SC1015 PROJECT:
Breast Cancer Prediction

FDAE - Team 5

Fong Zheng Feng Victor

Thuvaarakesh Kiruparan

Tiang Soon Yong

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PROBLEM DEFINITION & MOTIVATION

Statistics of cancers in Singapore

Ten most common cancers affecting men & women (2017 - 2021)

Men	No. of cases	Women	No. of cases
Prostate	6,912	Breast	12,735
Colon & rectum	6,697	Colorectal & rectum	5,542
Lung	5,567	Lung	3,388
Lymphoid neoplasms	2,986	Corpus uteri (uterus)	3,133
Liver	2,984	Lymphoid neoplasms	2,221
Non-melanoma skin	2,136	Ovary & fallopian tube	1,855
Kidney	1,734	Non-melanoma skin	1,713
Stomach	1,684	Thyroid	1,666
Myeloid neoplasms	1,430	Pancreas	1,187
Pancreas	1,417	Stomach	1,111
		Cervix uteri	1,106

12,735 cases, highest cases among the rest.
Forms up 18.4% of all the cases

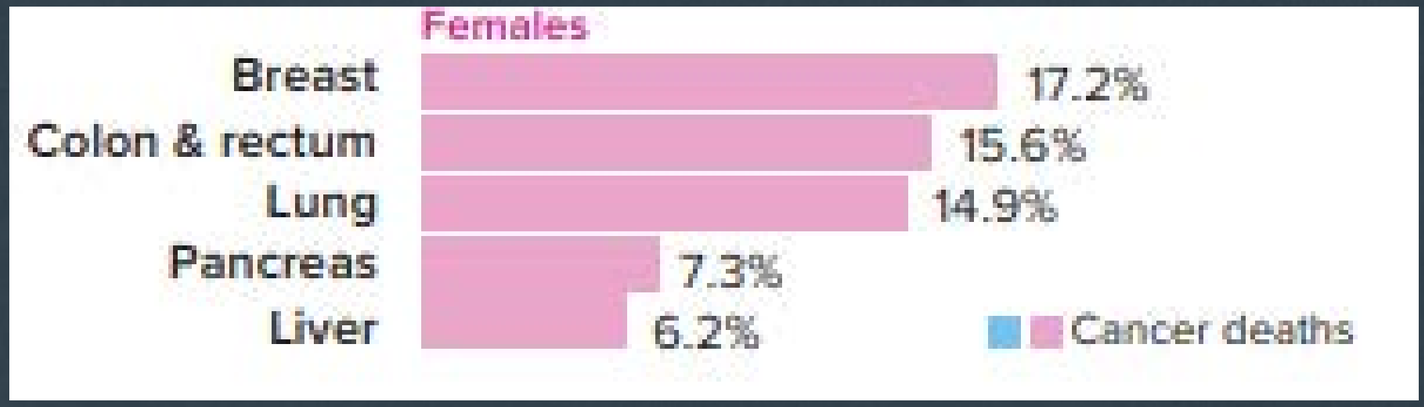
Statistics of cancers in Singapore

Overview. Breast cancer is the most commonly occurring cancer among women in Singapore accounting for 29.7% of all cancers diagnosed in females*.*1 in 13 women will get breast cancer in their lifetime. Breast cancer usually originates from the cells lining the milk ducts and glands.

Singapore Cancer Society
https://www.singaporecancersociety.org.sg › breast-can...

Breast Cancer - Singapore Cancer Society

About featured snippets • Feedback



Breast Cancer is the leading cause of cancer deaths in Singapore

Problem Definition & Motivation

Motivation: 

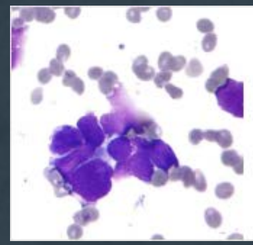
Breast cancer is one of the leading causes of cancer-related deaths among women. Early detection plays a crucial role in improving treatment outcomes and reducing mortality rates. By accurately predicting the malignancy of breast tumors, healthcare providers can intervene promptly and initiate appropriate treatment strategies.

Problem Definition: 

Develop a predictive model to classify breast tumors as malignant or benign based on relevant clinical and diagnostic features. The model should accurately distinguish between malignant and benign tumors to assist healthcare professionals in early diagnosis and treatment decision-making.

DATA PREPARATION & EXPLORATORY DATA ANALYSIS

Initial Insights



Breast Cancer Wisconsin (Diagnostic) Data Set

Predict whether the cancer is benign or malignant

k kaggle.com

# of Data Columns: 32
# of Data Samples: 569 non-null

“id” is irrelevant
# of Features: 30 Numerical
Response: 1 Categorical, “Diagnosis”

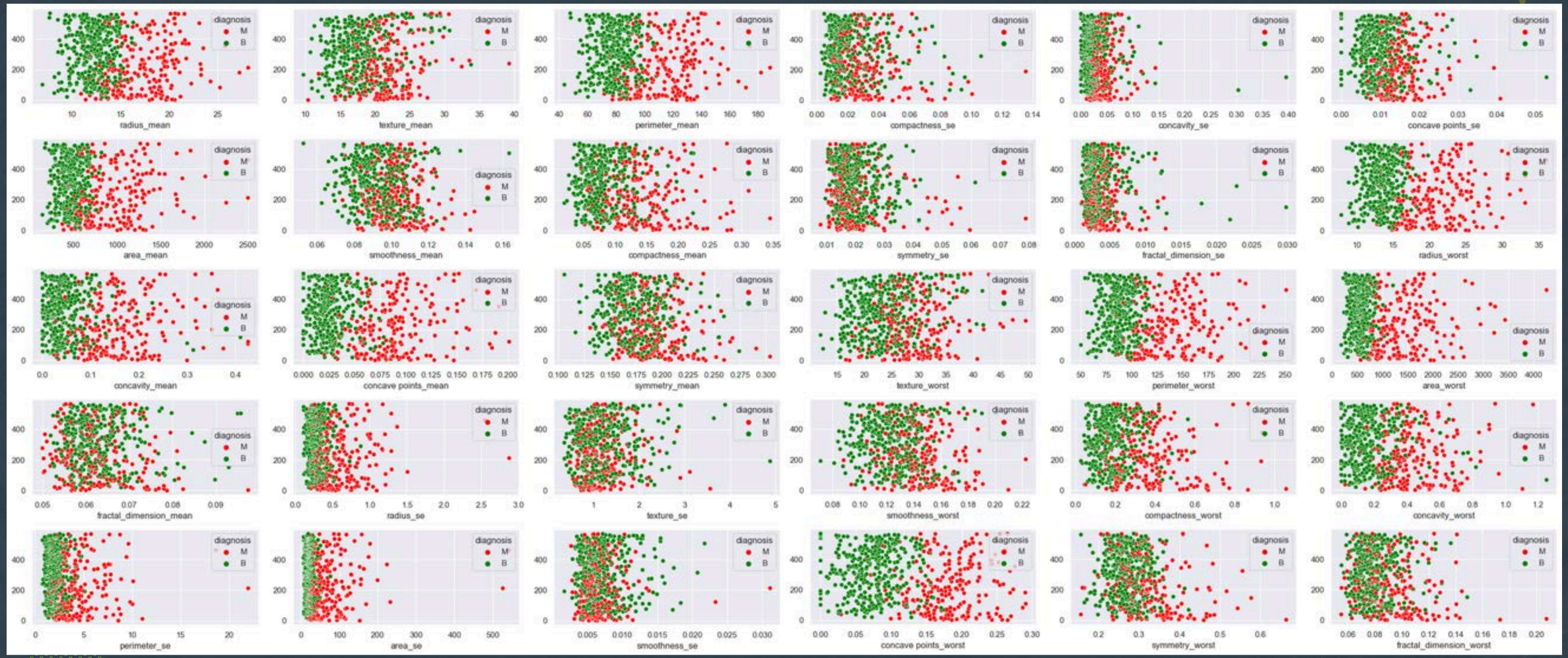
Classification Problem
Mixed Structured Data

	id	diagnosis	radius_mean	texture_mean	perimeter_mean	area_mean	smoothness_mean	compactness_mean	concavity_mean	concave points_mean	...	rac
0	842302	M	17.99	10.38	122.80	1001.0	0.11840	0.27760	0.3001	0.14710	...	
1	842517	M	20.57	17.77	132.90	1326.0	0.08474	0.07864	0.0869	0.07017	...	
2	84300903	M	19.69	21.25	130.00	1203.0	0.10960	0.15990	0.1974	0.12790	...	
3	84348301	M	11.42	20.38	77.58	386.1	0.14250	0.28390	0.2414	0.10520	...	
4	84358402	M	20.29	14.34	135.10	1297.0	0.10030	0.13280	0.1980	0.10430	...	

