ML-classification

December 30, 2024

1 Find data set

The dataset is from `Kaggle` Breast Cancer dataset by Rahma Sleam This diagnostic dataset is from Breast Cancer Wisconsin. https://www.kaggle.com/datasets/rahmasleam/breast-cancer ### Data Description

The data is a 569 by 31 matrix. It contains 569 patient samples as rows. "diagnosis" column is the diagnosis classified as either "M" for malignant(cancerous), or "B" for Benign(non-cancerous). It has 30 columns to characterize the patient's sample: `radius_mean`, `texture_mean`, `perimeter_mean`, `area_mean`, `smoothness_mean`, `compactness_mean`, `concavity_mean`, `concave points_mean`, `symmetry_mean`, `fractal_dimension_mean`, `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`, `perimeter_worst`, `area_worst`, `smoothness_worst`, `compactness_worst`, `concavity_worst`, `concave points_worst`, `symmetry_worst`, `fractal_dimension_worst`

2 Objective

- Understand and clean the dataset
- The main goal is to build classification models to predict if the breast cancer sample from this dataset is malignant or benign.
- Fine-tune hyperparameters and compare the performance of various classification algorithms.

[1]:
```
import pandas as pd
import seaborn as sns
%matplotlib inline
import matplotlib.pyplot as plt
from matplotlib.lines import Line2D
from sklearn.preprocessing import LabelEncoder, StandardScaler
from sklearn.model_selection import train_test_split,GridSearchCV
from sklearn.metrics import classification_report, confusion_matrix

# Ml Models
from sklearn.linear_model import LogisticRegression
from sklearn.neighbors import KNeighborsClassifier
from sklearn.svm import SVC
from sklearn.tree import DecisionTreeClassifier
```

```python
from sklearn.ensemble import RandomForestClassifier, AdaBoostClassifier,␣
↪GradientBoostingClassifier

import warnings
warnings.filterwarnings('ignore')
```

[2]:
```python
data=pd.read_csv("/Users/alexcui/Desktop/projects/Python/ML_IBM/data/
↪breast-cancer.csv")
data.head(5)
```

[2]:
```
         id diagnosis  radius_mean  texture_mean  perimeter_mean  area_mean  \
0    842302         M        17.99         10.38          122.80     1001.0
1    842517         M        20.57         17.77          132.90     1326.0
2  84300903         M        19.69         21.25          130.00     1203.0
3  84348301         M        11.42         20.38           77.58      386.1
4  84358402         M        20.29         14.34          135.10     1297.0

   smoothness_mean  compactness_mean  concavity_mean  concave points_mean  \
0          0.11840           0.27760          0.3001              0.14710
1          0.08474           0.07864          0.0869              0.07017
2          0.10960           0.15990          0.1974              0.12790
3          0.14250           0.28390          0.2414              0.10520
4          0.10030           0.13280          0.1980              0.10430

   …  radius_worst  texture_worst  perimeter_worst  area_worst  \
0  …         25.38          17.33           184.60      2019.0
1  …         24.99          23.41           158.80      1956.0
2  …         23.57          25.53           152.50      1709.0
3  …         14.91          26.50            98.87       567.7
4  …         22.54          16.67           152.20      1575.0

   smoothness_worst  compactness_worst  concavity_worst  concave points_worst  \
0            0.1622             0.6656           0.7119                0.2654
1            0.1238             0.1866           0.2416                0.1860
2            0.1444             0.4245           0.4504                0.2430
3            0.2098             0.8663           0.6869                0.2575
4            0.1374             0.2050           0.4000                0.1625

   symmetry_worst  fractal_dimension_worst
0          0.4601                  0.11890
1          0.2750                  0.08902
2          0.3613                  0.08758
3          0.6638                  0.17300
4          0.2364                  0.07678

[5 rows x 32 columns]
```

[3]:
```
data.info()
```

```
<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)
memory usage: 142.4+ KB
```

