Heart Disease Prediction Model

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***Abstract*—Cardiovascular disease (CVD) is a main reason for morbidity and mortality in today's world. Identification of CVD is very important and it is very sophisticated task as it needs good efficiency,effectiveness which can be made successful with automation. As a human beings , Not all doctors have same skill and also some may lack knowledge whereas some lacks experience and hence problems may arises in diagnosis of CVD so An automated system would enhance medical diagnosis and it can also reduce costs. In this Project, we have designed a Model which can efficiently identify the probability of CVD diseases and can also identify the factors which have effect on CVD.The performance of the Model is evaluated with the help of confusion matrix and the results shows that the Model is working efficiently and has great potential in predicting the heart disease risk level .**

***Index Terms*—Cardiovascular disease,HDPM,XGboost**

I. Introduction

Heart disease is a big problem nowadays everywhere around the globe and heart attacks are often common. It is observed that this disease do not occur all of a sudden but a continuous process and is the result of being on a particular lifestyle for a long time and also results after giving some basic and common symptoms being occurring all of a sudden. In case of heart attack, the heart is unable to pump the required amount of blood to different parts of the body and moreover it itself also does not get enough blood supply due to blocked arteries in the heart chambers and thus results in heart failure and deaths. The rate of heart disease is very high in countries like India. India is having a very high rate of deaths due to heart diseases. In this paper a lot of symptoms of heart diseases are included which can be used as the features that could be used to find the accurate diagnosis of the patient. So it is necessary to to start timely diagnosis of heart diseases to improve the security of the heart and life. And thus it is important to predict the heart diseases before it is too late. Heart Disease Prediction Model can help Predicting the heart diseases and can be used for early diagnosis of heart and results in saving a million lives.

II. Literature Survey

A lot of studies are done on HDPM with Machine learning techniques to improve heart diagnosis prediction . Statlog and Cleveland are two publicly available dataset which are majorly used in model creation and researchers widely uses them for model accuracy.Different types of algorithms are used by researchers to generate best possible model and they have got accuracy around 96% for statlog dataset and 98% for cleveland dataset.And they have compared there model with six other preexisting model.They found that there model was very efficient and getting very better result in term of accuracy. In the paper they have performed step by step methods to proceed towards training of the model. As data preprocessing is very essential and we know that it affects the accuracy of the model, so we need to do it very sincerely. They have focused on data preprocessing , and data balancing . But they have not used Genetic algorithm for the parameter tuning , so we thought of doing parameter tuning using Genetic algorithm , so that the best parameter will give better accuracy. And also we need to avoid overfitting the model. We compare our model with ten other models.

III. Methodology

The HDPM is a combination of different ML technique.A step by step procedure is followed to get an efficient model.Based on current condition of a patient,relevant information will be collected and based on information provided by the user model will predict the presence of heart disease.We need to load the dataset.As dataset can contain unnecessary information, we need to detect them and remove them from the dataset.In Data preprocessing, Attribute selection need to perform.It can be done based on PCC and information value.Then outlier detection using DBSCAN.Data balancing can be done using SMOTEENN.Apply genetic algorithm for parameter tuning.Then training of the model using XGboost . Finally, the performance metrics are presented to evaluate the performance of the proposed model. In our study, genetic algorithms used to get the best parameter value to get better accuracy and to avoid overfitting of the model.

A. DATA SOURCE

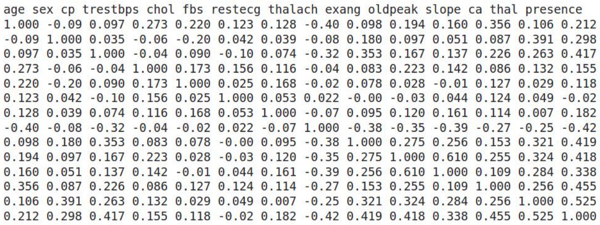
In this paper, we have used heart disease dataset from the machine learning(ML) repo of UCI . We have two dataset. Statlog - It consists of 270 data points,one output class and 13 attributes(where 120 subjects are positively labelled and 150 subjects are negatively labelled). Cleveland - It consists of 303 data points,one output class and 13 attributes(where 138 subjects are positively labelled and 165 subjects are negatively labelled).