5 rows × 32 columns

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 569 entries, 0 to 568
Data columns (total 32 columns):
 #   Column                   Non-Null Count  Dtype
---  ------                   --------------  -----
 0   id                       569 non-null    int64
 1   diagnosis                569 non-null    object
 2   radius_mean              569 non-null    float64
 3   texture_mean             569 non-null    float64
 4   perimeter_mean           569 non-null    float64
 5   area_mean                569 non-null    float64
 6   smoothness_mean          569 non-null    float64
 7   compactness_mean         569 non-null    float64
 8   concavity_mean           569 non-null    float64
 9   concave points_mean      569 non-null    float64
 10  symmetry_mean            569 non-null    float64
 11  fractal_dimension_mean   569 non-null    float64
 12  radius_se                569 non-null    float64
 13  texture_se               569 non-null    float64
 14  perimeter_se             569 non-null    float64
 15  area_se                  569 non-null    float64
 16  smoothness_se            569 non-null    float64
 17  compactness_se           569 non-null    float64
 18  concavity_se             569 non-null    float64
 19  concave points_se        569 non-null    float64
 20  symmetry_se              569 non-null    float64
 21  fractal_dimension_se     569 non-null    float64
 22  radius_worst             569 non-null    float64
 23  texture_worst            569 non-null    float64
 24  perimeter_worst          569 non-null    float64
 25  area_worst               569 non-null    float64
 26  smoothness_worst         569 non-null    float64
 27  compactness_worst        569 non-null    float64
 28  concavity_worst          569 non-null    float64
 29  concave points_worst     569 non-null    float64
 30  symmetry_worst           569 non-null    float64
 31  fractal_dimension_worst  569 non-null    float64
dtypes: float64(30), int64(1), object(1)
```

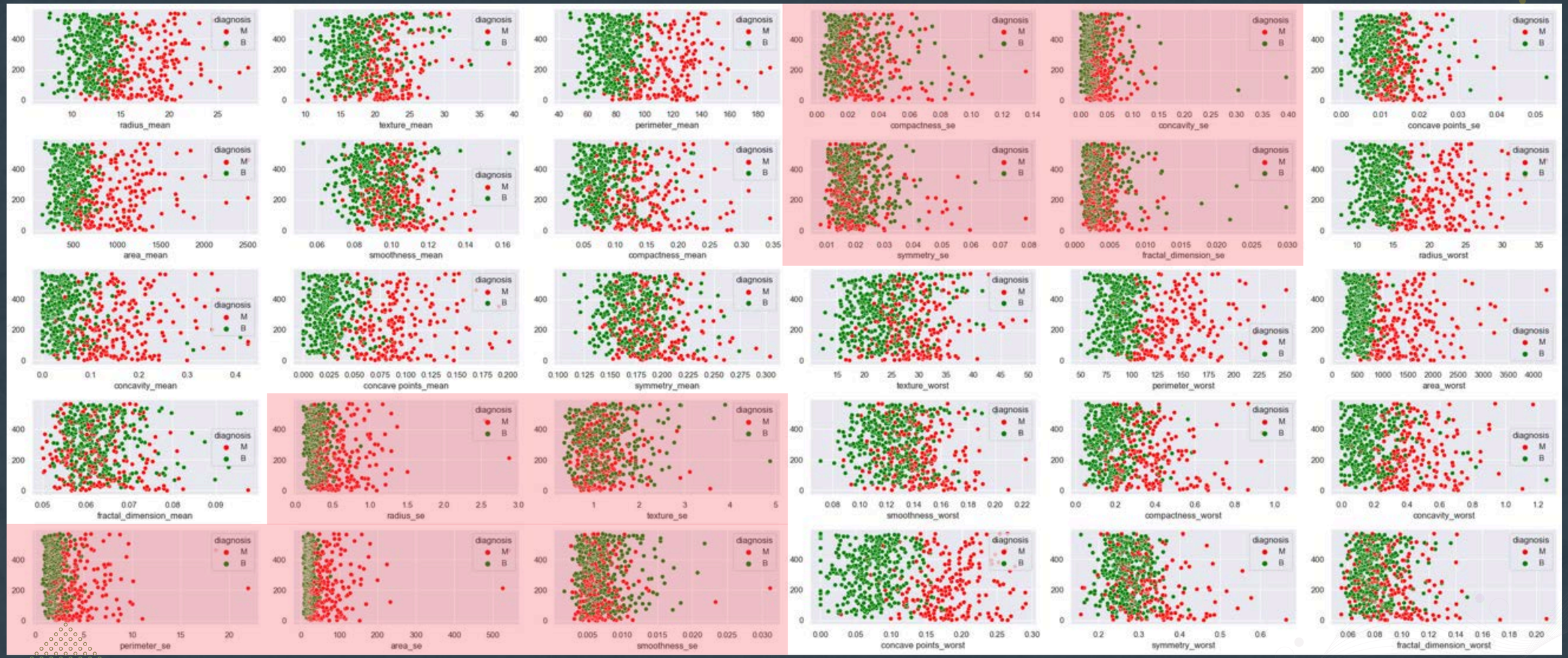
Initial Insights



Scatterplots of Features against Response

Legend: Malignant
Benign

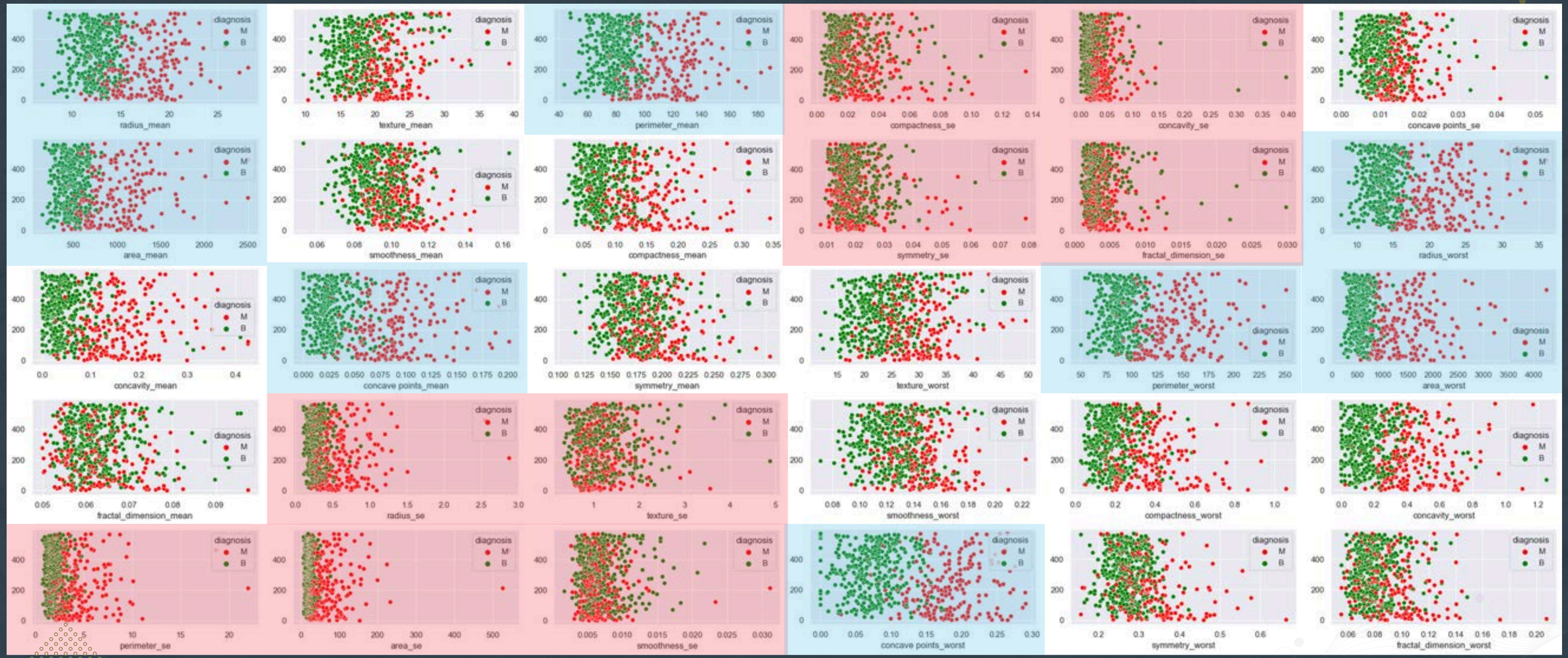
Initial Insights



Scatterplots of Features against Response

Legend: Malignant
Benign

Initial Insights



Scatterplots of Features against Response

Legend: Malignant
Benign

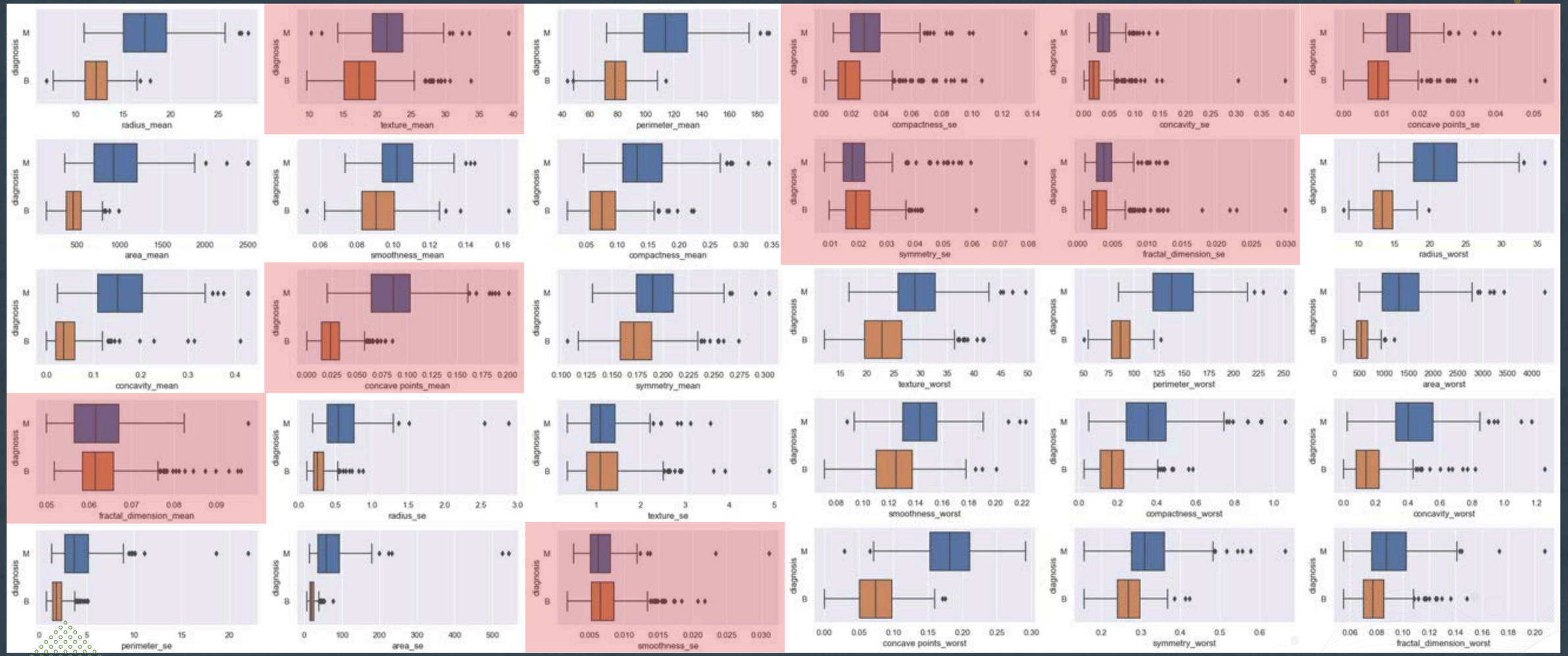
Initial Insights

Outliers Cleaning

Data Balancing

Feature Selection

Outlier Cleaning



Boxplots of Features against Response

Outlier Cleaning

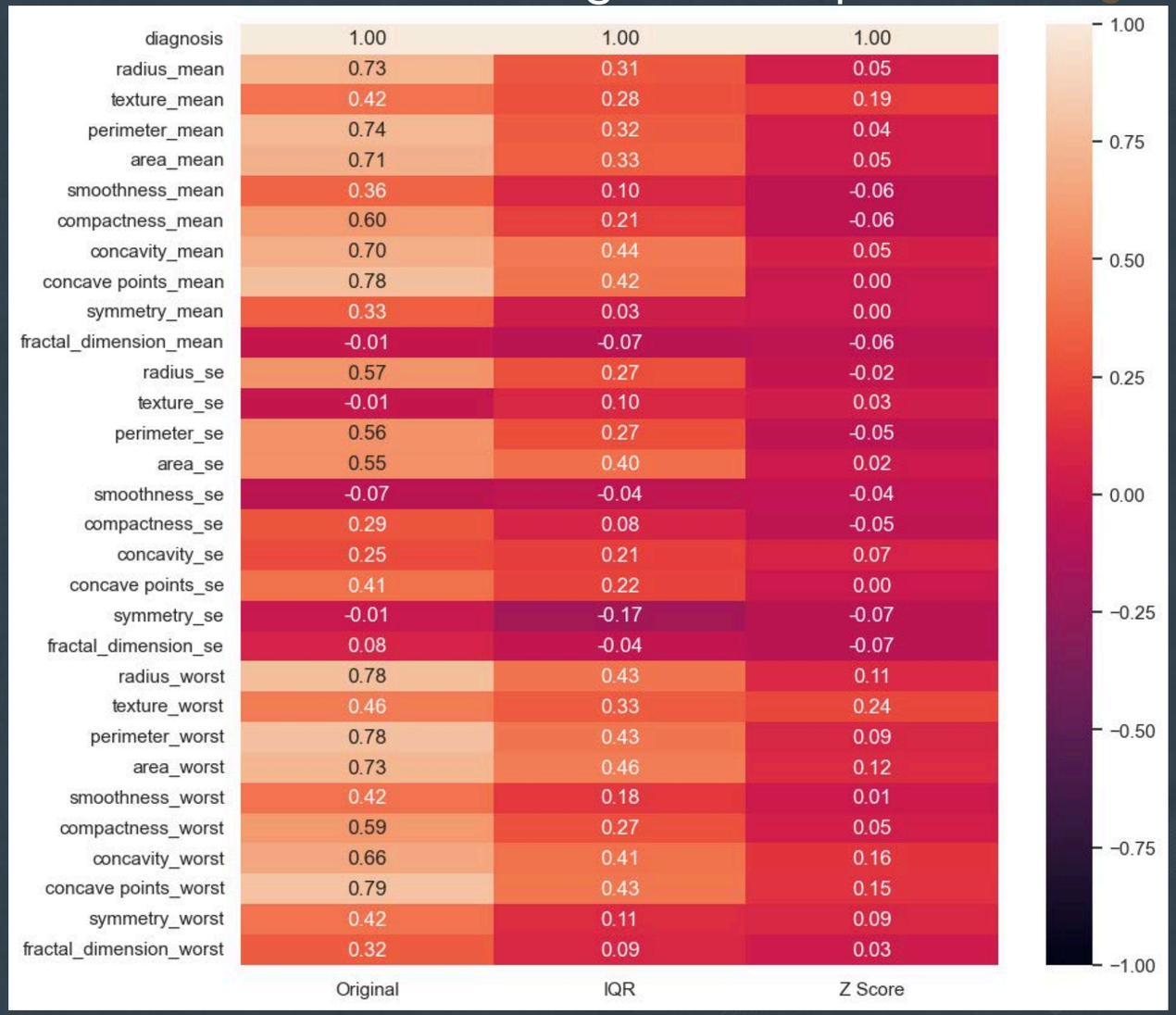
Method:
IQR Threshold: **1.5*IQR**
Z-Score Threshold: **2*S.D**

Findings:
Outliers removal causes

- Correlation **decreased**
- Lost of **meaningful** data
- Reduced **variability**

Decision:
Proceed with Original dataset

