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CLASSIFYING HEART DISEASE DATASET USING MACHINE LEARNING

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Abstract— Now a day's Heart disease is very common to both men and women. Across the World 610,000 people die with heart disease in the United States including African Americans, Hispanics, and whites every year–that's 1 in every 4 deaths. Heart disease is the leading cause of death for people of most ethnicities in the United States, including African Americans, Hispanics, and whites. For American Indians or Alaska Natives and Asians or Pacific Islanders, heart disease is second only to cancer. Heart disease is considered as one of the top preventable causes of the death in the United States. Some genetic factors can contribute, but the disease is largely attributed to poor life style habits So, I am going to predict the rate of heart diseases in this project. This project is predicting the heart rate of the dataset and it will helps for the government to take Prevention methods i.e making awareness and how to follow the diet control programs etc. It helps for the total analysis of the rate of heart disease persons.

Keywords— Heart disease; United States Department of Agriculture Economic Research Service (USDA ERS); Cleaning; Data exploration; Logistic Regression ; Support Vector Machine;

I. INTRODUCTION

In every healthcare organization like hospitals and medical centers is the delivery of quality services at affordable costs. Quality of service is very expensive towards heart disease in the hospitals. The main aim of my project is to predict the rate of heart disease. For this I selected the data set compiled from a wide range of sources and made publicly available by the United States Department of Agriculture Economic Research Service (USDA ERS). So, My goal is to predict the rate of heart diseases in U.S. Here I am using the classification models to find the accuracy of each model and select the best model which will have high accuracy to predict the rate of heart diseases. Here the input parameters are the training data and the outputs will either 0 or 1i.e having heart disease or not.

II.PROJECT DESIGN

The project is composed of different steps as follows:

Pre-processing: First task is to read the dataset and perform visualizations on it to get some insights about the data. After reading the data clean the data i.e. removing unwanted data or replacing null values with some constant values or removing duplicates. Then finding the correlation for each feature with the heart disease target variable.

After Data Exploration, I want to split the total data into training, validation and testing sets and normalize the data to make it suitable for .Then applying the Classifying models and then predicting the accuracy score to the selected models.

First step in training:

First, I want to choose a Benchmark model which will at least gives testing accuracy score around 50 % accuracy score.

Second step in training:

I want to apply classification models of my own and use on the data. I want to apply Support Vector Machine and Logistic Regression model then find the Accuracy score for both the models

Finally, I will declare the model which highest accuracy score on both training and testing data sets concluded as the best model for detecting the rate of heart diseases

III.ANALYSIS

Data Exploration:

The data set loaded in memory using read_csv()

This datasets contains 76 attributes, but all published experiments refer to using a subset of 14 of them. The "goal" field refers to the presence of heart disease in the patient. It is integer valued from 0 (no presence) to 4.Here the total samples in the data set is 6278(training data and testing data).Here the target variable is The data type of heart_diseases_mortality_per_100k is an integer, Output is integer value. The data set consists of Nan values for some features.I will remove it(clean the data)

Attributes:

> 1. age
> 2. sex
> 3. chest pain type (4 values)
> 4. resting blood pressure
> 5. serum cholestoral in mg/dl
> 6. fasting blood sugar > 120 mg/dl
> 7. resting electrocardiographic results (values 0,1,2)
> 8. maximum heart rate achieved
> 9. exercise induced angina
> 10. oldpeak = ST depression induced by exercise relative to rest
> 11. the slope of the peak exercise ST segment
> 12. number of major vessels (0-3) colored by flourosopy
> 13. thal: 3 = normal; 6 = fixed defect; 7 = reversable defect

