

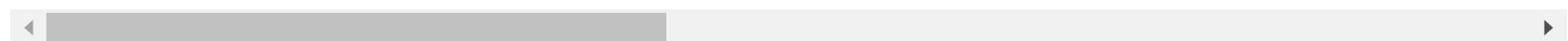
```
In [1]: import numpy as np # Linear algebra
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler,LabelEncoder
from sklearn.neighbors import KNeighborsClassifier
from sklearn.linear_model import LogisticRegression
from sklearn.tree import DecisionTreeClassifier
from sklearn.svm import SVC
from sklearn.metrics import *

import os
for dirname, _, filenames in os.walk('/kaggle/input'):
    for filename in filenames:
        print(os.path.join(dirname, filename))
import warnings
warnings.filterwarnings("ignore")
df=pd.read_csv("breast_cancer_expanded_dataset.csv")
df.head()
```

Out[1]:

	id	diagnosis	radius_mean	texture_mean	perimeter_mean	area_mean	smoothness_mean	compactness_mean	concavity_mean	concave points_mean	symmetry_mean	fractal_dimension_mean
0	3.048642e+06	M	17.971931	10.422523	123.038998	1010.679004	0.118376	0.276847	0.301	0.000	0.132432	0.000
1	3.248717e+06	M	20.504629	17.854892	133.010474	1329.620513	0.084951	0.078766	0.081	0.000	0.120482	0.000
2	8.308423e+07	M	19.733084	21.226184	130.072458	1206.386366	0.109611	0.161120	0.198	0.000	0.125000	0.000
3	8.440706e+07	M	11.423847	20.427818	77.653815	384.723555	0.142544	0.283623	0.241	0.000	0.125000	0.000
4	8.465858e+07	M	20.295838	14.297520	134.974219	1300.068231	0.100374	0.132542	0.196	0.000	0.125000	0.000

5 rows × 32 columns



In [2]: df.isnull().sum()

```
Out[2]: id          0  
diagnosis      0  
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_mean 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  
perimeter_worst  0  
area_worst        0  
smoothness_worst 0  
compactness_worst 0  
concavity_worst   0  
concave points_worst 0  
symmetry_worst    0  
fractal_dimension_worst 0  
dtype: int64
```

```
In [3]: import pandas as pd  
# Step 1: Selecting a dataset  
df = pd.read_csv('breast_cancer_expanded_dataset.csv')  
# Display the first few rows of the dataset  
print("First few rows of the dataset:")  
print(df.head())
```

```
# Display basic information about the dataset
print("\nDataset information:")
print(df.info())

# Summary statistics
print("\nSummary statistics of numerical columns:")
print(df.describe())

# Check for missing values
print("\nMissing values:")
print(df.isnull().sum())
```

First few rows of the dataset:

```

      id diagnosis radius_mean texture_mean perimeter_mean \
0 3.048642e+06      M    17.971931    10.422523    123.038998
1 3.248717e+06      M    20.504629    17.854892    133.010474
2 8.308423e+07      M    19.733084    21.226184    130.072458
3 8.440706e+07      M    11.423847    20.427818    77.653815
4 8.465858e+07      M    20.295838    14.297520    134.974219

      area_mean smoothness_mean compactness_mean concavity_mean \
0 1010.679004        0.118376        0.276847        0.301246
1 1329.620513        0.084951        0.078766        0.085893
2 1206.386366        0.109611        0.161120        0.198109
3 384.723555        0.142544        0.283623        0.241326
4 1300.068231        0.100374        0.132542        0.196814

      concave points_mean ... radius_worst texture_worst perimeter_worst \
0 0.147314   ...     25.500017    17.217229    184.775788
1 0.070364   ...     25.012428    23.414819    158.779310
2 0.128497   ...     23.565253    25.634042    152.280293
3 0.105410   ...     14.876205    26.476193    99.041551
4 0.104399   ...     22.438373    16.638056    152.383430

      area_worst smoothness_worst compactness_worst concavity_worst \
0 2023.940579        0.162339        0.666989        0.710214
1 1950.232129        0.124237        0.187702        0.241233
2 1702.704701        0.144531        0.427018        0.448880
3 564.829786         0.209767        0.863589        0.687396
4 1577.492830        0.137631        0.206669        0.401075

      concave points_worst symmetry_worst fractal_dimension_worst
0          0.265724        0.460163        0.119134
1          0.186230        0.274851        0.089053
2          0.243555        0.361381        0.087787
3          0.257700        0.663555        0.172784
4          0.162672        0.236337        0.076846

```

[5 rows x 32 columns]

Dataset information:

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 5000 entries, 0 to 4999
```

Data columns (total 32 columns):

#	Column	Non-Null Count	Dtype
0	id	5000 non-null	float64
1	diagnosis	5000 non-null	object
2	radius_mean	5000 non-null	float64
3	texture_mean	5000 non-null	float64
4	perimeter_mean	5000 non-null	float64
5	area_mean	5000 non-null	float64
6	smoothness_mean	5000 non-null	float64
7	compactness_mean	5000 non-null	float64
8	concavity_mean	5000 non-null	float64
9	concave points_mean	5000 non-null	float64
10	symmetry_mean	5000 non-null	float64
11	fractal_dimension_mean	5000 non-null	float64
12	radius_se	5000 non-null	float64
13	texture_se	5000 non-null	float64
14	perimeter_se	5000 non-null	float64
15	area_se	5000 non-null	float64
16	smoothness_se	5000 non-null	float64
17	compactness_se	5000 non-null	float64
18	concavity_se	5000 non-null	float64
19	concave points_se	5000 non-null	float64
20	symmetry_se	5000 non-null	float64
21	fractal_dimension_se	5000 non-null	float64
22	radius_worst	5000 non-null	float64
23	texture_worst	5000 non-null	float64
24	perimeter_worst	5000 non-null	float64
25	area_worst	5000 non-null	float64
26	smoothness_worst	5000 non-null	float64
27	compactness_worst	5000 non-null	float64
28	concavity_worst	5000 non-null	float64
29	concave points_worst	5000 non-null	float64
30	symmetry_worst	5000 non-null	float64
31	fractal_dimension_worst	5000 non-null	float64

dtypes: float64(31), object(1)

memory usage: 1.2+ MB

None

Summary statistics of numerical columns:

id radius_mean texture_mean perimeter_mean area_mean \

count	5.000000e+03	5000.000000	5000.000000	5000.000000	5000.000000
mean	2.989844e+07	14.135533	19.261524	92.026807	655.583620
std	1.232414e+08	3.518936	4.278956	24.266795	351.286487
min	-4.121749e+06	6.927863	9.626705	43.569989	139.607998
25%	3.822221e+05	11.693910	16.160488	75.130449	419.537486
50%	1.546392e+06	13.362077	18.822353	86.258332	550.326850
75%	8.480591e+06	15.830531	21.754581	104.322449	788.919500
max	9.150227e+08	28.138334	39.343381	189.027651	2505.483736

	smoothness_mean	compactness_mean	concavity_mean	concave points_mean	\
count	5000.000000	5000.000000	5000.000000	5000.000000	
mean	0.096377	0.104419	0.089036	0.049047	
std	0.014023	0.052902	0.079787	0.038808	
min	0.052476	0.018415	-0.002386	-0.000848	
25%	0.086344	0.064839	0.029247	0.020338	
50%	0.095930	0.092950	0.061493	0.033679	
75%	0.105262	0.130526	0.131597	0.074101	
max	0.163653	0.345700	0.428172	0.201719	

	symmetry_mean	...	radius_worst	texture_worst	perimeter_worst	\
count	5000.000000	...	5000.000000	5000.000000	5000.000000	
mean	0.181302	...	16.285191	25.648936	107.364586	
std	0.027461	...	4.831246	6.132811	33.566240	
min	0.105473	...	7.864242	11.984863	50.063108	
25%	0.161981	...	13.008701	21.065950	84.137958	
50%	0.179427	...	14.954424	25.369004	97.798772	
75%	0.195724	...	18.874108	29.673555	125.961081	
max	0.304494	...	36.116542	49.563874	251.791418	

	area_worst	smoothness_worst	compactness_worst	concavity_worst	\
count	5000.000000	5000.000000	5000.000000	5000.000000	
mean	882.095111	0.132389	0.254670	0.272709	
std	568.549258	0.022837	0.157807	0.208886	
min	178.654953	0.070779	0.024959	-0.006670	
25%	514.527050	0.116578	0.146428	0.114010	
50%	685.147018	0.131370	0.213824	0.227951	
75%	1090.604440	0.146111	0.339797	0.384436	
max	4260.299732	0.223145	1.059926	1.255012	

	concave points_worst	symmetry_worst	fractal_dimension_worst	
count	5000.000000	5000.000000	5000.000000	

mean	0.114834	0.290495	0.083959
std	0.065792	0.062075	0.018086
min	-0.001301	0.155650	0.054791
25%	0.064416	0.250614	0.071371
50%	0.100302	0.282350	0.079984
75%	0.162539	0.318474	0.092066
max	0.291860	0.664396	0.207723

[8 rows x 31 columns]

Missing values:

id	0
diagnosis	0
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_mean	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
perimeter_worst	0
area_worst	0
smoothness_worst	0
compactness_worst	0
concavity_worst	0
concave_points_worst	0

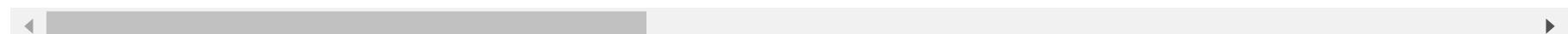
```
symmetry_worst      0
fractal_dimension_worst  0
dtype: int64
```

In [4]: `df.describe()`

Out[4]:

	id	radius_mean	texture_mean	perimeter_mean	area_mean	smoothness_mean	compactness_mean	concavity_mean
count	5.000000e+03	5000.000000	5000.000000	5000.000000	5000.000000	5000.000000	5000.000000	5000.000000
mean	2.989844e+07	14.135533	19.261524	92.026807	655.583620	0.096377	0.104419	0.089036
std	1.232414e+08	3.518936	4.278956	24.266795	351.286487	0.014023	0.052902	0.079787
min	-4.121749e+06	6.927863	9.626705	43.569989	139.607998	0.052476	0.018415	-0.002386
25%	3.822221e+05	11.693910	16.160488	75.130449	419.537486	0.086344	0.064839	0.029247
50%	1.546392e+06	13.362077	18.822353	86.258332	550.326850	0.095930	0.092950	0.061493
75%	8.480591e+06	15.830531	21.754581	104.322449	788.919500	0.105262	0.130526	0.131597
max	9.150227e+08	28.138334	39.343381	189.027651	2505.483736	0.163653	0.345700	0.428172

8 rows × 31 columns



In [5]:

```
# Define features and target
X = df.drop('diagnosis', axis=1)
y = df['diagnosis']

# Normalize features
scaler = StandardScaler()
X_scaled = scaler.fit_transform(X)
X_scaled
```

```
Out[5]: array([[-0.21788517,  1.09032416, -2.06589728, ...,  2.29365626,
   2.73357064,  1.94507838],
 [-0.21626157,  1.81013029, -0.32876528, ...,  1.08527968,
 -0.25204188,  0.28169359],
 [ 0.43160086,  1.59085314,  0.45919067, ...,  1.95667569,
  1.14206513,  0.21164974],
 ...,
 [-0.15964576, -0.59215304,  1.32032701, ...,  0.0853743 ,
 -0.50309821, -0.07264692],
 [-0.18241475,  1.03305298,  2.05527866, ...,  1.24026865,
  0.11126857,  0.36769246],
 [-0.1656325 ,  0.20014292, -0.34792339, ..., -0.47784217,
  1.11704771, -0.60219062]]))
```

```
In [6]: from sklearn.model_selection import train_test_split

X_train, X_test, y_train, y_test = train_test_split(X_scaled, y, test_size=0.3, random_state=42)
print("Shape of X_train:", X_train.shape)
print("Shape of X_test:", X_test.shape)
print("Shape of y_train:", y_train.shape)
print("Shape of y_test:", y_test.shape)
```

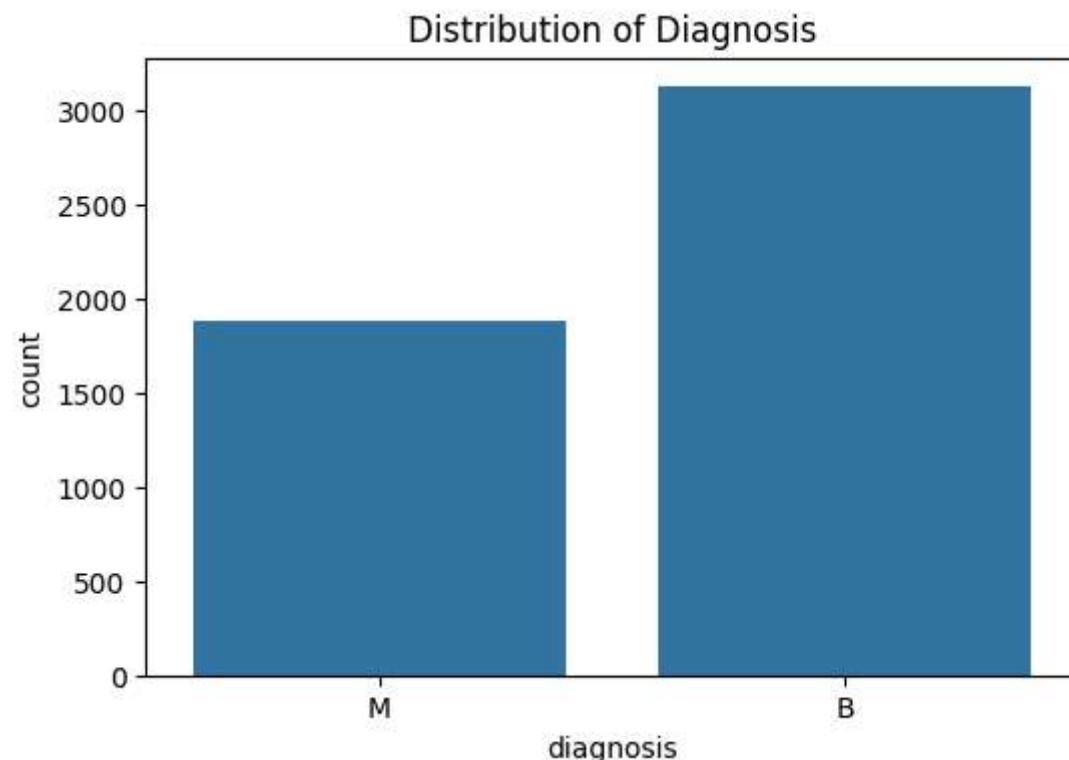
```
Shape of X_train: (3500, 31)
Shape of X_test: (1500, 31)
Shape of y_train: (3500,)
Shape of y_test: (1500,)
```

```
In [7]: plt.figure(figsize=(6, 4))
sns.countplot(x='diagnosis', data=df)
plt.title('Distribution of Diagnosis')
plt.show()

# Descriptive Statistics
print("Descriptive Statistics:\n", df.describe())

# Assuming df is your DataFrame
numeric_df = df.select_dtypes(include='number') # Selecting numeric columns
plt.figure(figsize=(12, 10))
sns.heatmap(numeric_df.corr(), annot=False, cmap='coolwarm')
```