[4]:
```
data.dtypes.value_counts()
```

[4]:
```
float64    30
int64       1
object      1
dtype: int64
```

[5]:
```
data.drop('id', axis=1, inplace=True)
```

[6]:
```
data["diagnosis"].value_counts()
```

[6]:
```
B    357
M    212
Name: diagnosis, dtype: int64
```

3 Encoding for the Target column

[7]:
```
le = LabelEncoder()
data['diagnosis'] = le.fit_transform(data.diagnosis)
data['diagnosis'].sample(5)
```

[7]:
```
406    0
364    0
141    1
4      1
198    1
Name: diagnosis, dtype: int64
```

4 Replacing outliers to lower and upper bound values

[8]:
```
data.describe()
```

[8]:
```
        diagnosis  radius_mean  texture_mean  perimeter_mean    area_mean  \
count  569.000000   569.000000    569.000000      569.000000   569.000000
mean     0.372583    14.127292     19.289649       91.969033   654.889104
std      0.483918     3.524049      4.301036       24.298981   351.914129
min      0.000000     6.981000      9.710000       43.790000   143.500000
25%      0.000000    11.700000     16.170000       75.170000   420.300000
50%      0.000000    13.370000     18.840000       86.240000   551.100000
75%      1.000000    15.780000     21.800000      104.100000   782.700000
max      1.000000    28.110000     39.280000      188.500000  2501.000000

       smoothness_mean  compactness_mean  concavity_mean  concave points_mean  \
count       569.000000        569.000000      569.000000           569.000000
mean          0.096360          0.104341        0.088799             0.048919
std           0.014064          0.052813        0.079720             0.038803
min           0.052630          0.019380        0.000000             0.000000
25%           0.086370          0.064920        0.029560             0.020310
50%           0.095870          0.092630        0.061540             0.033500
75%           0.105300          0.130400        0.130700             0.074000
max           0.163400          0.345400        0.426800             0.201200

       symmetry_mean  …  radius_worst  texture_worst  perimeter_worst  \
```

```
count     569.000000  …   569.000000    569.000000      569.000000
mean        0.181162  …    16.269190     25.677223      107.261213
std         0.027414  …     4.833242      6.146258       33.602542
min         0.106000  …     7.930000     12.020000       50.410000
25%         0.161900  …    13.010000     21.080000       84.110000
50%         0.179200  …    14.970000     25.410000       97.660000
75%         0.195700  …    18.790000     29.720000      125.400000
max         0.304000  …    36.040000     49.540000      251.200000

        area_worst  smoothness_worst  compactness_worst  concavity_worst  \
count   569.000000        569.000000         569.000000       569.000000
mean    880.583128          0.132369           0.254265         0.272188
std     569.356993          0.022832           0.157336         0.208624
min     185.200000          0.071170           0.027290         0.000000
25%     515.300000          0.116600           0.147200         0.114500
50%     686.500000          0.131300           0.211900         0.226700
75%    1084.000000          0.146000           0.339100         0.382900
max    4254.000000          0.222600           1.058000         1.252000

       concave points_worst  symmetry_worst  fractal_dimension_worst
count            569.000000      569.000000               569.000000
mean               0.114606        0.290076                 0.083946
std                0.065732        0.061867                 0.018061
min                0.000000        0.156500                 0.055040
25%                0.064930        0.250400                 0.071460
50%                0.099930        0.282200                 0.080040
75%                0.161400        0.317900                 0.092080
max                0.291000        0.663800                 0.207500

[8 rows x 31 columns]
```

[9]:
```python
def detect_outliers(column,data):
    Q1=data[column].quantile(0.25)
    Q3=data[column].quantile(0.75)

    # interquartile range
    IQR=Q3-Q1
    lower_bound=Q1-1.5*IQR
    upper_bound=Q3+1.5*IQR
    outliers = data[(data[column] < lower_bound) | (data[column] > upper_bound)]
    data[column] = data[column].clip(lower=lower_bound, upper=upper_bound)
    return data
```

