Heart Attack Detection Based On Mask Region Based Convolutional Neural Network Instance Segmentation and Hybrid Classification Using Machine Learning Techniques

Prasadgouda B Patil[a],Dr. P. M. Mallikarjun Shastry[b] and Dr. Ashokumar P S[c]

[a]Assistant Professor, Dept. of Computer Science, Secab Institute of Engineering & Technology, Vijayapur.
[b]Professor,Department of School of computing & Information Technology, Bangalore.
[c]Professor, Dept. of computer science, Don Bosco Institue of Technology,Bangalore.

Article History: Received: 10 January 2021; Revised: 12 February 2021; Accepted: 27 March 2021; Published online: 20 April 2021

Abstract: To predict and diagnose heart disease various methods based on machine learning were presented. Before occurrence of heart attack, to treat cardiac patients, it is significant to accurate heart disease prediction. Existing methods failed to improve performance of heart disease prediction and use conventional method to choose features from dataset. In this paper, proposed for heart disease prediction feature extraction approaches and classification using ensemble deep learning. First, Feature extraction using SIFT and ALEXANET from the Mask Region-Based Convolutional Neural Network **(**RCNN) instance segmented image. Second one, Hybrid Classification with the combination of Random forest and Gaussian Navies Bayes to detect the heart attack. Proposed method is calculated with heart disease data and then testing and training data is compared achieves better results. This outcome indicates that our method is more effective for heart attack prediction.

Keywords:SIFT, ALEXANET, mask RCNN, Heart attack, Random forest, Gaussian Navies Bayes.

1. Introduction

Heart diseases are number one source of death all-inclusive, medically called cardiovascular diseases (CVD) or strokes. According to 2016 World Heart Federation Report, notwithstanding element that mainstream of early heart attacks are inevitable, one out of three deaths is a consequence of CVD (Singh, 2016). There are different kinds of CVDs, but most prevalent type of heart disease is contracting or obstacle of coronary arteries; it happens progressively over time. Heart pains, tininess of breath, deadness, fatigue, and pain in chin spine, upper abdomen throat or back are particular of most frequent signs of heart failure. However, several control variables help us lower risk of heart failure, like control of BP, lowered cholesterol, abstinence from smoking and routine exercise. (Chauhan, 2015).

Mostly, before a heart attack, stroke, angina or heart disease happens, CVD cannot be predicted. It is therefore necessary to track and consult doctors for cardiovascular parameters (Raza, 2019). 17.5 million overall human deaths occur due to heart attacks and strokes, according to WHO (World Health Organization) report. Because of heart attack and stroke, 80% of deaths are due to CVDs (Shadman, 2018). Heart conditions account for one-third of all global deaths (KaanUyar, 2017). Therefore, early identification of cardiac abnormalities and heart disease predictive methods will save a lot of lives and help doctors establish a successful care strategy that effectively decreases death rate due to coronary diseases.

There is also a lot of medical data existing (i.e. Huge Data in Electronic Health Record System) that can be used to build predictive prototypes for heart diseases due to the advancement of automated healthcare networks. Machine learning or data mining is a method of experimentation for processing big data from several viewpoints and compressing it into usable info. Data Mining is a tacit, previously undisclosed and theoretically useful non-trivial extraction of data information (Patel, 2016).

Healthcare sectors produce a vast volume of data related to medical diagnosis, patients, etc. To discover data similarities and hidden patterns, data mining offers various methods. This paper, therefore, recommends a machine learning method for execution of cardiac disease prediction method that has been tested on two open-access cardiac disease prediction datasets. Machine learning methods are however, useful for forecasting performance from prevailing data. Therefore this paper smears one such approach for machine learning named risk factors grouping for cardiac disease risk forecasting (Vanisree, 2011).

This paper discusses detection of heart attack using machine learning techniques which are effective and results are enhanced based on the testing and training data with the help of heart attack dataset. Rest of paper discusses section 2 as literature survey, section 3 research methodology and its detailed description, section 4 describes the performance analysis of proposed work and finally section 5 is conclusion of the work.

2. Literature Review

Using K-means algorithm, risk factors that affect heart disease are considered and estimated, and prediction is conducted using publicly accessible heart disease data (Indrakumari, 2020). In addition to data analytics and simulation methods, K-means clustering algorithm is used to forecast heart disease. Pre-processing processes, classifier efficiency and measurement metrics are explored in this work.

In (Ali, 2020), using ensemble deep learning and function fusion methods, a smart healthcare framework is suggested for heart disease prophecy. Furthermore a particular function weight for each class is calculated by conditional probability method, which further increases device efficiency. Finally, ensemble deep learning ideal is qualified for prediction of heart disease. Suggested approach is checked with heart disease data as well as associated with conventional classifiers focused. Proposed system achieves 98.5% precision, which is better than current systems. Results reveal that, relative to other state-of-the-art systems, our approach is more powerful for estimation of heart disease.

In (Su, 2018), Denial-of-Service (DoS) attack is concerned with identification as well as recompense co-design challenge for cyber-physical networks.First, based on principle of packet receipt rate, a novel supervisory technique is introduced that can detect a DoS attacker's actions within a specified time window.A quantifiable overview of correlation between attack times, time window, victory rate of attack, and receipt rate of packets is determined. There is also a co-design compensation function, which will further ensure that attacked structure is stochastically stable or that mean square is eventually exponentially bounded.

Proposes system in (Ashrafuzzaman, 2013) that can use only a camera from a commercially available smartphone to estimate heartbeat rate and even use a handheld stethoscope to monitor heart sound to track incidence of cardiac failure and any other heart condition. Fuzzy Logic, which is part of Data Mining, specialist human disease dilemma approach, is used here. In general, as people face this problem, cases cannot be recognized by individuals and this is key cause of death. To minimize heart attack death rate, this research found this issue earlier. Value of this approach is that under almost any conditions, consumer does not require advanced hardware and he/she can take a measurement in almost any location. To improve users well being, effective telecare services and health coaching applications are use measurement as a tool.

To identify people with heart attack by finding heart attack characteristic postures proposed in (Rojas-Albarracin, 2019). This method used CNN. They have specially prepared image set which consists of simulating heart attack. 91.75% accuracy and 92.85 % sensitivity as demonstrated in infarct classification.

Propose an integrated method for study of HRV signals to arrest temporal, spectral, and compound dynamics by extracting multimodal functions (Hussain, 2020). To determine detection efficiency, robust machine learning methods were used. SVM linear kernel (TA= 93.1 percent, AUC= 0.97, 95 percent CI [lower bound= 0.04, upper bound= 0.89]) was the highest performance, surveyed by ensemble subspace discriminant (TA= 91.4 percent, AUC= 0.96, 95 percent CI [lower bound= 0.07, upper bound= 0.81]) and SVM medium Gaussian kernel (TA= 90.5 percent, AUC= 0.95, 95 percent CI [lower bound= 0.07, upper bound= 0.81]). Findings show that suggested solution will gives an effective as well as computationally efficient method for automated diagnosis of patients with congestive heart failure.

