1 Exploratory Data Analysis (EDA)

1.1. Understanding the data

1.2. Impuding missing values

1.1 Understand the data

In [198…
```
# Import all the tools we need
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.model_selection import train_test_split
```

In [199…
```
df_original = pd.read_excel('/content/cancer.xlsx')
```

In [200…
```
df = df_original.copy()
df.head()
```

Out[200]:

	index	id	radius_mean	texture_mean	perimeter_mean	area_mean	smoothness_mean	com
0	1	842302	17.99	10.38	122.80	1001.0	0.11840	
1	2	842517	20.57	17.77	132.90	1326.0	0.08474	
2	3	84300903	19.69	21.25	130.00	1203.0	0.10960	
3	4	84348301	11.42	20.38	77.58	386.1	0.14250	
4	5	84358402	20.29	14.34	135.10	1297.0	0.10030	

5 rows × 36 columns

1. Understanding the data

In [201…
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 569 entries, 0 to 568
Data columns (total 36 columns):
 #   Column                   Non-Null Count  Dtype  
---  ------                   --------------  -----  
 0   index                    569 non-null    int64  
 1   id                       569 non-null    int64  
 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           552 non-null    float64
 9   concave_points_mean      550 non-null    float64
 10  symmetry_mean            568 non-null    float64
 11  fractal_dimension        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             554 non-null    float64
 19  concave_points_se        550 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  texture_worst.1          569 non-null    float64
 25  area_worst               569 non-null    float64
 26  smoothness_worst         569 non-null    float64
 27  compactness_worst        568 non-null    float64
 28  concavity_worst          562 non-null    float64
 29  concave points_worst     563 non-null    float64
 30  symmetry_worst           569 non-null    float64
 31  fractal_dimension_worst  569 non-null    float64
 32  N Stage                  569 non-null    object 
 33  6th Stage                569 non-null    object 
 34  differentiate            569 non-null    object 
 35  diagnosis                569 non-null    object 
dtypes: float64(30), int64(2), object(4)
memory usage: 160.2+ KB
```

In [202…

```
df.columns
```

Out[202]:

```
Index(['index', 'id', 'radius_mean', 'texture_mean', 'perimeter_mean',
       'area_mean', 'smoothness_mean', 'compactness_mean', 'concavity_mean',
       'concave_points_mean', 'symmetry_mean', 'fractal_dimension',
       'radius_se', 'texture_se', 'perimeter_se', 'area_se', 'smoothness_se',
       'compactness_se', 'concavity_se', 'concave_points_se', 'symmetry_se',
       'fractal_dimension_se', 'radius_worst', 'texture_worst',
       'texture_worst.1', 'area_worst', 'smoothness_worst',
       'compactness_worst', 'concavity_worst', 'concave points_worst',
       'symmetry_worst', 'fractal_dimension_worst', 'N Stage', '6th Stage',
       'differentiate', 'diagnosis'],
      dtype='object')
```

In [203…