[10]:
```python
for i in data.columns[1:]:
    data=detect_outliers(i,data)
```

[11]:
```python
data.describe()
```

[11]:

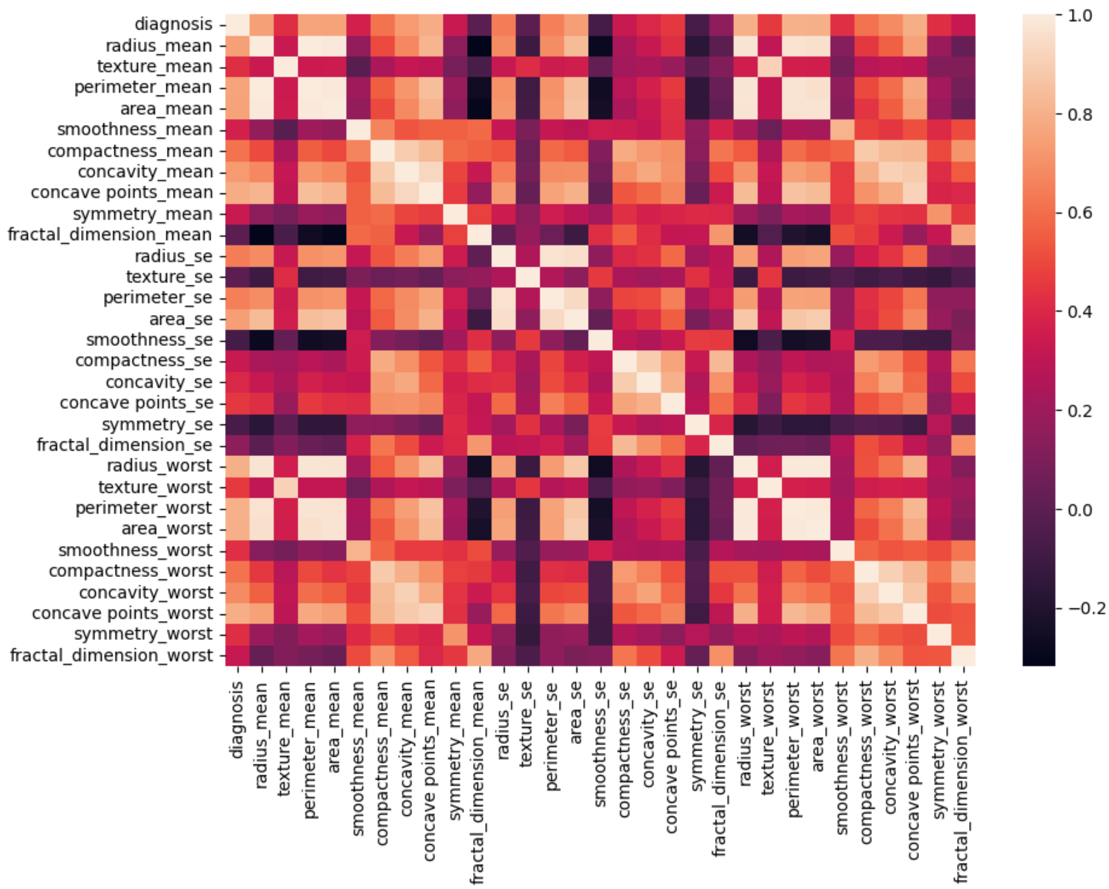
```
        diagnosis  radius_mean  texture_mean  perimeter_mean    area_mean  \
count  569.000000   569.000000    569.000000      569.000000   569.000000
mean     0.372583    14.062916     19.254736       91.543787   639.765202
std      0.483918     3.340025      4.187510       23.047218   305.343508
min      0.000000     6.981000      9.710000       43.790000   143.500000
25%      0.000000    11.700000     16.170000       75.170000   420.300000
50%      0.000000    13.370000     18.840000       86.240000   551.100000
75%      1.000000    15.780000     21.800000      104.100000   782.700000
max      1.000000    21.900000     30.245000      147.495000  1326.300000

       smoothness_mean  compactness_mean  concavity_mean  concave points_mean  \
count       569.000000        569.000000      569.000000           569.000000
mean          0.096266          0.103222        0.086937             0.048552
std           0.013685          0.049386        0.073900             0.037633
min           0.057975          0.019380        0.000000             0.000000
25%           0.086370          0.064920        0.029560             0.020310
50%           0.095870          0.092630        0.061540             0.033500
75%           0.105300          0.130400        0.130700             0.074000
max           0.133695          0.228620        0.282410             0.154535

       symmetry_mean  …  radius_worst  texture_worst  perimeter_worst  \
count     569.000000  …    569.000000     569.000000       569.000000
mean        0.180734  …     16.183882      25.648453       106.705369
std         0.026067  …      4.587249       6.054406        31.957777
min         0.111200  …      7.930000      12.020000        50.410000
25%         0.161900  …     13.010000      21.080000        84.110000
50%         0.179200  …     14.970000      25.410000        97.660000
75%         0.195700  …     18.790000      29.720000       125.400000
max         0.246400  …     27.460000      42.680000       187.335000

        area_worst  smoothness_worst  compactness_worst  concavity_worst  \
count   569.000000        569.000000         569.000000       569.000000
mean    849.907821          0.132209           0.249883         0.268754
std     475.645240          0.022320           0.142851         0.197461
min     185.200000          0.072500           0.027290         0.000000
25%     515.300000          0.116600           0.147200         0.114500
50%     686.500000          0.131300           0.211900         0.226700
75%    1084.000000          0.146000           0.339100         0.382900
max    1937.050000          0.190100           0.626950         0.785500

       concave points_worst  symmetry_worst  fractal_dimension_worst
count            569.000000      569.000000               569.000000
mean               0.114606        0.287616                 0.083342
std                0.065732        0.053868                 0.015993
min                0.000000        0.156500                 0.055040
25%                0.064930        0.250400                 0.071460
50%                0.099930        0.282200                 0.080040
```

```
75%          0.161400     0.317900               0.092080
max          0.291000     0.419150               0.123010

[8 rows x 31 columns]
```

