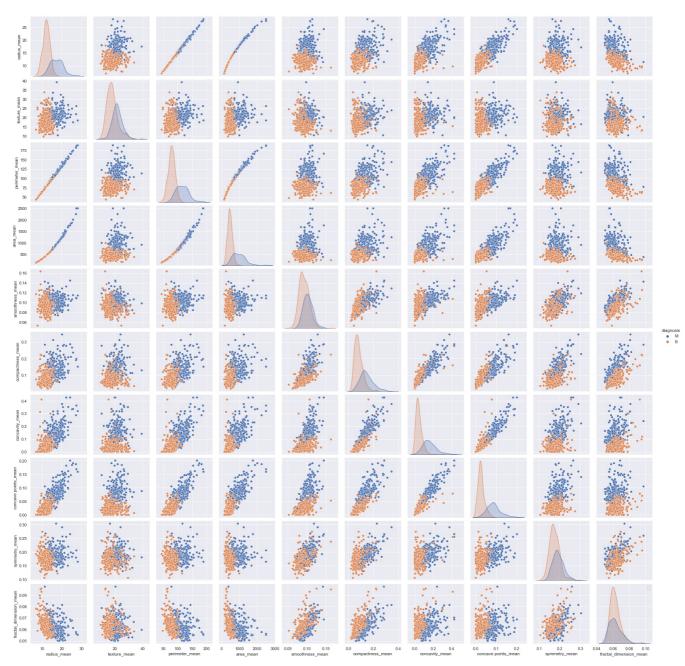
```
In [57]: import numpy as np
           import pandas as pd
           import seaborn as sns
           import matplotlib.pyplot as plt
           import warnings
           warnings.filterwarnings("ignore")
           from sklearn.model selection import train test split, GridSearchCV
           from sklearn.preprocessing import StandardScaler
           from sklearn.metrics import accuracy_score, confusion_matrix, roc_curve, roc_auc_score
           from sklearn.decomposition import PCA
           from sklearn.linear_model import LogisticRegression
           from sklearn.ensemble import RandomForestClassifier, GradientBoostingClassifier
           from sklearn.svm import SVC
In [58]: df=pd.read csv((r'C:\Users\mmi\Desktop\cancer.csv'))
In [59]:
           df.head(5)
           df.drop('id',axis=1,inplace=True)
df.drop('Unnamed: 32',axis=1,inplace=True)
           df
Out[59]:
                                                                                                                                      conca
                diagnosis radius_mean texture_mean perimeter_mean area_mean smoothness_mean compactness_mean concavity_mean
                                                                                                                                  points_mea
             0
                       Μ
                                17.99
                                              10.38
                                                            122.80
                                                                       1001.0
                                                                                        0.11840
                                                                                                           0.27760
                                                                                                                          0.30010
                                                                                                                                       0.147
                                20.57
                                              17.77
                                                            132.90
                                                                       1326.0
                                                                                        0.08474
                                                                                                           0.07864
                                                                                                                          0.08690
                                                                                                                                       0.070
             1
                       M
             2
                                19.69
                                                                                                           0.15990
                                                                                                                          0.19740
                       M
                                              21.25
                                                            130.00
                                                                       1203.0
                                                                                        0.10960
                                                                                                                                       0.127
             3
                                11.42
                                              20.38
                                                             77.58
                                                                        386.1
                                                                                        0.14250
                                                                                                           0.28390
                                                                                                                          0.24140
                                                                                                                                       0.105
                       M
             4
                                                                                                                          0.19800
                       M
                                20.29
                                              14.34
                                                            135.10
                                                                       1297.0
                                                                                        0.10030
                                                                                                           0.13280
                                                                                                                                       0.104
           564
                       M
                                21.56
                                              22.39
                                                            142.00
                                                                       1479.0
                                                                                        0.11100
                                                                                                           0.11590
                                                                                                                          0.24390
                                                                                                                                       0.138
                                20.13
                                              28.25
                                                                                                                          0.14400
                                                                                                                                       0.097
           565
                       M
                                                            131.20
                                                                       1261.0
                                                                                        0.09780
                                                                                                           0.10340
           566
                       M
                                16.60
                                              28.08
                                                            108.30
                                                                        858.1
                                                                                        0.08455
                                                                                                           0.10230
                                                                                                                          0.09251
                                                                                                                                       0.053
                                20.60
                                                            140.10
                                                                       1265.0
                                                                                                                          0.35140
           567
                       M
                                              29.33
                                                                                        0.11780
                                                                                                           0.27700
                                                                                                                                       0.152
                                                                                                                          0.00000
                       В
                                 7.76
                                                             47.92
                                                                        181.0
                                                                                        0.05263
                                                                                                           0.04362
                                                                                                                                       0.000
           568
                                              24.54
          569 rows × 31 columns
4
In [60]:
           sns.set()
           cols_to_pairplot = df.columns[:11]
           sns.pairplot(df[cols to pairplot], hue="diagnosis")
           plt.legend()
```

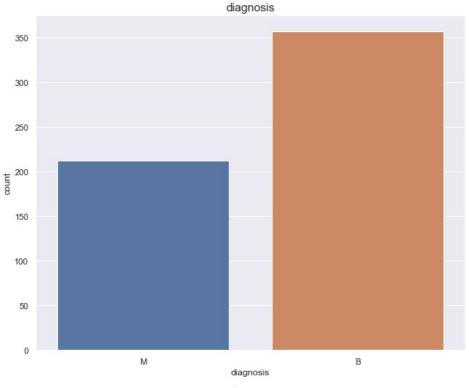
plt.show()

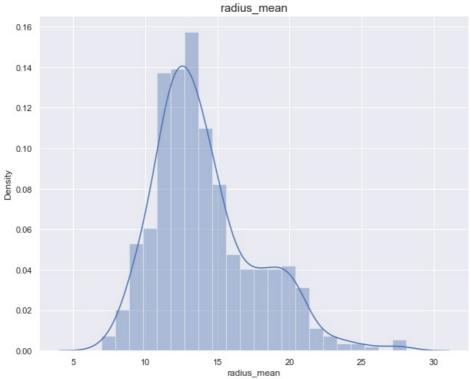
No artists with labels found to put in legend. Note that artists whose label start with an underscore are igno red when legend() is called with no argument.