```
plt.title('Correlation Matrix')
plt.show()
```

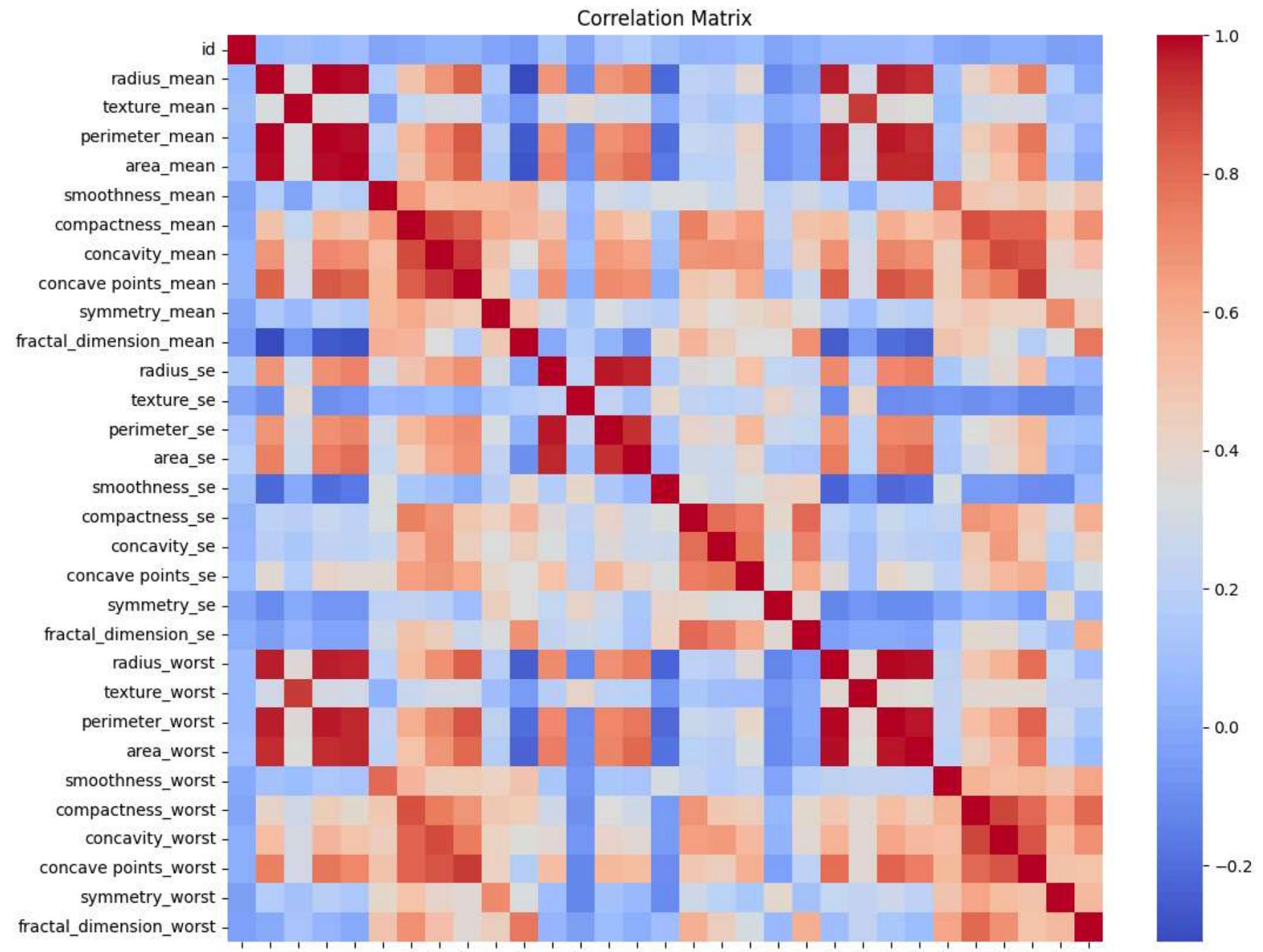


Descriptive Statistics:

	id	radius_mean	texture_mean	perimeter_mean	area_mean	\
count	5.000000e+03	5000.00000	5000.00000	5000.00000	5000.00000	
mean	2.989844e+07	14.135533	19.261524	92.026807	655.583620	
std	1.232414e+08	3.518936	4.278956	24.266795	351.286487	
min	-4.121749e+06	6.927863	9.626705	43.569989	139.607998	
25%	3.822221e+05	11.693910	16.160488	75.130449	419.537486	
50%	1.546392e+06	13.362077	18.822353	86.258332	550.326850	
75%	8.480591e+06	15.830531	21.754581	104.322449	788.919500	
max	9.150227e+08	28.138334	39.343381	189.027651	2505.483736	
	smoothness_mean	compactness_mean	concavity_mean	concave points_mean	points_mean	\
count	5000.00000	5000.00000	5000.00000	5000.00000	5000.00000	
mean	0.096377	0.104419	0.089036	0.049047		
std	0.014023	0.052902	0.079787	0.038808		
min	0.052476	0.018415	-0.002386	-0.000848		
25%	0.086344	0.064839	0.029247	0.020338		
50%	0.095930	0.092950	0.061493	0.033679		
75%	0.105262	0.130526	0.131597	0.074101		
max	0.163653	0.345700	0.428172	0.201719		
	symmetry_mean	...	radius_worst	texture_worst	perimeter_worst	\
count	5000.00000	...	5000.00000	5000.00000	5000.00000	
mean	0.181302	...	16.285191	25.648936	107.364586	
std	0.027461	...	4.831246	6.132811	33.566240	
min	0.105473	...	7.864242	11.984863	50.063108	
25%	0.161981	...	13.008701	21.065950	84.137958	
50%	0.179427	...	14.954424	25.369004	97.798772	
75%	0.195724	...	18.874108	29.673555	125.961081	
max	0.304494	...	36.116542	49.563874	251.791418	
	area_worst	smoothness_worst	compactness_worst	concavity_worst	\	
count	5000.00000	5000.00000	5000.00000	5000.00000		
mean	882.095111	0.132389	0.254670	0.272709		
std	568.549258	0.022837	0.157807	0.208886		
min	178.654953	0.070779	0.024959	-0.006670		
25%	514.527050	0.116578	0.146428	0.114010		
50%	685.147018	0.131370	0.213824	0.227951		
75%	1090.604440	0.146111	0.339797	0.384436		
max	4260.299732	0.223145	1.059926	1.255012		

	concave points_worst	symmetry_worst	fractal_dimension_worst
count	5000.000000	5000.000000	5000.000000
mean	0.114834	0.290495	0.083959
std	0.065792	0.062075	0.018086
min	-0.001301	0.155650	0.054791
25%	0.064416	0.250614	0.071371
50%	0.100302	0.282350	0.079984
75%	0.162539	0.318474	0.092066
max	0.291860	0.664396	0.207723

[8 rows x 31 columns]

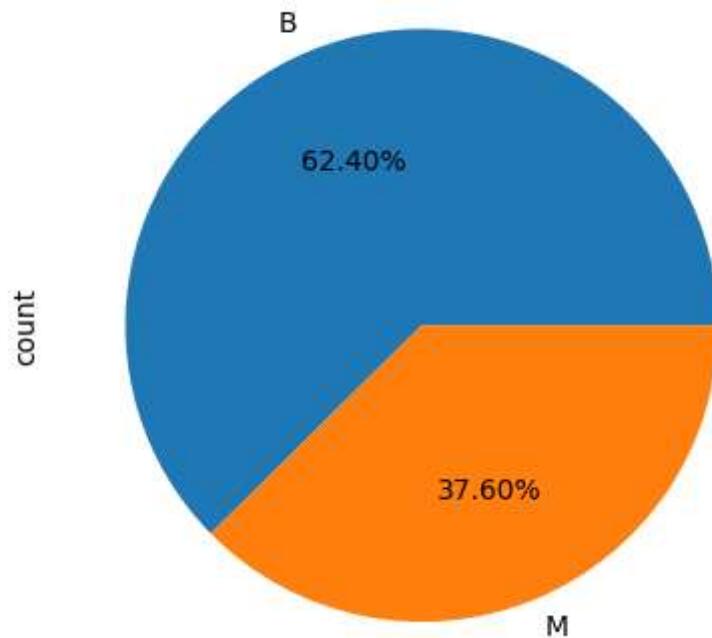