The sample values of the dataset is:

	row_id	area__rucc	area__urban_influence	econ__economic_typology	econ__pct_civilian_labor	econ__pct_unemployment	econ__pct_uninsured_adults	econ
0	0	Metro - Counties in metro areas of fewer than ...	Small-in a metro area with fewer than 1 millio...	Manufacturing-dependent	0.408	0.057	0.254	
1	1	Metro - Counties in metro areas of fewer than ...	Small-in a metro area with fewer than 1 millio...	Mining-dependent	0.556	0.039	0.260	
2	4	Metro - Counties in metro areas of 1 million p...	Large-in a metro area with at least 1 million ...	Nonspecialized	0.541	0.057	0.070	
3	5	Nonmetro - Urban population of 2,500 to 19,999...	Noncore adjacent to a small metro with town of...	Nonspecialized	0.500	0.061	0.203	
4	6	Nonmetro - Urban population of 2,500 to 19,999...	Noncore not adjacent to a metro/micro area and...	Nonspecialized	0.471	0.050	0.225	

5 rows × 34 columns

And features in the data set contains the missing values


```
In [86]: full_NA = full.isnull().sum()
         full_NA = full_NA.drop(full_NA[full_NA == 0].index).sort_values(ascending = False)

         print(full_NA)
```

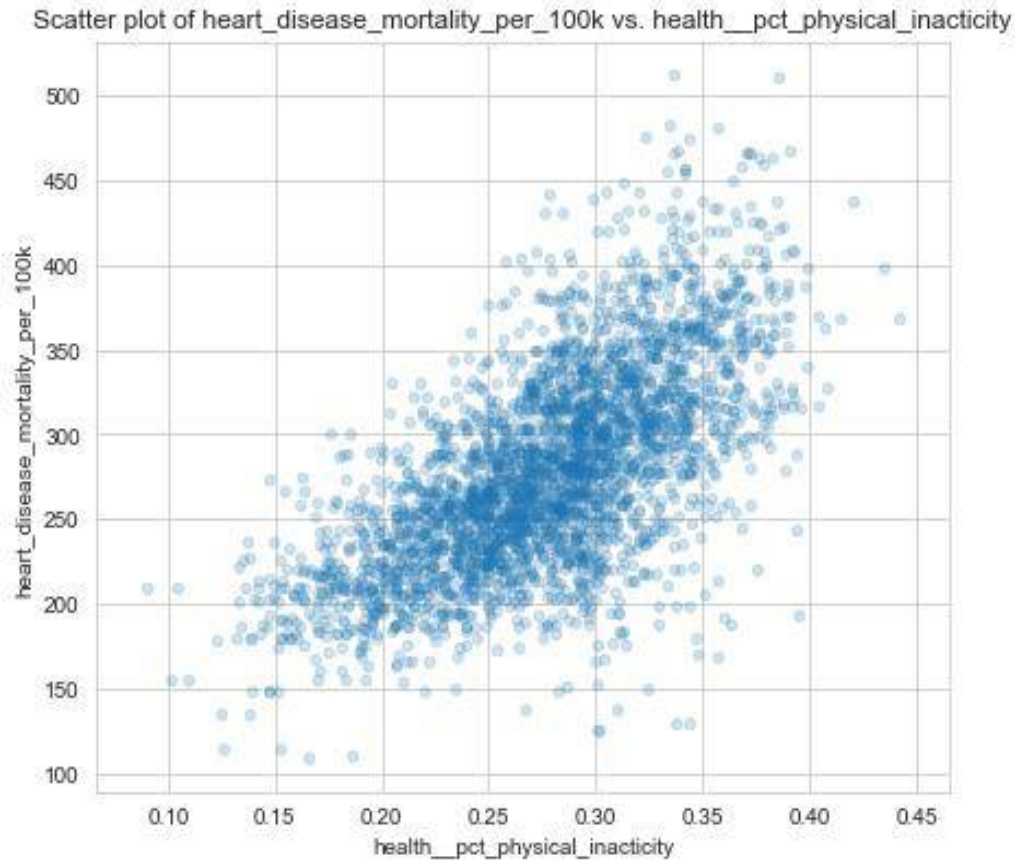
```
health__homicides_per_100k                    3797
health__pct_excessive_drinking                1838
health__pct_adult_smoking                      866
health__motor_vehicle_crash_deaths_per_100k    762
health__pop_per_dentist                        442
health__pop_per_primary_care_physician         414
health__pct_low_birthweight                    329
health__air_pollution_particulate_matter        66
demo__pct_non_hispanic_african_american         10
econ__pct_uninsured_children                    10
demo__pct_female                                10
demo__pct_below_18_years_of_age                 10
demo__pct_aged_65_years_and_older               10
demo__pct_hispanic                              10
health__pct_adult_obesity                       10
demo__pct_non_hispanic_white                    10
demo__pct_american_indian_or_alaskan_native     10
demo__pct_asian                                 10
health__pct_diabetes                            10
health__pct_physical_inacticity                 10
econ__pct_uninsured_adults                      10
dtype: int64
```