```
df.describe()
```

Out[203]:

	index	id	radius_mean	texture_mean	perimeter_mean	area_mean	smoothne
count	569.000000	5.690000e+02	569.000000	569.000000	569.000000	569.000000	56
mean	285.000000	3.037183e+07	14.127292	19.289649	91.969033	654.889104	
std	164.400426	1.250206e+08	3.524049	4.301036	24.298981	351.914129	
min	1.000000	8.670000e+03	6.981000	9.710000	43.790000	143.500000	
25%	143.000000	8.692180e+05	11.700000	16.170000	75.170000	420.300000	
50%	285.000000	9.060240e+05	13.370000	18.840000	86.240000	551.100000	
75%	427.000000	8.813129e+06	15.780000	21.800000	104.100000	782.700000	
max	569.000000	9.113205e+08	28.110000	39.280000	188.500000	2501.000000	

8 rows × 32 columns

In [204…
```
df.shape
```

Out[204]:
```
(569, 36)
```

In [205…
```
df.ndim
```

Out[205]:
```
2
```

In [206…
```
df.isnull().sum()
```

Out[206]:
```
index                     0
id                        0
radius_mean               0
texture_mean              0
perimeter_mean            0
area_mean                 0
smoothness_mean           0
compactness_mean          0
concavity_mean           17
concave_points_mean      19
symmetry_mean             1
fractal_dimension         0
radius_se                 0
texture_se                0
perimeter_se              0
area_se                   0
smoothness_se             0
compactness_se            0
concavity_se             15
concave_points_se        19
symmetry_se               0
fractal_dimension_se      0
radius_worst              0
texture_worst             0
texture_worst.1           0
area_worst                0
smoothness_worst          0
compactness_worst         1
concavity_worst           7
concave points_worst      6
symmetry_worst            0
fractal_dimension_worst   0
N Stage                   0
6th Stage                 0
differentiate             0
diagnosis                 0
dtype: int64
```

1.2 Imputing missing values

In [207…
```
df["concavity_mean"].fillna(df["concavity_mean"].median(),inplace = True)
df["concave_points_mean"].fillna(df["concave_points_mean"].mean(),inplace = True)
df["symmetry_mean"].fillna(df["symmetry_mean"].median(),inplace = True)
df["compactness_worst"].fillna(df["compactness_worst"].mean(),inplace = True)
df["concavity_se"].fillna(df["concavity_se"].mean(),inplace = True)
df["concave_points_se"].fillna(df["concave_points_se"].median(),inplace = True)
df["concavity_worst"].fillna(df["concavity_worst"].median(),inplace = True)
df["concave points_worst"].fillna(df["concave points_worst"].median(),inplace = True)
```

In [208…
```
df=df.drop(['index','id'],axis=1)
```

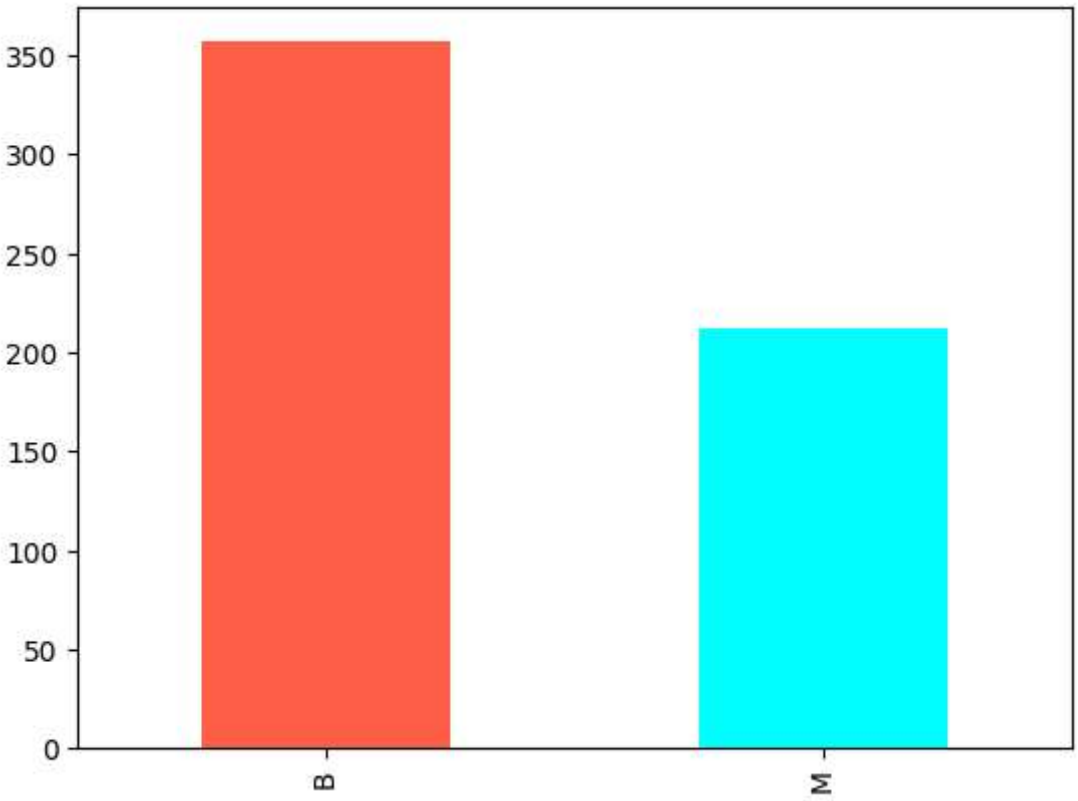
In [209…
```
df.isnull().sum()
```

Out[209]:
```
radius_mean               0
texture_mean              0
perimeter_mean            0
area_mean                 0
smoothness_mean           0
compactness_mean          0
concavity_mean            0
concave_points_mean       0
symmetry_mean             0
fractal_dimension         0
radius_se                 0
texture_se                0
perimeter_se              0
area_se                   0
smoothness_se             0
compactness_se            0
concavity_se              0
concave_points_se         0
symmetry_se               0
fractal_dimension_se      0
radius_worst              0
texture_worst             0
texture_worst.1           0
area_worst                0
smoothness_worst          0
compactness_worst         0
concavity_worst           0
concave points_worst      0
symmetry_worst            0
fractal_dimension_worst   0
N Stage                   0
6th Stage                 0
differentiate             0
diagnosis                 0
dtype: int64
```

In [210…
```
df["diagnosis"].value_counts()
```

Out[210]:
```
B    357
M    212
Name: diagnosis, dtype: int64
```

In [211…
```
df["diagnosis"].value_counts().plot(kind="bar",color=["tomato", "cyan"]);
```



2 Feature Selection

2.1. Correlation heatmap

2.2. Dropping features

2.3. Dealing with outliers

2.4. Converting Catergorical features to Numerical fretures

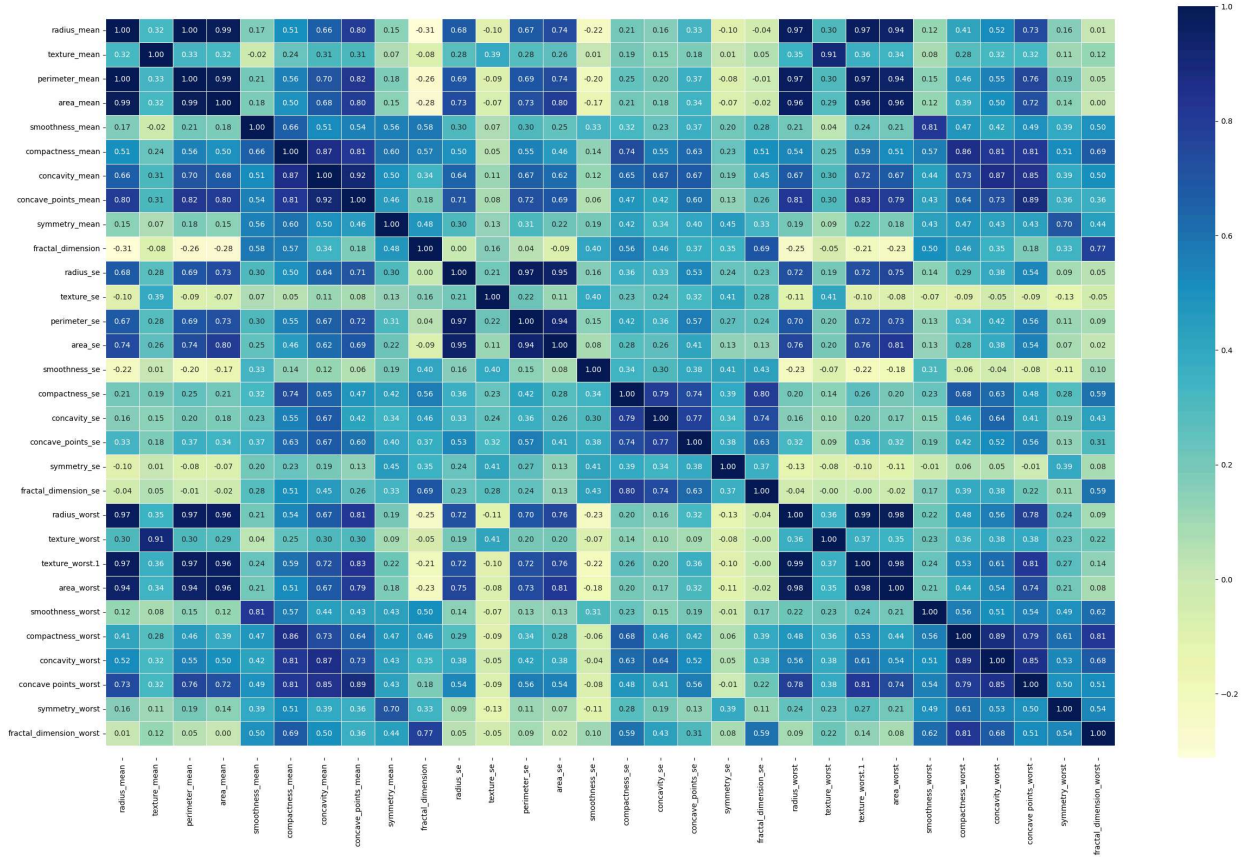
2.1 Correlation heatmap

In [212…