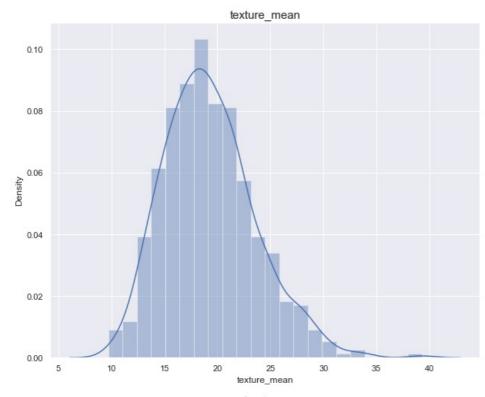


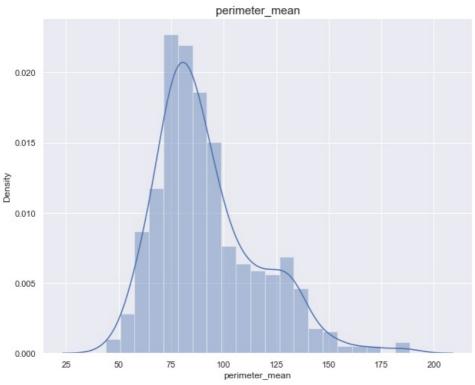
In [61]: plt.figure(figsize=(10,8))
 sns.countplot(df["diagnosis"])
 plt.title("diagnosis", size=15)
 plt.show()

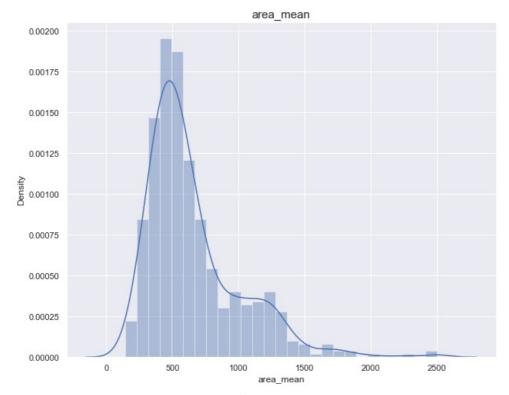
```
for col in df.drop("diagnosis", axis=1).columns:
    plt.figure(figsize=(10,8))
    sns.distplot(df[col])
    plt.title(f"{col}", size=15)
    plt.show()
```