B. FEATURES DESCRIPTION

Features	Description
age	age(in years)
sex	gender(M/F etc)
cp	type of chest pain
trestbps	rest blood pressure(bp)
chol	serum cholesterol(chol)
fbs	fasting blood sugar
restecg	resting electrocardiographic(ecg) result
thalach	maximum heart beat rate
exang	exercise induced angina
oldpeak	ST depression due to exercise compared to rest
slope	peak exercise ST segment slope
ca	count of major vessels colored with the help of fluoroscopy
thal	type of defect

C. DATA PREPROCESSING

In the process of feature selection , Correlation between attributes can be of great use like it can tell us the relationship between the attributes here in this project we have used PCC(Pearson's Correlation Coefficient) to predict correlation beteen attributes whose values varies between -1 to +1 and hence -1 defines negative relationship and +1 for positive relationship and 0 for no relation and hence since we are calculation PCC between class label and all other attributes so we can say that PCC whose value close to 0 does not have any contribution towards overall prediction of heart disease and hence those attributes can be dropped off from the dataset. We computed the PCC w.r.t. class attribute and found that two attributes(chol,fbs) have PCC value closer to zero.



```
age sex cp trestbps chol fbs restecg thalach exang oldpeak slope ca thal presence
1.000 -0.09 0.097 0.273 0.220 0.123 0.128 -0.40 0.098 0.194 0.160 0.356 0.106 0.212
-0.09 1.000 0.035 -0.06 -0.20 0.042 0.039 -0.08 0.180 0.097 0.051 0.087 0.391 0.298
0.097 0.035 1.000 -0.04 0.090 -0.10 0.074 -0.32 0.353 0.167 0.137 0.226 0.263 0.417
0.273 -0.06 -0.04 1.000 0.173 0.156 0.116 -0.04 0.083 0.223 0.142 0.086 0.132 0.155
0.220 -0.20 0.090 0.173 1.000 0.025 0.168 -0.02 0.078 0.028 -0.01 0.127 0.029 0.118
0.123 0.042 -0.10 0.156 0.025 1.000 0.053 0.022 -0.00 -0.03 0.044 0.124 0.049 -0.02
0.128 0.039 0.074 0.116 0.168 0.053 1.000 -0.07 0.095 0.120 0.161 0.114 0.007 0.182
-0.40 -0.08 -0.32 -0.04 -0.02 0.022 -0.07 1.000 -0.38 -0.35 -0.39 -0.27 -0.25 -0.42
0.098 0.180 0.353 0.083 0.078 -0.00 0.095 -0.38 1.000 0.275 0.256 0.153 0.321 0.419
0.194 0.097 0.167 0.223 0.028 -0.03 0.120 -0.35 0.275 1.000 0.610 0.255 0.324 0.418
0.160 0.051 0.137 0.142 -0.01 0.044 0.161 -0.39 0.256 0.610 1.000 0.109 0.284 0.338
0.356 0.087 0.226 0.086 0.127 0.124 0.114 -0.27 0.153 0.255 0.109 1.000 0.256 0.455
0.106 0.391 0.263 0.132 0.029 0.049 0.007 -0.25 0.321 0.324 0.284 0.256 1.000 0.525
0.212 0.298 0.417 0.155 0.118 -0.02 0.182 -0.42 0.419 0.418 0.338 0.455 0.525 1.000
```

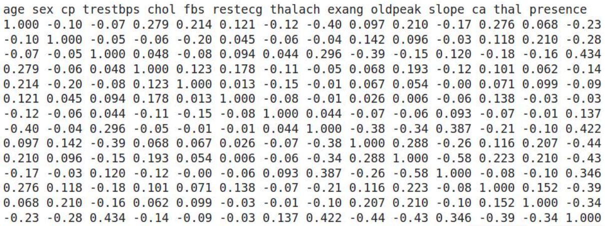
Fig. 1. PCC values of each attribute with class attribute of statlog dataset

We use information gain for the attribute selection. We computed the information gain w.r.t class attribute and found some attributes have information gain closer to zero. So we can drop these attributes from our dataset to get better results.

Finally we have 10 feature attributes with one class attribute as the dataset.