Several data mining methods for detection of heart disease have been used by researchers (Parthiban, 2012). Diabetes is a chronic syndrome that develops when pancreas does not contain enough insulin, or when insulin it provides cannot be used properly by body. Many of these applications also successfully used machine learning methods for purpose of classification, like Naïve Bayes and SVM. In field of machine learning, SVM is a modern technique and has been successfully used in numerous application fields.

Proposed method (Opeyemi, 2012) seeks to provide a neuro-fuzzy method for diagnosis of heart attacks. To make it suitable for testing, data set used was removed from database and modeled, then original configuration was established, network was trained with training data set, after which test data set was checked and validated. Patient simply has to include certain values that act as feedback to system and will be able to predict patient's risk level depending on values provided by system.

3. Research Methodology

Proposed architecture is shown in figure 1. The input data is taken from medical database which is given to preprocessing stage. The input can be arrhythmia 497, low ejection fraction 531, normal 617 is preprocessed by using resize the image and the contrast enhancement. In the segmentation stage the contrast-enhanced result is used for segmentation using mask RCNN instance segmentation then the output is mask which is given as an input for feature extraction stage. The segmented result has extracted the features using SIFT and ALEXNET. To determine right feature set for classification, combinations of multiple heart-disease traits were subsequently checked. The image is trained and the classification using Random Forest and Gaussian Navies Bayes. Then finally detect the heart attack.

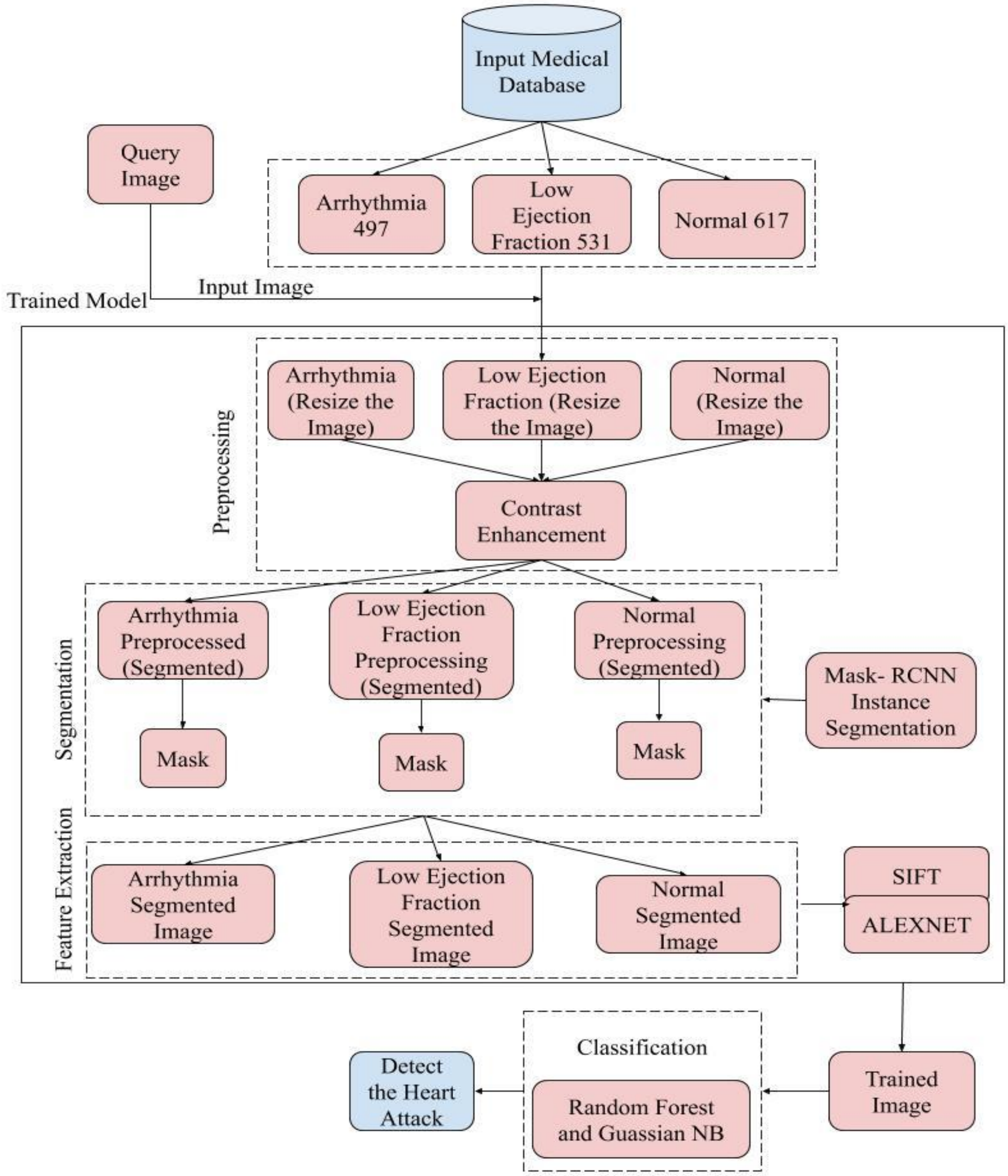

Figure 1. Proposed Architecture

3.1 Pre-processing

Owing to different noises found in these files, raw images captured from scan centers and websites are not appropriate for direct processing. It must then be pre-processed before it is tested. Pre-processing is an important step in converting, resizing, eliminating noise and improving consistency of pre-processing, creating an image in which minutiae can be accurately detected.

3.3.1 Image resizing

In image processing techniques, image resizing plays an important role in enlarging and decreasing specified image in pixel size format. Image interpolation is split into 2 distinct forms, which are image downsampling and upsampling, which are expected to fit either particular contact channel or output display when resizing data. Although sending low-resolution copies to client is more effective, an approximation of original high-resolution could be necessary for final visual data to be displayed. In several applications, precise resizing of image data is an important step, ranging from many consumer goods to vital functions in medical, safety and security sectors. This method makes final process for image processing very quick. Through use of technique, velocity of resizing should be determined and resulting image frequently includes block objects, which are not very physically visible but may usually often have a drastic negative effect on error measurements used to equate processes.

3.3.2 Contrast Enhancement

Contrast enhancement must be used to make image more suitable for particular applications. This increases image's clarity and transparency, and computer processing of original image is more appropriate. As low contrast image values are extreme, pixel intensity is stretched by contrast enhancement. Image will typically have poor statistical range or pixel misrepresentation, either because of low efficiency of imaging equipment or because of intense environmental circumstances during retrieval process. Among different methods of contrast enhancement, method of histogram adjustment is commonly used because of its simplicity and efficacy. Histogram equalization process is to extend input image amplitude to create a similar distribution such that image's active spectrum is entirely demoralized. Difference between maximum and low pixel intensity is contrast. Formula for stretching image histogram of image to enhance contrast is

$$a(x,y) = \frac{b(x,y) - b_{min}}{b_{max} - b_{min}} * 2bpp \qquad (1)$$

Formula includes determination of minimum and maximum pixel intensity to be multiplied by levels of grey. Image in our case is 8bpp, so grey levels are 256. A minimum value of 0 is given and a maximum value of 225 is given. So in our scenario, formula is

$$a(x,y) = \frac{b(x,y) - 0}{255 - 0} * 255 \qquad (2)$$

Where f(x,y) denotes each pixel intensity's value. We will compute this formula for each f(x,y) in an image.