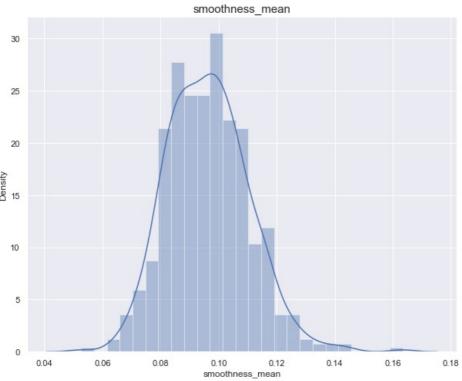


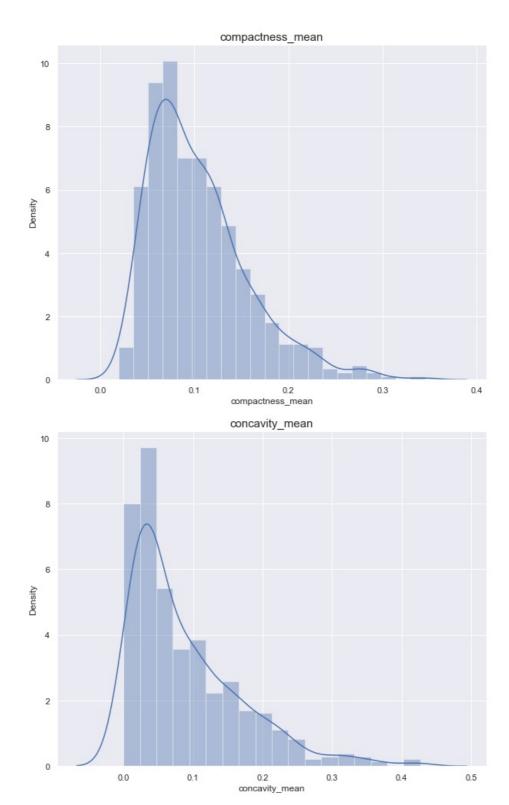


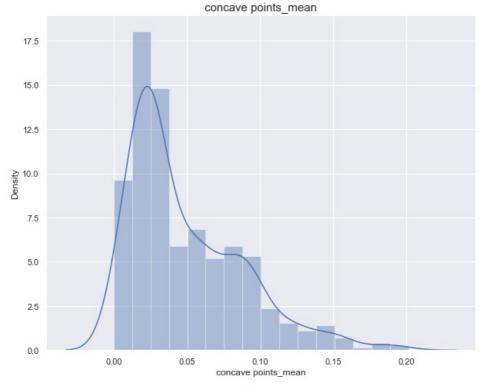


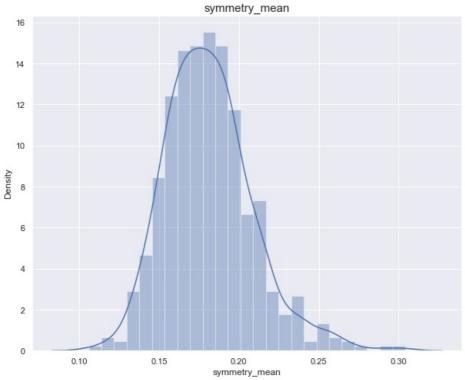


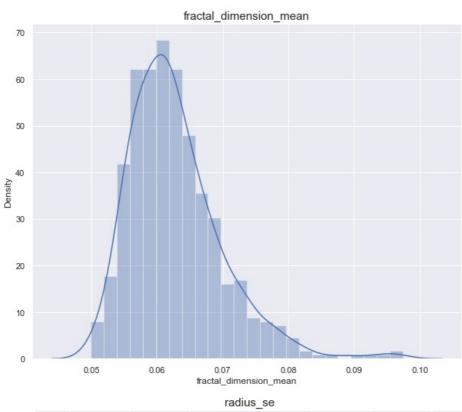


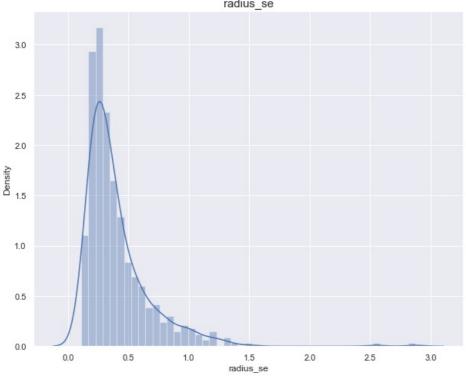


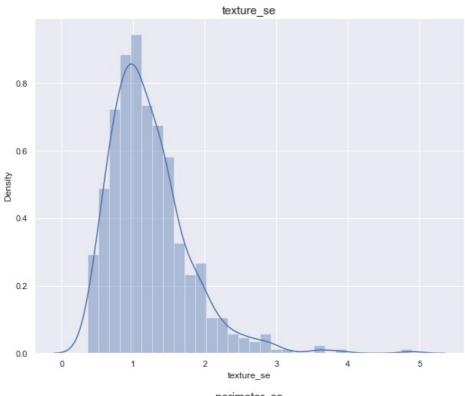


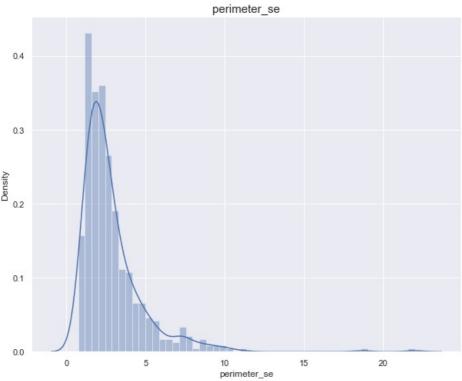


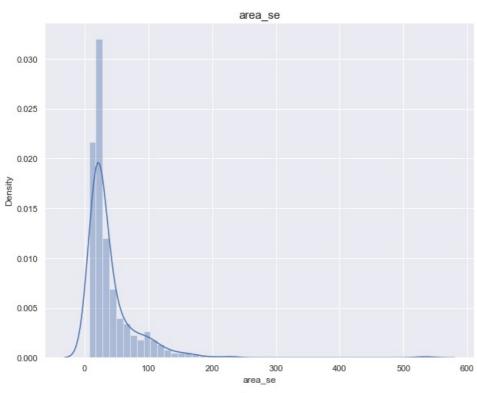


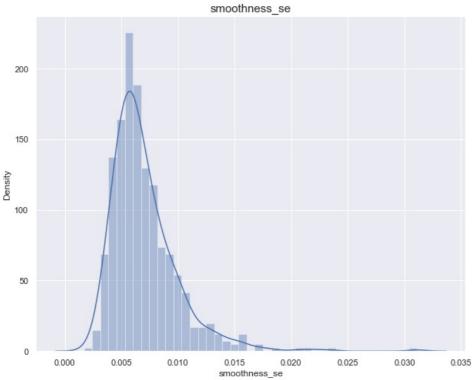


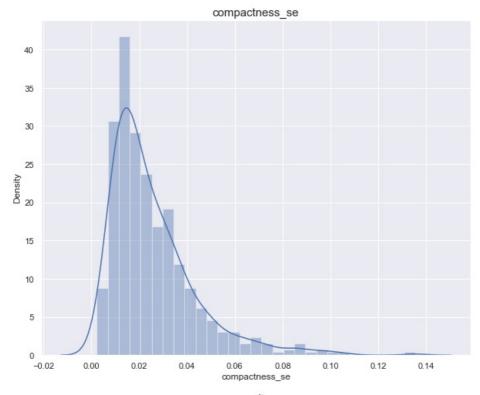


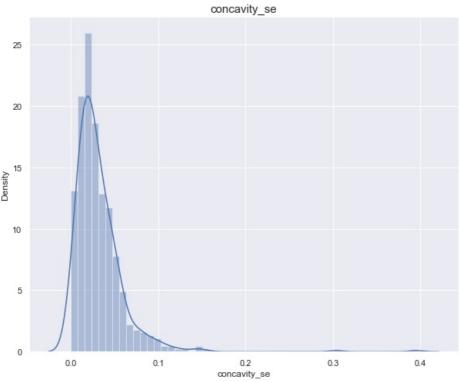


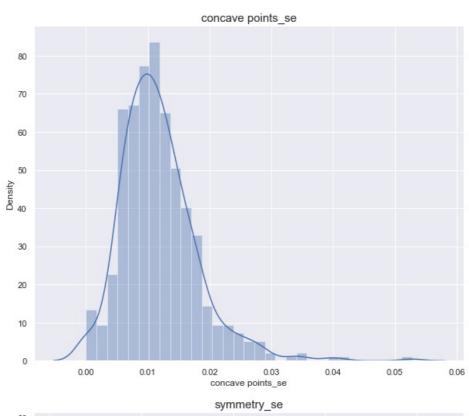


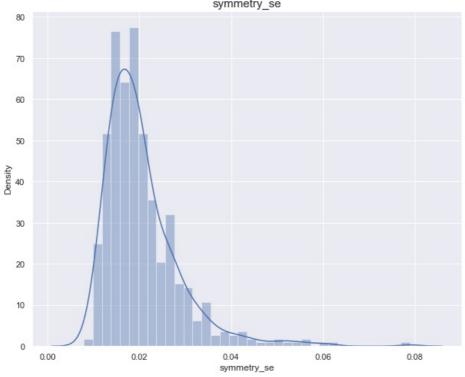


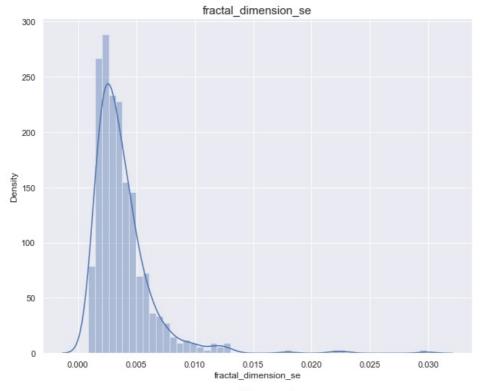


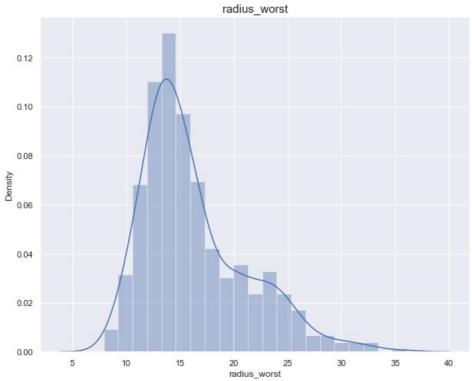