D. OUTLIER DETECTION AND REMOVAL

We use the DBSCAN algorithm to detect the Outlier points and we have used the optimal eps and minpts values for the DBSCAN algorithm.And the data points classified as outlier by DBSCAN are being removed from the dataset.



```
age sex cp trestbps chol fbs restecg thalach exang oldpeak slope ca thal presence
1.000 -0.10 -0.07 0.279 0.214 0.121 -0.12 -0.40 0.097 0.210 -0.17 0.276 0.068 -0.23
-0.10 1.000 -0.05 -0.06 -0.20 0.045 -0.06 -0.04 0.142 0.096 -0.03 0.118 0.210 -0.28
-0.07 -0.05 1.000 0.048 -0.08 0.094 0.044 0.296 -0.39 -0.15 0.120 -0.18 -0.16 0.434
0.279 -0.06 0.048 1.000 0.123 0.178 -0.11 -0.05 0.068 0.193 -0.12 0.101 0.062 -0.14
0.214 -0.20 -0.08 0.123 1.000 0.013 -0.15 -0.01 0.067 0.054 -0.00 0.071 0.099 -0.09
0.121 0.045 0.094 0.178 0.013 1.000 -0.08 -0.01 0.026 0.006 -0.06 0.138 -0.03 -0.03
-0.12 -0.06 0.044 -0.11 -0.15 -0.08 1.000 0.044 -0.07 -0.06 0.093 -0.07 -0.01 0.137
-0.40 -0.04 0.296 -0.05 -0.01 -0.01 0.044 1.000 -0.38 -0.34 0.387 -0.21 -0.10 0.422
0.097 0.142 -0.39 0.068 0.067 0.026 -0.07 -0.38 1.000 0.288 -0.26 0.116 0.207 -0.44
0.210 0.096 -0.15 0.193 0.054 0.006 -0.06 -0.34 0.288 1.000 -0.58 0.223 0.210 -0.43
-0.17 -0.03 0.120 -0.12 -0.00 -0.06 0.093 0.387 -0.26 -0.58 1.000 -0.08 -0.10 0.346
0.276 0.118 -0.18 0.101 0.071 0.138 -0.07 -0.21 0.116 0.223 -0.08 1.000 0.152 -0.39
0.068 0.210 -0.16 0.062 0.099 -0.03 -0.01 -0.10 0.207 0.210 -0.10 0.152 1.000 -0.34
-0.23 -0.28 0.434 -0.14 -0.09 -0.03 0.137 0.422 -0.44 -0.43 0.346 -0.39 -0.34 1.000
```

Fig. 2. PCC values of each attribute with class attribute of Cleveland dataset

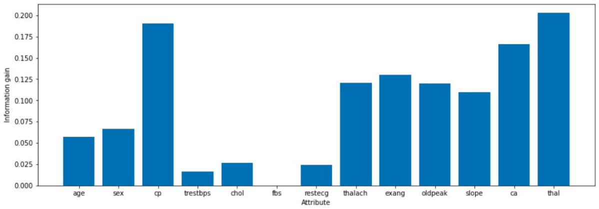


Fig. 3. Information gain of each attribute of statlog dataset

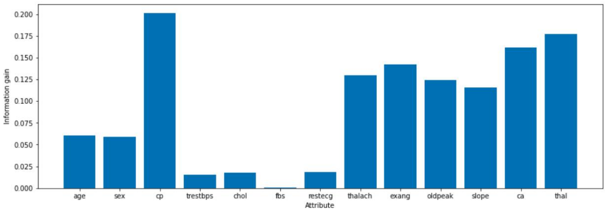


Fig. 4. Information gain of each attribute of Cleveland dataset

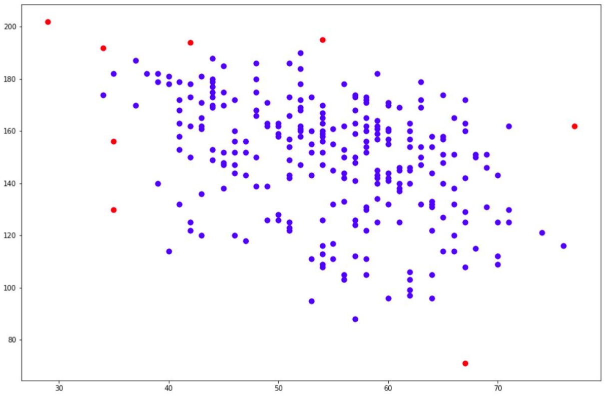


Fig. 5. Plot between attribute thalach and age (red points are outlier points) of statlog dataset.

So we got a dataset which is free from incomplete data, noise, outlier etc. But still there is a problem with the dataset. The dataset is not balanced.