Ability of image is increased by improvement after applying equations. Principal goal of method of contrast enhancement is twofold. Locally adaptive equalization of histograms and elimination of undesired objects like noise and object blocking.

Initially, the preprocessing of input images takes place in three different ways: skull stripping, noise removal using bilateral filtering (BF), and contrast limited adaptive histogram equalization (CLAHE) based contrast enhancement. Next to image preprocessing, segmentation task is done to identify the affected tumor regions. The segmentation process is carried out as a separate work as indicated. A vivid explanation of the pre-processing is given earlier module.

3.2 Segmentation

In a computer vision system, an image may be represented as a two or three-dimensional pixel matrix where each pixel from given intensity value. Radiation absorbed during x-rays in medical imaging, or acoustic pressure in ultrasonography, or radiofrequency signals in MRI, etc. Image segmentation is a process in which an image is divided into regions with certain homogeneous attributes, such as value of greyscale, color or texture.

3.2.1Mask R-CNN for Instance Segmentation

Segmentation of instance where model gives "individual object" mark to each pixel in image. Segmentation of an instance is a procedure used to detect a pixel-to-pixel object by masking or covering it. Mask R-CNN is one model that can do example segmentation work. Mask-RCNN is a DNN developed to solve issue of computer vision or machine learning instance segmentation. There are two Mask RCNN stages. Next it produces recommendations about regions where an object-centered input image might be present.

Predicts class of object produces a mask, refines bounding box at pixel level of object depends on first step proposal R-CNN Mask as shown in Figure 2 below. To get 3 model outputs, every Region of Interest (RoI) is used.

- Predicted final class for this RoI (object type, e.g. "person")
- Final projected bounding box is achieved from this RoI.
- Final predicted segmentation.

An RoI is assumed to be "positive" if it overlays sufficiently with a bounding box of ground-truth. R-CNN mask contains a mask loss that measures how well projected segmentation masks match with ground-reality segmentation disguises. Mask loss is only distinct when corresponding RoI reasonably overlaps with a true image object. Mask loss is defined only for positive ROIs.

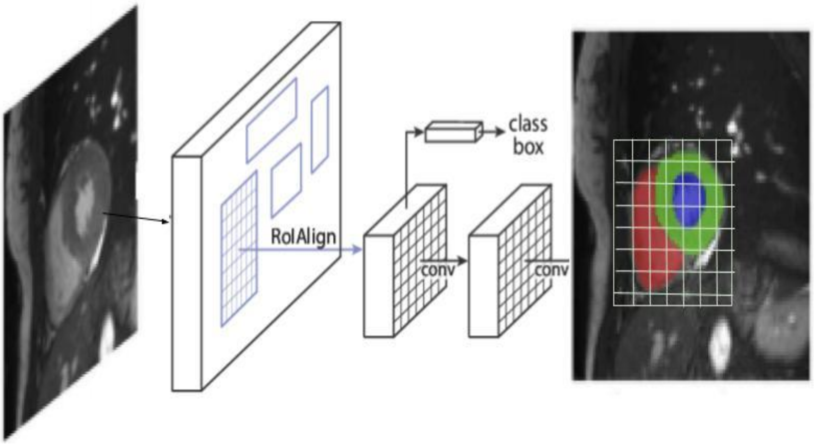

Figure 2. Mask RCNN model

R-CNN Mask has slightly misaligned states of feature map chosen by RoIPool from areas of creative graphic. Because image segmentation involves precision at pixel level of image, this clues to inaccuracies. Using RoIAlign, in which feature map is tested at various points and then a bilinear interruption is pragmatic to achieve a exact image of what will be at pixel 2933, this problem was solved.

For regions selected by ROI classifier, a convolutionary network is then used which takes and generates masks. Created masks have a low 28x28 pixel resolution. Masks are scaled down to 28x28 during testing to measure deficit, and projected masks are scaled up to size of ROI bounding box during inference. This provides us with final masks for each item.

3.2.2 Forming Data Set to Train an Instance Segmentation Model

The data sets are ideal for segmentation models of training instances. MS COCO, which includes 328,000 segmented images into instances, is one common instance segmentation data set. In three phases, MS COCO was created:

- Instance spot: With an "X." 8 workers per image, mark each instance of each object. 10,000 hours for a worker.
- Category labeling: With 8 workers per image, 91 possible categories and 20,000 worker hours, mark a single instance of each object.
- Instance segmentation: Perform any segmentation of instances, i.e. trace frameworks manually for all examples of objects. An picture was segmented by 1 professional worker and tested by 3-5 other employees. For a student, 55,000 hours

Entire cost function contains classification loss and location loss of detector frame, according to loss function architecture of mask RCNN instance-based segmentation method. In following equation, classification loss function is seen, which is calculated by likelihood corresponding to actual classification x. The loss function used for Mask RCNN instance segmentation,

$$LF = Class_L + Reg_L + Mask_L \qquad (3)$$

Where LF is the Loss Function, $Class_L$are the losses of classification and Reg_L is the loss of the regression.

$$Class_L = -log\ PC_x \qquad (4)$$

Where, PC_x is the probability of corresponding class x.

$$Mask_L = -\frac{1}{n}\sum_{i=1}^{n}\sum_{j=1}^{m\times m}(log\ Pi_{i,j}^{M}) \qquad (5)$$

Where, $Pi_{i,j}^{M}$ is jth pixel of ith mask generating.

Loss calculation of predicted and trained values are calculated by using the formula,

$$Loss(\{Pre_i\},\{tra_i\}) = 0.5\ \frac{1}{NP}\sum_{i} AL_{pos}\ (Pre_i, \widehat{Pre}_i)$$

$$+0.5\ \frac{1}{NN}\sum_{i} AL_{neg}\ (Pre_i, \widehat{Pre_i})$$

$$+\frac{1}{NR}\sum_i \widehat{Pre_i}\ AL_{FR}\ (Tra_i, \widehat{Tra_i}) \qquad (6)$$

Where, Pre_i is the Predicted image, Tra_i is the trained image, AL_{pos} is the Average loss of Positive case, AL_{neg} is Average loss of Negative case, AL_{FR} is average loss of frame regression.

3.3 Feature extraction

Simplest and quickest system to use depictive influence of pre-trained deep networks is to extract functions. Feature detection and extraction play a major role in computer vision field. Features are extracted from multi-scale images by using many algorithms. Among them Scale-invariant feature transform (SIFT) and ALEXANET are the best algorithms. Features are extracted from original collection of calculated data and derived values are constructed. There is a set of characteristics or model characteristics in feature extraction process, information gained from that image is very useful for interpretation and classification. Improving quality and usefulness of research and classification is main objective of feature extraction.