```
id  
radius_mean  
texture_mean  
perimeter_mean  
area_mean  
smoothness_mean  
compactness_mean  
concavity_mean  
concave_points_mean  
symmetry_mean  
fractal_dimension_mean  
radius_se  
texture_se  
perimeter_se  
area_se  
smoothness_se  
compactness_se  
concavity_se  
concave_points_se  
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
```

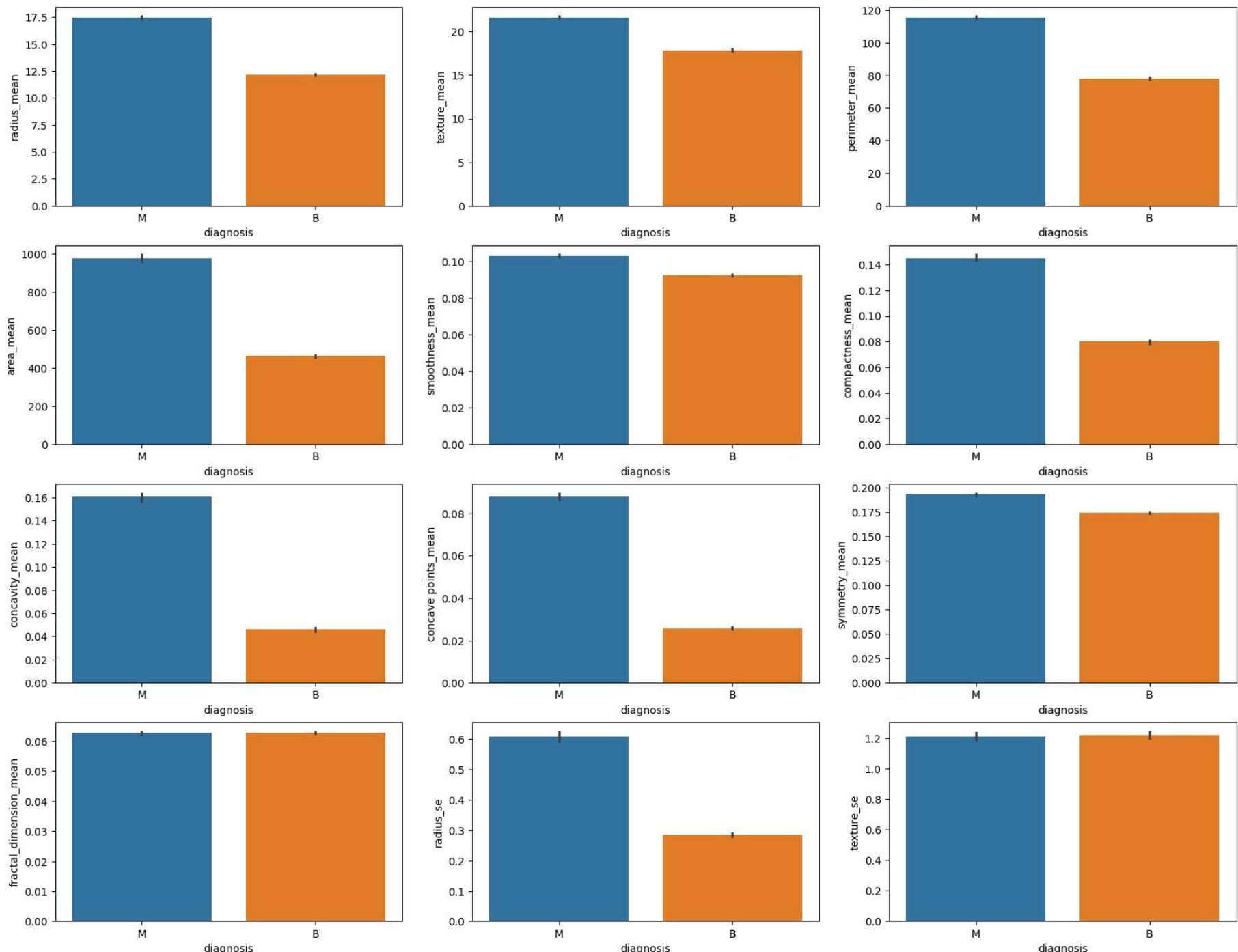
```
In [8]: df.drop(columns='id', inplace=True)
```

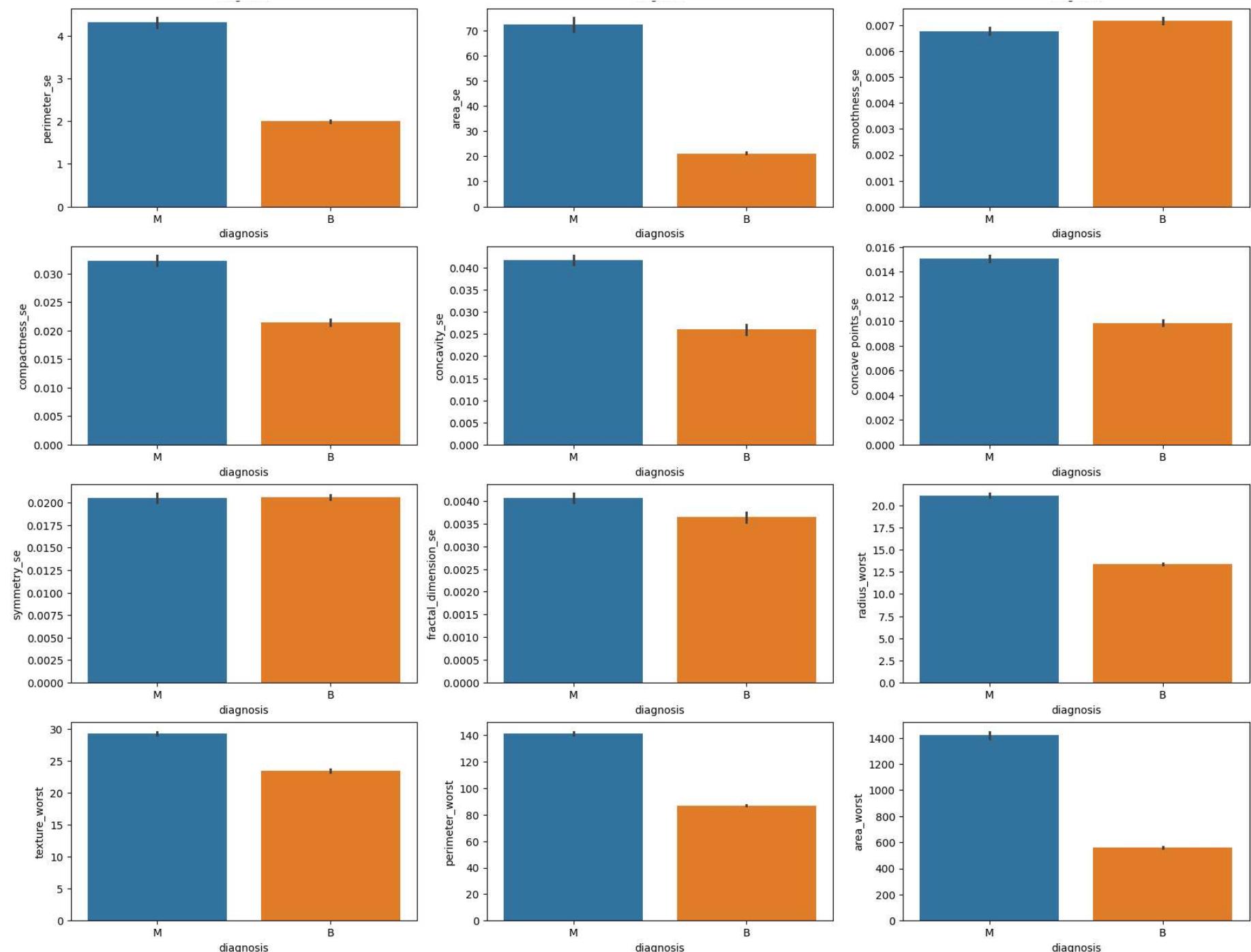
```
In [9]: df['diagnosis'].value_counts().plot(kind='pie', autopct='%.2f%%')
```

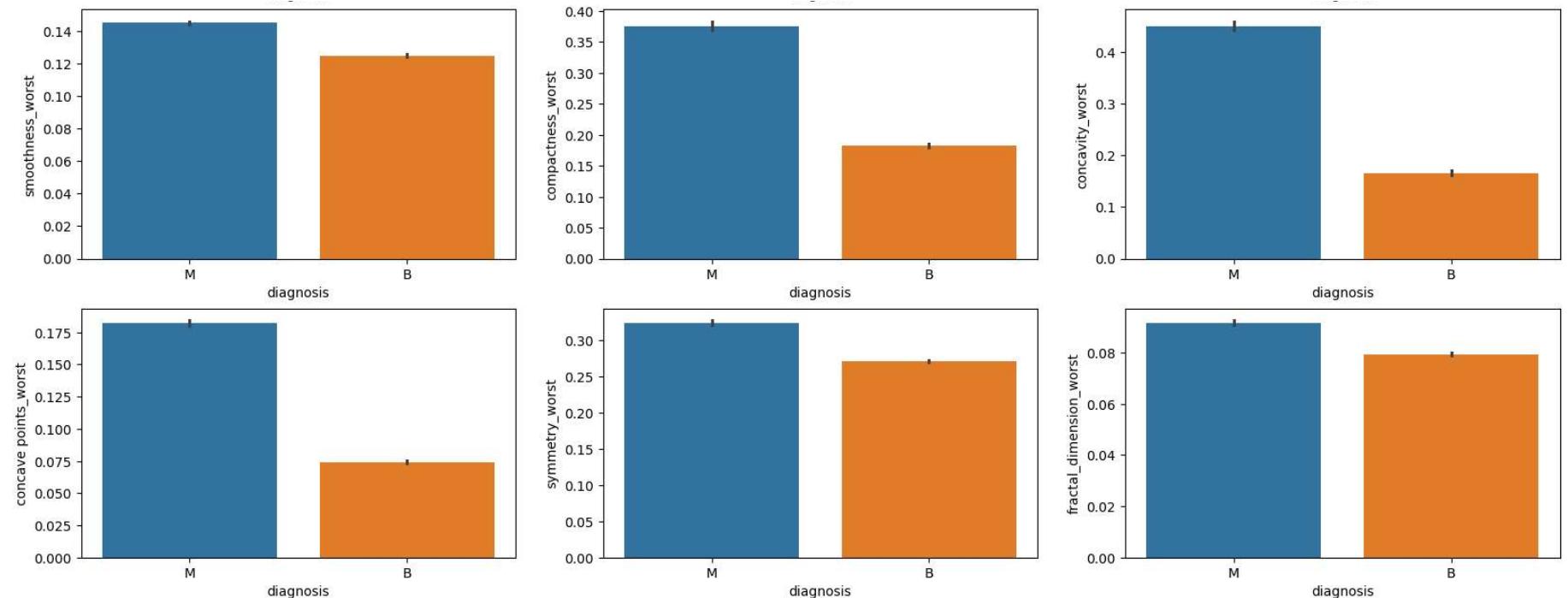
```
Out[9]: <Axes: ylabel='count'>
```



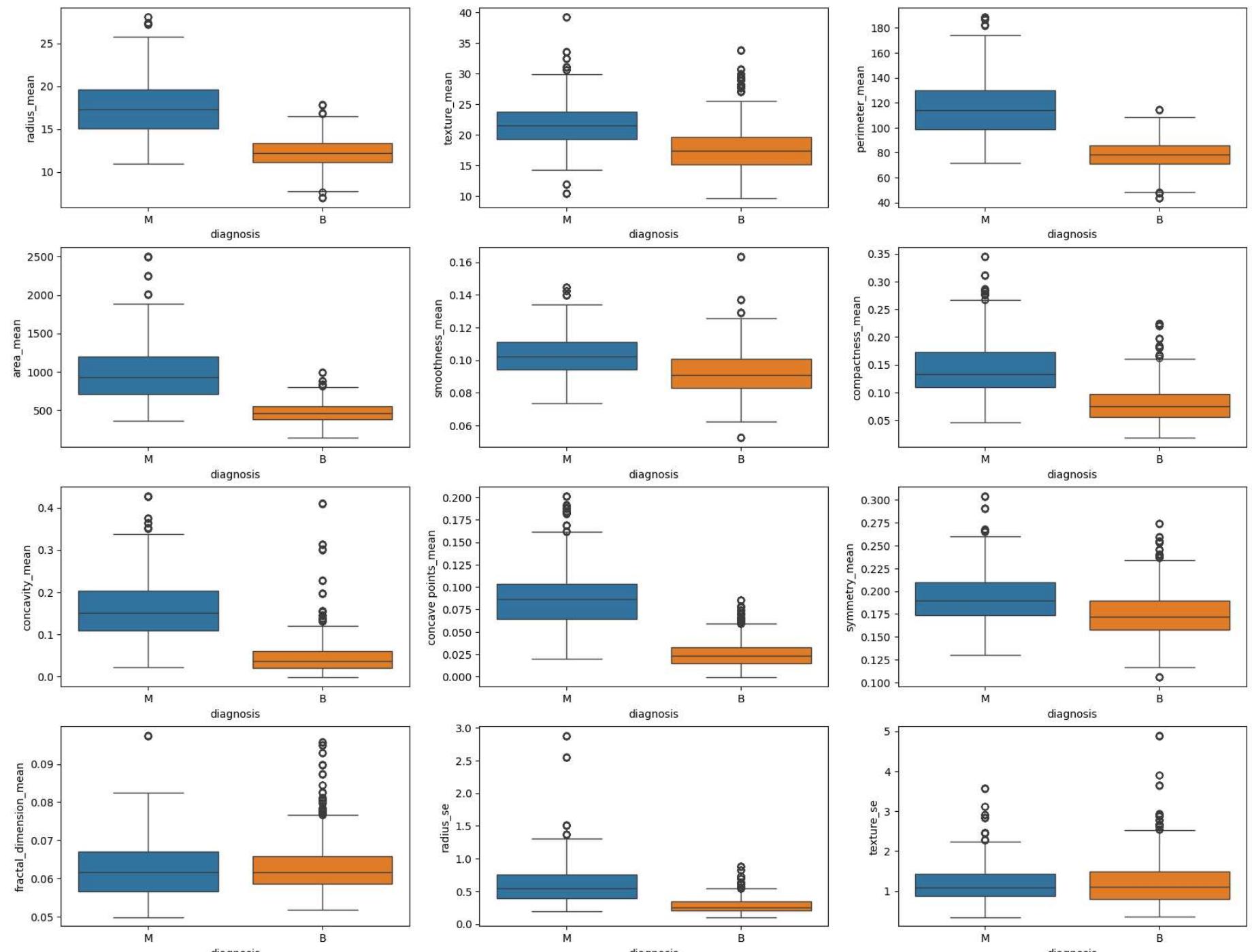
```
In [10]: fig,ax=plt.subplots(figsize=(20,40),nrows=10,ncols=3)
ax=ax.flatten()
for i,col in enumerate(df.columns[1:]):
    # df[col]=np.log(df[col])
    sns.barplot(x='diagnosis',y=col,data=df,ax=ax[i],hue='diagnosis');
```

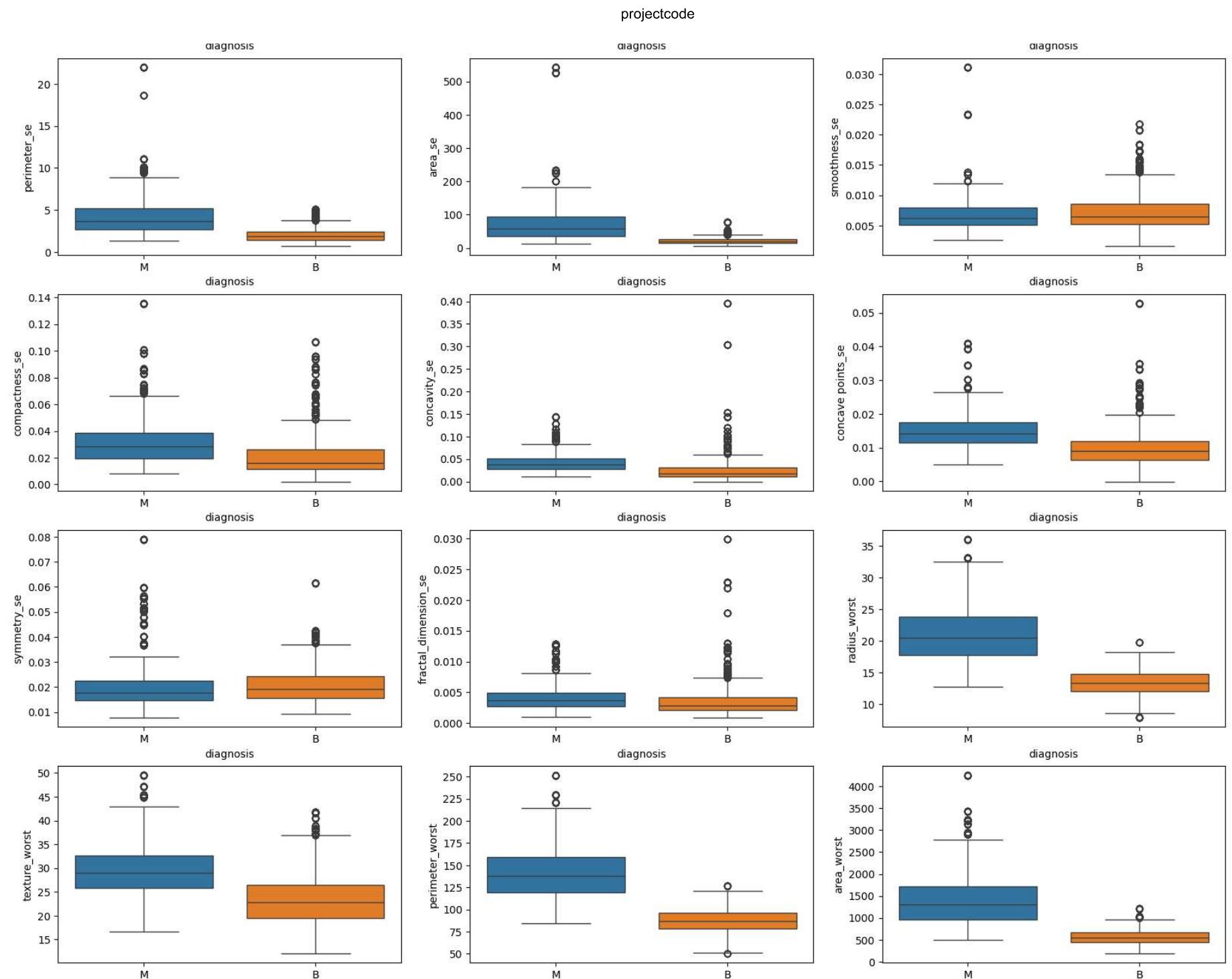


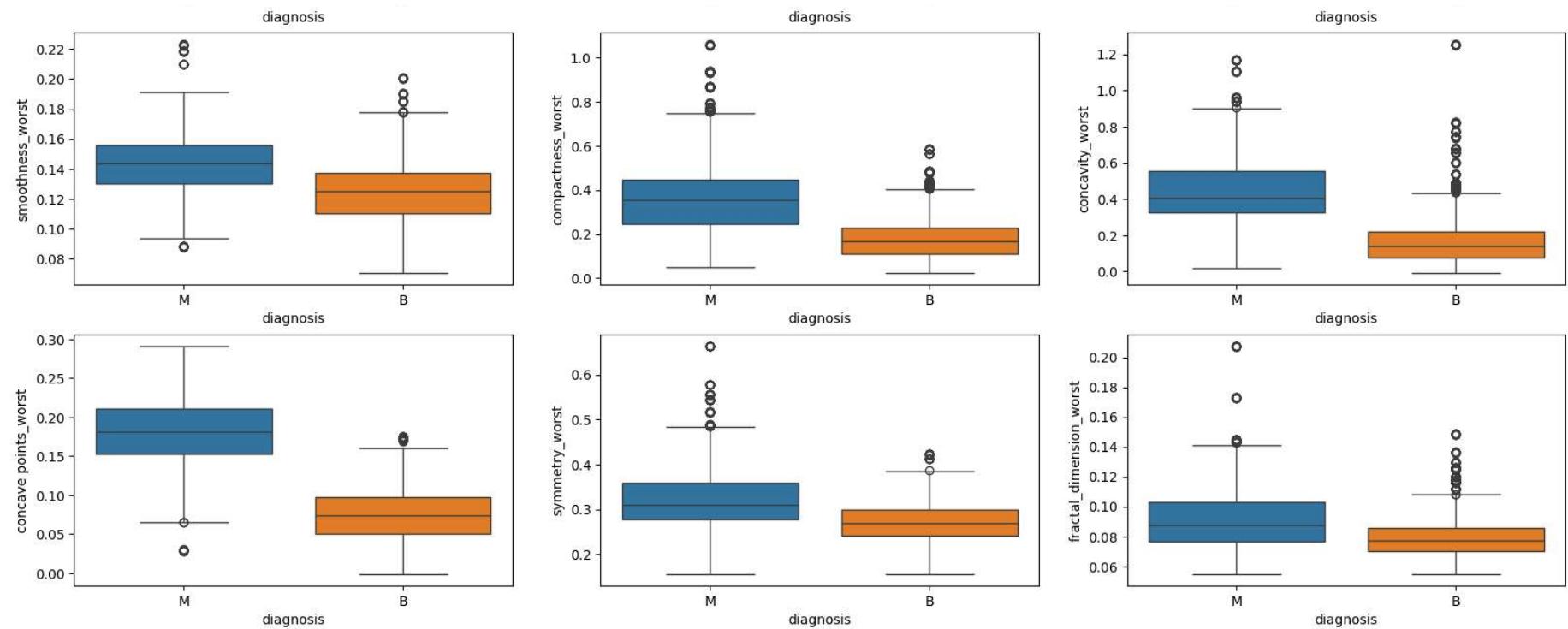