Correlation against Response



Data Balancing

Question:
Upsample before/after train_test_split()?

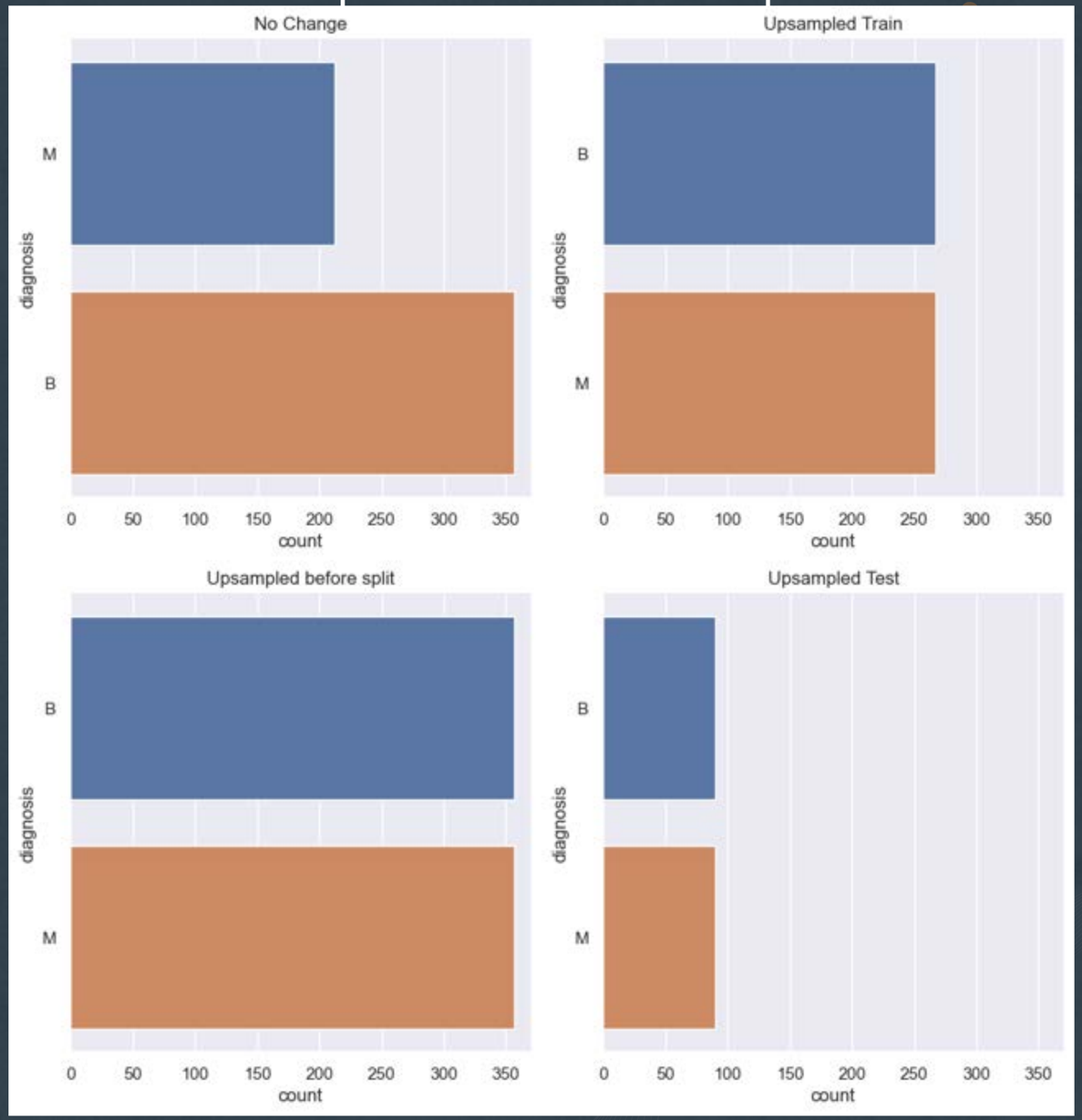
Method:
DecisionTreeClassifier()

Findings:
# of data samples before upsample: 569
# of data samples after upsample: 714
Classification Accuracy

	Train	Test
Original	1.0	0.909091
Upsample Before	1.0	0.966480
Upsample After	1.0	0.922222

Decision:
Proceed with the dataset upsampled before train_test_split()

Boxplots of Data Sample



Feature Selection

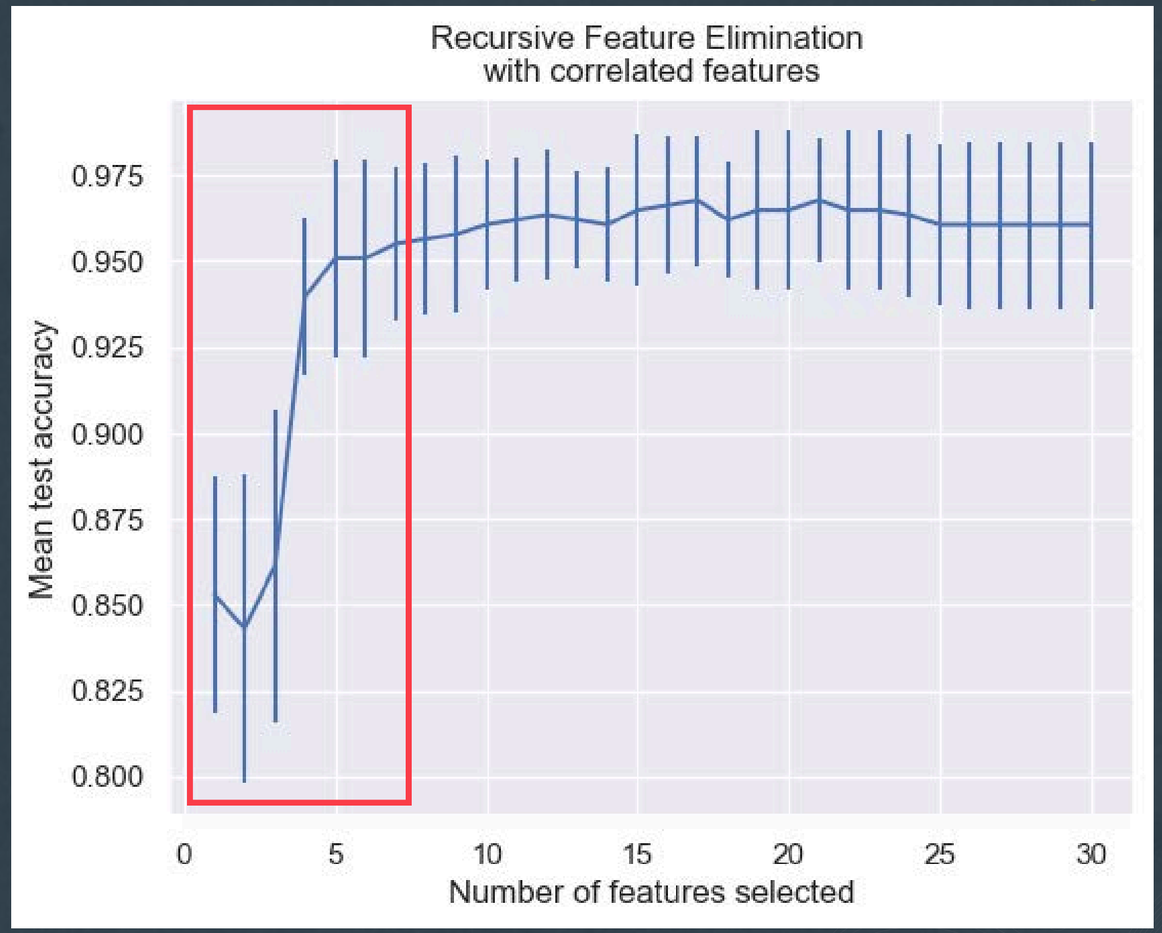
Question:
How many features should we use?

Method:
Recursive feature elimination with cross-validation **(RFECV)**

Findings:
Accuracy starts relatively **high** (0.85) even with 1 feature
Accuracy **stagnates** after 5 features
More Features = More **Vulnerable** to errors

Decision:
Test our models with [1, 3, 5, 7] Features

Line Plot with Errorbar



Feature Selection

Question:
Which features should we use?

Method:
SelectKBest
r_regression

Findings:
Sorted Feature List according to its score

Decision:
Feature List 0 = Top 7
Feature List 1 = Top 5
Feature List 2 = Top 3
Feature List 3 = Top 1

Top 7

	Features	F_Scores	Abs_Corr
27	concave points_worst	1268.834068	0.800347
22	perimeter_worst	1064.277962	0.774055
20	radius_worst	1043.774301	0.771026
7	concave points_mean	1026.771557	0.768450
2	perimeter_mean	844.058725	0.736501
0	radius_mean	788.349625	0.724875