The above image defines the missing value features of the dataset

Data Visualization:

The below image shows the relationship of feature with the heart disease. This is helped for predicting the value of heart disease for each feature after the data is cleaned.

Eg: for first feature is:



The above visualization helps to find which feature has the highest categorical value. This is fined after cleaning the data and splitting the data into training and testing. And finding the categorical value for each feature

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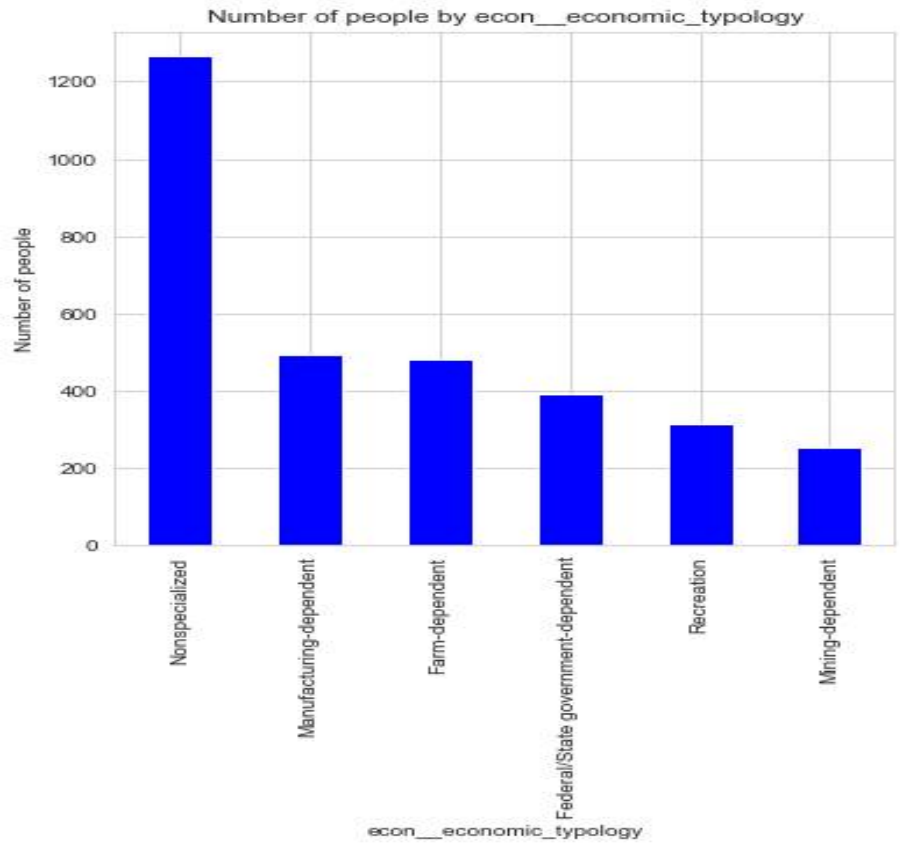
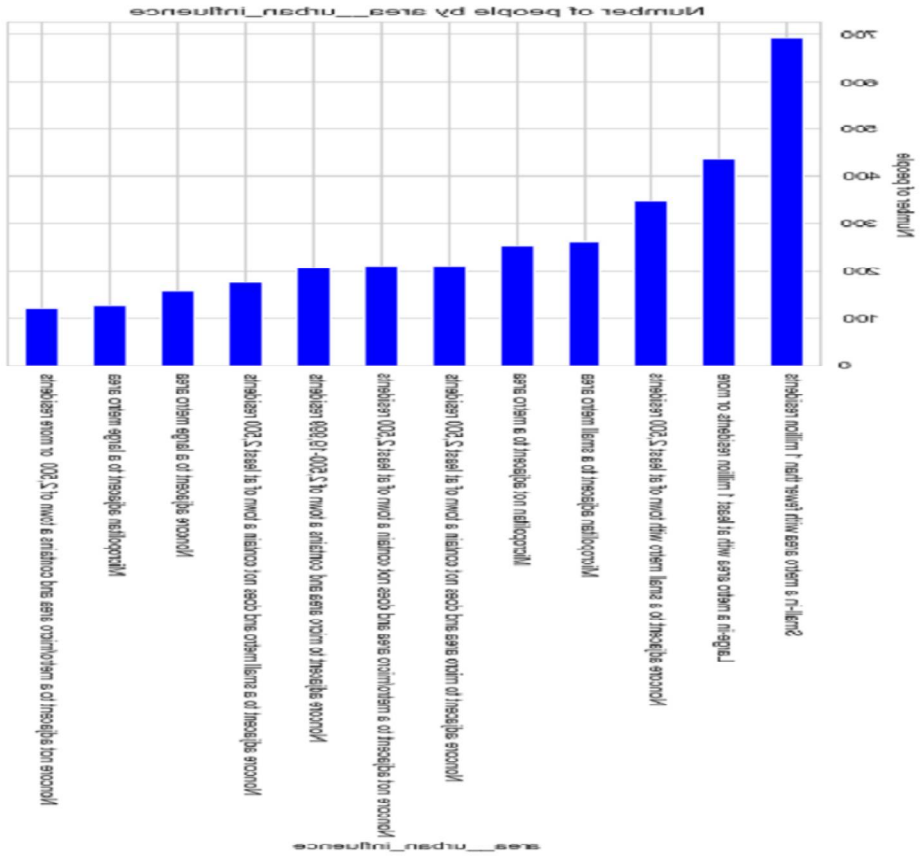
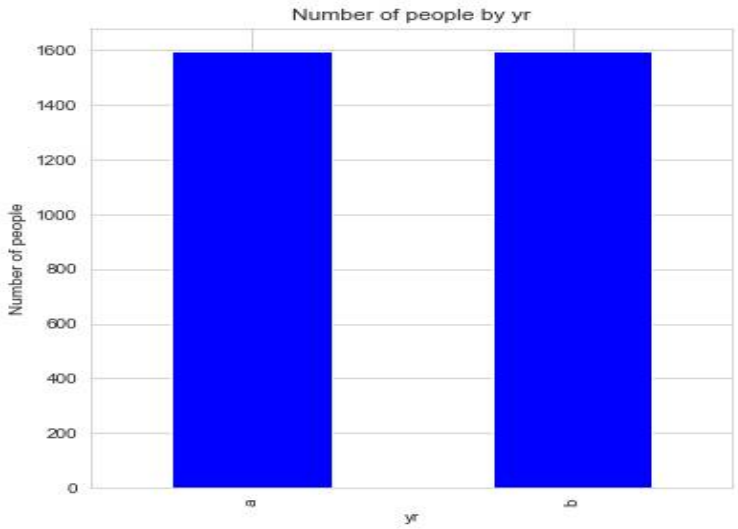
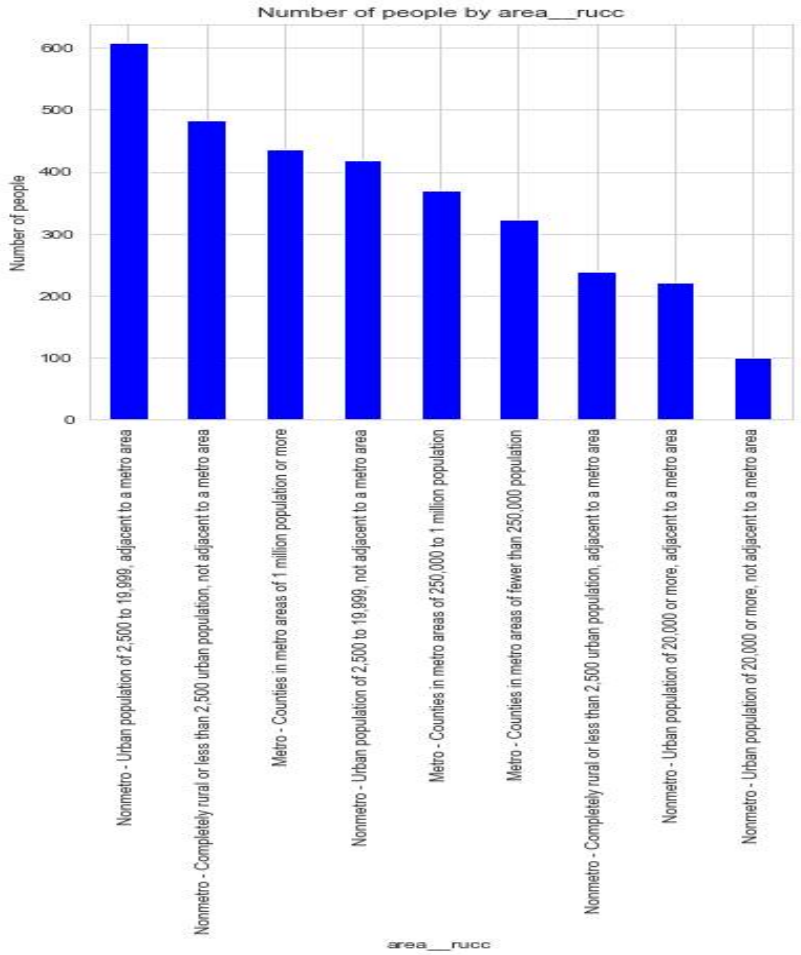