E. DATA BALANCING

Data balancing is necessary to get better result.It can done using different sampling technique.Like, oversam-

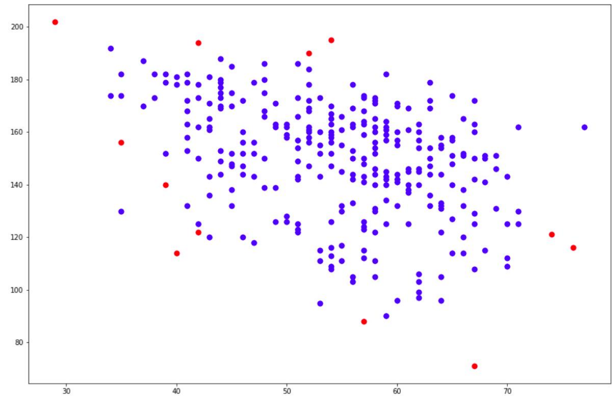


Fig. 6. Plot between attribute thalach and age (red points are outlier points) of Cleveland dataset.

pling(increasing the data point of minority class), undersampling(decreasing the data point of majority class), Hybrid(combination of oversampling and undersampling).Here we used SMMOTEENN that is Synthetic Minority Oversampling Technique Edited Nearest Neighbor. It is hybrid technique combination of oversampling and undersampling.First it will do oversampling for minority class.After doing this there may be overlapping data point, So it remove by doing undersampling.Now the dataset is ready for the training.

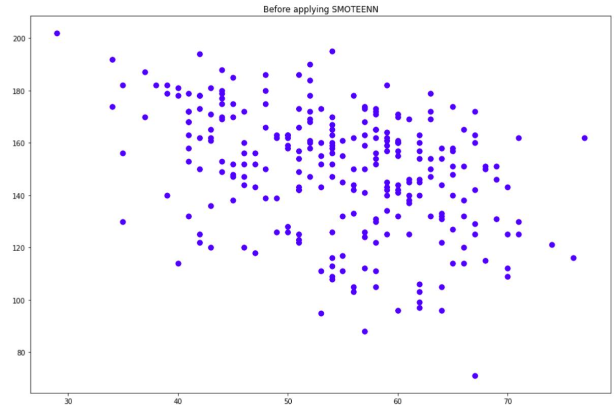


Fig. 7. Dataset(statlog) before applying SMOTEENN

After applying sampling the dataset is evenly balanced class distributions.

F. GENETIC ALGORITHM

Parameter tuning is very essential before training of the model. So we use genetic algorithms for parameter tuning. And finally we use those values for the training of models to get better accuracy.

G. TRAINING OF MODEL

We used XGboost algorithm for training of our model.It is a gradient boosting decision tree algorithm.It follows sequential model. It is basically designed for giving a high computational speed along with better model efficiency.We need to specify many parameter(i.e learing rate, n_estimator, gamma,reg_alpha etc) at the time of training.The output of genetic algorithm will be used as the parameters for the XGboost while training of the model.