3.3.1 SIFT - Scale Invariant Feature Transforms

Using SIFT technique, extracted features are partially invariant to 3D camera viewpoint and illumination and invariant to image transition, rotation and scaling. It is divided into 2 modules such as descriptor generation and key point detection module. Method used in descriptor generator model is changed to increase algorithm performance. It is divided into 4 main steps:

1. Key point Localization
2. Scale Space Extrema Exposure
3. Key point Descriptor
4. Orientation Task

3.3.2 Scale-Space Extrema Detection

This filtering stage aims to classify all positions and sizes that can be distinguished from same object's various views. Using a "scale-space" function, this can be easily done. It has also been shown that it is based on Gaussian equation under rational assumptions. It is defined as

$$L(x, y, \sigma) = G(x, y, \sigma) * L(x, y) \qquad (7)$$

Where convolution operator is *, Gaussian variable-scale is G(x, y, σ) and I(x, y) is input. In scale space, to perceive stable key point locations, various methods are used. One such method is variance of Gaussians, finding extreme scale-space, D(x, y, σ) by estimating variance between 2 images, 1 with scale of k times other. D(*x*, *y*, σ) is

$$D(x, y, \sigma) = L(x, y, k\sigma) - L(x, y, \sigma) \qquad (8)$$

Every point is contrasted with its 8 neighbors on same scale and its 9 neighbors up and down on one scale to identify local maximum and minimum of D(x, y, σ). This is an acute point where either of these points is minimal or constrained by this value.

3.3.3 Keypoint Localization

This process helps to exclude more points from keypoints list. This is done by measuring Laplacian value for every key point in step 1. Position of extremum z is defined by:

$$z = -\frac{\partial D^{-1}}{\delta x^2}\frac{\partial D}{\delta x} \qquad (9)$$

If point is omitted, value of function at z is below threshold value. This eliminates low contrast extrema. If this difference is less than ratio of largest to smallest own vector, key point is rejected from 2x2 Hessian matrix at position and key point size. If this difference is between ratio of largest vector to smallest vector at position of 2x2 Hessian matrix and keypoint size, keypoint would be refused.

3.3.4 Orientation Assignment

Based on local image properties, these steps allots consistent keypoints orientation. Related to this orientation, to attain invariance to rotation, keypoint descriptor is described.

To determine orientation, below steps are used:

- Gaussian smoothed image L is selected by using keypoint scale.
- Calculate gradient magnitude *m*,

$$m(x,y) = \sqrt{L(x+1,y) - L(x-1,y)^2 + L(x,y+1) - L(x,y-1)^2} \qquad (10)$$

- Calculate orientation θ,

$$\theta(x,y) = \tan\left(\frac{L(x,y+1)-L(x,y-1)}{L(x+1,y)-L(x-1,y)}\right) \qquad (11)$$

- From, sample points gradient orientation, orientation histogram is created.
- Histogram highest peak is located. To create orientation keypoint, this peak or any other peak with 80% is used.
- Multiple orientations are assigned by some points.
- To interpolate peaks position, fit parabola to 3 histogram values which is close to every peak value.

3.3.5Keypoint Descriptor

Tobuilt keypoint descriptors, local gradient data is used. With keypoint orientation, gradient data is rotated to line up and with 1.5 variance keypoint scale, Gaussian is weighted. In window centered on keypoint, histogram set is created by using data. It uses 16 histograms which are aligned in 4x4 grid with 8 orientation bins, one for each is focal compass and midpoint directions. It gives feature vector with 128 elements. Usually 500x500 pixel image is created in 2000 features area, significant occlusion levels are possible while this method still recognizes image.

3.3.6 *ALEXANET*

It consists of 8 layers, there are 3 fully connected and 5 convolutional layers. For wide range of images, network has rich feature representation. Features used for convolutional neural network is overlapping pooling. Without overlap CNN pool outputs of neighboring group neurons. Reduction in error about 0.5% occurs when overlap occurs and concludes that pool overlap is harder to overfit. For any object detection task, it is leading method as well as huge applications in AI issues in computer vision sector. To deep networks which are used nowadays, it is key step from shallow and it is surpassed by more effective methods.

3.4Classification

Classification is supervised learning method in which from input data, computer program studies and this learning is used to classify new observations in statistics and machine learning.

3.4.1.Random Forest

It is a bootstrapping method with cart model. To construct cart model, consider 5 random samples and 100 observation samples and it built multiple trees with various initial variables. For each observation, same process is repeated 10 times to take final prediction which is each prediction function. This method is also called a supervised learning method. This method produces multiple random trees known as forests during learning phase. For instance, dataset contains ‘x’ number of attributes and ‘y’ randomly selected features. By using best rift method it generates nodes using all features ‘y’. by repeating previous steps, this method work for developing complete forest.

Implementation of machine learning tool involves a wide variety of data science methods that are used to identify, classify and predict missing values. By following cases, Random forest is attractive.

(1) First of all, data from real-world is noisy and includes several incomplete values, some of which are categorical or semi-continuous attributes.

(2) Also, multiple data sources that pose the problem of weighting them must be combined.

(3) With highly correlated features, RF gives high predictive accuracy and is used in high dimensional issues basically in bioinformatics such as medical diagnosis.

3.4.2.Gaussian Navies Bayes:

A Naive Bayes version that assumes normal distribution of Gaussian and accepts continuous data is Gaussian Naive Bayes. Naive Bayes Classifier is executed on high dimensional datasets. Naive Bayes extension is known as Gaussian Naïve Bayes.For estimating distribution of data, other functions may be used, but Gaussian is simplest to deal with so you only need to approximate mean and SD from training data.An inference often taken when dealing with continuous data is that according to a normal (or Gaussian) distribution, continuous values associated with every class are distributed. Features likelihood is calculated as:

$$P\left(\frac{x_i}{y}\right) = \frac{1}{\sqrt{2\pi\sigma_y^2}}\exp\left(-\frac{(x_i-\mu_y)^2}{2\sigma_y^2}\right) \qquad (12)$$

Let us consider variance is independent of Y (i.e., σi) or independent of Xi (i.e., σk) or both (i.e., σ)

In conformity with a Gaussian (normal distribution, Gaussian Naive Bayes promotes continuous-valued features and models. When data is defined by Gaussian distribution with no-covariance between dimensions, method creates simple model. Within every label, standard deviation (SD) and mean is founded by this model which is required to define such distribution. For each class value, SD and mean values of each input variable (x) are evaluated.

$$mean\ (x) = \frac{1}{n} * sum(x) \qquad (13)$$

In training data, x is input variable value and n is number of instances. Using following equation, SD is calculated.

$$Standard\ Deviation\ (x) = sqrt\left(\frac{1}{n}\right) * sum(xi - mean\ (x)^2) \quad (14)$$

This is square root of mean square difference of each value of x and mean value of x, where n is number of examples, sqrt() is square root function, sum() is sum function, xi is unique value of x variable, and mean(x) is defined above and ^2 is square variable.

3.4.3Dataset Description

From Tanford university school of medicine's echonet-dynamic dataset research, data set was used. For training EchoNet-Dynamic, deidentified set of10,030 echocardiogram images are used. Open CV and pydicom have been used to preprocess these files, including de-identification and migration from DICOM format to AVI format videos. To evaluate heart activity and structure, echocardiography, or cardiac ultrasound, is most commonly used and readily available imaging modality. Echocardiography is one of most commonly used imaging tests in United States, incorporating compact instrumentation, fast image processing, high temporal resolution, all without dangers of ionizing radiation, and serves as cornerstone of cardiovascular imaging. Echocardiography is both necessary and appropriate to diagnose multiple cardiovascular disorders with diseases ranging from cardiac failure to vascular heart diseases.