5 Correlation between Diagnosis and Characters of the data

[12]:
```python
plt.figure(figsize=(10,7))
sns.heatmap(data.corr())
```

[12]: <Axes: >



6 Set Training and Testing Datasets

[13]:
```python
X = data.drop('diagnosis', axis=1)  # Drop the target column
y = data['diagnosis']  # Target column
```

7 Scaling

[14]:
```
scaler = StandardScaler()
X = scaler.fit_transform(X)
```

8 Split Dataset into Training and Testing Sets

[15]:
```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,␣
↪random_state=42)
```

9 Build Multiple Classification Models for Comparison

[16]:
```
models = {
    'Logistic Regression' : LogisticRegression(random_state=42),
    'SVM' : SVC(random_state = 42),
    'KNN': KNeighborsClassifier(),
    'Random Forest' : RandomForestClassifier(random_state = 42),
    "Ada Boost":AdaBoostClassifier(random_state = 42),
    'Gradient Boosting': GradientBoostingClassifier(random_state=42),
    'Decision Tree': DecisionTreeClassifier(random_state=42),
}
```

10 Define Parameters for Grid Search Cross Validation

[17]:
```
param_grids = {
    "Logistic Regression": {
        'C': [0.01, 0.1, 1, 10, 100],
        'penalty': ['l1', 'l2', 'elasticnet'],
        'solver': ['liblinear', 'lbfgs', 'saga'],
        'max_iter': [10000, 20000, 30000]
    },
    "SVM": {
        'C': [0.01, 0.1, 1, 10, 100],
        'gamma': ['scale', 'auto', 0.01, 0.1, 1, 10]
    },
    "KNN": {
        'n_neighbors': [3, 5, 7, 9],
        'weights': ['uniform', 'distance'],
        'metric': ['euclidean', 'manhattan']
    },
    "Random Forest": {
        'n_estimators': [100, 500, 1000],
        'max_depth': [None, 10, 20],
        'min_samples_split': [2, 5],
        'min_samples_leaf': [1, 2],
```

```
        'max_features': ['auto', 'sqrt', 'log2']
    },
    "Ada Boost": {
        'n_estimators': [50, 100, 150],
        'learning_rate': [0.01, 0.1, 1.0],
        'algorithm': ['SAMME']
    },
    "Gradient Boosting": {
        'n_estimators': [100, 200],
        'learning_rate': [0.01, 0.1, 0.2],
        'max_depth': [3, 5, 7],
        'subsample': [0.8, 1.0]
    },
    "Decision Tree": {
        'max_depth': [None, 10, 20],
        'min_samples_split': [2, 5],
        'min_samples_leaf': [1, 2],
        'criterion': ['gini', 'entropy']
    }
}
```

[18]:
```
# Store Results
results = {}

# Train each model and evaluate
for model_name, model in models.items():
    param_grid = param_grids[model_name]
    grid_search=GridSearchCV(estimator=model, param_grid=param_grid, cv=5,␣
↪n_jobs=-1, verbose=1)
    grid_search.fit(X_train, y_train)
    best_model=grid_search.best_estimator_
    best_score=grid_search.best_score_
    best_params=grid_search.best_params_
    y_pred = best_model.predict(X_test)
    results[model_name]={
        "Model": model_name,
        "Best Params":best_params,
        "Accuracy":best_score
    }

    print(f"Best score for {model_name} with {best_params}: {best_score:.4f}")
    print(classification_report(y_test, y_pred))
```

```
Fitting 5 folds for each of 135 candidates, totalling 675 fits
Best score for Logistic Regression with {'C': 0.1, 'max_iter': 10000, 'penalty':
'l2', 'solver': 'liblinear'}: 0.9780