Algorithm Techniques:

Two algorithm techniques I am using is:

1. Logistic Regression
2. Support Vector Machine

1. Logistic Regression:

Logistic regression is the classification counterpart to linear regression. Predictions are mapped to be between 0 and 1 through the logistic function, which means that predictions can be interpreted as class probabilities. The models themselves are still "linear," so they work well when your classes are linearly separable (i.e. they can be separated by a single decision surface). Logistic regression can also be regularized by penalizing coefficients with tunable penalty strength.

- Strengths: Outputs have a nice probabilistic interpretation, and the algorithm can be regularized to avoid over fitting. Logistic models can be updated easily with new data using stochastic gradient descent.
- Weaknesses: Logistic regression tends to underperform when there are multiple or non-linear decision boundaries. They are not flexible enough to naturally capture more complex relationships.

2. Support Vector Machine:

Support vector machines (SVM) use a mechanism called kernels, which essentially calculate distance between two observations. The SVM algorithm then finds a decision boundary that maximizes the distance between the closest members of separate classes.

For example, an SVM with a linear kernel is similar to logistic regression. Therefore, in practice, the benefit of SVM's typically comes from using non-linear kernels to model non-linear decision boundaries.

- Strengths: SVM's can model non-linear decision boundaries, and there are many kernels to choose from. They are also fairly robust against over fitting, especially in high-dimensional space.
- Weaknesses: However, SVM's are memory intensive, trickier to tune due to the importance of picking the right kernel, and don't scale well to larger datasets. Currently in the industry, random forests are usually preferred over SVM's.

IV.METHODOLOGY

DATA Preprocessing:

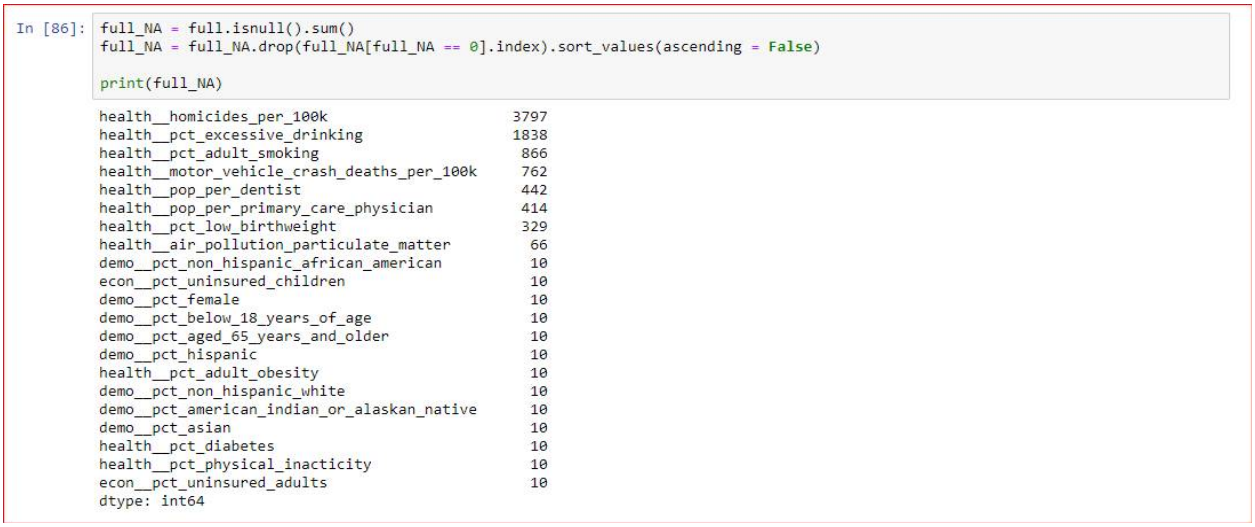
The preprocessing done in the “pre data” notebook consists of the following steps:

Data Cleaning:

- Checking the datasets contains any duplicate values or not: train data consists of 3198 unique values and test data consist of 3080 unique values

Content:

- After combining the train data and test the original dataset consists of 6728 rows
- It consists of 14 attributes. Here the data is cleaned so duplicate values are in this data
- Here the data set contains the missing values for some features. Here I am finding the missing count for each feature



Now replacing the each feature missing values with their respective feature median value. For further analysis the full data is further divided into the train data and test data

Correlation:

The statistical relationship of two variables is called correlation .If the correlation is positive it has strong relationship both move in one direction only and if the negative value is there with increasing of variable value the other variable decreases. The correlation value of each feature with the heart disease is:


```
heart_disease_mortality_per_100k                1.000000
health__pct_physical_inacticity                 0.649813
health__pct_diabetes                            0.631337
health__pct_adult_obesity                       0.593316
demo__pct_adults_less_than_a_high_school_diploma  0.527382
health__pct_low_birthweight                     0.464391
health__pct_adult_smoking                       0.463138
demo__death_rate_per_1k                         0.444757
health__motor_vehicle_crash_deaths_per_100k     0.435633
demo__pct_adults_with_high_school_diploma       0.428137
demo__pct_non_hispanic_african_american         0.375537
econ__pct_unemployment                          0.371620
econ__pct_uninsured_adults                      0.334027
health__pop_per_dentist                         0.292447
health__homicides_per_100k                      0.292377
health__pop_per_primary_care_physician          0.217936
health__air_pollution_particulate_matter        0.147028
demo__birth_rate_per_1k                         0.142176
demo__pct_below_18_years_of_age                 0.121884
demo__pct_female                                0.086765
demo__pct_american_indian_or_alaskan_native     0.004826
econ__pct_uninsured_children                   -0.034209
demo__pct_aged_65_years_and_older              -0.056081
demo__pct_hispanic                             -0.111976
demo__pct_non_hispanic_white                   -0.157797
demo__pct_asian                                -0.267016
health__pct_excessive_drinking                 -0.300781
demo__pct_adults_with_some_college             -0.340764
econ__pct_civilian_labor                       -0.476644
demo__pct_adults_bachelors_or_higher           -0.541385
Name: heart_disease_mortality_per_100k, dtype: float64
```

Now finding the relationship between the no. of categorical values for each feature.