In addition to our deep learning model, for computer vision research, echocardiograms new large video dataset was introduced. EchoNet-Dynamic database contains 10,030 labeled echocardiogram videos as well as human expert annotations (measurements, tracings, and calculations) to provide a baseline to study cardiac motion and chamber sizes.

Algorithm: Proposed method
Input: Echonet data **Output**: To classify the mammogram images as classified as (i) Arrhythmia (ii) Low Ejection Fraction (iii) Normal **Begin** 1.Initial Step 1: Load the input data for training Step 2: Preprocess the input images 2.Preprocessing the input images Step 1: Resize the input image

Step 2: Contrast enhance the resize image

3.Segmenting the Input image

Step 1: Segmenting the preprocessed image

Step 2: Segmenting by Mask RCNN

Step 3:Check the pixel values

Step 4: Exporting inference graph

Step 5: Train the masked data

Step 6: Record the masked data

4. Sequential model (AlexaNet, SIFT)

Input: Segmented images, batch normalization

Conv2D(filters =96, 227 x 227 x 3 ReLU)

Kernel size 11/11

Strides (4,4)

Batch Normalization

ReLU

Max pool 2x2

Up_Conv 2x2

Conv 2D (filter=256)

Kernel Size 5,5

Strides(1,1)

Batch Normalization

ReLU

Max pool 2x2

Up_Conv 2x2

Conv 2D (filter=384)

Kernel size 3,3

Strides(1,1)

Batch Normalization

ReLU

Repeat the above procedure for 2 times

Conv 2D (filter =256)

Kernel size 3x3

Strides 1,1

Batch Normalization

ReLU

Flatten the images

Dense the layers (4096)

Batch Normalization

ReLU, Dropout (0.4)

Repeat the above procedure by 2 times

Dense the layers (1000)

Batch Normalization

ReLU, Dropout (0.4)

End

4.Experimental Results

The experimental result is carried out in Python software and the parameters used for analysis are accuracy, precision, recall and F measure. Formula for analysis is discussed below:

4.1Accuracy

It shows overall prediction of proposed method**.** To predict presence and absence of heart attack, TP (True Positive) and TN (True Negative) measures classifier models' ability. Number of false predictions produced by models is identified by FP (False positive) and FN (False Negative).

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$

4.2Precision

In heart attack classification model, it is a measure of sensitivity and success. It is defined as classifier probability when disease present gives result as positive which is called TP (True Positive) and calculated as

$$Precision\ (P) = \frac{TP}{TP + FP}$$

4.3Recall

It is defined as classifier probability, when disease not presents gives result as negative which is called TN (True Negative) and calculated as

$$Recall\ (R) = \frac{TP}{TP + FN}$$

4.4 F1- Score

Itis utilized to determine the prediction performance. It is defined as precision and recall weighted average. While 0 is worst, score value 1 is taken as best. It does not consider TNs. It can be calculated as

$$F1 - Score = \frac{2 * P * R}{P + R}$$

Features	Classifier	Accuracy	Precision	Recall	F1-Score
SIFT	Gaussian NB	45.74%	51.24%	48.13%	43.59%
	Random Forest	82.64%	85.97%	81.54%	82.49%
ALEXANET	Gaussian NB	92.7%	93.17%	93.33%	92.92%
	Random Forest	96.43%	96.87%	96.09%	96.39%

Table 1. Classification Training data analysis

4.5 Classification Training data analysis

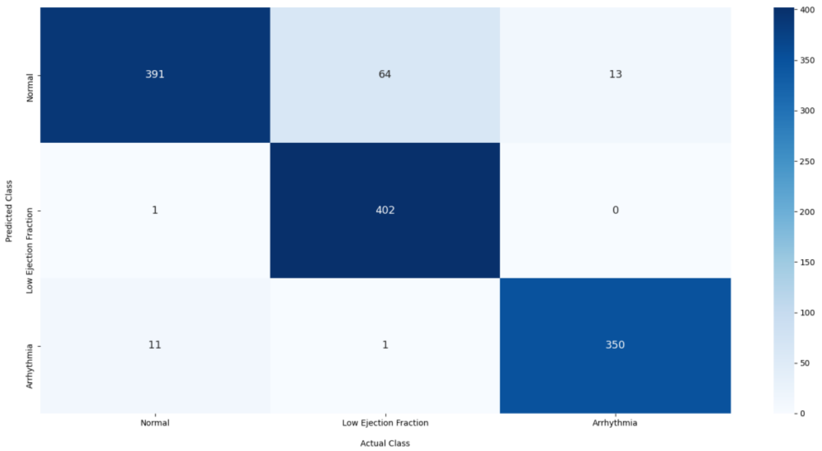

Figure 3: Confusion Matrix for ALEXANET feature Using Gaussian NB Classifier training

Figure 3 shows confusion matrix for ALEXANET features using Gaussian NB classifier training modelin which rows represent predicted class (output class) and columns denote actual class (target class) of data about heart disease. The diagonal blue and white cells denote the trained networks that are correctly and incorrectly classified. Right side column shows predicted class and bottom row shows performance of actual class. This confusion matrix plot for Gaussian NB using ALEXANET indicates overall classification attains 92.7% correct classification performance.

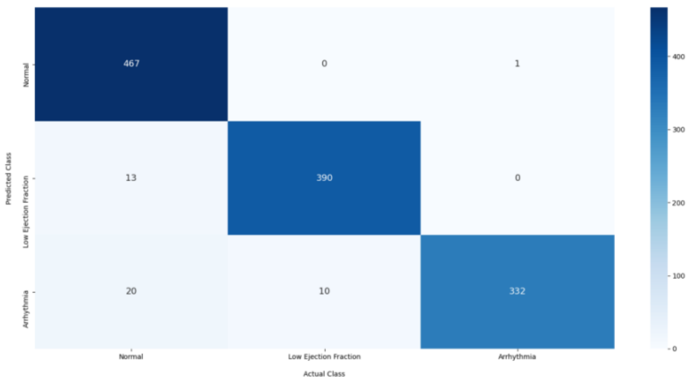

Figure 4: Confusion Matrix for ALEXANET feature Using Random Forest Classifier training

Figure 4 shows confusion matrix for ALEXANET features using Random Forest classifier training modelin which the rows represent predicted class and columns denote actual class of data about heart disease. The diagonal blue and white cells denote the trained networks that are correctly and incorrectly classified. Right side column shows predicted class and bottom row shows performance of actual class. This confusion matrix plot for Random Forest using ALEXANET indicates overall classification attains 96.43% correct classification performance.