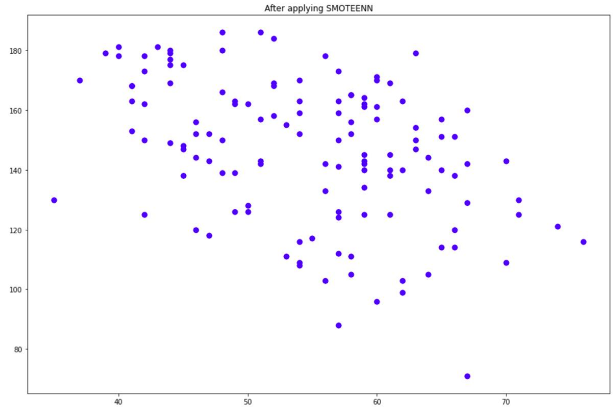


Fig. 8. Dataset(statlog) After applying SMOTEENN

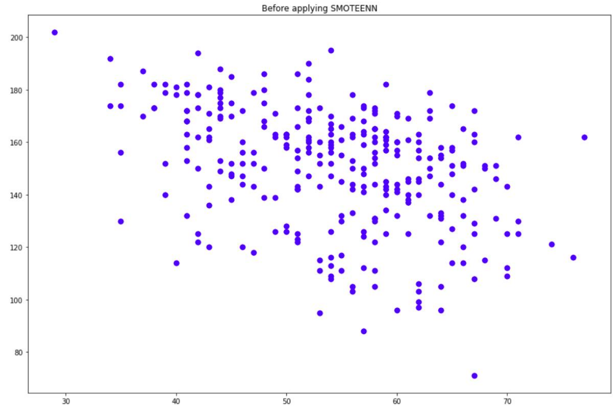


Fig. 9. Dataset(cleveland) before applying SMOTEENN

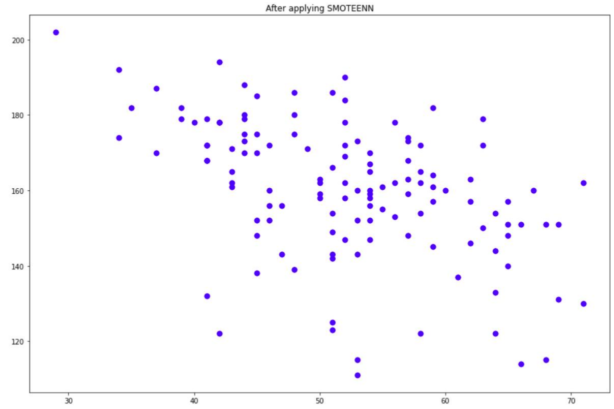
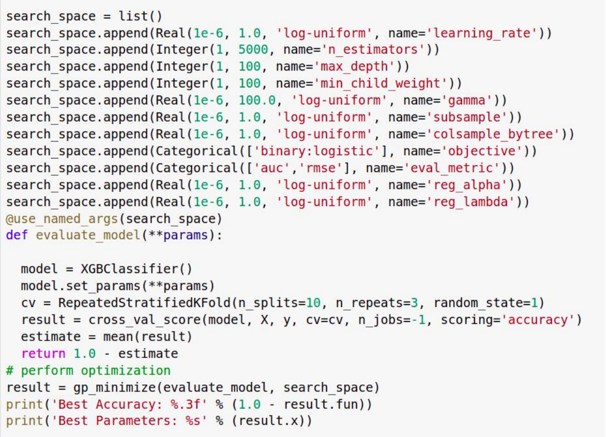


Fig. 10. Dataset(cleveland) After applying SMOTEENN

H. PERFORMANCE EVALUATION

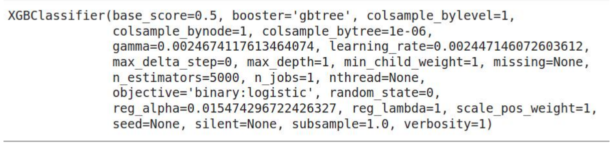
We used NINE performance metrics to evaluate the performance of the proposed model.Accuracy is the number of correct prediction per total number of prediction.F1_score is



```
search_space = list()
search_space.append(Real(1e-6, 1.0, 'log-uniform', name='learning_rate'))
search_space.append(Integer(1, 5000, name='n_estimators'))
search_space.append(Integer(1, 100, name='max_depth'))
search_space.append(Integer(1, 100, name='min_child_weight'))
search_space.append(Real(1e-6, 100.0, 'log-uniform', name='gamma'))
search_space.append(Real(1e-6, 1.0, 'log-uniform', name='subsample'))
search_space.append(Real(1e-6, 1.0, 'log-uniform', name='colsample_bytree'))
search_space.append(Categorical(['binary:logistic'], name='objective'))
search_space.append(Categorical(['auc','rmse'], name='eval_metric'))
search_space.append(Real(1e-6, 1.0, 'log-uniform', name='reg_alpha'))
search_space.append(Real(1e-6, 1.0, 'log-uniform', name='reg_lambda'))
@use_named_args(search_space)
def evaluate_model(**params):

  model = XGBClassifier()
  model.set_params(**params)
  cv = RepeatedStratifiedKFold(n_splits=10, n_repeats=3, random_state=1)
  result = cross_val_score(model, X, y, cv=cv, n_jobs=-1, scoring='accuracy')
  estimate = mean(result)
  return 1.0 - estimate
# perform optimization
result = gp_minimize(evaluate_model, search_space)
print('Best Accuracy: %.3f' % (1.0 - result.fun))
print('Best Parameters: %s' % (result.x))
```