V. IMPELMENTATION

The Implementation project is divided into two main stages:

1. The classifier training stage
2. The classification model development stage

Classifier training Stage :(Described in the jupyter Notebook)

The classifier was trained on the preprocessed data. Steps followed here is:

- Load the training and testing data into the memory and preprocess (means cleaning the data)Here the data is preprocessed by finding the unique values and finding the missing values then replacing the missing values with their respective feature median value
- Using displot() function for defining the visualization of distribution of target label
- Finding the correlation the every features with labels to know which feature has the strongest relationship with the target label
- Now split the data into training and test for further implementation
- By using StandardScaler() standardizing the train and test data

Model Development Stage:

- Here we want to define which models we are using for predicting the rate of heart disease
- Then fit the train and test to the selected models
- Then finding the accuracy score for the selected models(based on this we decide which model is best for predicting the rate of the heart disease)

Complications faced here:

- Cleaning and Spliting the data for testing and training
- Selecting the tuning parameters for the model to get the best accuracy score

Refinement:

As mentioned in the benchmark section, comparing the accuracy score of the two models. Here for the improving the results I used the hyper paremter is random_state() If you don't specify the random_state in your code, then every time you run(execute) your code a new random value is generated and the train and test datasets would have different values each time. However, if a fixed value is assigned like random_state =10 then no matter how many times you execute your code the result would be the same .i.e, same values in train and test datasets.

And the accuracy scores is as follows

The accuracy score I got for the logistic regression is 91%

The accuracy score I got for the SVM is 36.09%

Here the tuned parameters for making the model best in logistic regression is C and max_iters

- C : float, optional (default=1.0) Inverse of regularization strength; must be a positive float. Like in support vector machines, smaller values specify stronger regularization.
- Regularization is applying a penalty to increasing the magnitude of parameter values in order to reduce overfitting. When you train a model such as a logistic regression model, you are choosing parameters that give you the best fit to the data. This means minimizing the error between what the model predicts for your dependent variable given your data compared to what your dependent variable

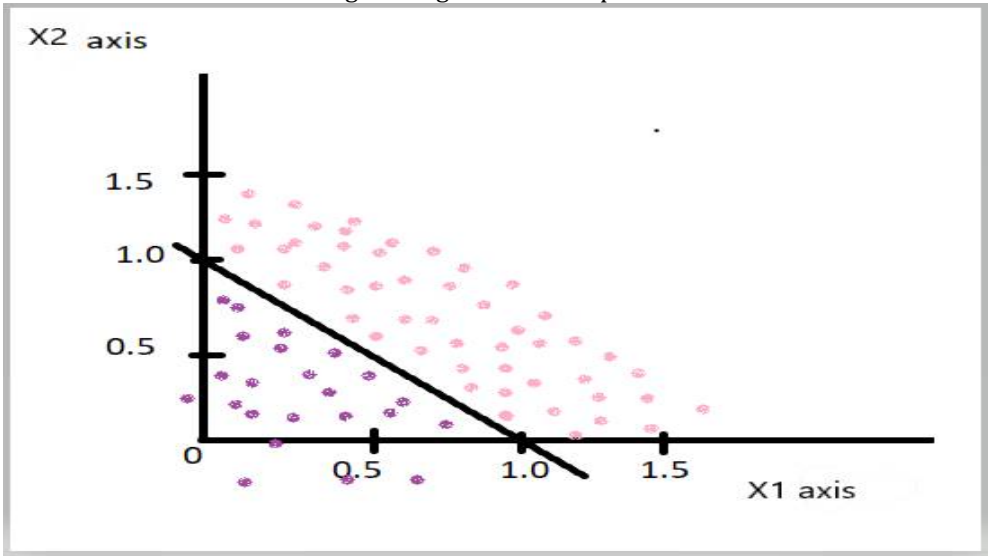
- Max_tiers: Useful only for the newton-cg, sag and lbfgs solvers. Maximum number of iterations taken for the solvers to converge.
- Here before using, I used the parameter penalty='l1' then I got the accuracy of 66 and then after using the C=2.0 I got the accuracy of 91
- I used it the C parameter to minimize the errors and overfitting

```
classification2=classification2.fit(x_test,y_test)
pred2=classification2.predict(x_test)
print(" accuracy score of Logistic Regression is")
score1=accuracy_score(y_test,pred2)
print(score1)

accuracy score of SVM is
0.3609375
 accuracy score of Logistic Regression is
0.84375

In [ ]:

In [ ]:
```