```
In [11]: fig,ax=plt.subplots(figsize=(20,40),nrows=10,ncols=3)
ax=ax.flatten()
for i,col in enumerate(df.columns[1:]):
    # df[col]=np.log(df[col])
    sns.boxplot(x='diagnosis',y=col,data=df,ax=ax[i], hue='diagnosis');
```

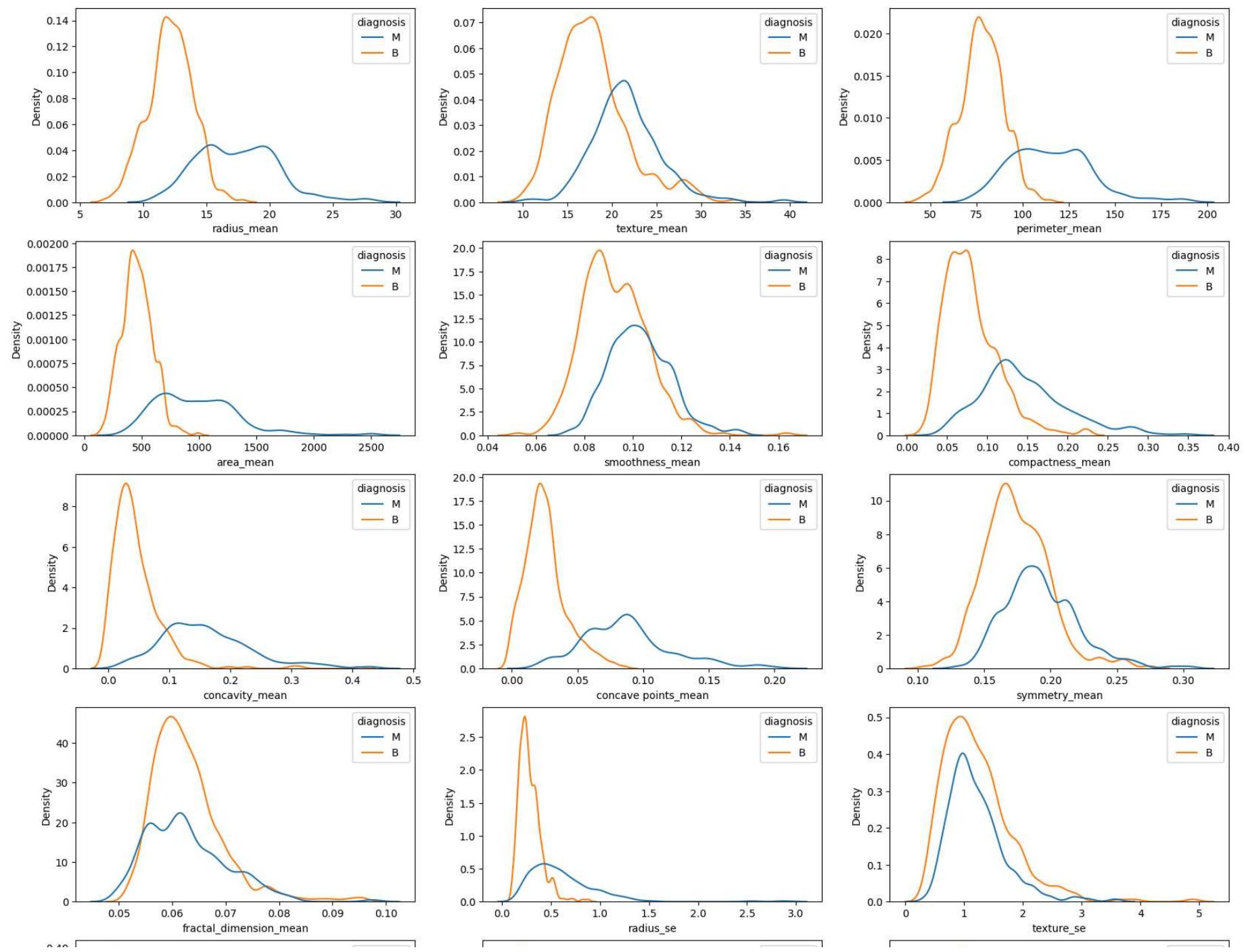


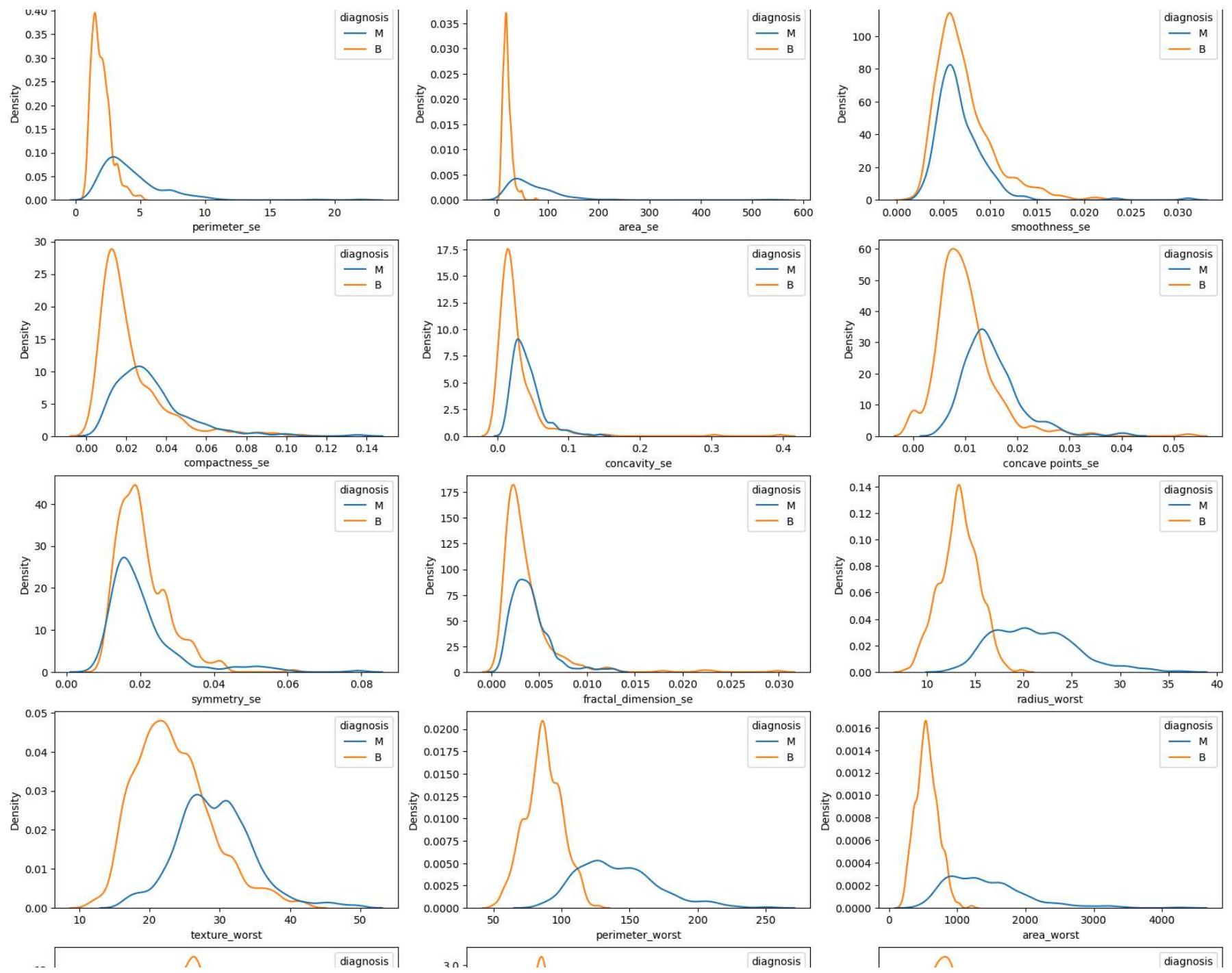


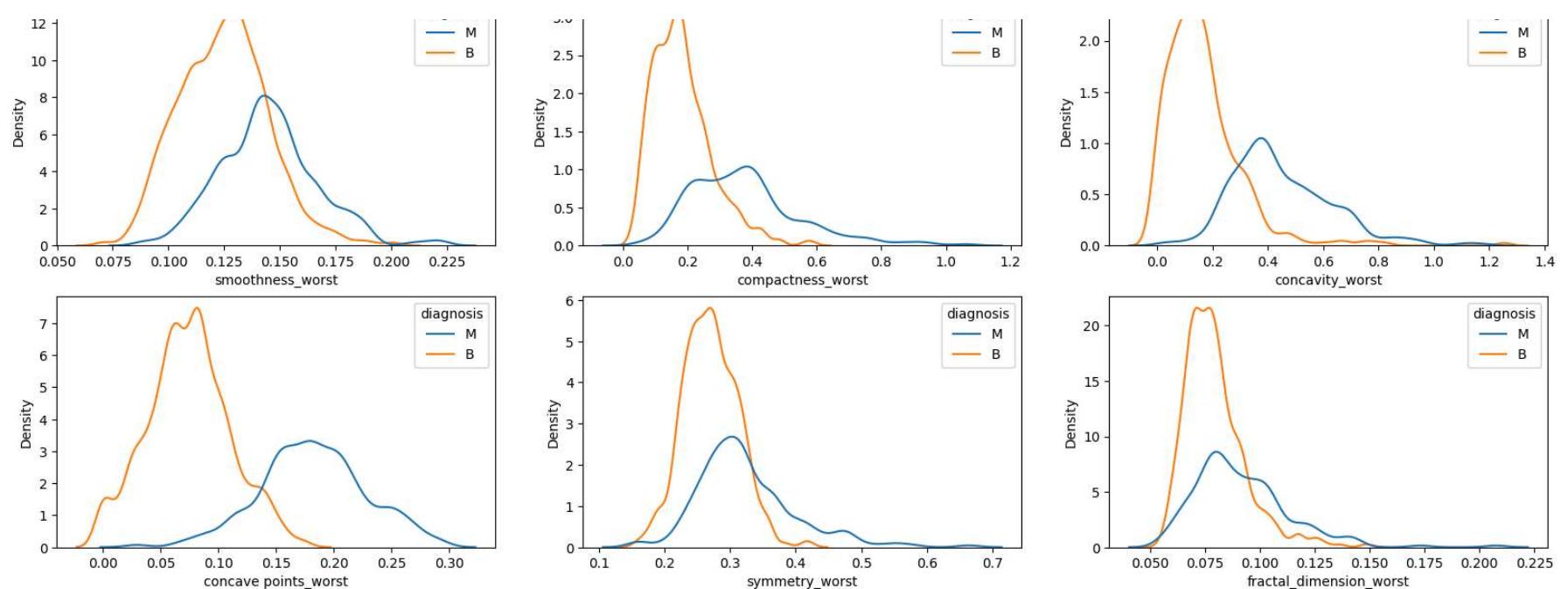


```
In [12]: fig,ax=plt.subplots(figsize=(20,40),nrows=10,ncols=3)
ax=ax.flatten()
for i,col in enumerate(df.columns[1:]):
    # df[col]=np.log(df[col])
    sns.kdeplot(x=col,data=df,ax=ax[i],hue='diagnosis');
```

projectcode







```
In [13]: from sklearn.feature_selection import SelectKBest, f_classif

# Apply SelectKBest class to extract top 10 features
bestfeatures = SelectKBest(score_func=f_classif, k=10)
fit = bestfeatures.fit(X,y)
dfscores = pd.DataFrame(fit.scores_)
dfcolumns = pd.DataFrame(X.columns)

# Concat two dataframes for better visualization
featureScores = pd.concat([dfcolumns,dfscores],axis=1)
featureScores.columns = ['Feature', 'Score'] # naming the dataframe columns
print(featureScores.nlargest(10,'Score')) # print 10 best features
```

	Feature	Score
28	concave points_worst	8540.218727
23	perimeter_worst	7914.084643
21	radius_worst	7583.737425
8	concave points_mean	7565.344127
3	perimeter_mean	6125.966416
24	area_worst	5830.067597
1	radius_mean	5686.059680
4	area_mean	5031.640067
7	concavity_mean	4661.311433
27	concavity_worst	3849.139920

```
In [14]: from sklearn.neural_network import MLPClassifier

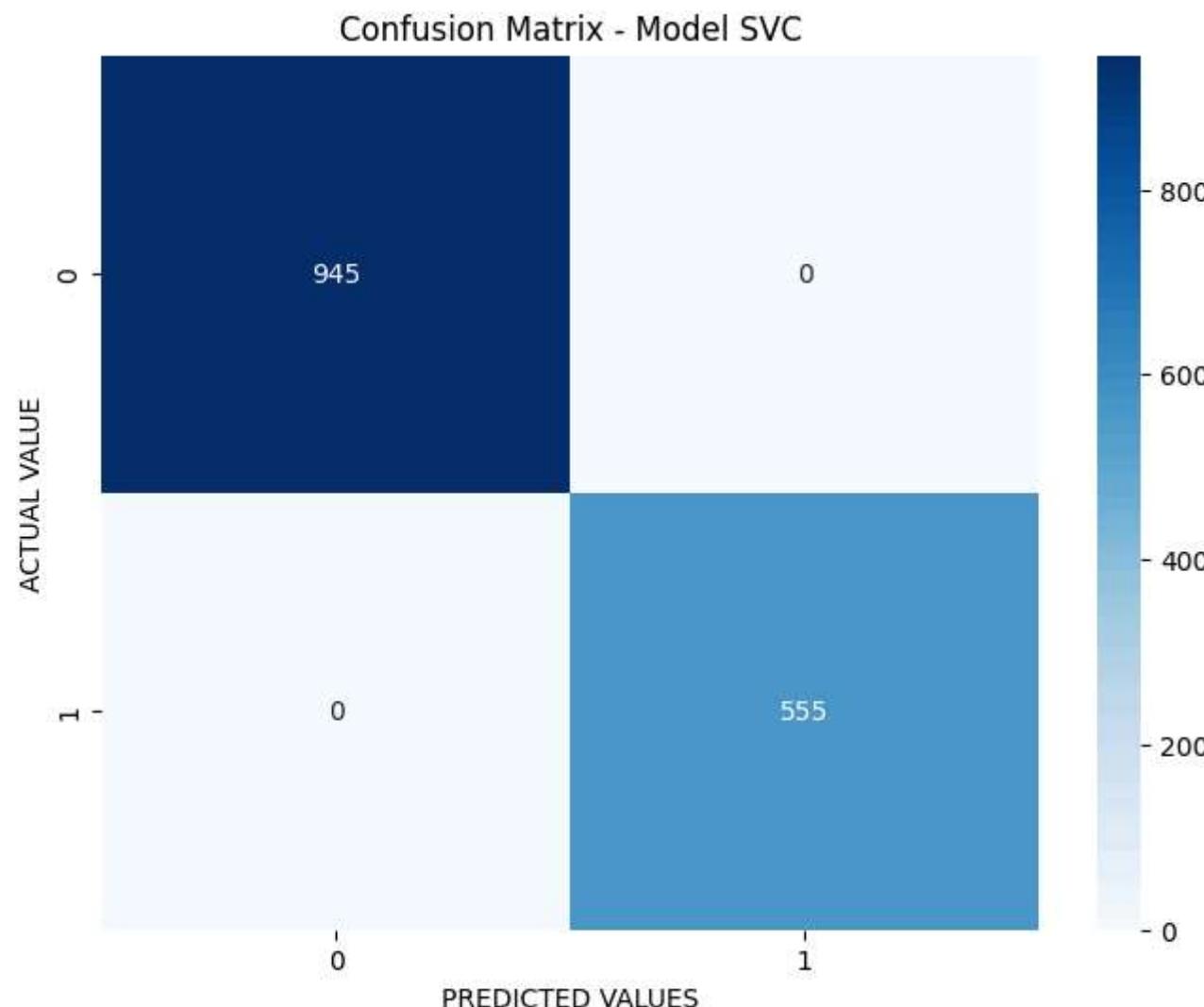
# Creating MLP classifier with adjusted parameters
mlp_classifier = MLPClassifier(max_iter=1000, solver='adam') # Adjust max_iter and solver as needed

# Training the classifier
mlp_classifier.fit(X_train, y_train)

# Predicting on test set
mlp_predictions = mlp_classifier.predict(X_test)

# Evaluating accuracy
mlp_accuracy = accuracy_score(y_test, mlp_predictions)
print("Neural Network Accuracy:", mlp_accuracy)
mlp_conf_matrix = confusion_matrix(y_test, mlp_predictions)
plt.figure(figsize=(8, 6))
sns.heatmap(mlp_conf_matrix, annot=True, fmt='d', cmap='Blues', cbar=True)
plt.title("Confusion Matrix - Model SVC")
plt.xlabel("PREDICTED VALUES")
plt.ylabel("ACTUAL VALUE")
plt.show()
```

Neural Network Accuracy: 1.0



```
In [15]: from sklearn.tree import DecisionTreeClassifier  
from sklearn.model_selection import train_test_split  
from sklearn.metrics import accuracy_score, confusion_matrix  
import matplotlib.pyplot as plt  
import seaborn as sns  
import numpy as np
```

```
# Assuming 'X_train', 'X_test', 'y_train', 'y_test' are already defined

# Creating Decision Tree classifier with default parameters
dt_classifier = DecisionTreeClassifier() # Default settings; you can adjust parameters like max_depth

# Training the classifier
dt_classifier.fit(X_train, y_train)

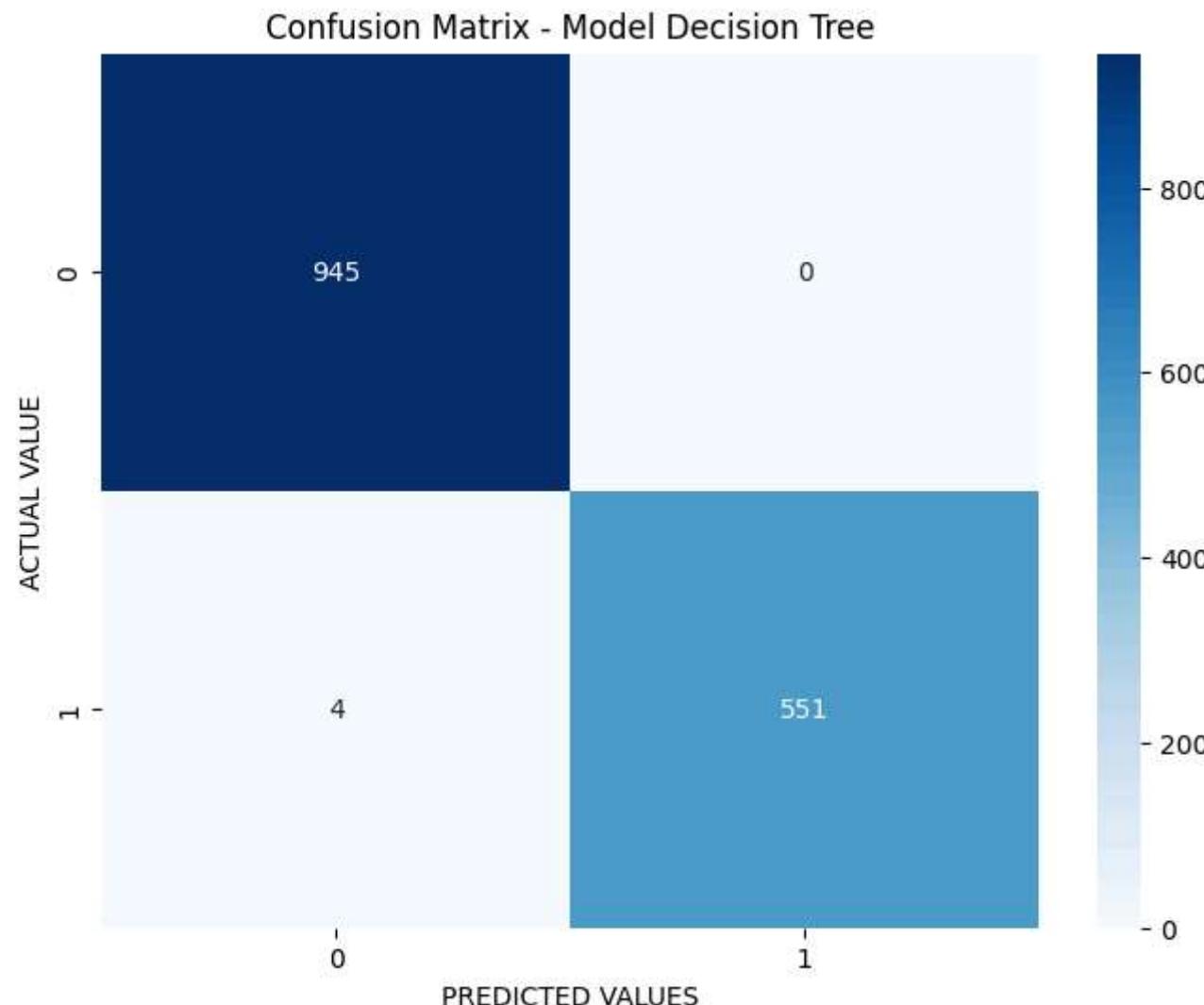
# Predicting on test set
dt_predictions = dt_classifier.predict(X_test)