```
corr_matrix = df.corr()
fig, ax = plt.subplots(figsize=(30, 18))
ax = sns.heatmap(corr_matrix,
                 annot=True,
                 linewidths=0.5,
                 fmt=".2f",
                 cmap="YlGnBu");
bottom, top = ax.get_ylim()
ax.set_ylim(bottom + 0.5, top - 0.5)
```

```
<ipython-input-212-23a60eaaf1d8>:1: FutureWarning: The default value of numeric_only
in DataFrame.corr is deprecated. In a future version, it will default to False. Selec
t only valid columns or specify the value of numeric_only to silence this warning.
  corr_matrix = df.corr()
```

Out[212]: (30.5, -0.5)



In [213...]
```
df1 = df.copy()
```

In [214...]
```
len(df1.columns)
```

Out[214]: 34

2.2 Dropping features

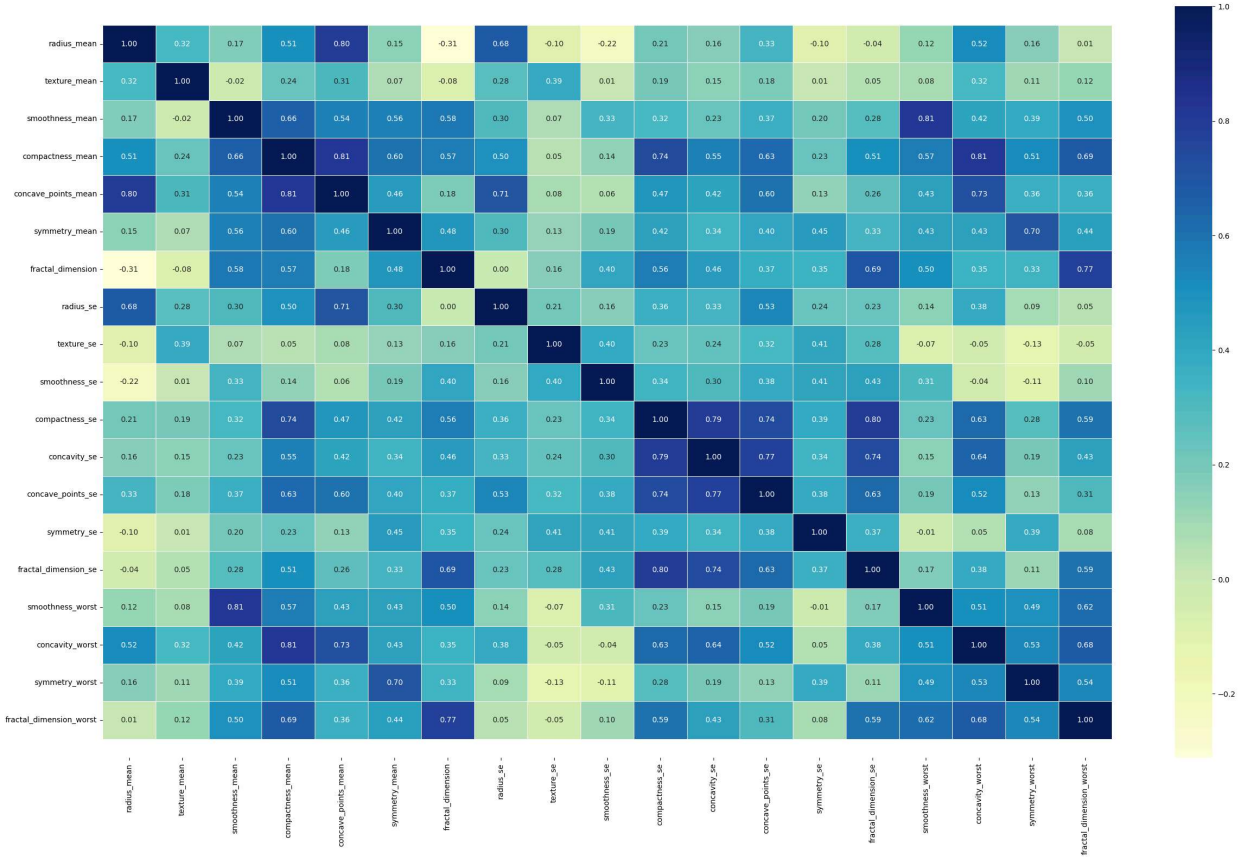
Dropping columns haveing correlation more than 0.85

In [215...]
```
df1.drop(['perimeter_mean','area_mean','radius_worst','texture_worst','texture_worst.1
```

In [216...]
```
corr_matrix = df1.corr()
fig, ax = plt.subplots(figsize=(30, 18))
ax = sns.heatmap(corr_matrix,
                 annot=True,
                 linewidths=0.5,
                 fmt=".2f",
                 cmap="YlGnBu");
bottom, top = ax.get_ylim()
ax.set_ylim(bottom + 0.5, top - 0.5)
```

