	0.69	12018
Hypertension Stage 2	0.27	0.15	0.19	4658
Normal	0.21	0.05	0.09	2851
Accuracy	0.22	0.06	0.10	2964
Macro avg	0.28	0.26	0.25	20462
Weighted avg	0.44	0.53	0.46	20462

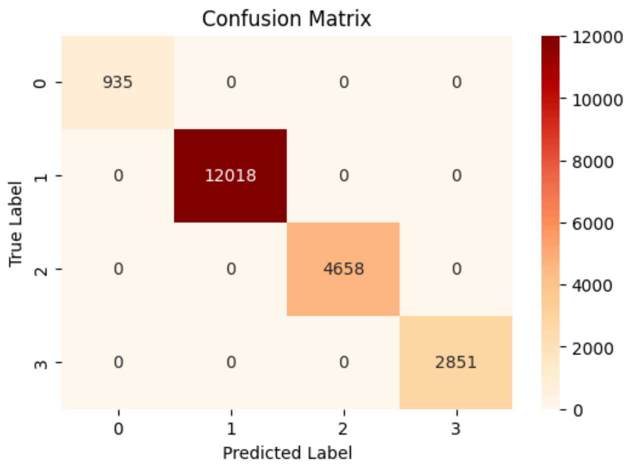

Fig. 9 Random forest confusion matrix

of various metrics. This model achieved an accuracy of 53% with supported by 20462 samples. In case of elevated stage, precision, recall, and F1-score values are 0.07, 0.02 &0.03 respectively. For hypertension stage 1, the values of these metrics are 0.59, 0.83 & 0.69 respectively whereas the hypertension stage 2 the values of precision, recall, and F1-score are 0.27,0.15 & 0.19 supported by 4658 instances. For Normal, three metrics values are 0.21,0.05 & 0.09 respectively. In case of macro average, the precision, recall, and F1-score values are 0.28, 0.26 & 0.25 respectively. For weighted average, these values are 0.44,0.53 and 0.46 which shows the worst classification performance.

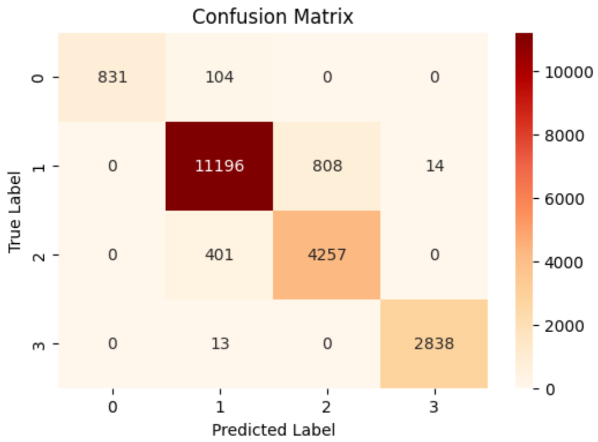

Fig. 10 Naïve bayes confusion matrix

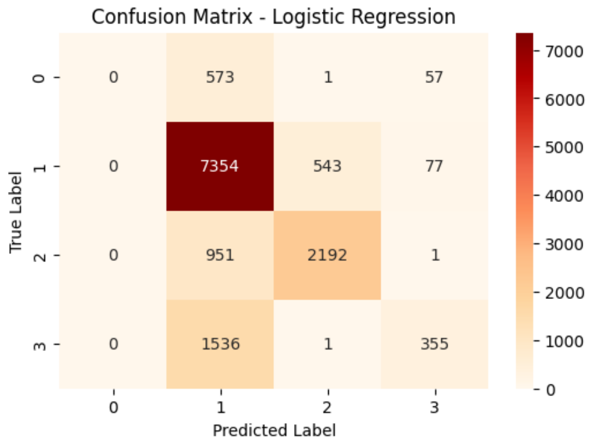

Fig. 11 Logistic regression confusion matrix

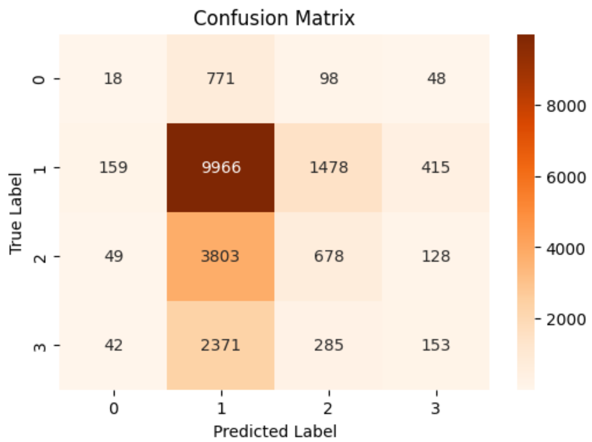

Fig. 12 KNN confusion matrix

Table 11 Showing accuracy of different classification models

Machine learning models with Attention Algorithm	Accuracy
KNN	0.532%
Naïve bayes	0.931%
Logistic regression	0.732%
Proposed AAB-RF	0.994%