23	area_worst	761.055501	0.718784
6	concavity_mean	668.240159	0.695807
3	area_mean	635.460792	0.686730
26	concavity_worst	591.151026	0.673522
5	compactness_mean	412.370230	0.605604
25	compactness_worst	374.511520	0.587105
10	radius_se	281.321498	0.532178
12	perimeter_se	254.017559	0.512790
13	area_se	232.364209	0.496038
21	texture_worst	211.132272	0.478239
1	texture_mean	174.173304	0.443334
24	smoothness_worst	166.290037	0.435125
17	concave points_se	157.303993	0.425387
28	symmetry_worst	155.327814	0.423188
4	smoothness_mean	130.955007	0.394148
8	symmetry_mean	111.988029	0.368659
29	fractal_dimension_worst	92.296412	0.338754
15	compactness_se	77.120465	0.312617
16	concavity_se	67.103586	0.293478
19	fractal_dimension_se	9.574370	0.115190
14	smoothness_se	4.053819	0.075242
18	symmetry_se	0.268262	0.019407
11	texture_se	0.125171	0.013258
9	fractal_dimension_mean	0.016431	0.004804

MACHINE LEARNING MODELS

- Logistic Regression
- Binary Decison Tree
- Random Forest
- K Nearest Neighbour

ACCURACY & FALSE NEGATIVE RATE (FNR)

LOGISTIC REGRESSION

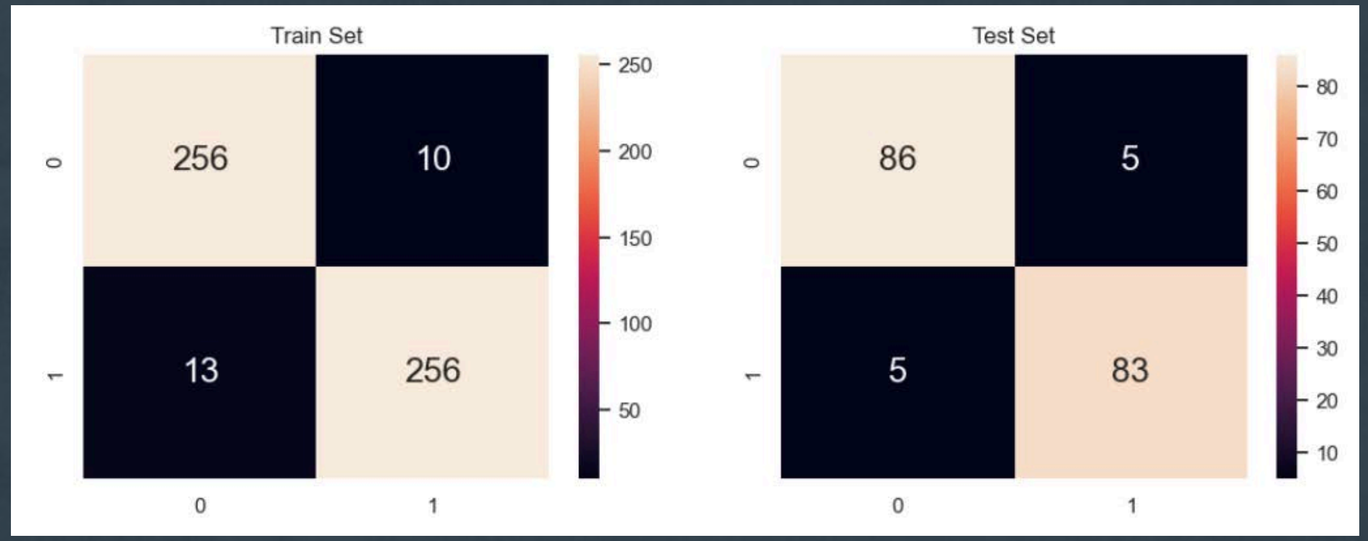
- Supervised Learning Model
- Test for binary outcomes
- Logistic Regression without parameter tuning
- Logisctic Regression with parameter tuning

Cross Validation Grid Search

LOGISTIC REGRESSION

Model without Parameter Tuning

➡ Feature List 0 was the best - 7 Best features



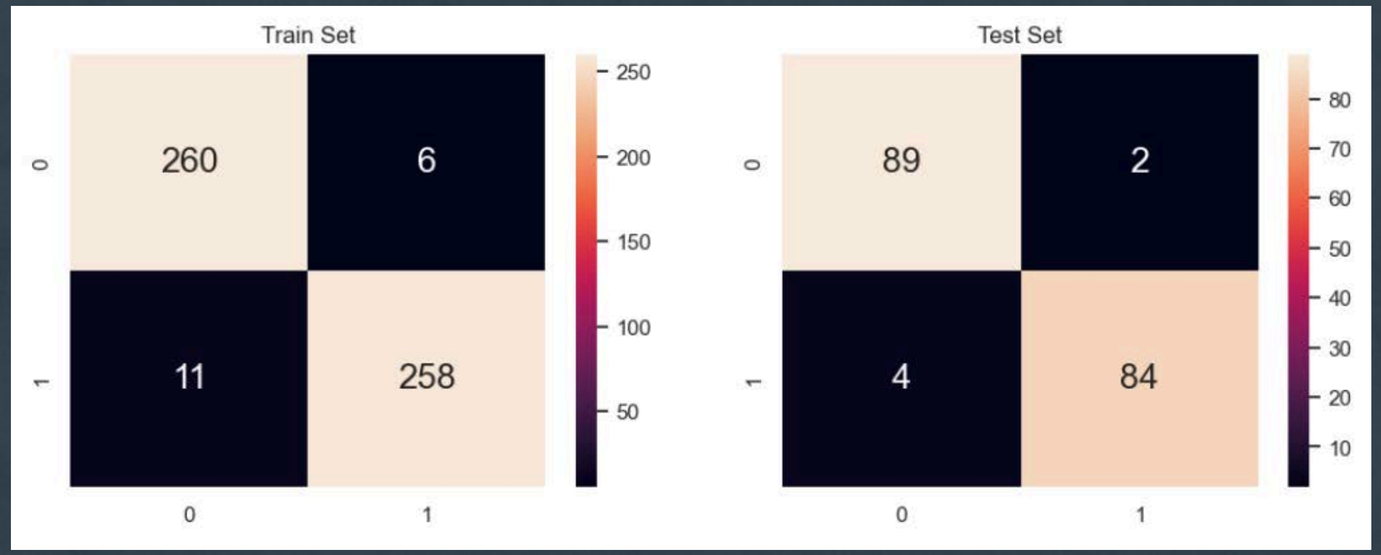