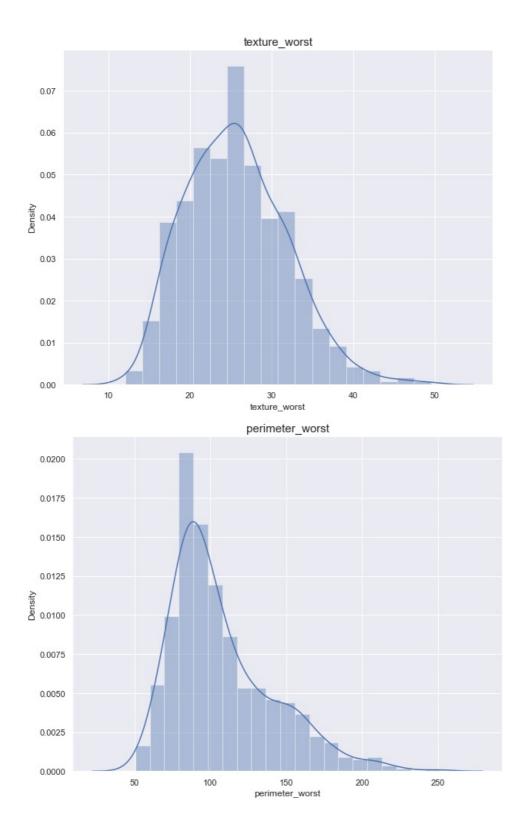


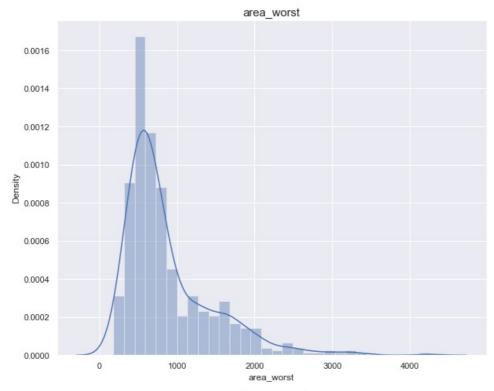


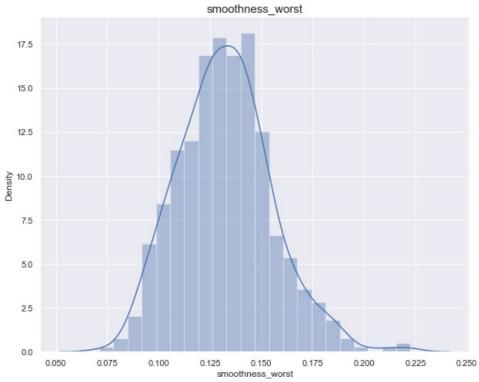


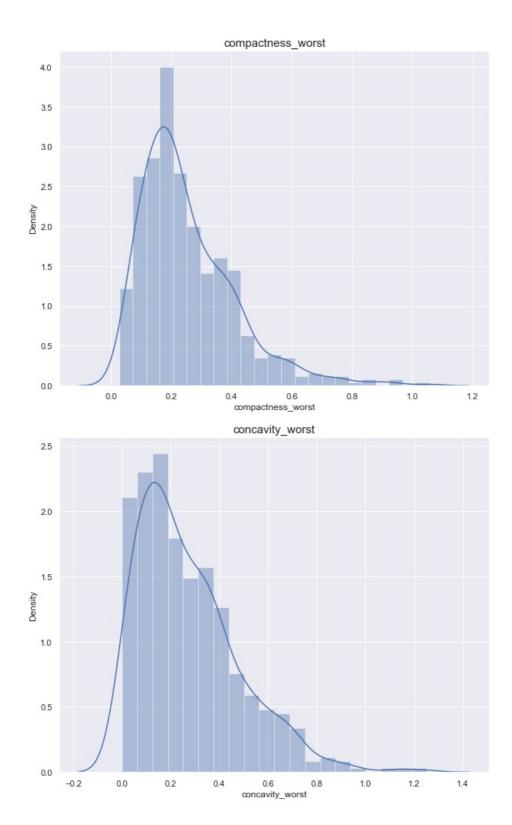


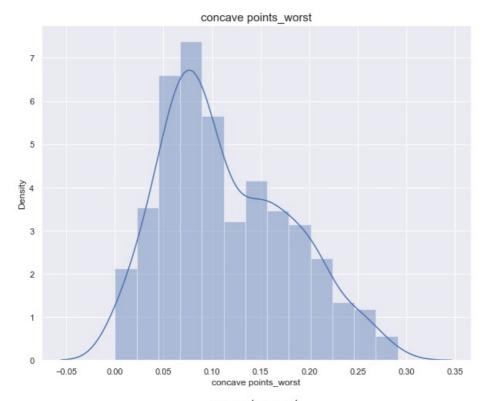


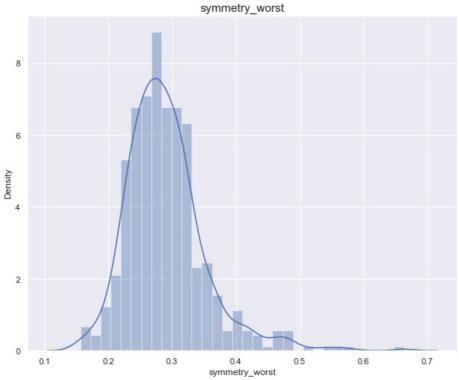


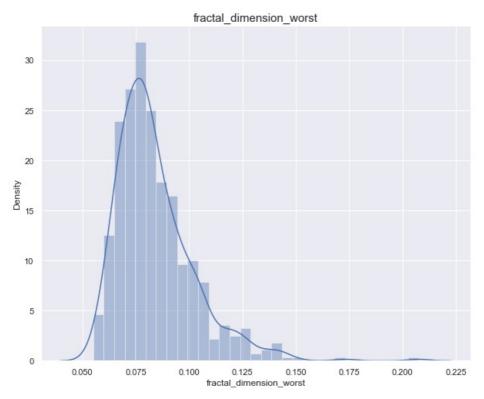




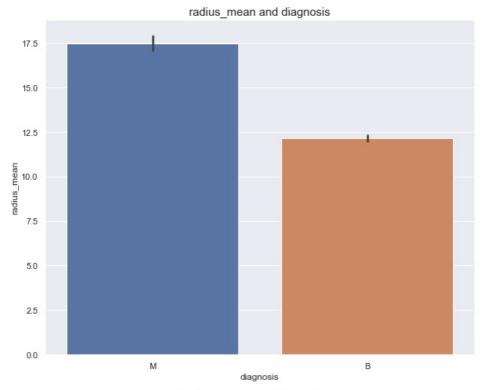


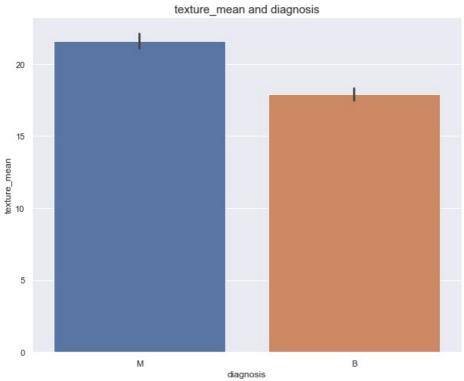


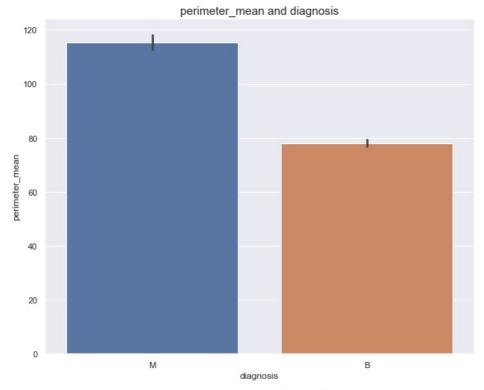


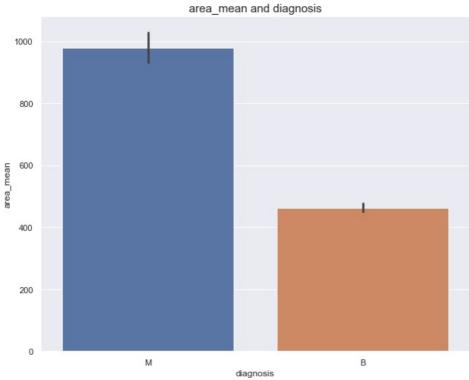


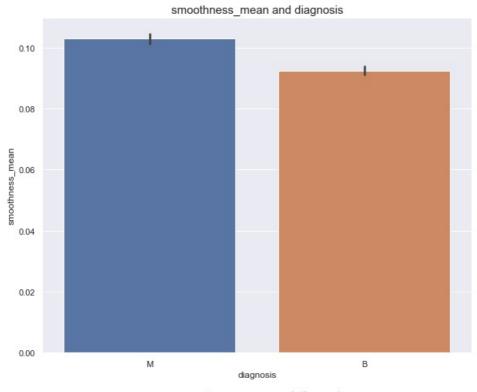
```
In [62]: for col in df.drop("diagnosis", axis=1).columns:
    plt.figure(figsize=(10,8))
    sns.barplot(x=df["diagnosis"], y=df[col])
    plt.title(f"{col} and diagnosis", size=15)
    plt.show()
```