Table 12 Comparison between existing and proposed architecture

Classification	Accuracy
CNN (Kusunose *et al*. 2020)	97%
VGG (Zhang *et al*. 2018)	84%
(Majid Vafaeezadeh *et al*. 2021)	99.00%
Proposed AAB-RF	99.40%

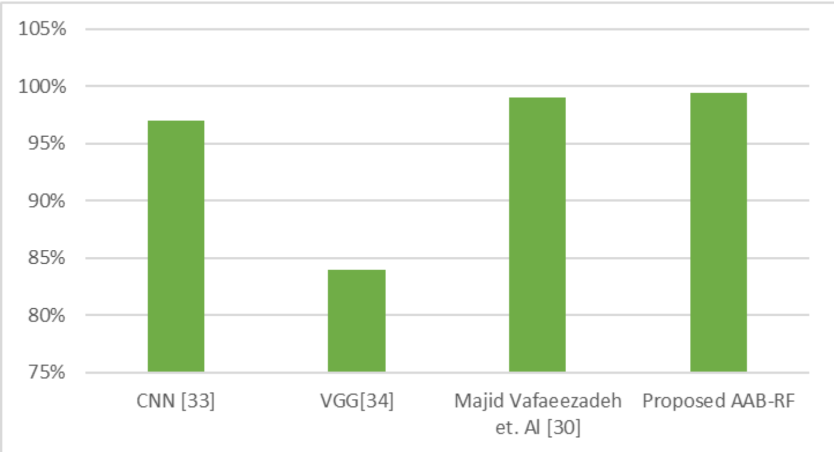

Fig. 13 Comparison between existing and proposed model

Confusion Matrix

The overall comparison accuracy of multiple classifiers is represented in Table 11. The KNN classifier exhibits the poor performance with achieved an accuracy of 53.2% whereas the Naïve Bayes achieved an accuracy of 93.1% and logistic regression shows a mediocre performance of 73.2 s%. The Random forest classifier outperforming the other models with achieved an outstanding accuracy of 99.4% which shows the effectiveness of this classifier which provides the robust and reliable model.

Table 12 shows the comparison outcomes of performance on dataset 2 between the proposed and existing models. Its bar chart representation is shown in Fig. 13. The existing VGG classifier achieved an accuracy of 84 % where the CNN classifier acquired an accuracy of 97%. The (Vafaeezadeh *et al*. 2021) model outperformed these models with an accuracy of 99%. But, the proposed AAB-RF classifier achieved an outstanding accuracy of 99.40% and performs superior to other models. This result shows that RF is having the great potential of interpreting and classifying the mitral valve features due to its effectiveness and robustness compared to other models.

5. Conclusions

In this research, the proposed Attention Algorithm-Based Random Forest (AAB-RF) model performs better than the other models in categorizing the cardiac disease and mitral valve datasets. In case of data set 1, the proposed model achieved an accuracy of 93% which outperforms the conventional classifiers such as Naive Bayes (88.52%) and SVM (89%). For data set 2, the proposed AAB-RF model achieved an outstanding accuracy of 99.40% outperforming the CNN (97%) and VGG (84%) models whereas it slightly performs superior to the (Vafaeezadeh *et al*. 2021) model's accuracy of 99.00%. This integration of attention method into the RF model improves the potential in order to mitigate the classification errors, highlighting the crucial features based on priority which enhancing the sustainability of the system. This enables the proposed AAB-RF model is well suited for the clinical datasets which is having the crucial feature interactions. An effectiveness of this model in analyzing the both datasets which showcasing its flexibility and efficiency in diverse clinical prognostic concerns.

Future Research

The future exploration should focus on integrating the AAB-RF model with various Deep learning techniques in order to optimize the diagnosis with high precision. Moreover, when integrating this model in clinical real time applications could enable this model as an effective method for medical diagnostic care, especially in heart disease diagnosis and mitral valve feature detection. Future research, we aim to study heart sound signals across different cardiac periods using DL models, focusing on identifying acoustic patterns for non-invasive diagnosis of mitral valve conditions. These advancements will provide a more accurate and comprehensive assessment of cardiovascular health.

• Further research may be directed at the further extension of the datasets comprising more cases of cardiac and mitral valves, and more clinical and physiological outcomes.

• Consider the possibility of combining various forms of patient data, including imaging and electronic health records, to enhance how heart disease and prosthetic valve abnormalities are identified to determine early.

• More validation in clinical real-life scenarios is required to determine the strength, trustworthiness, and efficacy of predictive models in providing proper diagnosis.

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