Train Set
Accuracy : 0.957
FNR : 0.0483

Test Set
Accuracy : 0.944
FNR : 0.0568

LOGISTIC REGRESSION

Model with Parameter Tuning using GridSearchCV

➡ Feature List 0 was the best - 7 Best features



Train Set
Accuracy : 0.968
FNR : 0.0409

Test Set
Accuracy : 0.966
FNR : 0.0455

LOGISTIC REGRESSION

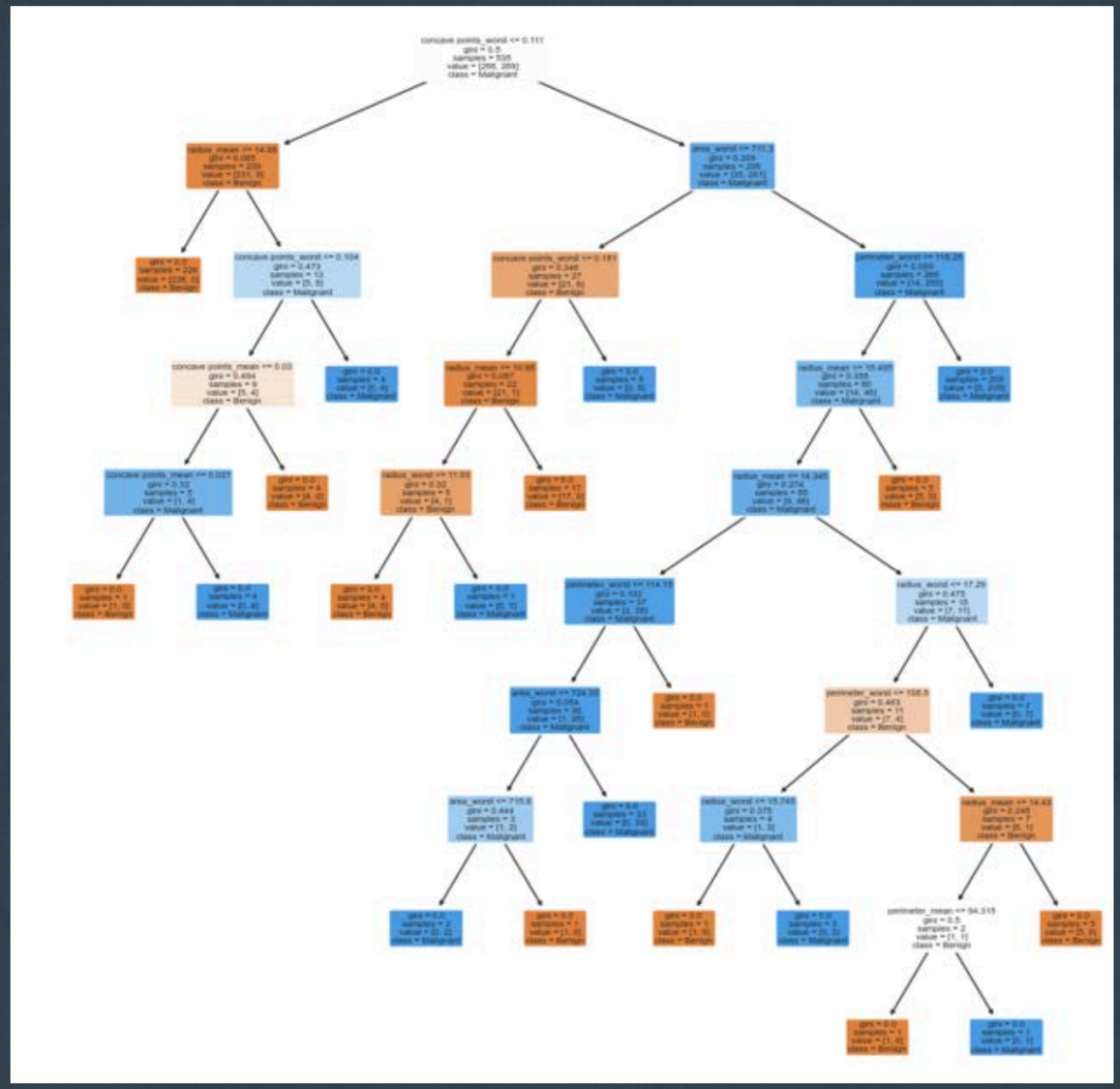
Tuned Logistic Regression (feature List 0) - 7 Best Features

- Accuracy increased from 0.944 to 0.966
- FNR decreased from 0.0568 to 0.0455

	accuracy	f1_score	precision	recall	balanced_accuracy	FNR
Logistic Regression (Feature List 0)	0.944134	0.943182	0.943182	0.943182	0.944118	0.056818
Tuned Logistic Regression (Feature List 0)	0.966480	0.965517	0.976744	0.954545	0.966284	0.045455

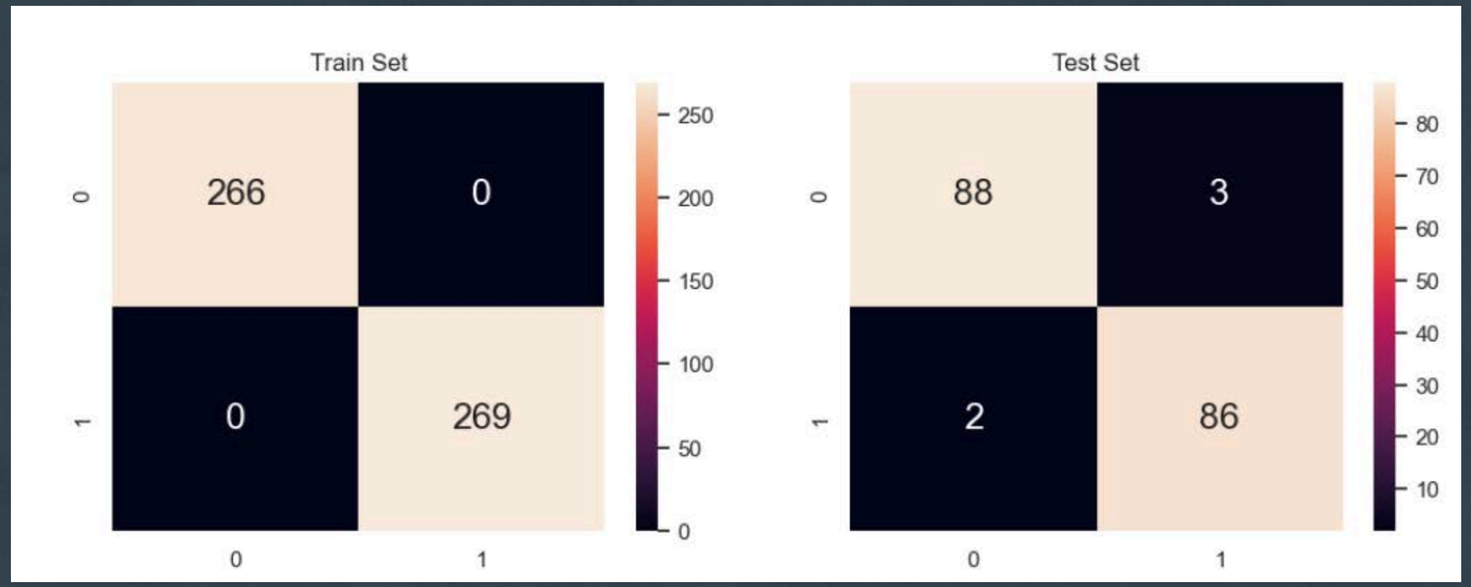
BINARY DECISION TREE

- Evaluate the accuracy of 4 different Trees
- Changed the optimal depth to “None” - expands until all leaf nodes are pure (no errors)



BINARY DECISION TREE

Feature List 0 was the best - 7 Best features



Train Set
Accuracy : 1.0
FNR : 1.0

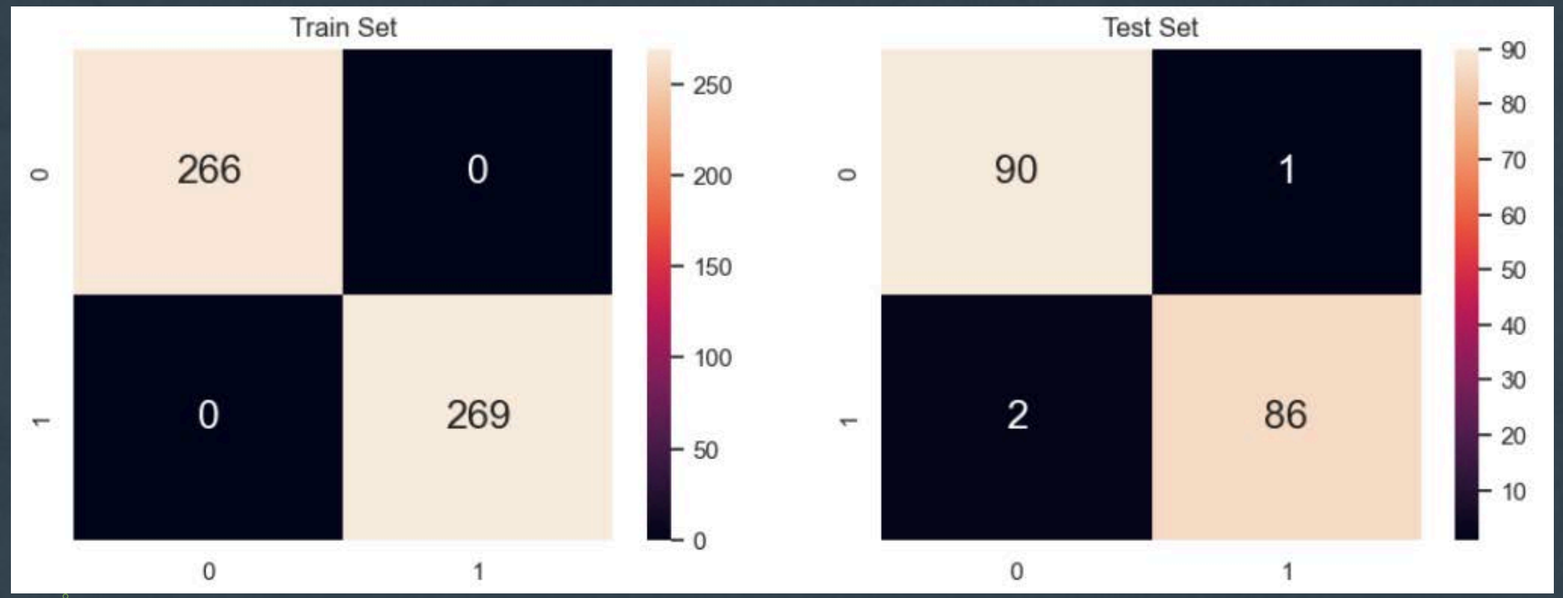
Test Set
Accuracy : 0.972
FNR : 0.0227

RANDOM FOREST CLASSIFIER

- Trains multiple decision trees on random subsets of train data
- Compares outcomes of all trees and derives a final prediction
- n_estimator = 200

RANDOM FOREST CLASSIFIER

- Feature List 0 - 7 Best Features
- Feature List 1 - 5 Best Features