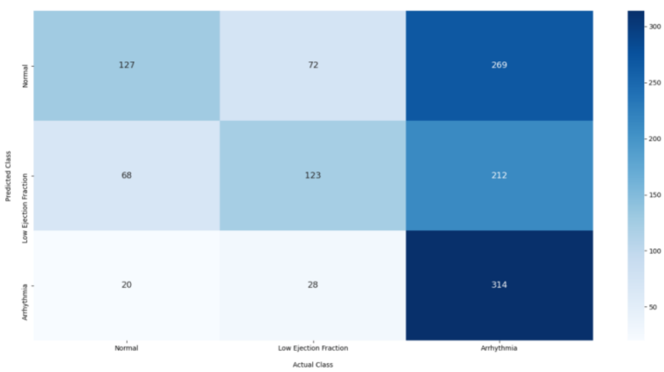

Figure 5: Confusion Matrix for SIFT feature Using Gaussian NB Classifier training

Figure 5 shows confusion matrix for SIFT features using Gaussian NB classifier training modelin which rows represent predicted class and columns denote actual class of data about heart disease. The diagonal blue and white cells denote the trained networks that are correctly and incorrectly classified. Right side column shows predicted class and bottom row shows performance of actual class. This confusion matrix plot for Gaussian NB using SIFT indicates overall classification attains 45.74% correct classification performance.

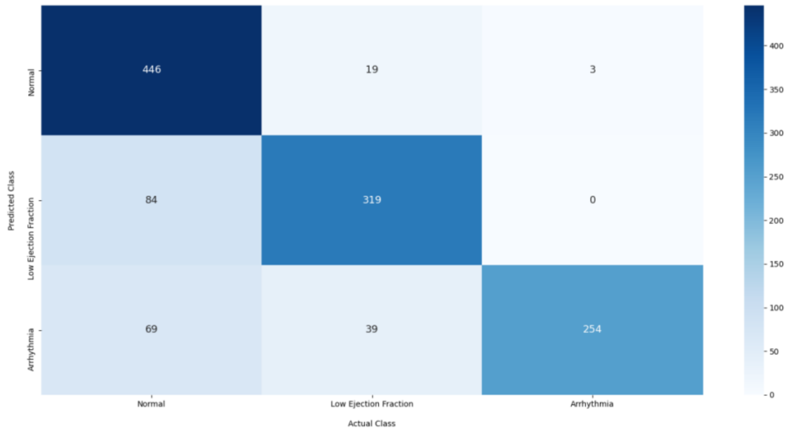

Figure 6: Confusion Matrix for SIFT feature Using Random Forest Classifier training

Figure 6 shows confusion matrix for SIFT features using Random Forest classifier training modelin which the rows represent the predicted class and columns denote actual class of data about heart disease. The diagonal blue and white cells denote the trained networks that are correctly and incorrectly classified. Right side column shows predicted class and bottom row shows performance of actual class. This confusion matrix plot for Random Forest using SIFT indicates overall classification attains 82.64% correct classification performance.

Table 2: Classification testing data analysis

Features	Classifier	Accuracy	Precision	Recall	F1-Score
SIFT	Gaussian NB	46.12%	48.28%	46.44%	43.62%
	Random Forest	55.34%	62.01%	54.72%	54.61%
ALEXANET	Gaussian NB	91.99%	92.2%	92.37%	92.04%
	Random Forest	89.56%	90.92%	89.35%	89.54%

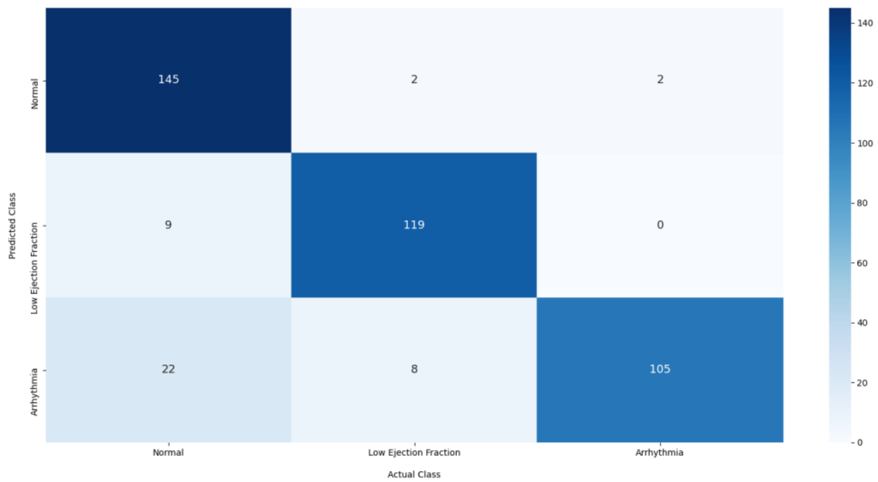

Figure 7: Confusion Matrix for ALEXANET feature Using Random Forest Classifier testing

Figure 7 shows confusion matrix for ALEXANET features using Random Forest classifier training modelin which rows represent predicted class and columns denote actual class of data about heart disease. The diagonal blue and white cells denote the trained networks that are correctly and incorrectly classified. Right side column shows predicted class and bottom row shows performance of actual class. This confusion matrix plot for Random Forest using ALEXANET indicates overall classification attains 89.56% correct classification performance.

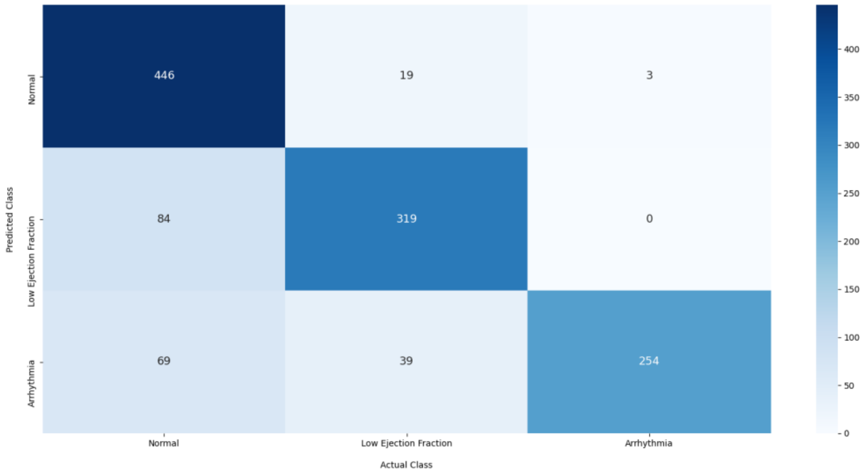

Figure 8: Confusion Matrix for ALEXANET feature Using Gaussian NB Classifier testing

Figure 8 shows confusion matrix for ALEXANET features using Gaussian NB classifier training modelin which the rows represent predicted class and columns denote actual class of data about heart disease. The diagonal blue and white cells denote the trained networks that are correctly and incorrectly classified. Right side column shows predicted class and bottom row shows performance of actual class. This confusion matrix plot for Gaussian NB using ALEXANET indicates overall classification attains 91.99% correct classification performance.