Fig. 11. Applying GA for parameter tuning.



```
XGBClassifier(base_score=0.5, booster='gbtree', colsample_bylevel=1,
              colsample_bynode=1, colsample_bytree=1e-06,
              gamma=0.0024674117613464074, learning_rate=0.002447146072603612,
              max_delta_step=0, max_depth=1, min_child_weight=1, missing=None,
              n_estimators=5000, n_jobs=1, nthread=None,
              objective='binary:logistic', random_state=0,
              reg_alpha=0.015474296722426327, reg_lambda=1, scale_pos_weight=1,
              seed=None, silent=None, subsample=1.0, verbosity=1)
```

Fig. 12. The Optimal parameter for XGboost

the harmonic mean of precision and recall of the model.Then metric like precision score, recall score is used.True positive rate is called as sensitivity of the model. True negative rate is called as specificity of the model.Matthews correlation coefficient is used , value 1 signify perfect prediction and value -1 signify inverse prediction and value 0 signify average prediction. Metric like TPR,TNR,FPR,FNR are also used for the performance evaluation.

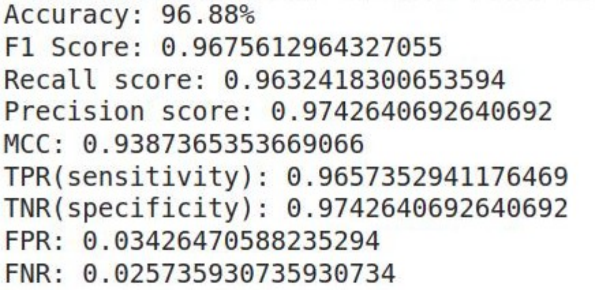
Metrics are:

- Accuracy
- F1 Score
- Recall Score
- Precision Score
- MCC(Matthews correlation coefficient)
- TPR(true positive rate)
- TNR(true negative rate)
- FPR(false positive rate)
- FNR(false negative rate)

We are getting around 97% accuracy for the statlog dataset and around 98% accuracy for the cleveland dataset.

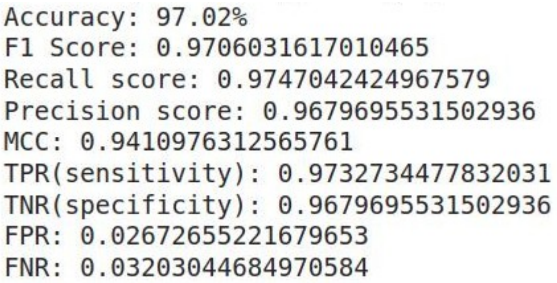
IV. RESULT AND ANALYSIS

The proposed HDPM was applied to both datasets and showed positive results for increasing the prediction accuracy as compared to other models. We selected 10 ML techniques that have been widely used in the research community and have a proven track record for accuracy and efficiency for comparison.



```
Accuracy: 96.88%
F1 Score: 0.9675612964327055
Recall score: 0.9632418300653594
Precision score: 0.9742640692640692
MCC: 0.9387365353669066
TPR(sensitivity): 0.9657352941176469
TNR(specificity): 0.9742640692640692
FPR: 0.03426470588235294
FNR: 0.025735930735930734
```

Fig. 13. Result for statlog dataset



```
Accuracy: 97.02%
F1 Score: 0.9706031617010465
Recall score: 0.9747042424967579
Precision score: 0.9679695531502936
MCC: 0.9410976312565761
TPR(sensitivity): 0.9732734477832031
TNR(specificity): 0.9679695531502936
FPR: 0.02672655221679653
FNR: 0.03203044684970584
```