              precision    recall  f1-score   support
```

```
           0       0.99      1.00      0.99        71
           1       1.00      0.98      0.99        43

    accuracy                           0.99       114
   macro avg       0.99      0.99      0.99       114
weighted avg       0.99      0.99      0.99       114

Fitting 5 folds for each of 30 candidates, totalling 150 fits
Best score for SVM with {'C': 100, 'gamma': 'scale'}: 0.9780
              precision    recall  f1-score   support

           0       0.97      0.94      0.96        71
           1       0.91      0.95      0.93        43

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

Fitting 5 folds for each of 16 candidates, totalling 80 fits
Best score for KNN with {'metric': 'euclidean', 'n_neighbors': 7, 'weights':
'distance'}: 0.9670
              precision    recall  f1-score   support

           0       0.96      0.97      0.97        71
           1       0.95      0.93      0.94        43

    accuracy                           0.96       114
   macro avg       0.96      0.95      0.95       114
weighted avg       0.96      0.96      0.96       114

Fitting 5 folds for each of 108 candidates, totalling 540 fits
Best score for Random Forest with {'max_depth': None, 'max_features': 'log2',
'min_samples_leaf': 1, 'min_samples_split': 5, 'n_estimators': 100}: 0.9626
              precision    recall  f1-score   support

           0       0.96      0.99      0.97        71
           1       0.98      0.93      0.95        43

    accuracy                           0.96       114
   macro avg       0.97      0.96      0.96       114
weighted avg       0.97      0.96      0.96       114

Fitting 5 folds for each of 9 candidates, totalling 45 fits
Best score for Ada Boost with {'algorithm': 'SAMME', 'learning_rate': 1.0,
'n_estimators': 50}: 0.9780
              precision    recall  f1-score   support

           0       0.96      0.99      0.97        71
```

```
           1       0.98      0.93      0.95        43

    accuracy                           0.96       114
   macro avg       0.97      0.96      0.96       114
weighted avg       0.97      0.96      0.96       114

Fitting 5 folds for each of 36 candidates, totalling 180 fits
Best score for Gradient Boosting with {'learning_rate': 0.2, 'max_depth': 5,
'n_estimators': 100, 'subsample': 0.8}: 0.9670
              precision    recall  f1-score   support

           0       0.96      0.97      0.97        71
           1       0.95      0.93      0.94        43

    accuracy                           0.96       114
   macro avg       0.96      0.95      0.95       114
weighted avg       0.96      0.96      0.96       114

Fitting 5 folds for each of 24 candidates, totalling 120 fits
Best score for Decision Tree with {'criterion': 'entropy', 'max_depth': None,
'min_samples_leaf': 1, 'min_samples_split': 2}: 0.9341
              precision    recall  f1-score   support

           0       0.93      0.99      0.96        71
           1       0.97      0.88      0.93        43

    accuracy                           0.95       114
   macro avg       0.95      0.93      0.94       114
weighted avg       0.95      0.95      0.95       114
```