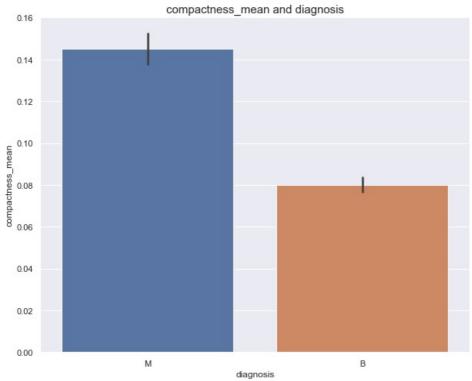


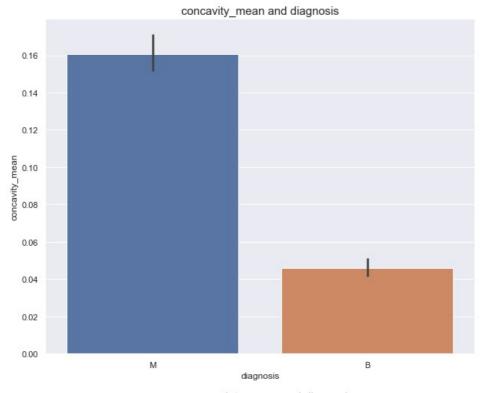


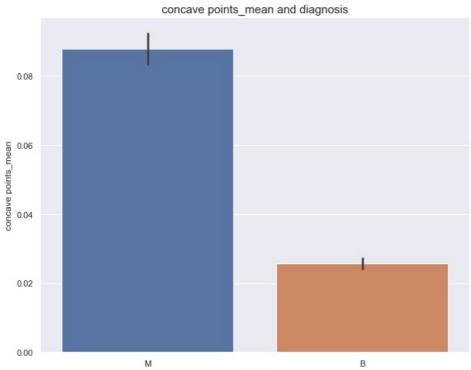




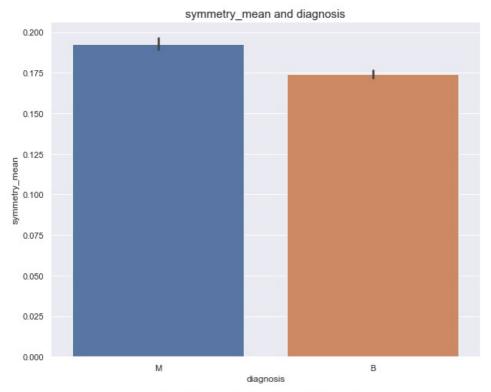


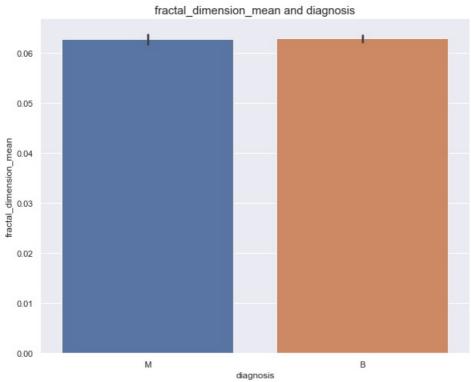


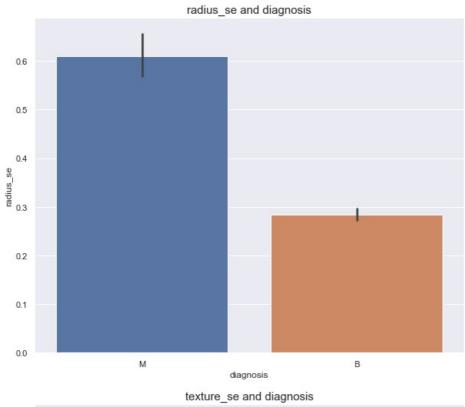


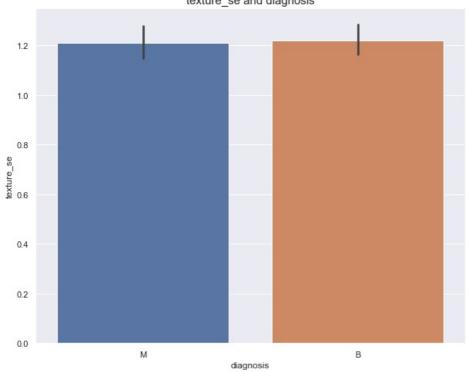


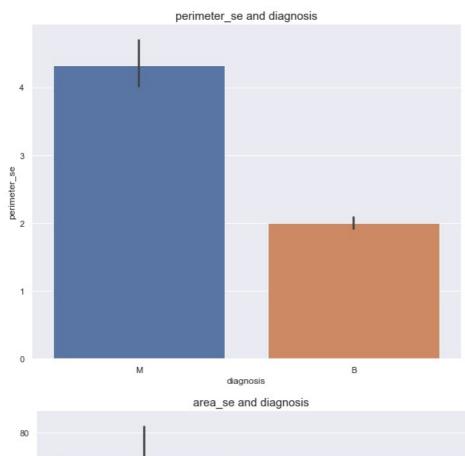
diagnosis

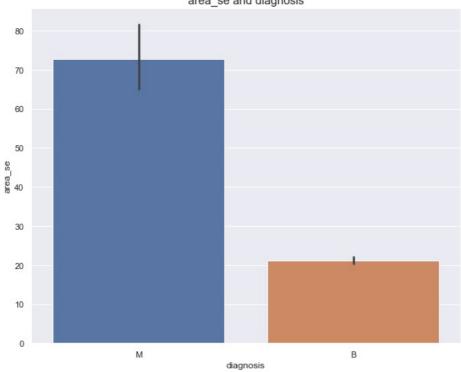


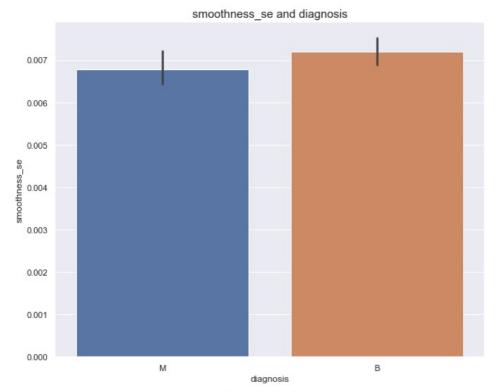


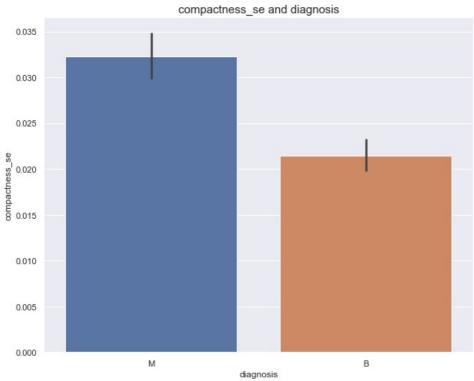


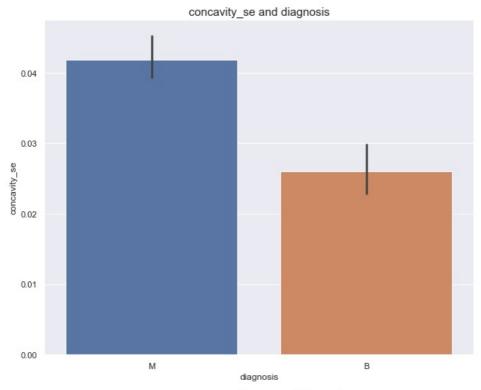


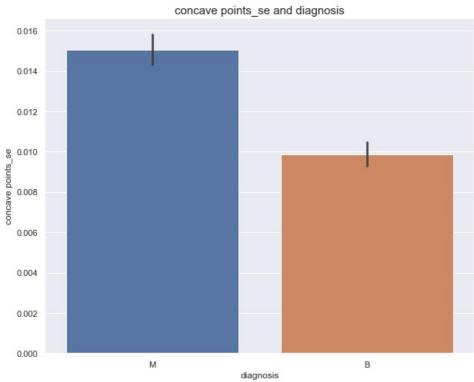


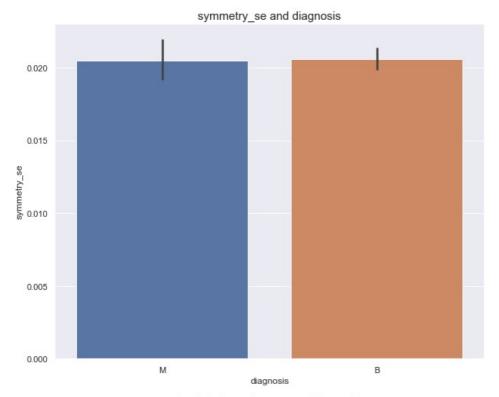


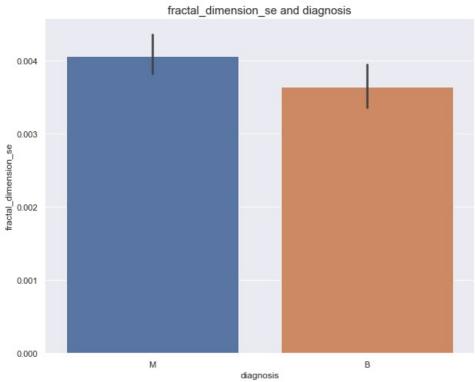


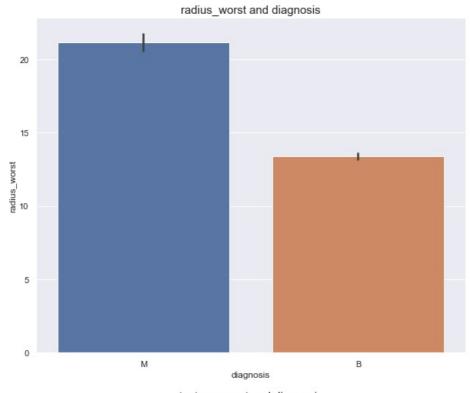


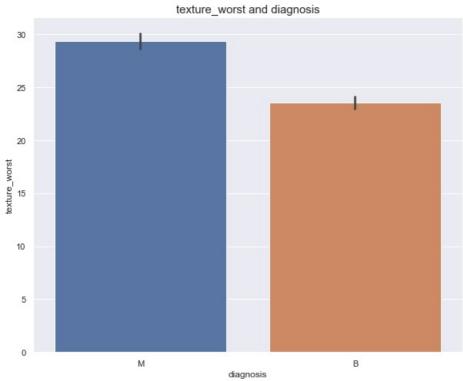


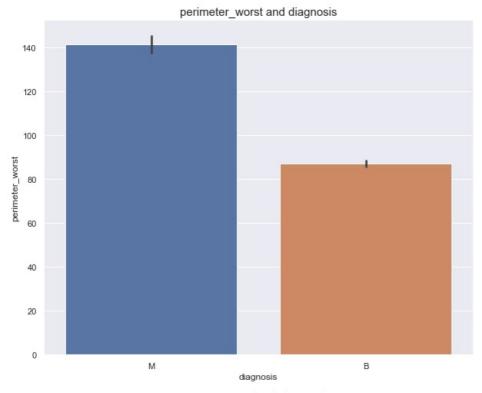


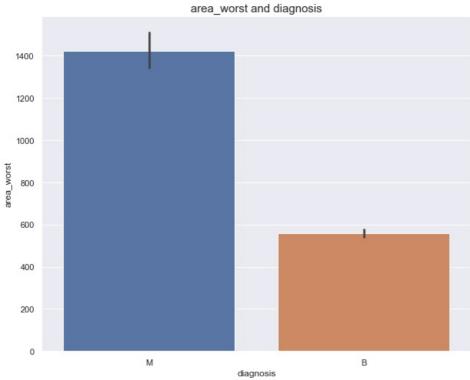


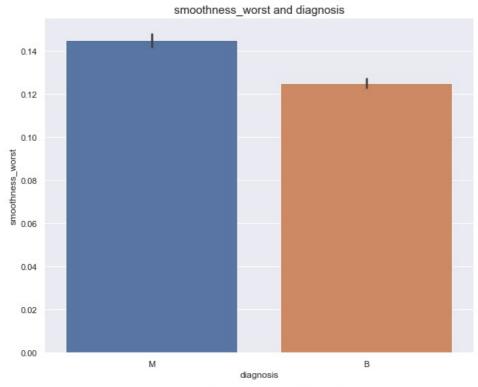


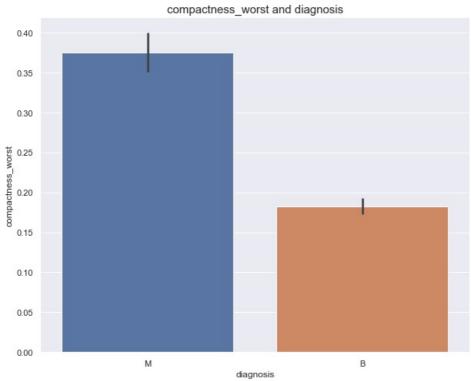


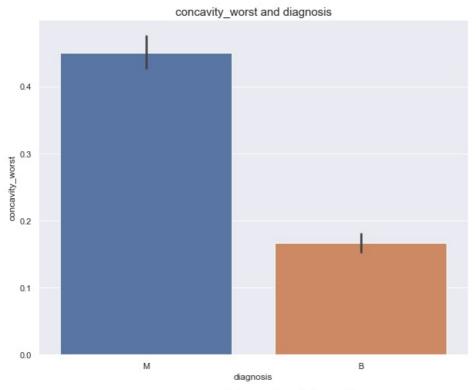


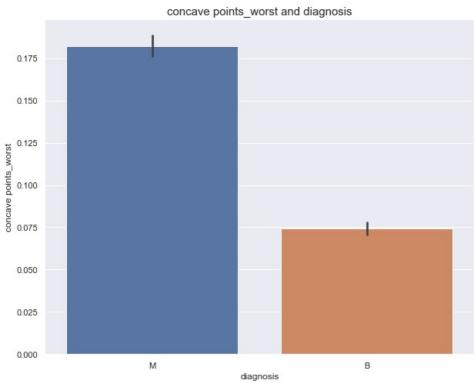


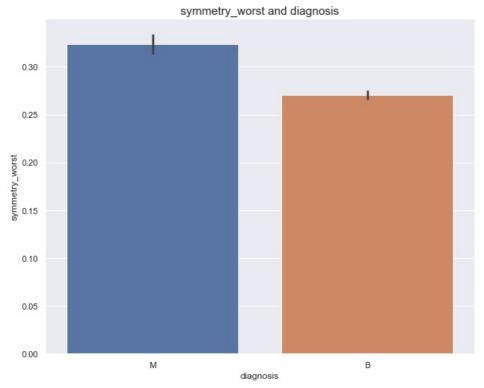


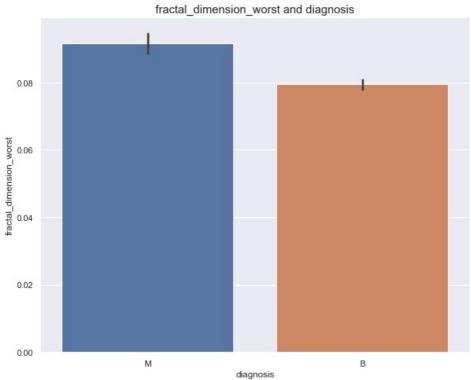




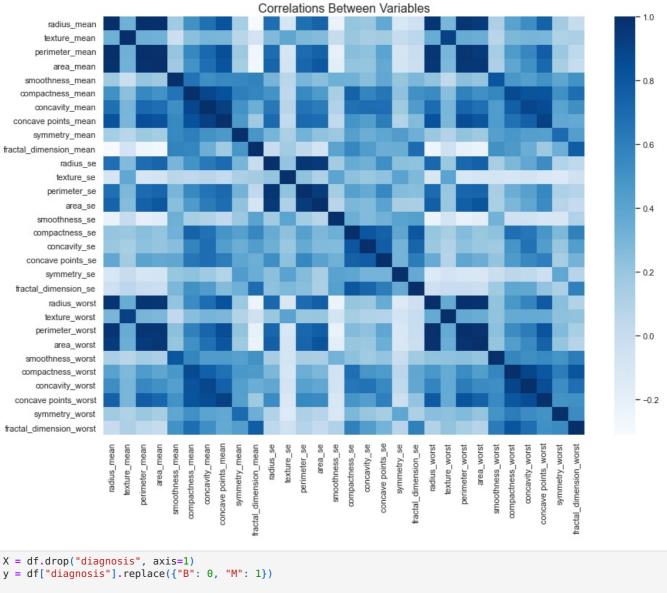








```
In [63]: plt.figure(figsize=(14,10))
    sns.heatmap(df.corr(), cmap="Blues")
    plt.title("Correlations Between Variables", size=16)
    plt.show()
```

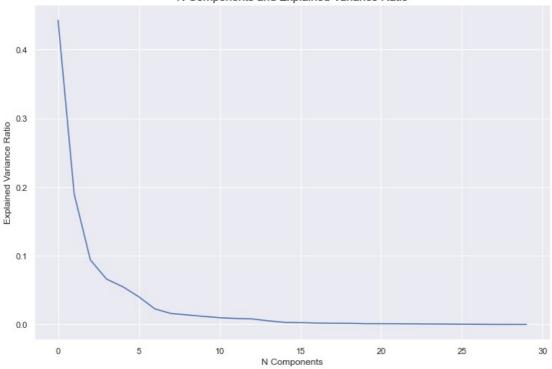


```
In [64]: X = df.drop("diagnosis", axis=1)
y = df["diagnosis"].replace({"B": 0, "M": 1})

In [65]: scaler = StandardScaler()
X = scaler.fit_transform(X)

In [66]: pca = PCA()
pca.fit(X)
plt.figure(figsize=(12,8))
plt.plot(pca.explained_variance_ratio_)
plt.title("N Components and Explained Variance Ratio", size=15)