```
<ipython-input-216-2aa323b57d04>:1: FutureWarning: The default value of numeric_only
in DataFrame.corr is deprecated. In a future version, it will default to False. Selec
t only valid columns or specify the value of numeric_only to silence this warning.
  corr_matrix = df1.corr()
```

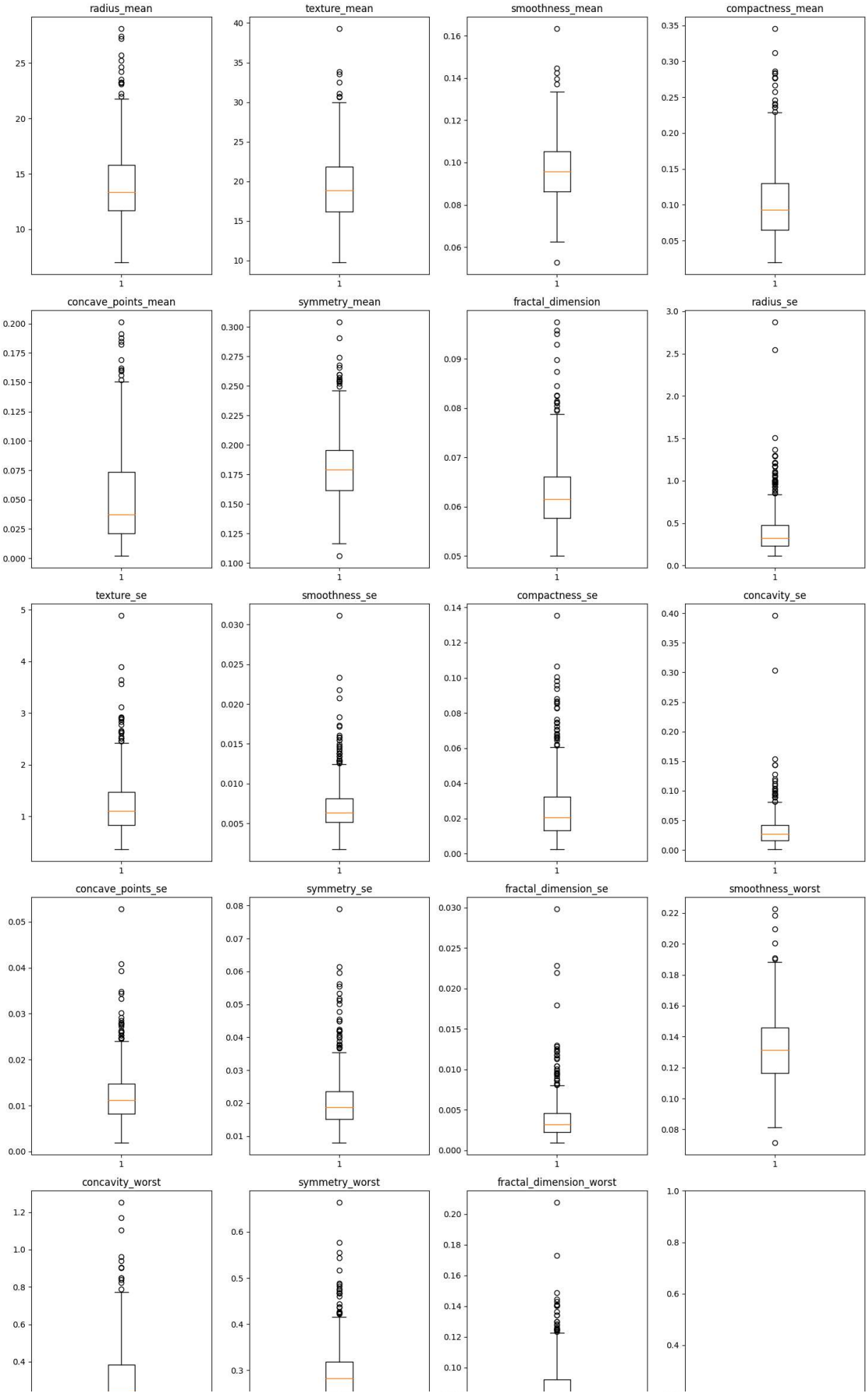
Out[216]: (19.5, -0.5)



2.3 Dealing with outliers

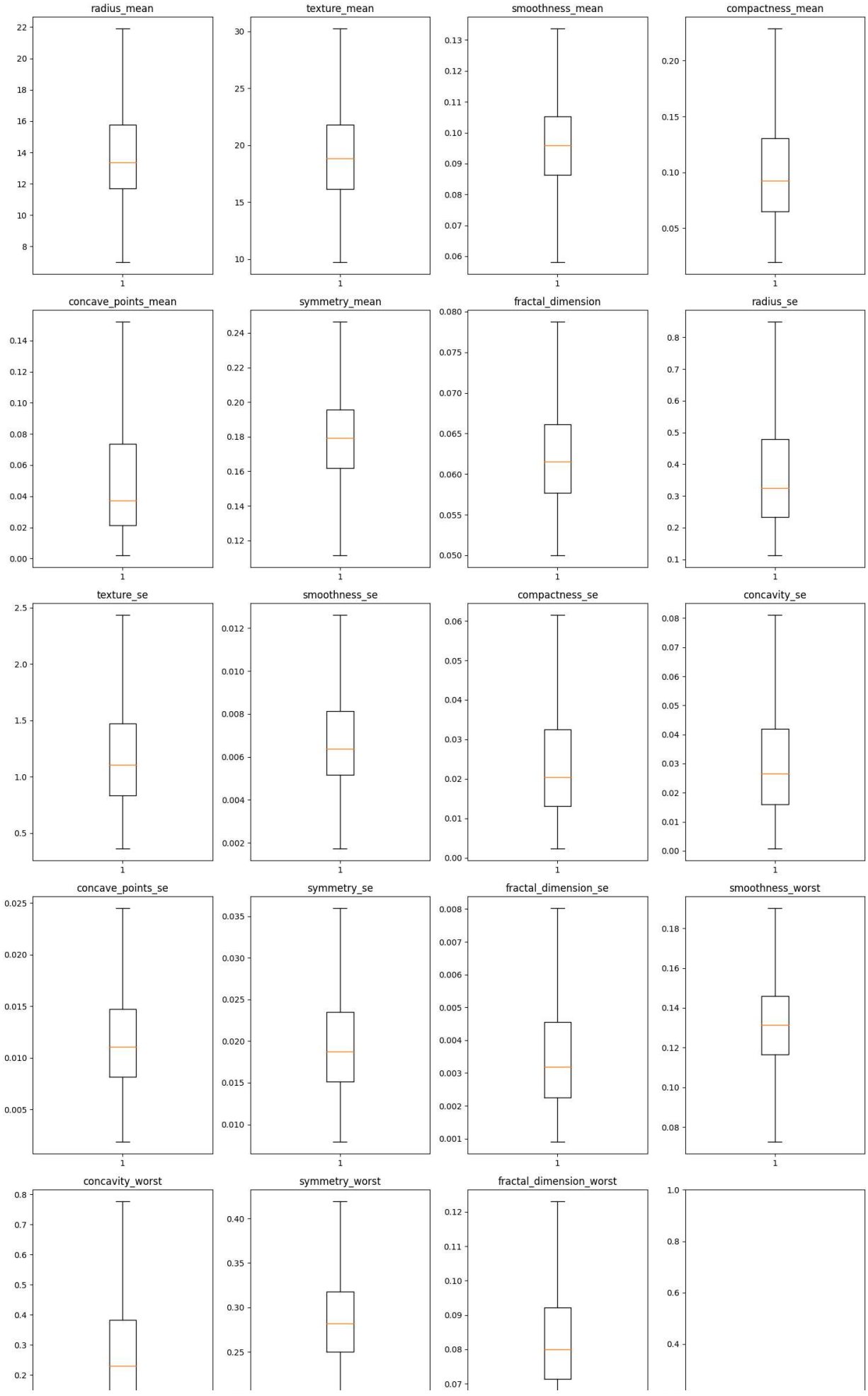
In [217…