[19]:

```python
df = pd.DataFrame.from_dict(results, orient='index')
df['Accuracy'] = round(df['Accuracy'], 4)
df
```

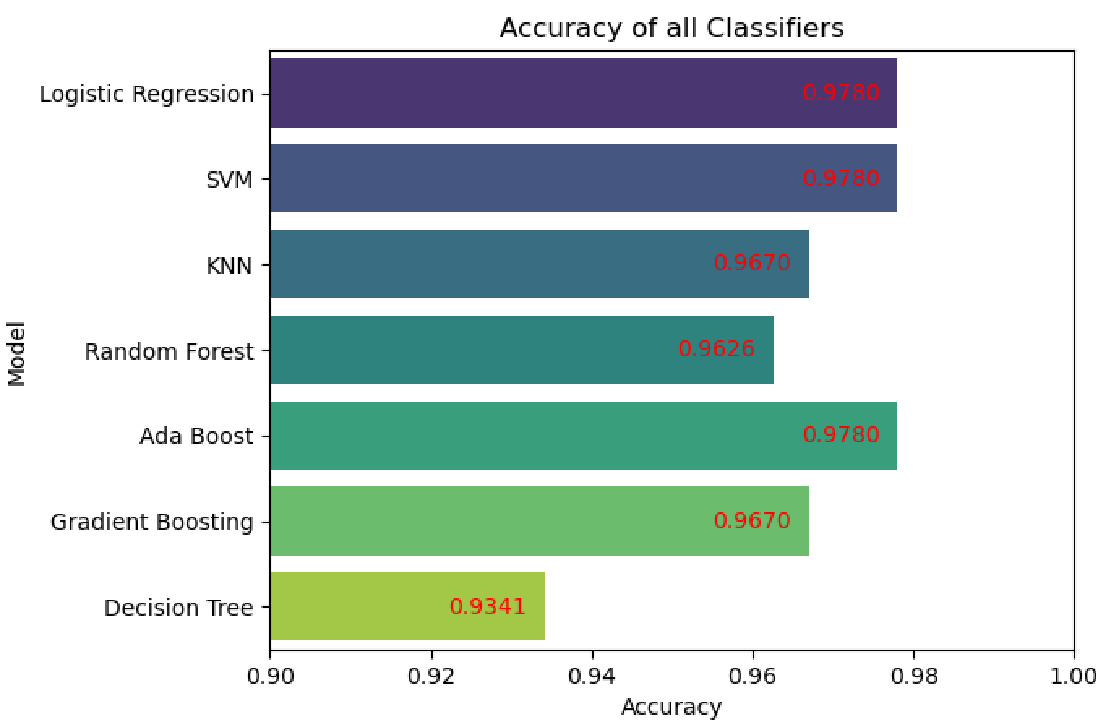
[19]:

```
                                   Model  \
Logistic Regression  Logistic Regression
SVM                                  SVM
KNN                                  KNN
Random Forest              Random Forest
Ada Boost                      Ada Boost
Gradient Boosting      Gradient Boosting
Decision Tree              Decision Tree

                                                          Best Params  \
Logistic Regression  {'C': 0.1, 'max_iter': 10000, 'penalty': 'l2',…
SVM                                          {'C': 100, 'gamma': 'scale'}
```

```
KNN                    {'metric': 'euclidean', 'n_neighbors': 7, 'wei…
Random Forest          {'max_depth': None, 'max_features': 'log2', 'm…
Ada Boost              {'algorithm': 'SAMME', 'learning_rate': 1.0, '…
Gradient Boosting      {'learning_rate': 0.2, 'max_depth': 5, 'n_esti…
Decision Tree          {'criterion': 'entropy', 'max_depth': None, 'm…

                       Accuracy
Logistic Regression      0.9780
SVM                      0.9780
KNN                      0.9670
Random Forest            0.9626
Ada Boost                0.9780
Gradient Boosting        0.9670
Decision Tree            0.9341
```