plt.xlabel("N Components")
plt.ylabel("Explained Variance Ratio")
plt.show()
```





```
pca = PCA(n_components = 5)
In [67]:
          X = pca.fit_transform(X)
          pca.explained_variance_ratio_.sum()
          0.8473427431679001
Out[67]:
In [68]: X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3, random_state=42)
In [69]: models = pd.DataFrame(columns=["Model", "Accuracy Score"])
In [70]:
          log_reg = LogisticRegression()
          log_reg.fit(X_train, y_train)
          predictions = log_reg.predict(X_test)
          score = accuracy_score(y_test, predictions)
print("Accuracy Score:", score)
          new_row = {"Model": "LogisticRegression", "Accuracy Score": score}
          models = models.append(new_row, ignore_index=True)
          Accuracy Score: 0.9883040935672515
In [71]: rfc = RandomForestClassifier()
          rfc.fit(X_train, y_train)
          predictions = rfc.predict(X_test)
          score = accuracy_score(y_test, predictions)
print("Accuracy Score:", score)
          new_row = {"Model": "RandomForestClassifier", "Accuracy Score": score}
          models = models.append(new_row, ignore_index=True)
          Accuracy Score: 0.9707602339181286
In [72]: gbc = GradientBoostingClassifier()
          gbc.fit(X_train, y_train)
          predictions = gbc.predict(X_test)
          score = accuracy_score(y_test, predictions)
          print("Accuracy Score:", score)
          new row = {"Model": "GradientBoostingClassifier", "Accuracy Score": score}
          models = models.append(new_row, ignore_index=True)
          Accuracy Score: 0.9766081871345029
```