```
num_cols = 4  # Number of columns in each row of subplots
num_rows = (len(df1.columns) + num_cols - 1) // num_cols  # Calculate the number of ro
num_rows -= 1
# Create subplots
fig, axes = plt.subplots(num_rows, num_cols, figsize=(15, 5*num_rows))
# Flatten axes if needed
if num_rows == 1:
    axes = [axes]
# Plot boxplots for each numerical column
for i, column in enumerate(df1.columns):
    if df1[column].dtype != 'O':  # Check if column is numeric
        row_index = i // num_cols
        col_index = i % num_cols
        axes[row_index][col_index].boxplot(df1[column])
        axes[row_index][col_index].set_title(column)
# Adjust layout and display plots
plt.tight_layout()
plt.show()
```


radius_mean
texture_mean
smoothness_mean
compactness_mean
concave_points_mean
symmetry_mean
fractal_dimension
radius_se
texture_se
smoothness_se
compactness_se
concavity_se
concave_points_se
symmetry_se
fractal_dimension_se
smoothness_worst
concavity_worst
symmetry_worst
fractal_dimension_worst

In [218…
```
for i in df1.columns:
  if(df1[i].dtype != object):
    IQR = df1[i].quantile(0.75) - df1[i].quantile(0.25)
    upper_bound = df1[i].quantile(0.75) + 1.5*IQR
    lower_bound = df1[i].quantile(0.25) - 1.5*IQR
    df1.loc[df1[i] >= upper_bound,i] = upper_bound
    df1.loc[df1[i] <= lower_bound,i] = lower_bound
```

In [219…
```
num_cols = 4  # Number of columns in each row of subplots
num_rows = (len(df1.columns) + num_cols - 1) // num_cols  # Calculate the number of rc
num_rows -= 1
# Create subplots
fig, axes = plt.subplots(num_rows, num_cols, figsize=(15, 5*num_rows))
# Flatten axes if needed
if num_rows == 1:
    axes = [axes]
# Plot boxplots for each numerical column
for i, column in enumerate(df1.columns):
    if df1[column].dtype != 'O':  # Check if column is numeric
        row_index = i // num_cols
        col_index = i % num_cols
        axes[row_index][col_index].boxplot(df1[column])
        axes[row_index][col_index].set_title(column)
# Adjust layout and display plots
plt.tight_layout()
plt.show()
```


radius_mean
texture_mean
smoothness_mean
compactness_mean
concave_points_mean
symmetry_mean
fractal_dimension
radius_se
texture_se
smoothness_se
compactness_se
concavity_se
concave_points_se
symmetry_se
fractal_dimension_se
smoothness_worst
concavity_worst
symmetry_worst
fractal_dimension_worst

In [220…
```
df1.to_csv("cleanedCancerDate.csv")
```

2.4 Categorical to numerical

In [221…
```
df1.columns
```

Out[221]:
```
Index(['radius_mean', 'texture_mean', 'smoothness_mean', 'compactness_mean',
       'concave_points_mean', 'symmetry_mean', 'fractal_dimension',
       'radius_se', 'texture_se', 'smoothness_se', 'compactness_se',
       'concavity_se', 'concave_points_se', 'symmetry_se',
       'fractal_dimension_se', 'smoothness_worst', 'concavity_worst',
       'symmetry_worst', 'fractal_dimension_worst', 'N Stage', '6th Stage',
       'differentiate', 'diagnosis'],
      dtype='object')
```

In [222…
```
#find the categorical features
for i in df1.columns:
  if(df1[i].dtype == 'O'):
    print(i," \t",df1[i].nunique())
```