[20]:

```python
ax = sns.barplot(x="Accuracy", y="Model", data=df, palette="viridis")
for index, value in enumerate(df['Accuracy']):
    ax.text(value - 0.012, index, f'{value:.4f}', va='center', color="red", ha='left', fontsize=10)
plt.title("Accuracy of all Classifiers")
plt.xlim(0.9, 1)
plt.show()
```



[21]:
```
df
```

[21]:
```
                                       Model  \
Logistic Regression  Logistic Regression
SVM                                  SVM
KNN                                  KNN
Random Forest              Random Forest
Ada Boost                      Ada Boost
Gradient Boosting      Gradient Boosting
Decision Tree              Decision Tree

                                                         Best Params  \
Logistic Regression  {'C': 0.1, 'max_iter': 10000, 'penalty': 'l2',…
SVM                                     {'C': 100, 'gamma': 'scale'}
KNN                  {'metric': 'euclidean', 'n_neighbors': 7, 'wei…
Random Forest        {'max_depth': None, 'max_features': 'log2', 'm…
Ada Boost            {'algorithm': 'SAMME', 'learning_rate': 1.0, '…
Gradient Boosting    {'learning_rate': 0.2, 'max_depth': 5, 'n_esti…
Decision Tree        {'criterion': 'entropy', 'max_depth': None, 'm…

                     Accuracy
Logistic Regression    0.9780
SVM                    0.9780
KNN                    0.9670
Random Forest          0.9626
Ada Boost              0.9780
Gradient Boosting      0.9670
Decision Tree          0.9341
```

[22]:
```python
best_accuracy = df['Accuracy'].max()
best_models = df[df['Accuracy'] == best_accuracy]

# Output the best models and their corresponding parameters and accuracy
print("Best models with their corresponding accuracy:\n")
print(best_models[['Model', 'Best Params', 'Accuracy']])
```