```
In [73]: svc = SVC()
    svc.fit(X_train, y_train)
    predictions = svc.predict(X_test)
    score = accuracy_score(y_test, predictions)
    print("Accuracy Score:", score)
    new_row = {"Model": "SVC", "Accuracy Score": score}
    models = models.append(new_row, ignore_index=True)
    models.sort_values(by="Accuracy Score", ascending=False)
```

Accuracy Score: 0.9707602339181286

```
        0ut[73]:
        Model
        Accuracy Score

        0
        LogisticRegression
        0.988304

        2
        GradientBoostingClassifier
        0.976608

        1
        RandomForestClassifier
        0.97076

        3
        SVC
        0.97076
```

```
In [74]: plt.figure(figsize=(12,8))
    sns.barplot(x=models["Model"], y=models["Accuracy Score"])
    plt.title("Models' Accuracy Scores", size=15)
    plt.xticks(rotation=30)
    plt.show()
```



```
In [75]: def visualize_roc_auc_curve(model, model_name):
    pred_prob = model.predict_proba(X_test)
    fpr, tpr, thresh = roc_curve(y_test, pred_prob[:,1], pos_label=1)

    score = roc_auc_score(y_test, pred_prob[:, 1])

    plt.figure(figsize=(10,8))
    plt.plot(fpr, tpr, linestyle="--", color="orange", label="ROC curve (area = %0.5f)" % score)
    plt.plot([0, 1], [0, 1], color="navy", lw=2, linestyle="--")

    plt.title(f"{model_name} ROC Curve", size=15)
    plt.xlabel("False Positive Rate")
    plt.ylabel("True Positive Rate")
    plt.legend(loc="lower right", prop={'size': 15})
    plt.show()
```

```
In [76]: tuned_models = pd.DataFrame(columns=["Model", "Accuracy Score"])
    param_grid_log_reg = {"C": [0.0001, 0.001, 0.01, 1, 10]}
```