```
N Stage          3
6th Stage        5
differentiate    4
diagnosis        2
```

Performing ONE HOT ENCODING

In [223…
```
# Perform one-hot encoding
one_hot_encoded1 = pd.get_dummies(df['N Stage'])
one_hot_encoded2 = pd.get_dummies(df['6th Stage'])
one_hot_encoded3 = pd.get_dummies(df['differentiate'])
# Concatenate the one-hot encoded columns with the original DataFrame
df_encoded = pd.concat([df1, one_hot_encoded1, one_hot_encoded2, one_hot_encoded3], ax
df_encoded.drop(['N Stage','6th Stage','differentiate'],axis=1,inplace=True)
df_encoded.columns
```

Out[223]:
```
Index(['radius_mean', 'texture_mean', 'smoothness_mean', 'compactness_mean',
       'concave_points_mean', 'symmetry_mean', 'fractal_dimension',
       'radius_se', 'texture_se', 'smoothness_se', 'compactness_se',
       'concavity_se', 'concave_points_se', 'symmetry_se',
       'fractal_dimension_se', 'smoothness_worst', 'concavity_worst',
       'symmetry_worst', 'fractal_dimension_worst', 'diagnosis', 'N1', 'N2',
       'N3', 'IIA', 'IIB', 'IIIA', 'IIIB', 'IIIC', 'Moderately differentiated',
       'Poorly differentiated', 'Undifferentiated', 'Well differentiated'],
      dtype='object')
```

In [224…
```
df_encoded['diagnosis'] = df_encoded['diagnosis'].map({'B': 0, 'M': 1})
df_encoded["diagnosis"].value_counts()
```

Out[224]:
```
0    357
1    212
Name: diagnosis, dtype: int64
```

In [225…
```
df_encoded.to_csv("cleanedEncodedCancerDate.csv")
df_encoded.to_csv("cleanedEncodedCancerDate.xlsx")
```

Modelling

We're going to try 6 different machine learning models:

1. Logistic Regression
2. K-Nearest Neighbours Classifier
3. Random Forest Classifier
4. Decision Tree
5. Support Vector Machine
6. Naive Bayes

In [226…
```
X = df_encoded.drop("diagnosis", axis=1)

y = df_encoded["diagnosis"]

# Split data into train and test sets
np.random.seed(42)

# Split into train & test set
X_train, X_test, y_train, y_test = train_test_split(X,
                                                    y,
                                                    test_size=0.2)
```

In [227…
```
from sklearn.linear_model import LogisticRegression
from sklearn.neighbors import KNeighborsClassifier
from sklearn.ensemble import RandomForestClassifier
from sklearn.tree import DecisionTreeClassifier
from sklearn.svm import SVC
from sklearn.naive_bayes import GaussianNB
from sklearn.metrics import accuracy_score, precision_score, recall_score, f1_score, c
from sklearn.metrics import confusion_matrix
import numpy as np

# Put models in a dictionary
models = {"Logistic Regression": LogisticRegression(),
          "KNN": KNeighborsClassifier(),
          "Random Forest": RandomForestClassifier(),
          "Decision Tree": DecisionTreeClassifier(),
          "SVM": SVC(),
          "Naive Bayes": GaussianNB()}

# Create a function to fit and score models
def fit_and_score(models, X_train, X_test, y_train, y_test):
    """
    Fits and evaluates given machine learning models.
    models : a dict of different Scikit-Learn machine learning models
    X_train : training data (no labels)
    X_test : testing data (no labels)
    y_train : training labels
    y_test : test labels
    """
```