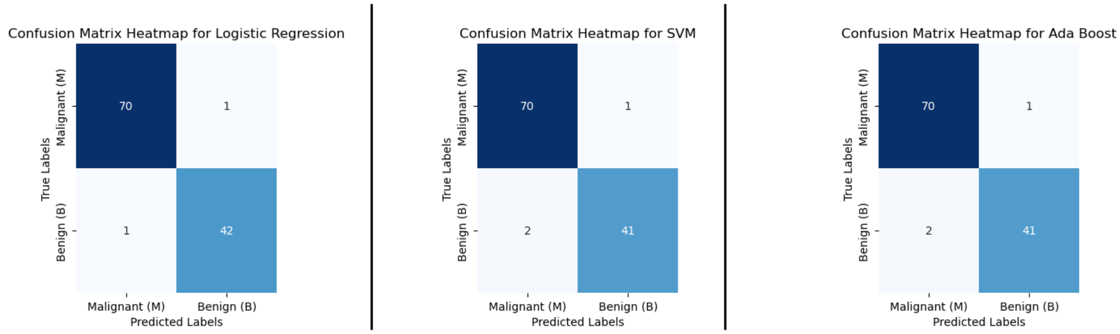
```
Best models with their corresponding accuracy:

                                       Model  \
Logistic Regression  Logistic Regression
SVM                                  SVM
Ada Boost                      Ada Boost

                                                         Best Params  \
Logistic Regression  {'C': 0.1, 'max_iter': 10000, 'penalty': 'l2',…
SVM                                     {'C': 100, 'gamma': 'scale'}
Ada Boost            {'algorithm': 'SAMME', 'learning_rate': 1.0, '…
```

```
                        Accuracy
Logistic Regression        0.978
SVM                        0.978
Ada Boost                  0.978
```

[23]:

```
# Create a 1x3 subplot grid
fig, axes = plt.subplots(1, 3, figsize=(16, 4))  # 1 row, 3 columns

# Iterate over the best models DataFrame
for index, (row, ax) in enumerate(zip(best_models.iterrows(), axes)):
    model_name = row[1]['Model']  # Get the model name
    best_params = row[1]['Best Params']  # Get the best parameters for the model

    model = models.get(model_name)  # Retrieve the model from the models␣
 ↪dictionary
    model.fit(X_train, y_train)  # Fit the model on the training data

    # Predict using the current model
    y_pred_best = model.predict(X_test)

    # Generate the confusion matrix
    cm = confusion_matrix(y_test, y_pred_best)

    # Plot the heatmap for the confusion matrix on the appropriate subplot
    sns.heatmap(cm, annot=True, fmt='d', cmap='Blues', xticklabels=['Malignant␣
 ↪(M)', 'Benign (B)'],
                yticklabels=['Malignant (M)', 'Benign (B)'], cbar=False, ax=ax)

    # Set the title and labels
    ax.set_title(f'Confusion Matrix Heatmap for {model_name}')
    ax.set_xlabel('Predicted Labels')
    ax.set_ylabel('True Labels')

# Add a black vertical line between the subplots
# We are going to manually add vertical lines at the boundaries of the subplots
for i in range(1, len(axes)):
    # Get the x positions for the right edge of the previous subplot and the␣
 ↪left edge of the current subplot
    x1 = axes[i-1].get_position().xmax  # Right side of the previous subplot
    x2 = axes[i].get_position().xmin    # Left side of the current subplot

    # Draw a vertical line at the boundary between subplots
    fig.add_artist(Line2D([x1, x1], [0, 1], color='black', linewidth=2,␣
 ↪transform=fig.transFigure))

# Adjust layout for better spacing
plt.subplots_adjust(wspace=1)
```

```
plt.show()
```



11 Summary

The result shows `Logistic Regression`, `Support Vector Machine (SVM)` and `Ada Boost` models all show great performance for this dataset. They have the same mean accuracy score (`0.978`) across the folds of cross-validation for the best hyperparameters found by the grid search. The only difference is Logistic Regression model identified only 1 false negative cases which means the sample is actually Malignant but the model classified it as a Benign one. The SVM and Ada Boost models both have 2 false positive cases, even with same mean accuracy score as the Logistic Regression model.

So, for this reason, I'd chooose `Logistic Regression` model for this dataset, with the following parameters:

{C= 0.1, max_iter= 10000, penalty= 'l2', solver= 'liblinear'}

12 Next Step

Apply the `Logistic Regerssion` model on a larger sacle dataset to evaluate its performance, and use Grid Search Cross Validation to see if current best parameters are still hold for more data. The current approach uses the lower and upper interquartile range as the replacement values for clipping the outliers, which introduces artificial boundaries and may distort the data distribution. This requires careful selection of clipping thresholds, which can be arbitrary.