# Evaluating accuracy
dt_accuracy = accuracy_score(y_test, dt_predictions)
print("Decision Tree Accuracy:", dt_accuracy)

# Generating confusion matrix
dt_conf_matrix = confusion_matrix(y_test, dt_predictions)

# Visualizing the confusion matrix
plt.figure(figsize=(8, 6))
sns.heatmap(dt_conf_matrix, annot=True, fmt='d', cmap='Blues', cbar=True)
plt.title("Confusion Matrix - Model Decision Tree")
plt.xlabel("PREDICTED VALUES")
plt.ylabel("ACTUAL VALUE")
plt.show()
```

Decision Tree Accuracy: 0.9973333333333333



```
In [16]: from sklearn.svm import SVC
from sklearn.model_selection import train_test_split
from sklearn.metrics import accuracy_score, confusion_matrix
import matplotlib.pyplot as plt
import seaborn as sns
import numpy as np
```

```
# Assuming 'X_train', 'X_test', 'y_train', 'y_test' are already defined

# Creating SVM classifier with default parameters
svm_classifier = SVC(kernel='linear') # Using a linear kernel; adjust as needed

# Training the classifier
svm_classifier.fit(X_train, y_train)

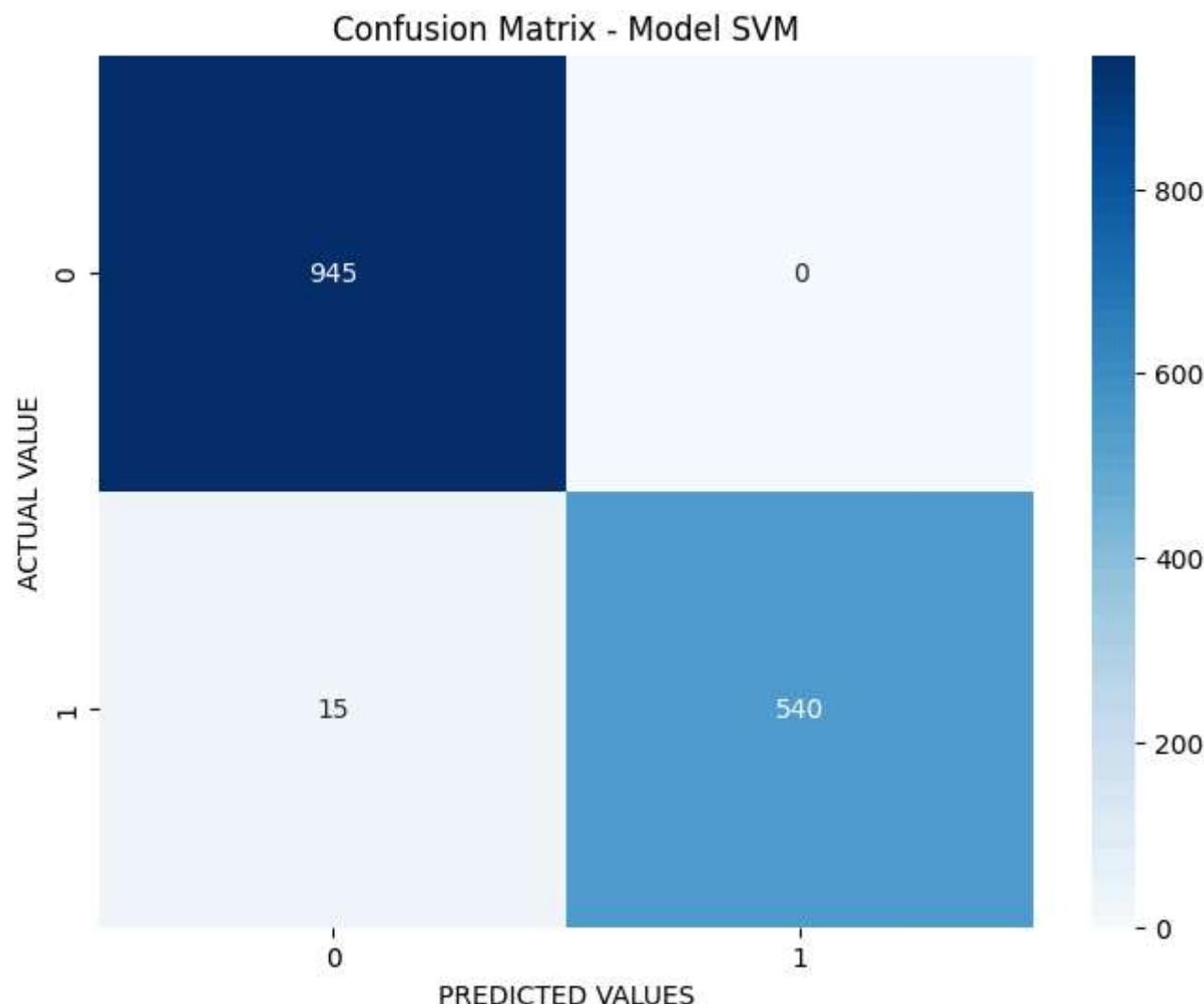
# Predicting on test set
svm_predictions = svm_classifier.predict(X_test)

# Evaluating accuracy
svm_accuracy = accuracy_score(y_test, svm_predictions)
print("SVM Accuracy:", svm_accuracy)

# Generating confusion matrix
svm_conf_matrix = confusion_matrix(y_test, svm_predictions)

# Visualizing the confusion matrix
plt.figure(figsize=(8, 6))
sns.heatmap(svm_conf_matrix, annot=True, fmt='d', cmap='Blues', cbar=True)
plt.title("Confusion Matrix - Model SVM")
plt.xlabel("PREDICTED VALUES")
plt.ylabel("ACTUAL VALUE")
plt.show()
```

SVM Accuracy: 0.99



```
In [17]: from sklearn.neural_network import MLPClassifier  
from sklearn.model_selection import GridSearchCV  
from sklearn.metrics import accuracy_score  
import matplotlib.pyplot as plt  
import seaborn as sns  
import pandas as pd
```

```
# Assuming you have your data loaded into X_train and y_train

# Neural Network hyperparameters
param_grid_nn = {
    'hidden_layer_sizes': [(50,), (100,), (50, 50), (100, 100)],
    'activation': ['tanh', 'relu'],
    'solver': ['sgd', 'adam'],
    'alpha': [0.0001, 0.001, 0.01] # Regularization term
}

# Creating the GridSearchCV object
grid_search_nn = GridSearchCV(MLPClassifier(max_iter=1000, random_state=42), param_grid_nn, refit=True, verbose=2, cv=3)

# Fit the grid search to your data
grid_search_nn.fit(X_train, y_train)

# Get the best neural network model
best_nn_model = grid_search_nn.best_estimator_

# Use the best model to predict on your test set
y_pred = best_nn_model.predict(X_test)

# Calculate accuracy on the test set
test_accuracy = accuracy_score(y_test, y_pred)

# Displaying the best parameters and the score achieved with them
print("Best Neural Network Parameters:", grid_search_nn.best_params_)
print("Best Neural Network Score:", grid_search_nn.best_score_)
print("Test Set Accuracy:", test_accuracy)
```

```
Fitting 3 folds for each of 48 candidates, totalling 144 fits
[CV] END activation=tanh, alpha=0.0001, hidden_layer_sizes=(50,), solver=sgd; total time= 4.4s
[CV] END activation=tanh, alpha=0.0001, hidden_layer_sizes=(50,), solver=sgd; total time= 4.6s
[CV] END activation=tanh, alpha=0.0001, hidden_layer_sizes=(50,), solver=sgd; total time= 4.8s
[CV] END activation=tanh, alpha=0.0001, hidden_layer_sizes=(50,), solver=adam; total time= 5.3s
[CV] END activation=tanh, alpha=0.0001, hidden_layer_sizes=(50,), solver=adam; total time= 5.2s
[CV] END activation=tanh, alpha=0.0001, hidden_layer_sizes=(50,), solver=adam; total time= 5.6s
[CV] END activation=tanh, alpha=0.0001, hidden_layer_sizes=(100,), solver=sgd; total time= 5.3s
[CV] END activation=tanh, alpha=0.0001, hidden_layer_sizes=(100,), solver=sgd; total time= 5.0s
[CV] END activation=tanh, alpha=0.0001, hidden_layer_sizes=(100,), solver=sgd; total time= 5.5s
[CV] END activation=tanh, alpha=0.0001, hidden_layer_sizes=(100,), solver=adam; total time= 5.7s
[CV] END activation=tanh, alpha=0.0001, hidden_layer_sizes=(100,), solver=adam; total time= 6.0s
[CV] END activation=tanh, alpha=0.0001, hidden_layer_sizes=(100,), solver=adam; total time= 5.9s
[CV] END activation=tanh, alpha=0.0001, hidden_layer_sizes=(50, 50), solver=sgd; total time= 8.8s
[CV] END activation=tanh, alpha=0.0001, hidden_layer_sizes=(50, 50), solver=sgd; total time= 7.9s
[CV] END activation=tanh, alpha=0.0001, hidden_layer_sizes=(50, 50), solver=sgd; total time= 8.9s
[CV] END activation=tanh, alpha=0.0001, hidden_layer_sizes=(50, 50), solver=adam; total time= 5.0s
[CV] END activation=tanh, alpha=0.0001, hidden_layer_sizes=(50, 50), solver=adam; total time= 5.5s
[CV] END activation=tanh, alpha=0.0001, hidden_layer_sizes=(50, 50), solver=adam; total time= 4.5s
[CV] END activation=tanh, alpha=0.0001, hidden_layer_sizes=(100, 100), solver=sgd; total time= 8.5s
[CV] END activation=tanh, alpha=0.0001, hidden_layer_sizes=(100, 100), solver=sgd; total time= 7.6s
[CV] END activation=tanh, alpha=0.0001, hidden_layer_sizes=(100, 100), solver=sgd; total time= 8.6s
[CV] END activation=tanh, alpha=0.0001, hidden_layer_sizes=(100, 100), solver=adam; total time= 4.6s
[CV] END activation=tanh, alpha=0.0001, hidden_layer_sizes=(100, 100), solver=adam; total time= 4.7s
[CV] END activation=tanh, alpha=0.0001, hidden_layer_sizes=(100, 100), solver=adam; total time= 5.0s
[CV] END activation=tanh, alpha=0.001, hidden_layer_sizes=(50,), solver=sgd; total time= 4.5s
[CV] END activation=tanh, alpha=0.001, hidden_layer_sizes=(50,), solver=sgd; total time= 4.5s
[CV] END activation=tanh, alpha=0.001, hidden_layer_sizes=(50,), solver=sgd; total time= 4.9s
[CV] END activation=tanh, alpha=0.001, hidden_layer_sizes=(50,), solver=adam; total time= 5.5s
[CV] END activation=tanh, alpha=0.001, hidden_layer_sizes=(50,), solver=adam; total time= 5.3s
[CV] END activation=tanh, alpha=0.001, hidden_layer_sizes=(50,), solver=adam; total time= 5.8s
[CV] END activation=tanh, alpha=0.001, hidden_layer_sizes=(100,), solver=sgd; total time= 5.6s
[CV] END activation=tanh, alpha=0.001, hidden_layer_sizes=(100,), solver=sgd; total time= 5.2s
[CV] END activation=tanh, alpha=0.001, hidden_layer_sizes=(100,), solver=sgd; total time= 5.6s
[CV] END activation=tanh, alpha=0.001, hidden_layer_sizes=(100,), solver=adam; total time= 5.8s
[CV] END activation=tanh, alpha=0.001, hidden_layer_sizes=(100,), solver=adam; total time= 5.9s
[CV] END activation=tanh, alpha=0.001, hidden_layer_sizes=(100,), solver=adam; total time= 5.9s
[CV] END activation=tanh, alpha=0.001, hidden_layer_sizes=(50, 50), solver=sgd; total time= 8.8s
[CV] END activation=tanh, alpha=0.001, hidden_layer_sizes=(50, 50), solver=sgd; total time= 8.0s
[CV] END activation=tanh, alpha=0.001, hidden_layer_sizes=(50, 50), solver=sgd; total time= 9.0s
[CV] END activation=tanh, alpha=0.001, hidden_layer_sizes=(50, 50), solver=adam; total time= 4.9s
```