Fig. 14. Result for cleveland dataset

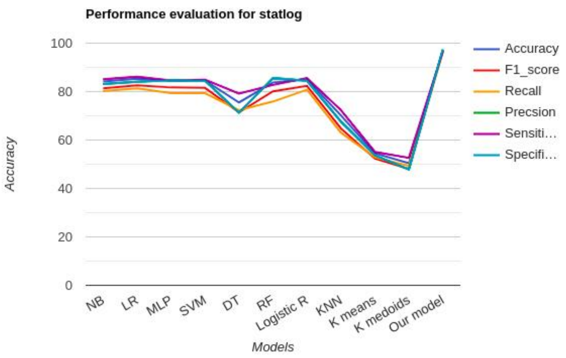


Fig. 15. Line chart for performance evaluation on Statlog dataset

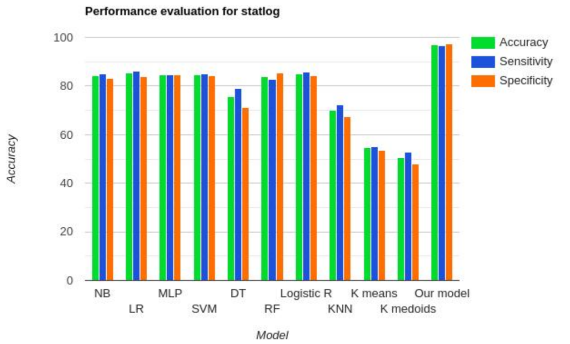


Fig. 16. Bar chart for performance evaluation on Statlog dataset

Model	Accuracy(%)	F1 score(%)	Recall (%)	precision (%)	MCC	TPR(%)	TNR(%)	FPR(%)	FNR(%)
NB	84.20	81.37	80.16	83.14	0.67	85.11	83.14	14.88	16.86
LR	85.30	82.60	81.38	84.07	0.70	86.16	84.07	13.83	15.92
MLP	84.54	81.72	79.41	84.70	0.68	84.57	84.69	15.42	15.30
SVM	84.59	81.53	79.34	84.45	0.68	84.92	84.45	15.08	15.54
DT	75.53	71.40	72.30	71.27	0.50	79.16	71.27	20.83	28.73
RF	83.81	80.13	75.90	85.57	0.67	82.77	85.57	17.22	14.42
Logistic R	85.05	82.35	80.81	84.45	0.69	85.64	84.45	14.35	15.54
KNN	70.16	64.80	63.05	67.60	0.39	72.35	67.60	27.65	32.40
K means cluster	54.54	52.32	52.90	53.67	0.086	55.12	53.67	44.87	46.32
K medoids	50.41	48.01	49.31	47.86	0.005	52.65	47.86	47.34	52.13
Our Model	96.88	96.75	96.32	97.42	0.94	96.57	97.42	3.42	2.57

Table 1: Performance evaluation for statlog

Model	Accuracy(%)	F1 score(%)	Recall (%)	precision (%)	MCC	TPR(%)	TNR(%)	FPR(%)	FNR(%)
NB	82.09	83.72	84.82	82.89	0.64	81.22	82.89	18.77	17.10
LR	83.44	84.83	85.57	84.27	0.67	82.50	84.27	17.49	15.72
MLP	70.18	66.70	66.03	79.79	0.45	70.74	79.79	29.26	20.20
SVM	81.92	84.09	89.38	79.66	0.64	85.53	79.66	14.46	20.33
DT	76.13	78.19	79.18	77.67	0.51	74.57	77.67	25.42	22.32
RF	82.48	84.78	89.36	80.94	0.65	85.16	80.94	14.83	19.05
Logistic R	82.78	84.79	88.18	81.95	0.65	84.41	81.95	15.58	18.04
KNN	65.39	68.83	70.84	67.52	0.30	63.11	67.52	36.88	32.47
K means cluster	51.03	50.08	51.01	50.21	0.017	51.44	50.21	48.55	49.78
K medoids	52.03	52.43	52.50	53.33	0.042	50.80	53.33	49.20	46.66
Our Model	97.02	97.06	97.47	96.80	0.94	97.32	96.80	2.67	3.20