VI.RESULTS

Model Evaluation and Validation:

I used accuracy score as evaluation metric for prediction of rate of heart disease. Here I am predicting the accuracy score for the selected models. In multilabel classification, this function computes subset accuracy: the set of labels predicted for a sample must *exactly* match the corresponding set of labels in y_true. Here accuracy score which model have the high value it is selected as the best model So, Based on the highest accuracy score which model is I get is the best model for my project. The accuracy score I got for the logistic regression is 91%. The accuracy score I got for the SVM is 36.09% and the best model for this project is logistic regression because it has the highest accuracy value and the architecture of the logistic regression example is :



This line is known as the **decision boundary** because it separates the regions that are used to predict outcomes 1 and 0. When the prediction is done to find the probability of an outcome as 1, the region to the right of the line, which is shaded in **pink** is considered. On the other hand, when we need to find values for the outcome of 0, we consider the region below the line, which is shaded in **purple**.

```
In [44]: classification1 = SVC(kernel="rbf",random_state=10)
classififcation1=classification1.fit(x_test, y_test)
pred1=classification1.predict(x_test)
print("accuracy score of SVM is")
score=metrics.accuracy_score(y_test,pred1)
print(score)
classification2=LogisticRegression(random_state=10,max_iter=10,C=2.0)
classification2=classification2.fit(x_test,y_test)
pred2=classification2.predict(x_test)
print(" accuracy score of Logistic Regression is")
score1=metrics.accuracy_score(y_test,pred2)
print(score1)

accuracy score of SVM is
0.3609375
 accuracy score of Logistic Regression is
0.9109375
```


In general, after the values for theta is found, there is no need to plot this graph, because the values for theta itself helps us define the decision boundary. The above defines the accuracy score of the optimized model here used the tuning parameters for best score .The accuracy score of the unoptimised model is 34% for SVM and 84% for logistic regression. Here I am using the C parameter in the logistic regression. By using this parameter the model minimize the over fitting and reduces the errors. And I can say that my models are helpful for predicting the rate of the heart disease for the same features of datasets. And here I am cleaning the data and replacing the null values with the median values and then fitting the training and testing data into the model. So I can believe that my project works correctly for predict the value of heart disease rate.

JUSTIFICATION:

Here by using SVM I got the accuracy score is 36.09%. And by using Logistic Regression I got the accuracy score is 91%. As mentioned in the bench mark by comparing the two models accuracy score, the Logistic Regression has the high accuracy score than the SVM So, Logistic Regression is the best model for predicting the rate of heart diseases

VII.CONCLUSION

Free-Form Visualization:

One thing I see quite often is a visual examination of the feature importance metrics, to investigate what information in the dataset matters. But again, there are many options here, so just get creative. For example: Suppose a logistic regression model is used to predict whether an online shopper will purchase a product (outcome: purchase), after he clicked a set of online adverts (predictors: Ad1, Ad2, and Ad3). The outcome is a binary variable: 1 (purchased) or 0 (not purchased). The predictors are also binary variables: 1 (clicked) or 0 (not clicked). So all variables are on the same scale. If the resulting coefficients of Ad1, Ad2, and Ad3 are 0.1, 0.2, and 03, we can conclude that Ad3 is more important than Ad2, and Ad2 is more important than Ad1. Furthermore, since all variables are on the same scale, the standardized and un-standardized coefficients should be same, and we can further conclude that Ad2 is twice important than Ad1 in terms of its influence on the logic (log-odds) level. Here The feature importance is having the heart disease are not is in the form: The relationship of each feature with the heart disease target label as follows: From correlation and from scatter plots we can say that the patient who has the health_pct_physcial disease may have the heart because this feature has the highest correlation with the target label.

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