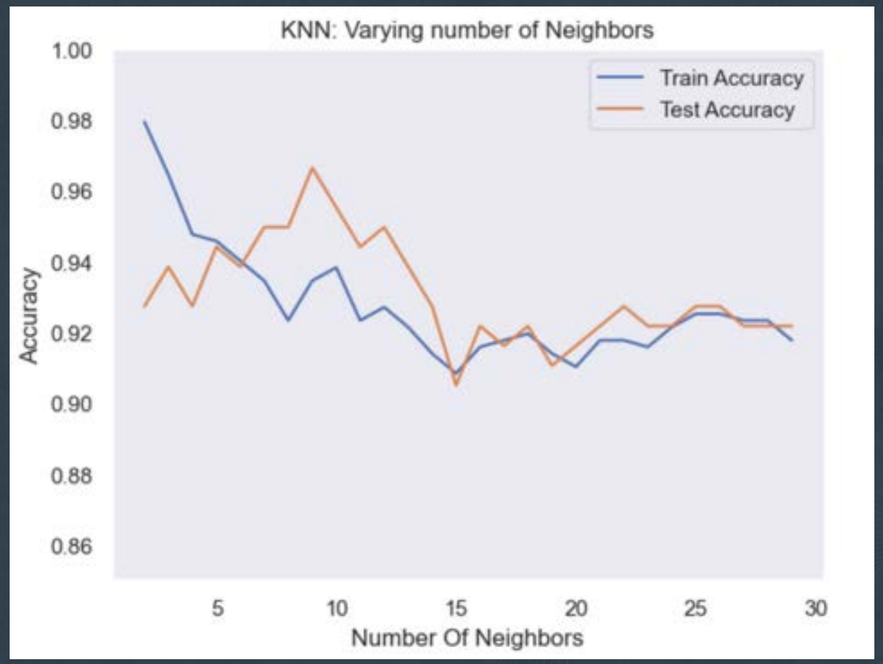


Train Set
Accuracy : 1.0
FNR : 1.0

Test Set
Accuracy : 0.983
FNR : 0.0227

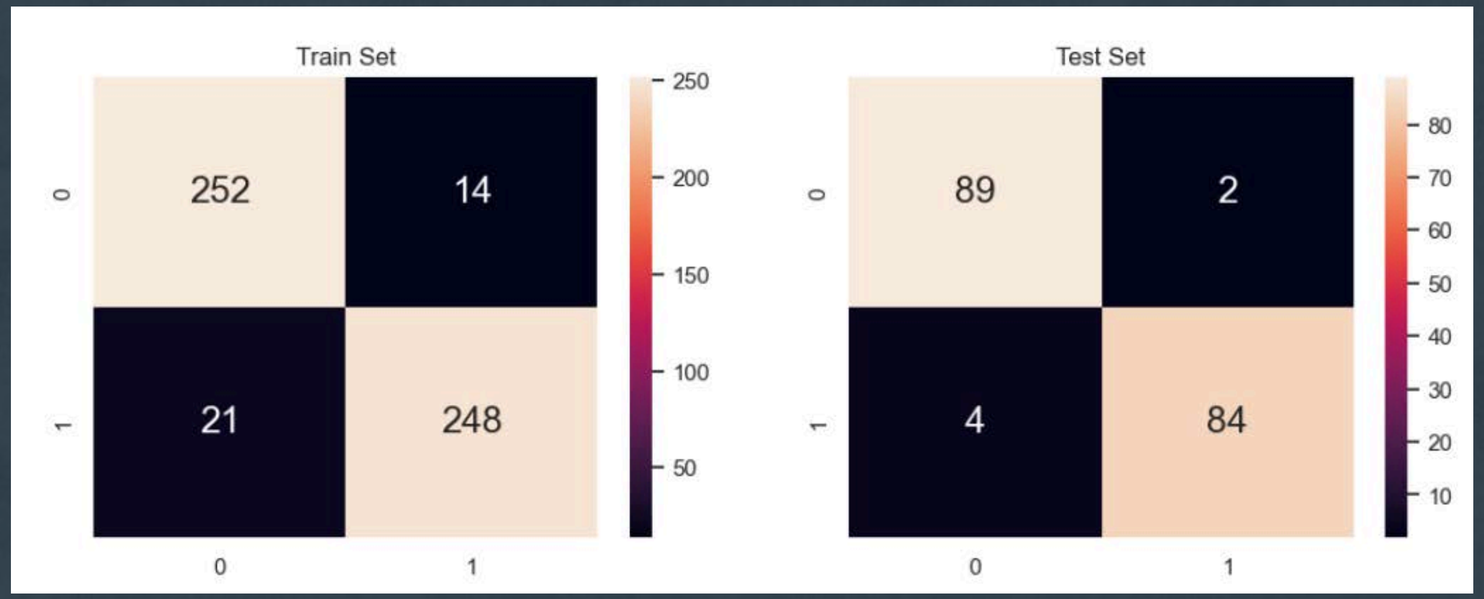
K-NEAREST NEIGHBOUR CLASSIFICATION

- Uses proximity to make classifications and predictions
- l parameter - “n_neighbours”
- Tuned the parameter by iteratively plotting classification accuracy while incrementing number of neighbour.
- Considered the Test Set
- Number of Neighbours = 9



NEAREST NEIGHBOUR CLASSIFICATION

Feature List 0 was the best - 7 Best features



Train Set
Accuracy : 0.935
FNR : 0.0781

Test Set
Accuracy : 0.966
FNR : 0.0455

FINAL DECISION

	accuracy	f1_score	precision	recall	balanced_accuracy	FNR
Random Forest (Feature List 0)	0.983240	0.982857	0.988506	0.977273	0.983142	0.022727
Random Forest (Feature List 1)	0.983240	0.982857	0.988506	0.977273	0.983142	0.022727
Decision Tree (Feature List 0)	0.972067	0.971751	0.966292	0.977273	0.972153	0.022727
Random Forest (Feature List 2)	0.972067	0.971751	0.966292	0.977273	0.972153	0.022727
Tuned Logistic Regression (Feature List 0)	0.966480	0.965517	0.976744	0.954545	0.966284	0.045455
KNearNeighbours (Feature List 0)	0.966480	0.965517	0.976744	0.954545	0.966284	0.045455
Decision Tree (Feature List 1)	0.960894	0.960000	0.965517	0.954545	0.960789	0.045455
Decision Tree (Feature List 2)	0.955307	0.955056	0.944444	0.965909	0.955482	0.034091