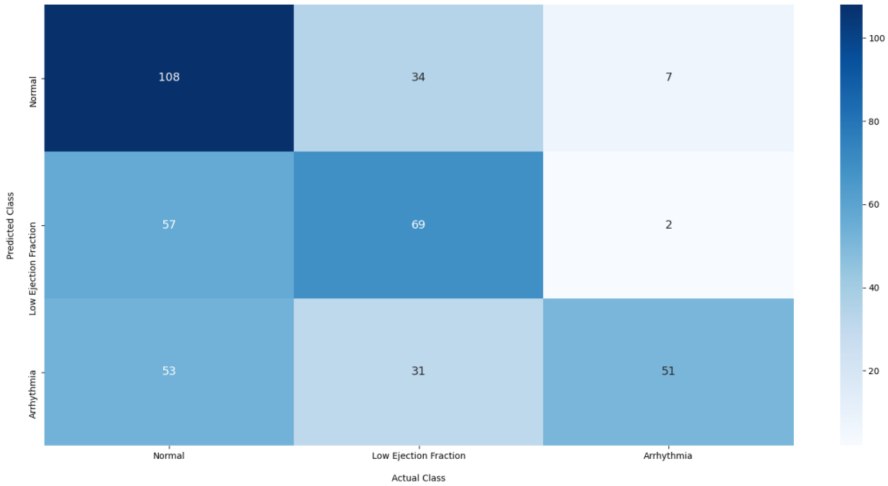

Figure 9: Confusion Matrix for SIFT feature Using Random Forest Classifier testing

Figure 9 shows confusion matrix for SIFT features using Random Forest classifier training modelin which the rows represent the predicted class and columns denote actual class of data about heart disease. The diagonal blue and white cells denote the trained networks that are correctly and incorrectly classified. Right side column shows predicted class and bottom row shows performance of actual class. This confusion matrix plot for Random Forest using SIFT indicates overall classification attains 55.34% correct classification performance.

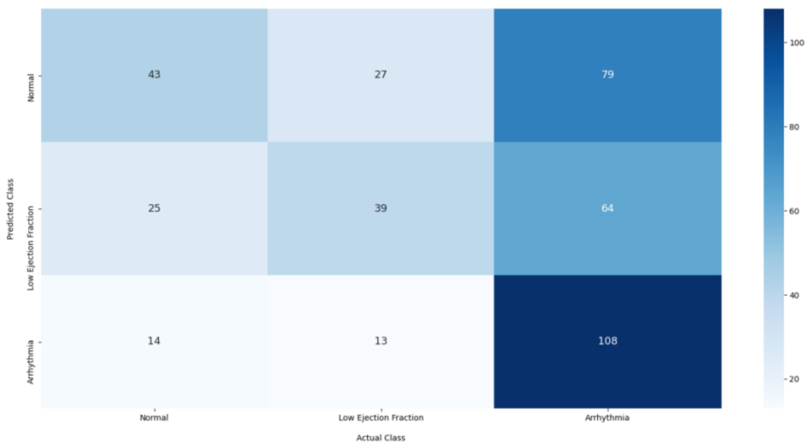

Figure 10. Confusion Matrix for SIFT feature using Gaussian NB Classifier testing

Figure 10 represents confusion matrix for SIFT features using Gaussian NB classifier training modelin which rows represent predicted class and columns denote actual class of data about heart disease. The diagonal blue and white cells denote the trained networks that are correctly and incorrectly classified. Right side column shows predicted class and bottom row shows performance of actual class. This confusion matrix plot for Gaussian NB using SIFT indicates overall classification achieves 46.12% correct classification performance.

The figure 11 shows the SIFT features using Gaussian NB classifier for testing and training model. The X-axis shows the Parameters to be used for analysis and Y-axis shows the values obtained in percentage. The Purple and Olive Color indicate training and testing model. The testing data of Gaussian NB achieves the accuracy 46.12%, precision achieves 48.28%, Recall achieves 46.44%, and F1-Score achieves 43.62%. The training data of Gaussian NB achieves the accuracy 45.74%, precision achieves 51.24%, Recall achieves 48.13%, and F1-Score achieves 43.59%.

The figure 12 shows the SIFT features using Random Forest classifier for testing and training model. The X axis shows the Parameters to be used for analysis and Y axis shows the values obtained in percentage. The Purple and Olive Color indicates training and testing model. The testing data of Random forest achieves the accuracy 55.34%, precision achieves 62.01%, Recall achieves 54.72%, and F1-Score achieves 54.61%. The training data of Random Forest achieves the accuracy 82.64%, precision achieves 85.97%, Recall achieves 81.54%, and F1-Score achieves 82.49%.

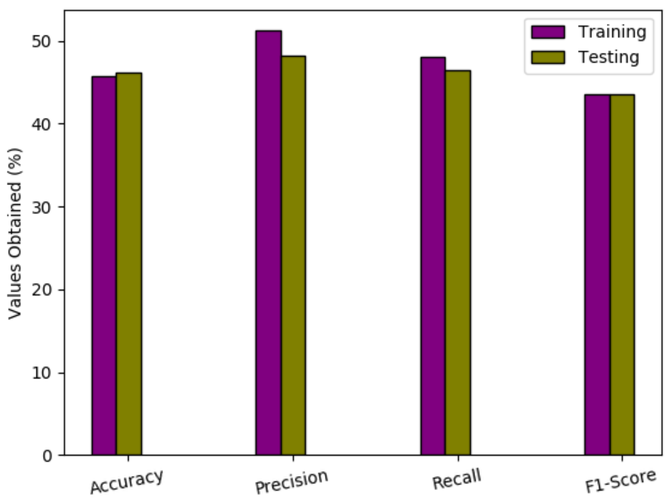

Figure 11. SIFT feature using Gaussian NB classifier

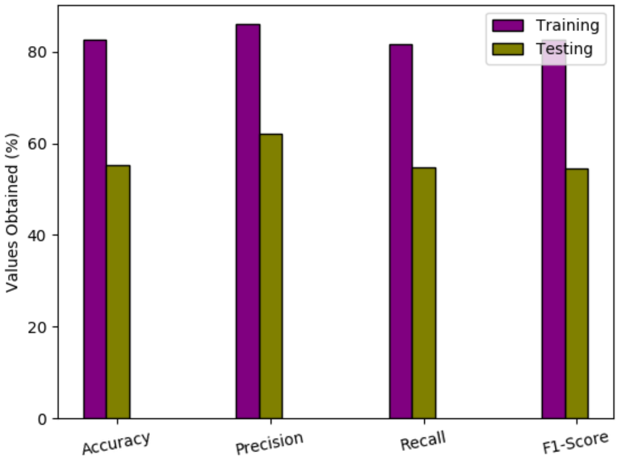

Figure 12. SIFT feature using Random Forest classifier

The figure 13 shows the ALEXANET features using Gaussian NB classifier for testing and training model. The X axis shows the Parameters to be used for analysis and Y axis shows the values obtained in percentage. The Purple and Olive Color indicates training and testing model. The testing data of Gaussian NB achieves the accuracy 91.99%, precision achieves 92.2%, Recall achieves 92.37%, and F1-Score achieves 92.04%. The training data of Gaussian NB achieves the accuracy 92.7%, precision achieves 93.17%, Recall achieves 93.33%, and F1-Score achieves 92.92%.