```
[CV] END activation=tanh, alpha=0.001, hidden_layer_sizes=(50, 50), solver=adam; total time= 5.5s
[CV] END activation=tanh, alpha=0.001, hidden_layer_sizes=(50, 50), solver=adam; total time= 4.6s
[CV] END activation=tanh, alpha=0.001, hidden_layer_sizes=(100, 100), solver=sgd; total time= 8.5s
[CV] END activation=tanh, alpha=0.001, hidden_layer_sizes=(100, 100), solver=sgd; total time= 7.5s
[CV] END activation=tanh, alpha=0.001, hidden_layer_sizes=(100, 100), solver=sgd; total time= 8.4s
[CV] END activation=tanh, alpha=0.001, hidden_layer_sizes=(100, 100), solver=adam; total time= 4.5s
[CV] END activation=tanh, alpha=0.001, hidden_layer_sizes=(100, 100), solver=adam; total time= 4.6s
[CV] END activation=tanh, alpha=0.001, hidden_layer_sizes=(100, 100), solver=adam; total time= 4.9s
[CV] END activation=tanh, alpha=0.01, hidden_layer_sizes=(50,), solver=sgd; total time= 4.5s
[CV] END activation=tanh, alpha=0.01, hidden_layer_sizes=(50,), solver=sgd; total time= 4.5s
[CV] END activation=tanh, alpha=0.01, hidden_layer_sizes=(50,), solver=sgd; total time= 4.9s
[CV] END activation=tanh, alpha=0.01, hidden_layer_sizes=(50,), solver=adam; total time= 5.4s
[CV] END activation=tanh, alpha=0.01, hidden_layer_sizes=(50,), solver=adam; total time= 5.2s
[CV] END activation=tanh, alpha=0.01, hidden_layer_sizes=(50,), solver=adam; total time= 5.6s
[CV] END activation=tanh, alpha=0.01, hidden_layer_sizes=(100,), solver=sgd; total time= 5.3s
[CV] END activation=tanh, alpha=0.01, hidden_layer_sizes=(100,), solver=sgd; total time= 5.0s
[CV] END activation=tanh, alpha=0.01, hidden_layer_sizes=(100,), solver=sgd; total time= 5.5s
[CV] END activation=tanh, alpha=0.01, hidden_layer_sizes=(100,), solver=adam; total time= 5.7s
[CV] END activation=tanh, alpha=0.01, hidden_layer_sizes=(100,), solver=adam; total time= 5.9s
[CV] END activation=tanh, alpha=0.01, hidden_layer_sizes=(100,), solver=adam; total time= 5.8s
[CV] END activation=tanh, alpha=0.01, hidden_layer_sizes=(50, 50), solver=sgd; total time= 8.8s
[CV] END activation=tanh, alpha=0.01, hidden_layer_sizes=(50, 50), solver=sgd; total time= 7.9s
[CV] END activation=tanh, alpha=0.01, hidden_layer_sizes=(50, 50), solver=sgd; total time= 8.9s
[CV] END activation=tanh, alpha=0.01, hidden_layer_sizes=(50, 50), solver=adam; total time= 5.0s
[CV] END activation=tanh, alpha=0.01, hidden_layer_sizes=(50, 50), solver=adam; total time= 5.5s
[CV] END activation=tanh, alpha=0.01, hidden_layer_sizes=(50, 50), solver=adam; total time= 4.6s
[CV] END activation=tanh, alpha=0.01, hidden_layer_sizes=(100, 100), solver=sgd; total time= 8.5s
[CV] END activation=tanh, alpha=0.01, hidden_layer_sizes=(100, 100), solver=sgd; total time= 7.5s
[CV] END activation=tanh, alpha=0.01, hidden_layer_sizes=(100, 100), solver=sgd; total time= 8.4s
[CV] END activation=tanh, alpha=0.01, hidden_layer_sizes=(100, 100), solver=adam; total time= 4.5s
[CV] END activation=tanh, alpha=0.01, hidden_layer_sizes=(100, 100), solver=adam; total time= 4.6s
[CV] END activation=tanh, alpha=0.01, hidden_layer_sizes=(100, 100), solver=adam; total time= 5.3s
[CV] END activation=relu, alpha=0.0001, hidden_layer_sizes=(50,), solver=sgd; total time= 5.8s
[CV] END activation=relu, alpha=0.0001, hidden_layer_sizes=(50,), solver=sgd; total time= 5.5s
[CV] END activation=relu, alpha=0.0001, hidden_layer_sizes=(50,), solver=sgd; total time= 5.8s
[CV] END activation=relu, alpha=0.0001, hidden_layer_sizes=(50,), solver=adam; total time= 4.2s
[CV] END activation=relu, alpha=0.0001, hidden_layer_sizes=(50,), solver=adam; total time= 3.9s
[CV] END activation=relu, alpha=0.0001, hidden_layer_sizes=(50,), solver=adam; total time= 4.0s
[CV] END activation=relu, alpha=0.0001, hidden_layer_sizes=(100,), solver=sgd; total time= 6.9s
[CV] END activation=relu, alpha=0.0001, hidden_layer_sizes=(100,), solver=sgd; total time= 6.8s
[CV] END activation=relu, alpha=0.0001, hidden_layer_sizes=(100,), solver=sgd; total time= 7.0s
```



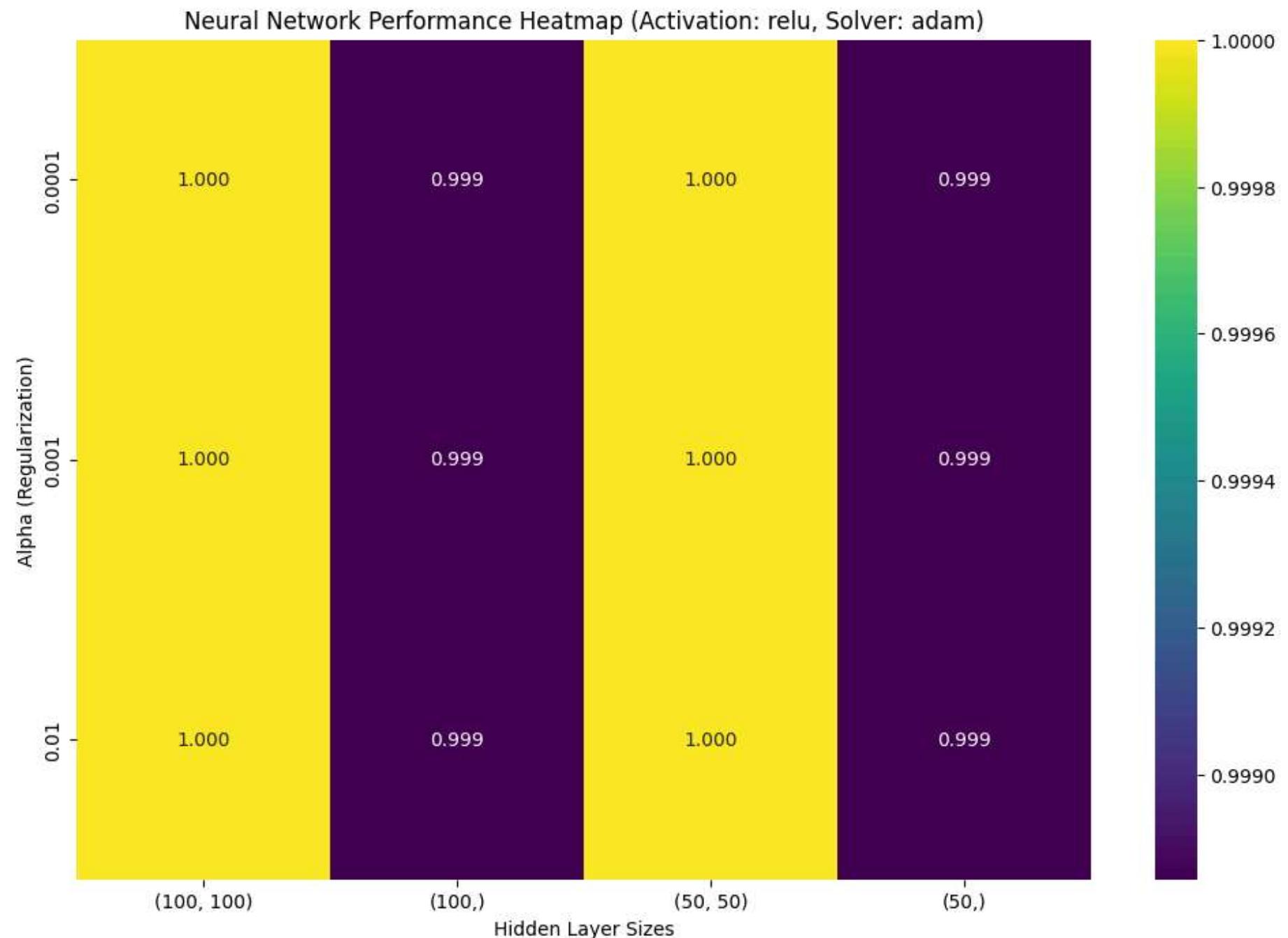
```
[CV] END activation=relu, alpha=0.01, hidden_layer_sizes=(50,), solver=sgd; total time= 5.9s
[CV] END activation=relu, alpha=0.01, hidden_layer_sizes=(50,), solver=adam; total time= 3.8s
[CV] END activation=relu, alpha=0.01, hidden_layer_sizes=(50,), solver=adam; total time= 3.9s
[CV] END activation=relu, alpha=0.01, hidden_layer_sizes=(50,), solver=adam; total time= 4.0s
[CV] END activation=relu, alpha=0.01, hidden_layer_sizes=(100,), solver=sgd; total time= 6.9s
[CV] END activation=relu, alpha=0.01, hidden_layer_sizes=(100,), solver=sgd; total time= 6.9s
[CV] END activation=relu, alpha=0.01, hidden_layer_sizes=(100,), solver=sgd; total time= 7.0s
[CV] END activation=relu, alpha=0.01, hidden_layer_sizes=(100,), solver=adam; total time= 4.4s
[CV] END activation=relu, alpha=0.01, hidden_layer_sizes=(100,), solver=adam; total time= 4.1s
[CV] END activation=relu, alpha=0.01, hidden_layer_sizes=(100,), solver=adam; total time= 4.0s
[CV] END activation=relu, alpha=0.01, hidden_layer_sizes=(50, 50), solver=sgd; total time= 12.7s
[CV] END activation=relu, alpha=0.01, hidden_layer_sizes=(50, 50), solver=sgd; total time= 10.6s
[CV] END activation=relu, alpha=0.01, hidden_layer_sizes=(50, 50), solver=sgd; total time= 11.3s
[CV] END activation=relu, alpha=0.01, hidden_layer_sizes=(50, 50), solver=adam; total time= 3.2s
[CV] END activation=relu, alpha=0.01, hidden_layer_sizes=(50, 50), solver=adam; total time= 4.0s
[CV] END activation=relu, alpha=0.01, hidden_layer_sizes=(50, 50), solver=adam; total time= 3.0s
[CV] END activation=relu, alpha=0.01, hidden_layer_sizes=(100, 100), solver=sgd; total time= 13.1s
[CV] END activation=relu, alpha=0.01, hidden_layer_sizes=(100, 100), solver=sgd; total time= 11.9s
[CV] END activation=relu, alpha=0.01, hidden_layer_sizes=(100, 100), solver=sgd; total time= 13.2s
[CV] END activation=relu, alpha=0.01, hidden_layer_sizes=(100, 100), solver=adam; total time= 2.8s
[CV] END activation=relu, alpha=0.01, hidden_layer_sizes=(100, 100), solver=adam; total time= 3.3s
[CV] END activation=relu, alpha=0.01, hidden_layer_sizes=(100, 100), solver=adam; total time= 2.8s
Best Neural Network Parameters: {'activation': 'tanh', 'alpha': 0.0001, 'hidden_layer_sizes': (50, 50), 'solver': 'adam'}
Best Neural Network Score: 1.0
Test Set Accuracy: 1.0
```

```
In [18]: # Extracting results from the GridSearchCV object
results = pd.DataFrame(grid_search_nn.cv_results_)
params = results[['param_hidden_layer_sizes', 'param_alpha', 'mean_test_score']]
params['param_alpha'] = params['param_alpha'].astype(float)
params['mean_test_score'] = params['mean_test_score'].astype(float)

# Converting tuple representation for easier plotting
params['param_hidden_layer_sizes'] = params['param_hidden_layer_sizes'].apply(lambda x: str(x))

# Creating a pivot table for a chosen activation and solver, example: 'relu' and 'adam'
chosen_activation = 'relu'
chosen_solver = 'adam'
filtered_params = params[(results['param_activation'] == chosen_activation) & (results['param_solver'] == chosen_solver)]
pivot = filtered_params.pivot_table(index='param_alpha', columns='param_hidden_layer_sizes', values='mean_test_score')
```

```
# Plotting the heatmap
plt.figure(figsize=(12, 8))
sns.heatmap(pivot, annot=True, fmt=".3f", cmap='viridis', cbar=True)
plt.title(f'Neural Network Performance Heatmap (Activation: {chosen_activation}, Solver: {chosen_solver})')
plt.xlabel('Hidden Layer Sizes')
plt.ylabel('Alpha (Regularization)')
plt.show()
```



```
In [19]: from sklearn.tree import DecisionTreeClassifier
from sklearn.model_selection import GridSearchCV
import matplotlib.pyplot as plt
import seaborn as sns
import pandas as pd

# Decision Tree hyperparameters
param_grid_dt = {
    'max_depth': [None, 10, 20, 30, 40],
    'min_samples_split': [2, 10, 20],
    'min_samples_leaf': [1, 5, 10]
}

# Creating the GridSearchCV object
grid_search_dt = GridSearchCV(DecisionTreeClassifier(), param_grid_dt, refit=True, verbose=2, cv=3)
grid_search_dt.fit(X_train, y_train)