Table 2: Performance evaluation for cleveland

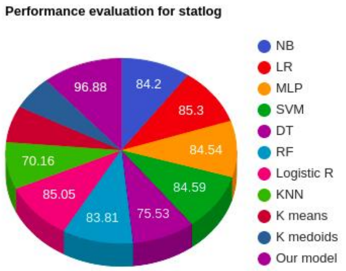


Fig. 17. Pie chart for accuracy on statlog dataset

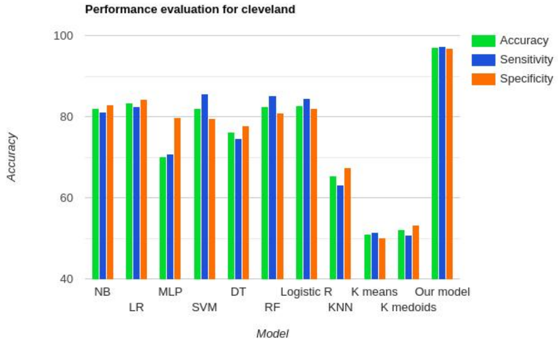


Fig. 19. Bar chart for performance evaluation on Cleveland dataset

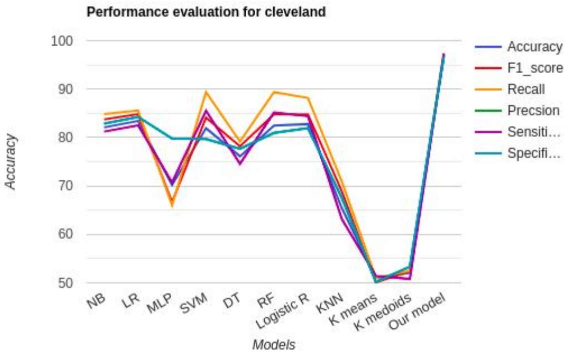


Fig. 18. Line chart for performance evaluation on Cleveland dataset

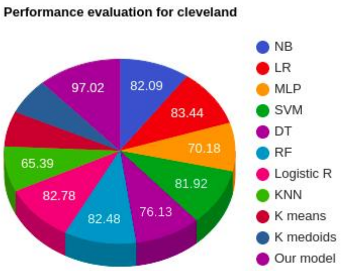


Fig. 20. Pie chart for accuracy on Cleveland dataset

V. CONCLUSION

Heart disease prediction is a very wonderful technique to the mankind. By using this many life's can be saved. In this modern era, with help of technology we can make impossible things as possible.So our heart disease model is a hybrid model combination of different ML technique like DBSCAN,SMOTEENN, GA,XGboost to get a efficient model with high accuracy in prediction.If the people start using it, then the rate of people dying due to heart disease will reduced eventually.

REFERENCES

[1] World Health Organization. (2017). Cardiovascular Diseases (CVDs).

[2] E. J. Benjamin et al., "Heart disease and stroke statistics—2019

[3] Statistics Korea. (2018). Causes of Death Statistics in 2018. [Online].

[4] World Health Organization. (2017). Cardiovascular Diseases (CVDs).

[5] P. Greenland, J. S. Alpert, G. A. Beller, E. J. Benjamin, M. J. Budoff, Z. A. Fayad, E. Foster, M. A. Hlatky, J. M. Hodgson, F. G. Kushner, M. S. Lauer, L. J. Shaw, S. C. Smith, A. J. Taylor, W. S. Weintraub, and N. K. Wenger, "2010 ACCF/AHA guideline for assessment of cardiovascular risk in asymptomatic adults.

[6] J. Perk et al., "European guidelines on cardiovascular disease prevention in clinical practice (version 2012)

[7] G.-M. Park and Y.-H. Kim, "Model for predicting cardiovascular disease: Insights from a Korean cardiovascular risk model," Pulse, vol. 3, no. 2, pp. 153–157, 2015, doi: 10.1159/000438683.

[8] G. J. Njie, K. K. Proia, A. B. Thota, R. K. C. Finnie, D. T. Lackland, and T. E. Kottke, "Clinical decision support systems and prevention," Amer. J. Preventive Med., vol. 49, no. 5, pp. 784–795, Nov. 2015.

[9] V. Sintchenko, E. Coiera, J. R. Iredell, and G. L. Gilbert, "Comparative impact of guidelines, clinical data, and decision support on prescribing decisions: An interactive Web experiment with simulated cases,"

[10] K. Kawamoto, C. A. Houlihan, E. A. Balas, and D. F. Lobach, "Improving clinical practice using clinical decision support systems: A systematic review of trials to identify features critical to success,".

[11] J.R. Quinlan. 1993, C4.5: Programs for Machine Learning. Morgan Kaufmann Publishers, San Mateo-California.

[12] Machine learning based decision support systems (DSS) for heart disease diagnosis: a review. Online: 25 March 2017 DOI: 10.1007/s10462-01.

[13] Alexander, Cheryl Wang, Lidong. (2017). Big Data Analytics in Heart Attack Prediction. Journal of Nursing Care. 06. 10.4172/2167-1168.1000393

[14] Data Science Bowl. 2020. Transforming how I measure heart disease. [ONLINE] Available at: https://datasciencebowl.com/transforming-how-we-dia gnose-heart-disease/. [Accessed 2 February 2020]

[15] Wynne Hsu, Mong-Li Lee, Bing Liu, Tok Wang Ling, 2000, "Exploration mining in diabetic patients databases: findings and conclusions", KDD 2000: pp: 430-436.