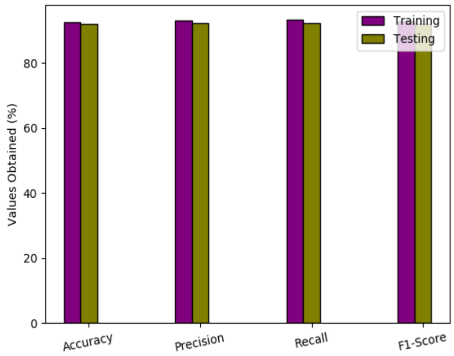

Figure 13. ALEXANET feature using Gaussian NB classifier

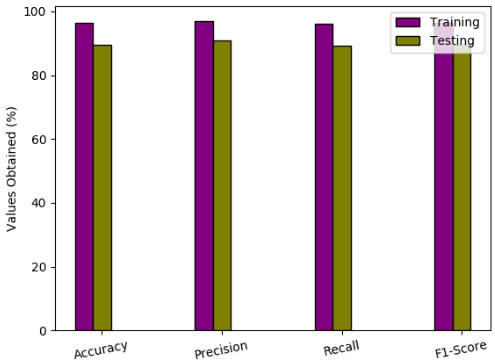

Figure 14. ALEXANET feature using Random Forest classifier

Figure 14 shows the ALEXANET features using Random Forest classifier for testing and training model. The X axis shows the Parameters to be used for analysis and Y axis shows the values obtained in percentage. The Purple and Olive Color indicate training and testing model. The testing data of Random forest achieves the accuracy 89.56%, precision achieves 90.92%, Recall achieves 89.35%, and F1-Score achieves 89.54%. The training data of Random forest achieves the accuracy 96.43%, precision achieves 96.87%, Recall achieves 96.09%, and F1-Score achieves 96.39%.

5. Conclusion

The proportion of heart disease patients has been growing every day. There is a necessity for a framework that creates guidelines or identifies data by means of machine learning methods to solve this risky condition and worsen risks of heart failure disease. Proposed method is based on machine learning classification which determines features extracted from clinical databases. Detection of heart attack using machine learning is effective and also experimental results show evaluated with heart disease data and then testing and training data is compared also achieves better results. In future, to enhance this work with IoT based real time healthcare application which is used to know the status of patient health.

References

1. Ali, Farman, Shaker El-Sappagh, SM Riazul Islam, Daehan Kwak, Amjad Ali, Muhammad Imran, and Kyung-Sup Kwak. (2020) *A smart healthcare monitoring system for heart disease prediction based on ensemble deep learning and feature fusion." Information Fusion 63: 208-222*
2. Aroulanandam, V.V., Latchoumi, T.P., Bhavya, B., Sultana, S.S. (2019). Object detection in convolution neural networks using iterative refinements. Revue d'Intelligence Artificielle, Vol. 33, No. 5, pp. 367-372. https://doi.org/10.18280/ria.330506
3. Arunkarthikeyan, K. and Balamurugan, K., 2020, July. Performance improvement of Cryo treated insert on turning studies of AISI 1018 steel using Multi objective optimization. In 2020 International Conference on Computational Intelligence for Smart Power System and Sustainable Energy (CISPSSE) (pp. 1-4). IEEE.
4. Bhasha, A.C., Balamurugan, K. End mill studies on Al6061 hybrid composite prepared by ultrasonic-assisted stir casting. Multiscale and Multidiscip. Model. Exp. and Des. (2020). https://doi.org/10.1007/s41939-020-00083-1
5. Chauhan, S. and Aeri, B.T., (2015)*The rising incidence of cardiovascular diseases in India: Assessing its economic impact. J. Preventive Cardiology, 4(4), pp.735-740.*
6. Chinnamahammad Bhasha, A., Balamurugan, K. Fabrication and property evaluation of Al 6061 + x% (RHA + TiC) hybrid metal matrix composite. SN Appl. Sci. **1,** 977 (2019). https://doi.org/10.1007/s42452-019-1016-0
7. Deepthi, T. and Balamurugan, K., 2019. Effect of Yttrium (20%) doping on mechanical properties of rare earth nano lanthanum phosphate (LaPO4) synthesized by aqueous sol-gel process. Ceramics International, 45(15), pp.18229-18235.
8. Hussain, Lal, Imtiaz Ahmed Awan, Wajid Aziz, Sharjil Saeed, Amjad Ali, Farukh Zeeshan, and Kyung Sup Kwak. (2020) *Detecting Congestive Heart Failure by Extracting Multimodal Features and Employing Machine Learning Techniques, BioMed Research International.*
9. Indrakumari, R., Poongodi, T., & Jena, S. R. (2020) *Heart Disease Prediction using Exploratory Data Analysis. Procedia Computer Science, 173, 130-139*
10. KaanUyar Ahmet Ilhan. (2017) *Diagnosis of heart disease using genetic algorithm based trained recurrent fuzzy neural networks. 9th international conference on theory and application of soft computing, computing with words and perception. Budapest, Hungary: ICSCCW; 2017.*
11. Latchoumi, T.P. and Kannan, V.V., 2013. Synthetic Identity of Crime Detection. International Journal, 3(7), pp.124-129.
12. Loganathan, J., Latchoumi, T.P., Janakiraman, S. and parthiban, L., 2016, August. A novel multi-criteria channel decision in co-operative cognitive radio network using E-TOPSIS. In *Proceedings of the International Conference on Informatics and Analytics* (pp. 1-6). https://doi.org/10.1145/2980258.2982107
13. Md. Ashrafuzzaman, Md Mazaharul Huq, Chandan Chakraborty, Md. Rafi Monjur Khan, Taslima Tabassum, Rashedul Hasan, (2013) *Heart Attack Detection Using Smart Phone, International Journal of Technology Enhancements and Emerging Engineering Research, vol 1, issue 3, pp.23-27.*
14. Opeyemi, O., & Justice, E. O. (2012) *Development of neuro-fuzzy system for early prediction of heart attack. International Journal of Information Technology and Computer Science, 4(9), 22-28.*

15. Parthiban, G., & Srivatsa, S. K. (2012) *Applying machine learning methods in diagnosing heart disease for diabetic patients. International Journal of Applied Information Systems (IJAIS), 3(7), 25-30.*
16. Patel, J., Upadhyay, P. and Patel, D. (2016) *Heart Disease Prediction Using Machine learning and Data Mining Technique. Journals of Computer Science &Electronics , vol. 7, pp. 129-137.*
17. Raza, K. (2019)Improving the prediction accuracy of heart disease with ensemble learning and majority voting rule.In U-Healthcare Monitoring Systems, pp. 179-196.
18. Rojas-Albarracin, Gabriel, Miguel Ángel Chaves, Antonio Fernandez-Caballero, and Maria T. Lopez. (2019). *Heart Attack Detection in Colour Images Using Convolutional Neural Networks, Applied Sciences 9, no. 23, pp. 5065.*
19. Shadman Nashif, Md. Rakib Raihan, Md. Rasedul Islam, Mohammad Hasan Imam, (2018) *Heart Disease Detection by Using Machine Learning Algorithms and a Real-Time Cardiovascular Health Monitoring System", World Journal of Engineering and Technology, vol. 6, pp.854-873.*
20. Singh, Jagwant, and Rajinder Kaur.(2016) *Cardio vascular disease classification ensemble optimization using genetic algorithm and neural network, Indian Journal of Science and Technology 9, no. S1.*
21. Su, Lei, and Dan Ye.(2018) *A cooperative detection and compensation mechanism against denial-of-service attack for cyber-physical systems." Information Sciences 444: 122-134*
22. Vanisree K, JyothiSingaraju. (2011) *Decision support system for congenital heart disease diagnosis based on signs and symptoms using neural networks. International Journal Comput Appl;19(6).*