```
    # Set random seed
    np.random.seed(42)
    # Make a dictionary to keep model scores
    model_scores = {}
    model_accuracy = {}
    report ={}
    y_prediction = {}
    # Loop through models
    for name, model in models.items():
        # Fit the model to the data
        model.fit(X_train, y_train)
        # Evaluate the model and append its score to model_scores
        model_scores[name] = model.score(X_test, y_test)
        # Accuracy
        y_pred = model.predict(X_test)
        y_prediction[name] = y_pred
        model_accuracy[name] = accuracy_score(y_test, y_pred)
        report[name] = classification_report(y_test, y_pred, target_names=['malignant'
    return model_scores,model_accuracy,report,y_prediction
```

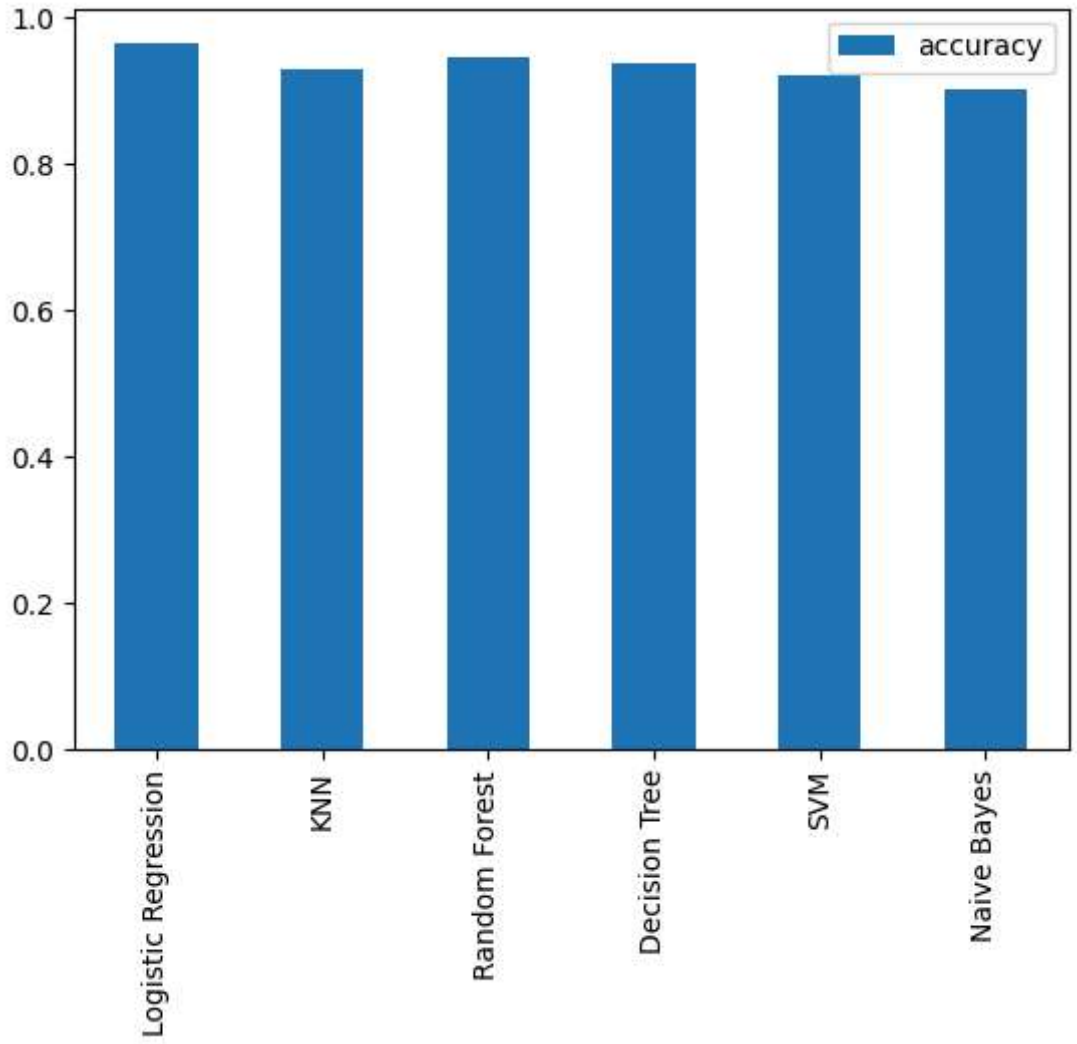
In [228…

```
model_scores,model_accuracy,report,y_prediction = fit_and_score(models=models,
                                X_train=X_train,
                                X_test=X_test,
                                y_train=y_train,
                                y_test=y_test)

# for key in model_scores.keys():
#   print(f'{key}\t{model_scores[key]}')

max_length = max(len(key) for key in model_scores.keys())
for key, value in model_scores.items():
    print(f'{key.ljust(max_length)}\t{value}')

for key in report.keys():
  print(key,'\t',report[key])
```

```
/usr/local/lib/python3.10/dist-packages/sklearn/linear_model/_logistic.py:458: Conver
genceWarning: lbfgs failed to converge (status=1):
STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.

Increase the number of iterations (max_iter) or scale the data as shown in:
    https://scikit-learn.org/stable/modules/preprocessing.html
Please also refer to the documentation for alternative solver options:
    https://scikit-learn.org/stable/modules/linear_model.html#logistic-regression
  n_iter_i = _check_optimize_result(
```

```
Logistic Regression     0.9649122807017544
KNN                     0.9298245614035088
Random Forest           0.9473684210526315
Decision Tree           0.9385964912280702
SVM                     0.9210526315789473
Naive Bayes             0.9035087719298246
Logistic Regression                   precision    recall  f1-score   support

   malignant       0.97      0.97      0.97        71
      benign       0.95      0.95      0.95        43

    accuracy                           0.96       114
   macro avg       0.96      0.96      0.96       114
weighted avg       0.96      0.96      0.96       114

KNN                   precision    recall  f1-score   support

   malignant       0.93      0.96      0.94        71
      benign       0.93      0.88      0.90        43

    accuracy                           0.93       114
   macro avg       0.93      0.92      0.92       114
weighted avg       0.93      0.93      0.93       114

Random Forest                precision    recall  f1-score   support

   malignant       0.95      0.97      0.96        71
      benign       0.95      0.91      0.93        43

    accuracy                           0.95       114
   macro avg       0.95      0.94      0.94       114
weighted avg       0.95      0.95      0.95       114

Decision Tree                precision    recall  f1-score   support

   malignant       0.96      0.94      0.95        71
      benign       0.91      0.93      0.92        43

    accuracy                           0.94       114
   macro avg       0.93      0.94      0.93       114
weighted avg       0.94      0.94      0.94       114

SVM                   precision    recall  f1-score   support

   malignant       0.92      0.96      0.94        71
      benign       0.93      0.86      0.89        43

    accuracy                           0.92       114
   macro avg       0.92      0.91      0.91       114
weighted avg       0.92      0.92      0.92       114

Naive Bayes                  precision    recall  f1-score   support

   malignant       0.88      0.99      0.93        71
      benign       0.97      0.77      0.86        43

    accuracy                           0.90       114
   macro avg       0.92      0.88      0.89       114
weighted avg       0.91      0.90      0.90       114
```

In [229…
```
model_compare = pd.DataFrame(model_scores, index=["accuracy"])
model_compare.T.plot.bar();
```



In [230…
```
import pickle

# Find the model with the highest accuracy
best_model_name = max(model_scores, key=model_scores.get)
print(best_model_name)
best_model = models[best_model_name]