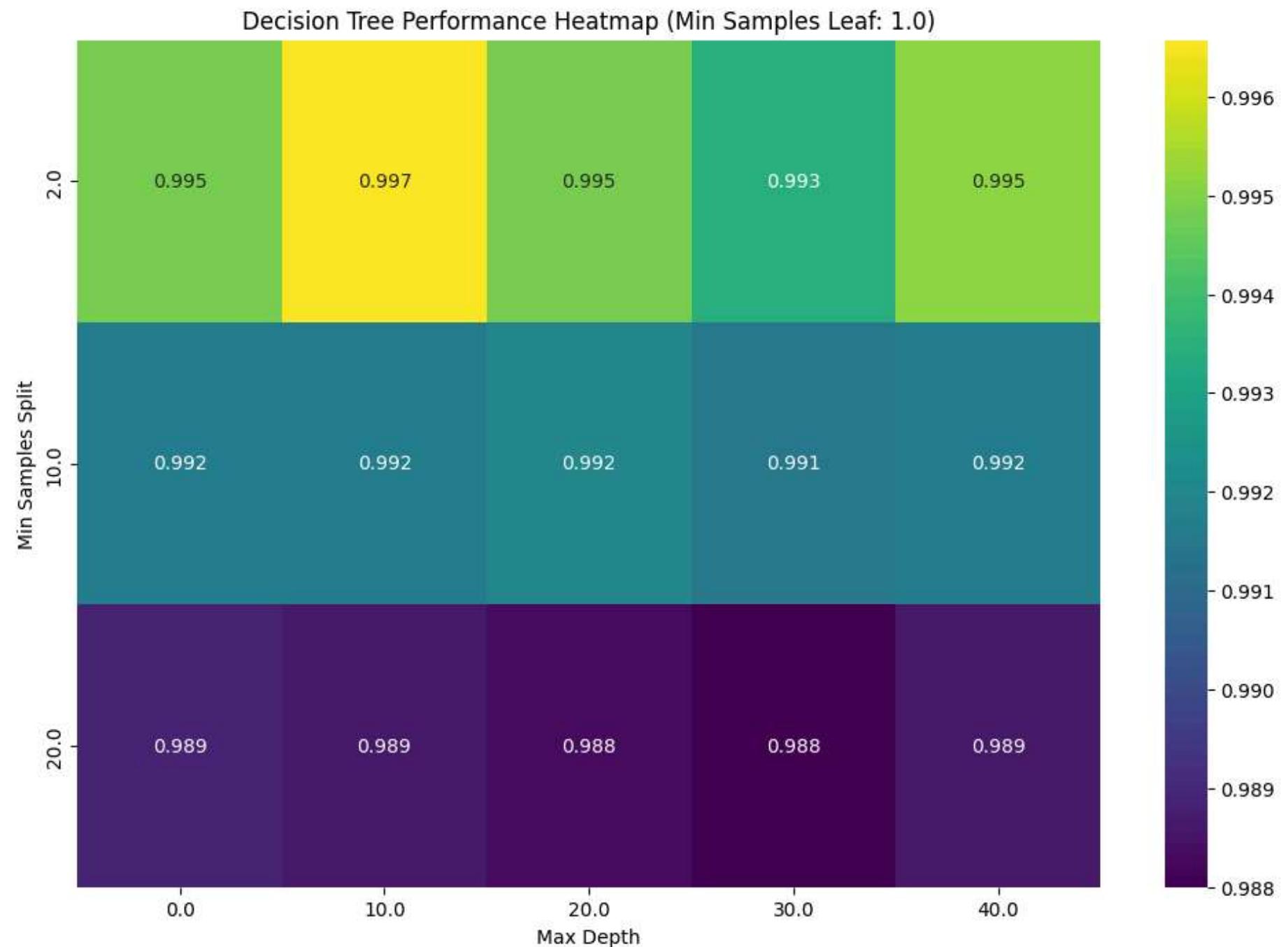
# Displaying the best parameters and the score achieved with them
print("Best Decision Tree Parameters:", grid_search_dt.best_params_)
print("Best Decision Tree Score:", grid_search_dt.best_score_)
```

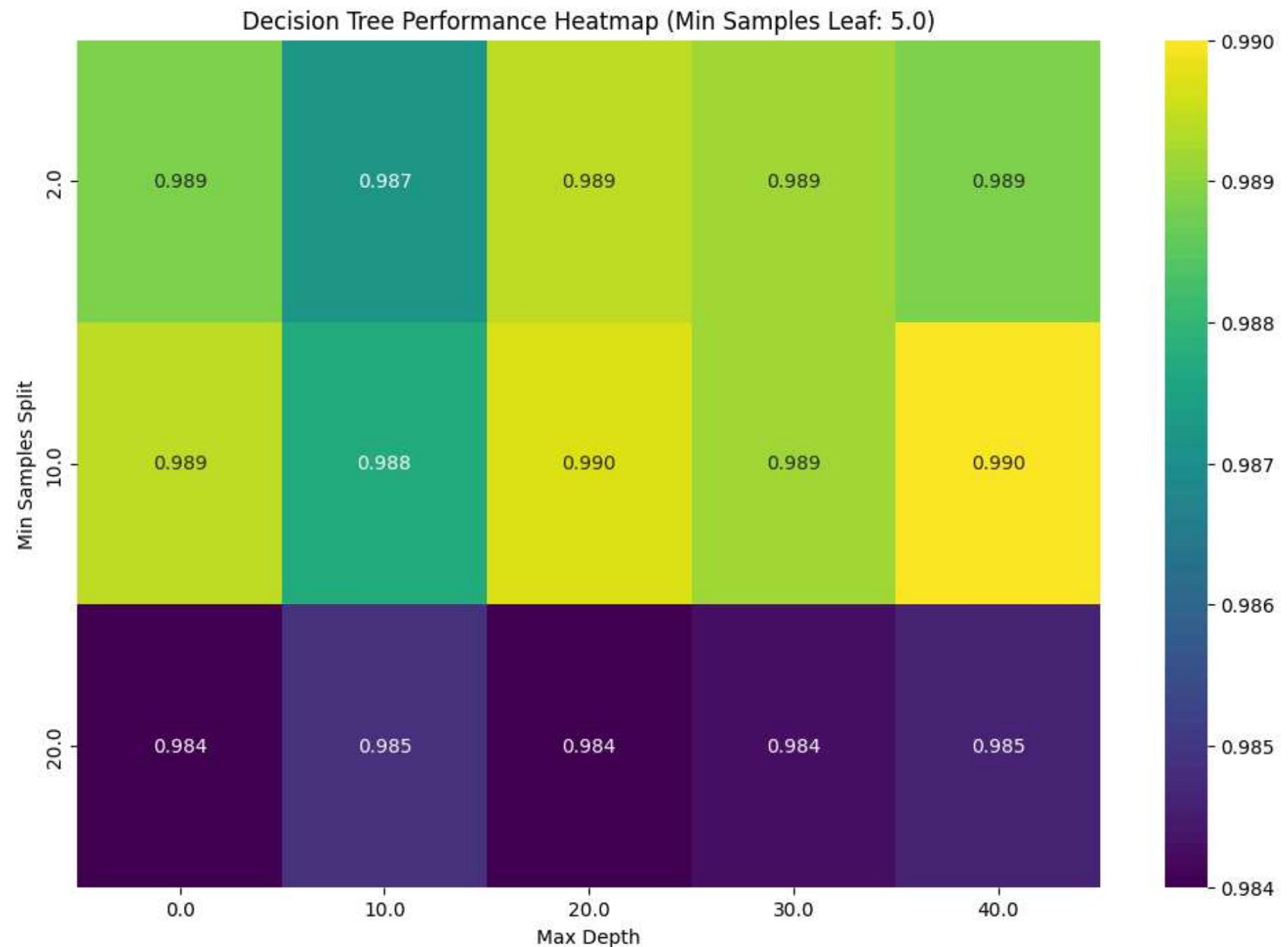


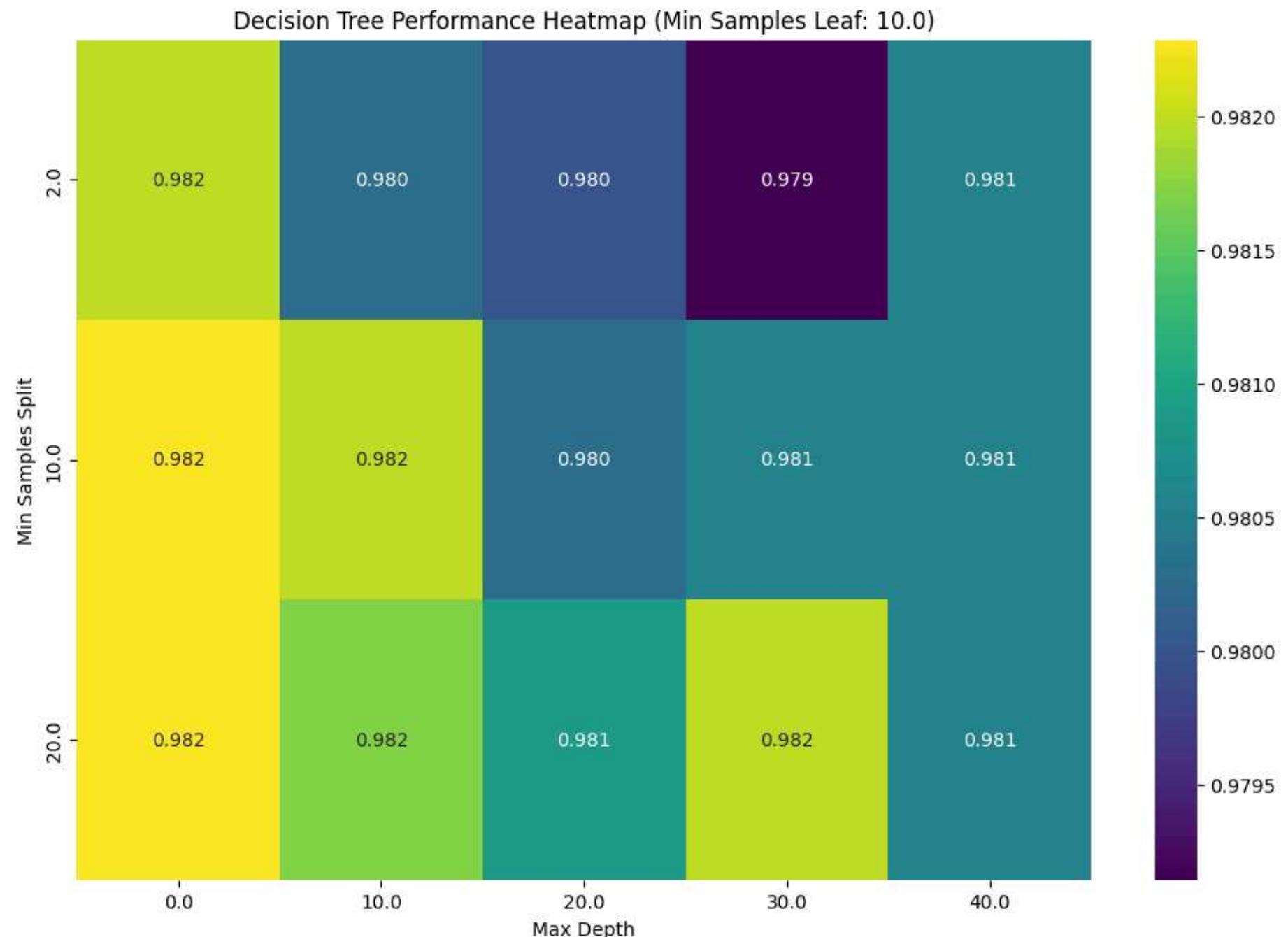
```
[CV] END max_depth=40, min_samples_leaf=5, min_samples_split=10; total time= 0.0s
[CV] END max_depth=40, min_samples_leaf=5, min_samples_split=20; total time= 0.0s
[CV] END max_depth=40, min_samples_leaf=5, min_samples_split=20; total time= 0.0s
[CV] END max_depth=40, min_samples_leaf=5, min_samples_split=20; total time= 0.0s
[CV] END max_depth=40, min_samples_leaf=10, min_samples_split=2; total time= 0.0s
[CV] END max_depth=40, min_samples_leaf=10, min_samples_split=2; total time= 0.0s
[CV] END max_depth=40, min_samples_leaf=10, min_samples_split=2; total time= 0.0s
[CV] END max_depth=40, min_samples_leaf=10, min_samples_split=10; total time= 0.0s
[CV] END max_depth=40, min_samples_leaf=10, min_samples_split=10; total time= 0.0s
[CV] END max_depth=40, min_samples_leaf=10, min_samples_split=10; total time= 0.0s
[CV] END max_depth=40, min_samples_leaf=10, min_samples_split=20; total time= 0.0s
[CV] END max_depth=40, min_samples_leaf=10, min_samples_split=20; total time= 0.0s
[CV] END max_depth=40, min_samples_leaf=10, min_samples_split=20; total time= 0.0s
Best Decision Tree Parameters: {'max_depth': 10, 'min_samples_leaf': 1, 'min_samples_split': 2}
Best Decision Tree Score: 0.9965716729794917
```

```
In [20]: # Extracting results from the GridSearchCV object
results = pd.DataFrame(grid_search_dt.cv_results_)
params = results[['param_max_depth', 'param_min_samples_split', 'param_min_samples_leaf', 'mean_test_score']]
params['param_max_depth'] = params['param_max_depth'].astype(float).fillna(0) # Convert 'None' to a numeric value if needed
params['param_min_samples_split'] = params['param_min_samples_split'].astype(float)
params['param_min_samples_leaf'] = params['param_min_samples_leaf'].astype(float)
params['mean_test_score'] = params['mean_test_score'].astype(float)

# Plotting the heatmaps for each 'min_samples_Leaf'
min_samples_leaves = params['param_min_samples_leaf'].unique()
for leaf in min_samples_leaves:
    pivot = params[params['param_min_samples_leaf'] == leaf].pivot_table(
        index='param_min_samples_split',
        columns='param_max_depth',
        values='mean_test_score'
    )
    plt.figure(figsize=(12, 8))
    sns.heatmap(pivot, annot=True, fmt=".3f", cmap='viridis', cbar=True)
    plt.title(f'Decision Tree Performance Heatmap (Min Samples Leaf: {leaf})')
    plt.xlabel('Max Depth')
    plt.ylabel('Min Samples Split')
    plt.show()
```







```
In [21]: from sklearn.svm import SVC
from sklearn.model_selection import GridSearchCV
import matplotlib.pyplot as plt
import seaborn as sns
import pandas as pd

# SVM hyperparameters
param_grid_svm = {
    'C': [0.1, 1, 10],
    'gamma': ['scale', 0.1, 0.01],
    'kernel': ['rbf', 'linear']
}

# Creating the GridSearchCV object
grid_search_svm = GridSearchCV(SVC(), param_grid_svm, refit=True, verbose=2, cv=3)
grid_search_svm.fit(X_train, y_train)

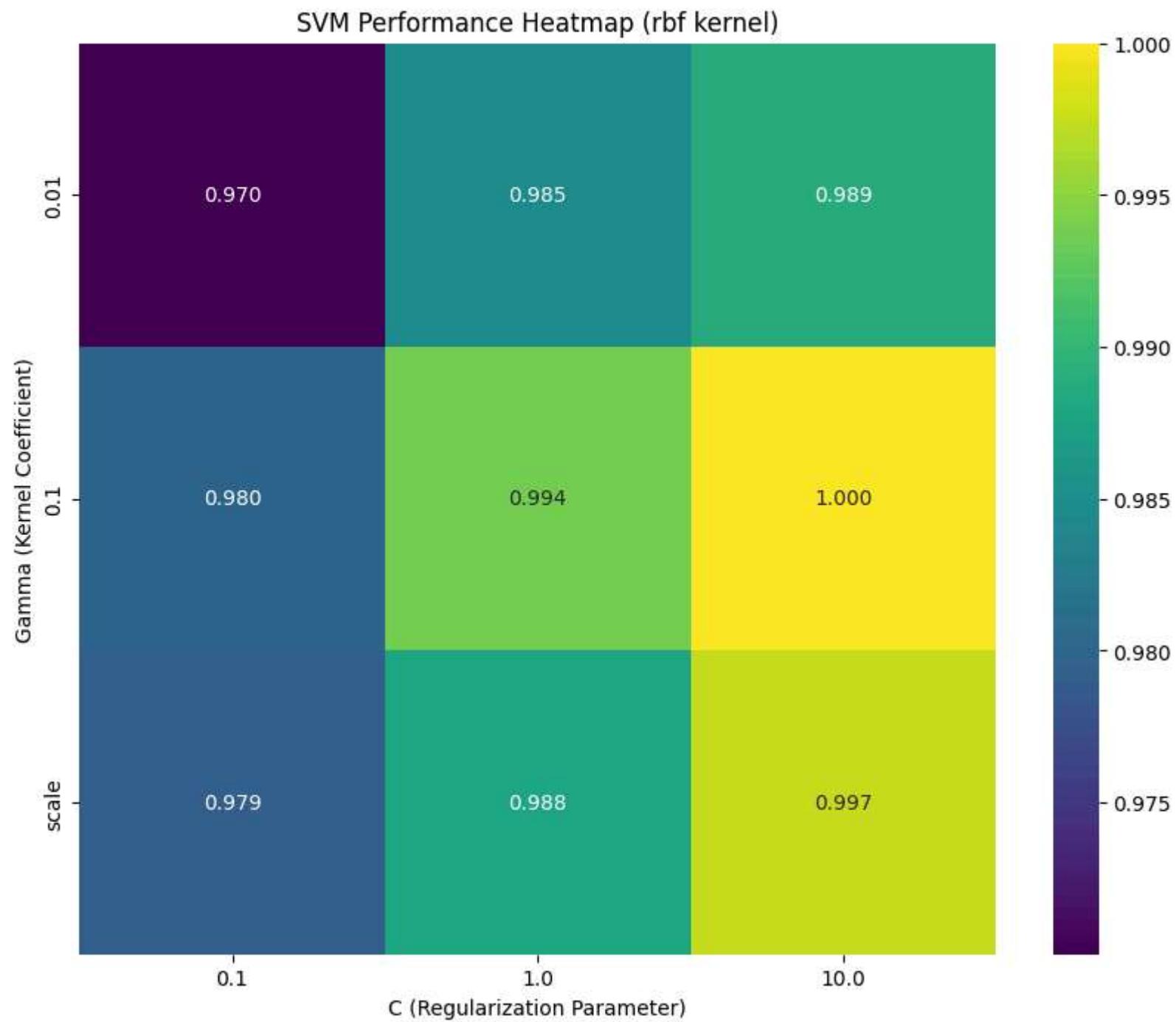
# Displaying the best parameters and the score achieved with them
print("Best SVM Parameters:", grid_search_svm.best_params_)
print("Best SVM Score:", grid_search_svm.best_score_)
```

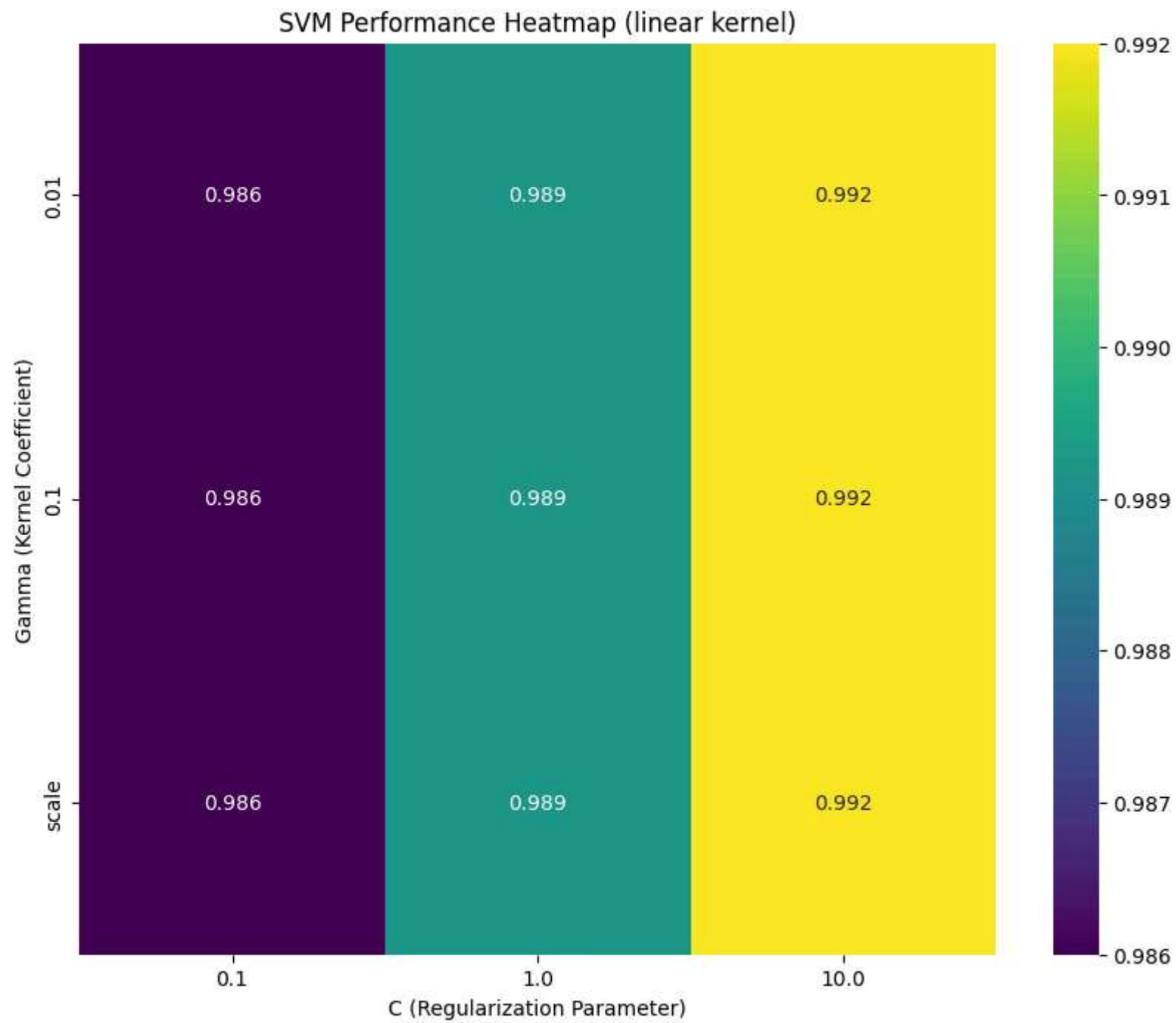
```
Fitting 3 folds for each of 18 candidates, totalling 54 fits
[CV] END .....C=0.1, gamma=scale, kernel=rbf; total time= 0.2s
[CV] END .....C=0.1, gamma=scale, kernel=rbf; total time= 0.3s
[CV] END .....C=0.1, gamma=scale, kernel=rbf; total time= 0.2s
[CV] END .....C=0.1, gamma=scale, kernel=linear; total time= 0.0s
[CV] END .....C=0.1, gamma=scale, kernel=linear; total time= 0.0s
[CV] END .....C=0.1, gamma=scale, kernel=linear; total time= 0.0s
[CV] END .....C=0.1, gamma=0.1, kernel=rbf; total time= 0.5s
[CV] END .....C=0.1, gamma=0.1, kernel=rbf; total time= 0.4s
[CV] END .....C=0.1, gamma=0.1, kernel=rbf; total time= 0.4s
[CV] END .....C=0.1, gamma=0.1, kernel=linear; total time= 0.0s
[CV] END .....C=0.1, gamma=0.1, kernel=linear; total time= 0.0s
[CV] END .....C=0.1, gamma=0.1, kernel=linear; total time= 0.0s
[CV] END .....C=0.1, gamma=0.01, kernel=rbf; total time= 0.3s
[CV] END .....C=0.1, gamma=0.01, kernel=rbf; total time= 0.3s
[CV] END .....C=0.1, gamma=0.01, kernel=rbf; total time= 0.2s
[CV] END .....C=0.1, gamma=0.01, kernel=linear; total time= 0.0s
[CV] END .....C=0.1, gamma=0.01, kernel=linear; total time= 0.0s
[CV] END .....C=0.1, gamma=0.01, kernel=linear; total time= 0.0s
[CV] END .....C=1, gamma=scale, kernel=rbf; total time= 0.1s
[CV] END .....C=1, gamma=scale, kernel=rbf; total time= 0.0s
[CV] END .....C=1, gamma=scale, kernel=rbf; total time= 0.1s
[CV] END .....C=1, gamma=scale, kernel=linear; total time= 0.0s
[CV] END .....C=1, gamma=scale, kernel=linear; total time= 0.0s
[CV] END .....C=1, gamma=scale, kernel=linear; total time= 0.0s
[CV] END .....C=1, gamma=0.1, kernel=rbf; total time= 0.1s
[CV] END .....C=1, gamma=0.1, kernel=rbf; total time= 0.1s
[CV] END .....C=1, gamma=0.1, kernel=rbf; total time= 0.1s
[CV] END .....C=1, gamma=0.1, kernel=linear; total time= 0.0s
[CV] END .....C=1, gamma=0.1, kernel=linear; total time= 0.0s
[CV] END .....C=1, gamma=0.1, kernel=linear; total time= 0.0s
[CV] END .....C=1, gamma=0.01, kernel=rbf; total time= 0.1s
[CV] END .....C=1, gamma=0.01, kernel=rbf; total time= 0.1s
[CV] END .....C=1, gamma=0.01, kernel=rbf; total time= 0.1s
[CV] END .....C=1, gamma=0.01, kernel=linear; total time= 0.0s
[CV] END .....C=1, gamma=0.01, kernel=linear; total time= 0.0s
[CV] END .....C=1, gamma=0.01, kernel=linear; total time= 0.0s
[CV] END .....C=10, gamma=scale, kernel=rbf; total time= 0.0s
[CV] END .....C=10, gamma=scale, kernel=rbf; total time= 0.0s
[CV] END .....C=10, gamma=scale, kernel=rbf; total time= 0.0s
[CV] END .....C=10, gamma=scale, kernel=linear; total time= 0.0s
```