KNearNeighbours (Feature List 1)	0.949721	0.948571	0.954023	0.943182	0.949613	0.056818
Logistic Regression (Feature List 0)	0.944134	0.943182	0.943182	0.943182	0.944118	0.056818
KNearNeighbours (Feature List 2)	0.938547	0.937853	0.932584	0.943182	0.938624	0.056818
Random Forest (Feature List 3)	0.916201	0.917127	0.892473	0.943182	0.916646	0.056818
KNearNeighbours (Feature List 3)	0.916201	0.914286	0.919540	0.909091	0.916084	0.090909
Decision Tree (Feature List 3)	0.910615	0.911111	0.891304	0.931818	0.910964	0.068182

Random Forest (Feature List 0)

Accuracy : 0.983

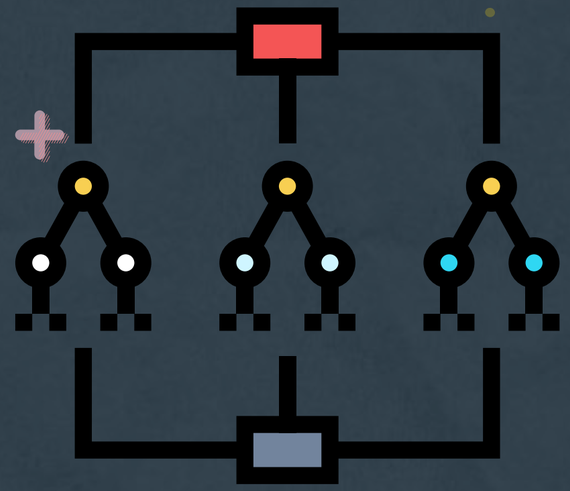
FNR : 0.0227

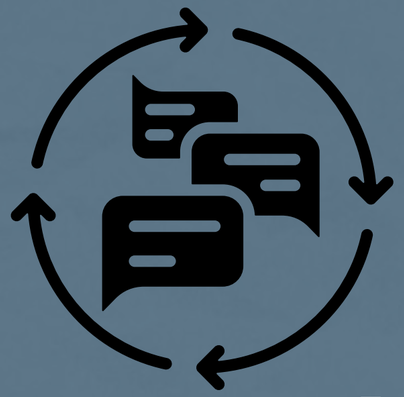
OUTCOME , INSIGHTS AND RECOMMENDATIONS

Outcome and Insights

- concave points_worst
- perimeter_worst
- radius_worst
- concave points_mean
- perimeter_mean
- radius_mean
- area_worst

Random Forest





Recommendations

- Validate the performance of the developed models through collaboration with healthcare professionals. Ensure that the model generalize well to diverse patient populations and is robust.

- Regular updates to incorporate new data, emerging research findings. Continuous improvement ensures that the models remain relevant and effective over time.

- Many models are available for a classification problem, can possibly look into other models that can also achieve a high if not better accuracy score

WE WANT TO SAY

THANK YOU

FOR YOUR ATTENTION