# Pickle the best model
with open(f'best_model_{best_model_name}.pkl', 'wb') as f:
    pickle.dump(best_model, f)
```

```
Logistic Regression
```

Cross validation on Logistic Regression Model

In [231…
```
# Initialize logistic regression model
model = LogisticRegression(max_iter=1000)

# Perform cross-validation
```

```
# Here, cv=5 means 5-fold cross-validation
# You can adjust cv parameter as needed
scores = cross_val_score(model, X, y, cv=5)

# Print the cross-validation scores
print("Cross-validation scores:", scores)

# Print the mean and standard deviation of the cross-validation scores
print("Mean accuracy:", scores.mean())
print("Standard deviation of accuracy:", scores.std())
```

```
Cross-validation scores: [0.89473684 0.92982456 0.97368421 0.93859649 0.9380531 ]
Mean accuracy: 0.934979040521658
Standard deviation of accuracy: 0.025165965701401824
```

In [232…

```
y_prediction
```

Out[232]:

```
{'Logistic Regression': array([0, 1, 1, 0, 0, 1, 1, 1, 0, 0, 0, 1, 0, 1, 0, 1, 0, 0,
0, 1, 0, 0,
       1, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 1, 0, 1, 0, 0, 1, 0, 0,
       0, 0, 0, 0, 0, 0, 1, 1, 0, 0, 0, 0, 0, 1, 1, 0, 0, 1, 1, 1, 0, 0,
       1, 1, 0, 0, 1, 1, 0, 1, 0, 0, 0, 0, 0, 0, 1, 0, 1, 1, 1, 1, 1, 1,
       0, 0, 0, 0, 0, 0, 0, 0, 1, 1, 0, 1, 1, 0, 1, 1, 0, 0, 0, 1, 0, 0,
       1, 0, 1, 1]),
 'KNN': array([0, 1, 1, 0, 0, 1, 1, 0, 0, 0, 0, 1, 0, 1, 0, 1, 0, 0, 0, 1, 0, 0,
       1, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 1, 0, 1, 1, 0, 1, 0, 0,
       0, 0, 0, 0, 0, 0, 1, 1, 1, 0, 0, 0, 0, 1, 1, 0, 0, 1, 1, 0, 0, 1,
       1, 1, 0, 0, 0, 1, 0, 1, 0, 0, 0, 0, 0, 0, 1, 0, 1, 1, 1, 0, 1, 1,
       0, 0, 0, 0, 0, 0, 0, 0, 1, 1, 0, 1, 1, 0, 1, 1, 0, 0, 0, 1, 0, 0,
       1, 0, 0, 1]),
 'Random Forest': array([0, 1, 1, 0, 0, 1, 1, 1, 1, 0, 0, 1, 0, 1, 0, 1, 0, 0, 0, 1,
0, 0,
       1, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 1, 0, 0,
       0, 0, 0, 0, 0, 0, 1, 1, 1, 0, 0, 0, 0, 1, 1, 0, 0, 1, 1, 0, 0, 0,
       1, 1, 0, 0, 1, 1, 0, 1, 0, 0, 0, 0, 0, 0, 1, 0, 0, 1, 1, 1, 1, 1,
       0, 0, 0, 0, 0, 0, 0, 0, 1, 1, 0, 1, 1, 0, 1, 1, 0, 0, 0, 1, 0, 0,
       1, 0, 0, 1]),
 'Decision Tree': array([0, 1, 1, 0, 0, 1, 1, 0, 1, 0, 0, 1, 0, 1, 0, 1, 0, 0, 0, 1,
0, 0,
       1, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 1, 0, 1, 0, 0, 1, 0, 0,
       0, 0, 1, 0, 0, 0, 1, 1, 1, 0, 0, 0, 0, 1, 1, 0, 0, 1, 1, 1, 0, 0,
       1, 1, 0, 0, 1, 1, 0, 1, 0, 0, 0, 1, 0, 0, 1, 0, 0, 1, 1, 1, 1, 1,
       0, 0, 0, 0, 0, 0, 0, 0, 1, 1, 0, 1, 1, 0, 1, 1, 0, 0, 0, 1, 0, 0,
       1, 0, 0, 1]),
 'SVM': array([0, 1, 1, 0, 0, 1, 1, 1, 0, 0, 0, 1, 0, 1, 0, 1, 0, 0, 0, 1, 0, 0,
       1, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 1, 0, 1, 1, 0, 1, 0, 0,
       0, 0, 0, 0, 0, 0, 1, 1, 0, 0, 0, 0, 0, 1, 0, 0, 0, 1, 1, 1, 0, 0,
       1, 1, 0, 0, 0, 1, 0, 1, 0, 0, 0, 0, 0, 0, 1, 0, 1, 1, 1, 0, 0, 1,
       0, 0, 0, 0, 0, 0, 0, 0, 1, 1, 0, 1, 1, 0, 1, 1, 0, 0, 0, 1, 0, 0,
       1, 0, 1, 1]),
 'Naive Bayes': array([0, 1, 1, 0, 0, 1, 1, 1, 1, 0, 0, 1, 0, 1, 0, 1, 0, 0, 0, 1, 0,
0,
       1, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0,
       0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 1, 0, 0, 0, 1, 1, 0, 0, 0,
       1, 1, 0, 0, 1, 1, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 1, 1, 1,
       0, 0, 0, 0, 0, 0, 0, 0, 1, 1, 0, 1, 0, 0, 1, 1, 0, 0, 0, 1, 0, 0,
       1, 0, 0, 1])}
```

In [233…

```
actual    = np.array(y_test)
predicted = np.array(y_prediction['Logistic Regression'])
```

```
cm = confusion_matrix(actual,predicted)
```

In [234…

```
sns.heatmap(cm,
            annot=True,
            fmt='g',
            xticklabels=['B','M'],
            yticklabels=['B','M'])
plt.ylabel('Prediction',fontsize=13)
plt.xlabel('Actual',fontsize=13)
plt.title('Confusion Matrix',fontsize=17)
plt.show()
```