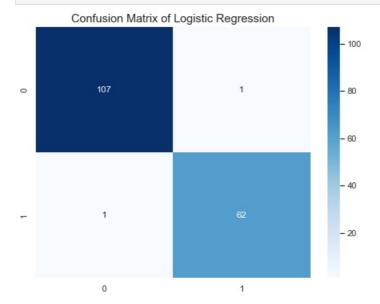
```
In [77]: grid_log_reg = GridSearchCV(LogisticRegression(), param_grid_log_reg, scoring="accuracy", cv=5, verbose=0, n_jo
    grid_log_reg.fit(X_train, y_train)
    log_reg_params = grid_log_reg.best_params_
    log_reg = LogisticRegression(**log_reg_params)
    log_reg.fit(X_train, y_train)
    predictions = log_reg.predict(X_test)
    score = accuracy_score(y_test, predictions)
    print("Accuracy Score:", score)

new_row = {"Model": "LogisticRegression", "Accuracy Score": score}
    tuned_models = tuned_models.append(new_row, ignore_index=True)
```

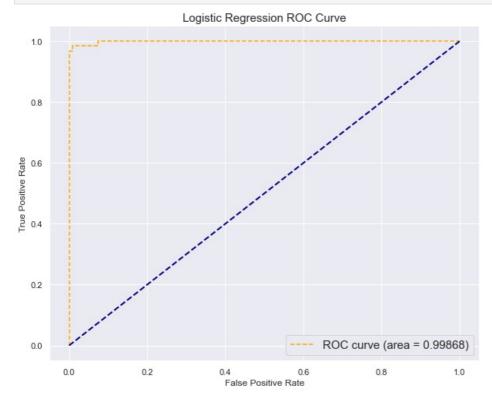
Accuracy Score: 0.9883040935672515

```
In [78]:
    plt.figure(figsize=(8,6))
    sns.heatmap(confusion_matrix(y_test, predictions), annot=True, cmap="Blues", fmt="d")
    plt.title("Confusion Matrix of Logistic Regression", size=15)
```

## plt.show()

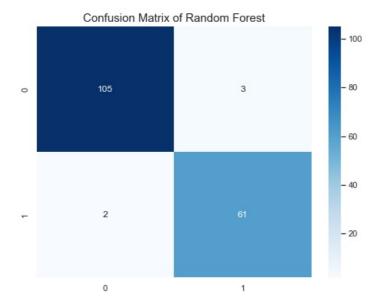


In [79]: visualize\_roc\_auc\_curve(log\_reg, "Logistic Regression")

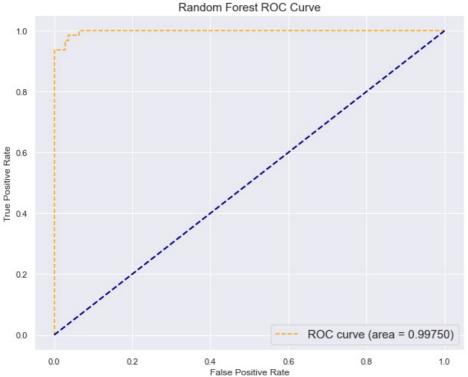


Accuracy Score: 0.9707602339181286

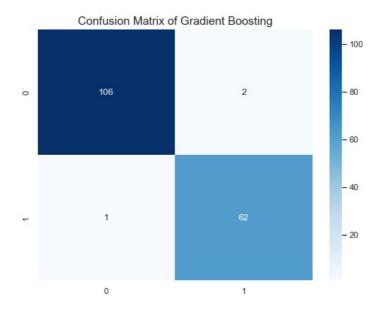
```
In [81]:
    plt.figure(figsize=(8,6))
    sns.heatmap(confusion_matrix(y_test, predictions), annot=True, cmap="Blues", fmt='d')
    plt.title("Confusion Matrix of Random Forest", size=15)
    plt.show()
```



```
In [82]: visualize_roc_auc_curve(rfc, "Random Forest")
```



```
In [85]: plt.figure(figsize=(8,6))
    sns.heatmap(confusion_matrix(y_test, predictions), annot=True, cmap="Blues", fmt='d')
    plt.title("Confusion Matrix of Gradient Boosting", size=15)
    plt.show()
```



```
In [86]: visualize_roc_auc_curve(gbc, "Gradient Boosting")
```

In [89]:

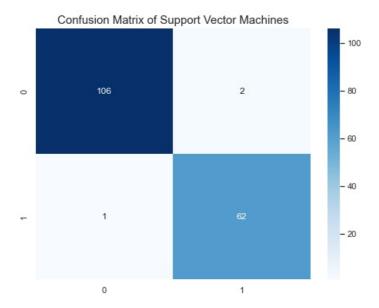
plt.figure(figsize=(8,6))

plt.show()

```
False Positive Rate
        In [87]:
         \label{eq:grid_svc} grid\_svc = GridSearchCV(SVC(), param\_grid\_svc, scoring="accuracy", cv=5, verbose=0, n\_jobs=-1)
         grid_svc.fit(X_train, y_train)
        Out[87]:
                                'gamma': [0.001, 0.01, 0.1, 1, 10]},
                     scoring='accuracy')
In [88]:
         svc_params = grid_svc.best_params_
         svc = SVC(**svc_params)
svc.fit(X_train, y_train)
         predictions = svc.predict(X_test)
         score = accuracy_score(y_test, predictions)
print("Accuracy Score:", score)
         new_row = {"Model": "SVC", "Accuracy Score": score}
         tuned models = tuned models.append(new row, ignore index=True)
         Accuracy Score: 0.9824561403508771
```

 $sns.heatmap(confusion\_matrix(y\_test, predictions), annot = \textbf{True}, cmap = "Blues", fmt = 'd')$ 

plt.title("Confusion Matrix of Support Vector Machines", size=15)



In [90]: tuned\_models.sort\_values(by="Accuracy Score", ascending=False)

 Out [90]:
 Model
 Accuracy Score

 0
 LogisticRegression
 0.988304

2 GradientBoostingClassifier 0.982456
 3 SVC 0.982456

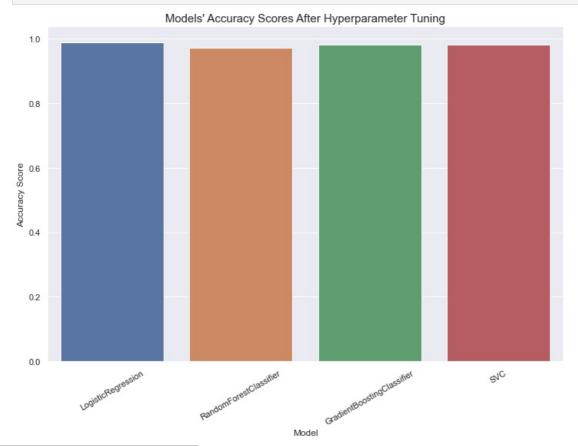
1 RandomForestClassifier 0.97076

In [91]: plt.figure(figsize=(12, 8))
 sns.barplot(x=tuned models["Model"], v=tuned models["A

sns.barplot(x=tuned\_models["Model"], y=tuned\_models["Accuracy Score"])
plt.title("Models' Accuracy Scores After Hyperparameter Tuning", size=15)

plt.xticks(rotation=30)

plt.show()



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