```
[CV] END .....C=10, gamma=scale, kernel=linear; total time= 0.0s
[CV] END .....C=10, gamma=scale, kernel=linear; total time= 0.1s
[CV] END .....C=10, gamma=0.1, kernel=rbf; total time= 0.1s
[CV] END .....C=10, gamma=0.1, kernel=rbf; total time= 0.1s
[CV] END .....C=10, gamma=0.1, kernel=rbf; total time= 0.1s
[CV] END .....C=10, gamma=0.1, kernel=linear; total time= 0.0s
[CV] END .....C=10, gamma=0.1, kernel=linear; total time= 0.0s
[CV] END .....C=10, gamma=0.1, kernel=linear; total time= 0.1s
[CV] END .....C=10, gamma=0.01, kernel=rbf; total time= 0.0s
[CV] END .....C=10, gamma=0.01, kernel=rbf; total time= 0.0s
[CV] END .....C=10, gamma=0.01, kernel=rbf; total time= 0.0s
[CV] END .....C=10, gamma=0.01, kernel=linear; total time= 0.0s
[CV] END .....C=10, gamma=0.01, kernel=linear; total time= 0.0s
[CV] END .....C=10, gamma=0.01, kernel=linear; total time= 0.1s
Best SVM Parameters: {'C': 10, 'gamma': 0.1, 'kernel': 'rbf'}
Best SVM Score: 1.0
```

```
In [22]: # Extracting results from the GridSearchCV object
results = pd.DataFrame(grid_search_svm.cv_results_)
params = results[['param_C', 'param_gamma', 'param_kernel', 'mean_test_score']]
params['param_C'] = params['param_C'].astype(float)
params['param_gamma'] = params['param_gamma'].astype(str)
params['mean_test_score'] = params['mean_test_score'].astype(float)

# Create pivot tables for each kernel type and plot them
for kernel in params['param_kernel'].unique():
    pivot = params[params['param_kernel'] == kernel].pivot_table(
        index='param_gamma',
        columns='param_C',
        values='mean_test_score'
    )
    plt.figure(figsize=(10, 8))
    sns.heatmap(pivot, annot=True, fmt=".3f", cmap='viridis')
    plt.title(f'SVM Performance Heatmap ({kernel} kernel)')
    plt.xlabel('C (Regularization Parameter)')
    plt.ylabel('Gamma (Kernel Coefficient)')
    plt.show()
```





```
In [23]: from sklearn.metrics import roc_curve, auc, accuracy_score, classification_report
from sklearn.preprocessing import LabelEncoder

# Encode Labels
encoder = LabelEncoder()
y_train = encoder.fit_transform(y_train)
y_test = encoder.transform(y_test)

models = {
    'SVM': SVC(probability=True),
    'Decision Tree': DecisionTreeClassifier(),
    'Neural Network': MLPClassifier(max_iter=1000)
}

results = {}
for name, model in models.items():
    model.fit(X_train, y_train)
    predictions = model.predict(X_test)
    probability = model.predict_proba(X_test)[:, 1] # Assuming positive class is 1
    fpr, tpr, _ = roc_curve(y_test, probability, pos_label=1)
    auc_score = auc(fpr, tpr)

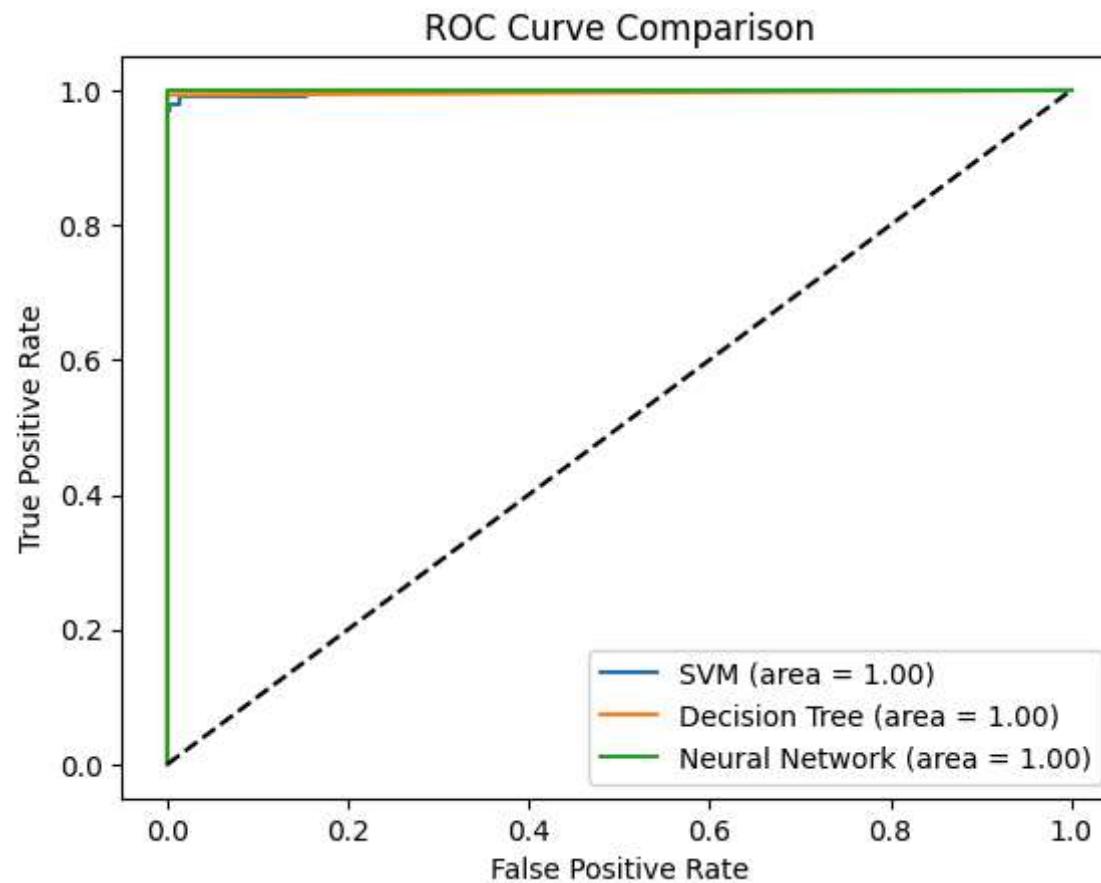
    results[name] = {
        'Accuracy': accuracy_score(y_test, predictions),
        'ROC AUC': auc_score,
        'Classification Report': classification_report(y_test, predictions, output_dict=True)
    }

# Plotting ROC Curve
plt.plot(fpr, tpr, label=f'{name} (area = {auc_score:.2f})')

plt.plot([0, 1], [0, 1], 'k--')
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('ROC Curve Comparison')
plt.legend(loc='best')
plt.show()

# Print the results
```

```
for model_name, metrics in results.items():
    print(f'\n{model_name} Model Metrics:')
    print('Accuracy:', metrics['Accuracy'])
    print('ROC AUC:', metrics['ROC AUC'])
    print('Classification Report:')
    print(pd.DataFrame(metrics['Classification Report']).transpose())
```



SVM Model Metrics:

Accuracy: 0.9886666666666667

ROC AUC: 0.9983545450212116

Classification Report:

	precision	recall	f1-score	support
0	0.982328	1.000000	0.991085	945.000000
1	1.000000	0.969369	0.984446	555.000000
accuracy	0.988667	0.988667	0.988667	0.988667
macro avg	0.991164	0.984685	0.987766	1500.000000
weighted avg	0.988867	0.988667	0.988629	1500.000000

Decision Tree Model Metrics:

Accuracy: 0.9973333333333333

ROC AUC: 0.9963963963963964

Classification Report:

	precision	recall	f1-score	support
0	0.995785	1.000000	0.997888	945.000000
1	1.000000	0.992793	0.996383	555.000000
accuracy	0.997333	0.997333	0.997333	0.997333
macro avg	0.997893	0.996396	0.997136	1500.000000
weighted avg	0.997345	0.997333	0.997331	1500.000000

Neural Network Model Metrics:

Accuracy: 1.0

ROC AUC: 1.0

Classification Report:

	precision	recall	f1-score	support
0	1.0	1.0	1.0	945.0
1	1.0	1.0	1.0	555.0
accuracy	1.0	1.0	1.0	1.0
macro avg	1.0	1.0	1.0	1500.0
weighted avg	1.0	1.0	1.0	1500.0

```
In [24]: from sklearn.svm import SVC
from sklearn.tree import DecisionTreeClassifier
from sklearn.neural_network import MLPClassifier
import time

# Initialize classifiers
svm_classifier = SVC()
decision_tree_classifier = DecisionTreeClassifier()
```

```
mlp_classifier = MLPClassifier()

classifiers = {
    "SVM": svm_classifier,
    "Decision Tree": decision_tree_classifier,
    "MLP": mlp_classifier
}

# Training time comparison
training_times = {}
for name, clf in classifiers.items():
    start_time = time.time()
    clf.fit(X_train, y_train)
    end_time = time.time()
    training_times[name] = end_time - start_time

# Prediction time comparison
prediction_times = {}
for name, clf in classifiers.items():
    start_time = time.time()
    clf.predict(X_test)
    end_time = time.time()
    prediction_times[name] = end_time - start_time

# Print out training and prediction times
print("Training Times:")
for name, time_taken in training_times.items():
    print(f"{name}: {time_taken:.4f} seconds")

print("\nPrediction Times:")
for name, time_taken in prediction_times.items():
    print(f"{name}: {time_taken:.4f} seconds")
```

Training Times:

SVM: 0.1137 seconds

Decision Tree: 0.1665 seconds

MLP: 5.4011 seconds

Prediction Times:

SVM: 0.1005 seconds

Decision Tree: 0.0000 seconds

MLP: 0.0121 seconds

In [25]:

```
import matplotlib.pyplot as plt
import numpy as np

# Names of the models
models = ['SVM', 'Decision Tree', 'Neural Network']

# Metrics to compare
accuracy = [0.98, 0.99, 1.0]
precision = [0.98, 0.99, 1.0]
recall = [1.00, 1.0, 1.0]
f1_scores = [0.99, 0.99, 1.0]

# Creating index for each tick in bar plot
bar_width = 0.25
r1 = np.arange(len(accuracy))
r2 = [x + bar_width for x in r1]
r3 = [x + bar_width for x in r2]

# Creating the bar plot
plt.figure(figsize=(10, 5))
plt.bar(r1, accuracy, color='b', width=bar_width, edgecolor='grey', label='Accuracy')
plt.bar(r2, precision, color='r', width=bar_width, edgecolor='grey', label='Precision')
plt.bar(r3, recall, color='g', width=bar_width, edgecolor='grey', label='Recall')

# Adding Labels
plt.xlabel('Models', fontweight='bold', fontsize=15)
plt.xticks([r + bar_width for r in range(len(accuracy))], models)
plt.ylabel('Metrics')
plt.title('Comparison of Machine Learning Models')

# Create legend & Show graphic
```

```
plt.legend()  
plt.show()
```

