Report Analysis Home Assignment 5

1. Input data

```
from sklearn.datasets import make_blobs

n_samples_1 = 1000
n_samples_2 = 100
centers = [[0.0, 0.0], [2.0, 2.0]]
clusters_std = [1.5, 0.5]

X_blobs, y_blobs = make_blobs(n_samples=[n_samples_1, n_samples_2],
                              centers=centers,
                              cluster_std=clusters_std,
                              random_state=0, shuffle=False)
print(X_blobs, y_blobs)
```

```
[[ 2.64607852  0.60023581]
 [ 1.46810698  3.3613398 ]
 [ 2.80133699 -1.46591682]
 ...
 [ 1.68550965  2.53503626]
 [ 1.68945865  2.86728609]
 [ 1.45085528  2.28630668]] [0 0 0 ... 1 1 1]
```

In the initial stage, the sample data is given as input for the cluster named x_blobs and labels are given as y_blobs. Here is the following output with input codes for first step (a).

2. Input data another dataset for the task.

```
from sklearn.datasets import make_circles

X_circles, y_circles = make_circles(500, factor=0.1, noise=0.1)
print(X_circles, y_circles)
```

Output of this data set is.

```
[[ 1.47134451e-01  4.01869085e-02]
 [ 1.52481027e-01 -3.23220864e-01]
 [-5.12567084e-01  8.65794692e-01]
 [ 5.81100581e-02  4.86311744e-03]
 [ 9.54114999e-01 -3.89511692e-01]
 [ 2.56223868e-01  2.06433993e-01]
 [-2.08548980e-01  1.54664837e-01]
 [-1.98656510e-01  1.12280809e-01]
 [-5.07226667e-01 -5.87821855e-01]
 [-5.48517200e-02  7.67338492e-02]
 [ 1.08796360e+00 -2.91252871e-02]
 [-1.27054438e-01  1.55751306e-01]
 [ 3.51948861e-02  2.64501472e-01]
 [-1.01911736e+00  2.79414906e-01]
 [ 9.49080138e-01  3.11553017e-02]
 [-1.74463435e-01 -7.82435682e-02]
 [-1.53032836e-01  6.95498245e-02]
 [ 1.25845757e-01  1.28902748e-01]
```

```
 [ 1.25413069e-01  1.01207340e-01]] [1 1 0 1 0 1 1 1 0 1 0 1 1 0 0 1 1 1 1 0 1 1 0 1 0 1 0 0 0 0 1 1 0 0 1 0 1
 1 0 0 1 1 0 0 1 1 1 0 1 1 1 0 1 1 0 1 1 0 1 1 0 0 0 1 0 0 1 1 1 0 0 0 1 1
 1 1 0 0 1 1 0 0 0 1 0 0 1 0 0 1 0 1 1 0 0 0 1 1 0 0 1 0 0 0 1 1 1 0 1 1 1
 0 0 1 1 0 0 1 0 1 0 0 1 1 0 1 1 1 1 0 0 0 0 0 0 0 1 0 0 0 1 1 1 0 1 0 1
 0 1 1 0 1 1 1 0 0 1 0 0 0 0 1 0 0 1 0 0 0 0 0 1 0 0 0 0 1 0 1 0 0 1 1 0 1
 0 0 0 1 1 0 0 0 0 1 1 0 0 0 1 1 1 1 1 1 1 1 1 1 1 0 0 0 0 0 1 1 1 0 1 1
 0 0 1 1 0 1 0 1 0 0 0 0 0 0 1 0 0 0 1 1 1 1 0 0 1 1 1 1 1 1 1 1 1 0 1 0 0
 1 1 1 0 0 1 1 1 1 0 0 0 1 0 0 0 0 1 0 1 0 1 1 0 1 1 1 1 1 0 0 0 1 0 0 0 0
 1 0 1 1 1 1 1 0 1 0 0 0 1 1 0 0 1 1 0 1 0 1 0 0 0 0 0 0 0 1 1 1 1 1 1 1 1
 1 1 0 1 1 1 0 0 1 0 0 1 0 0 0 1 0 1 0 1 1 1 0 0 0 0 0 0 0 1 0 0 0 0 1 1 1
 0 0 0 1 1 0 0 1 0 0 0 1 1 0 0 1 1 1 0 1 1 1 1 0 0 1 1 1 0 1 0 0 0 1 0 0 1
 1 1 0 1 1 1 0 1 1 1 0 0 0 1 1 0 0 0 0 1 1 0 0 0 1 1 0 0 1 1 1 0 0 1 1 1 0
 0 0 1 0 1 0 0 0 1 0 1 1 1 0 0 0 1 1 1 0 1 1 0 0 0 1 0 0 0 0 0 0 1 0 1 1 1
```

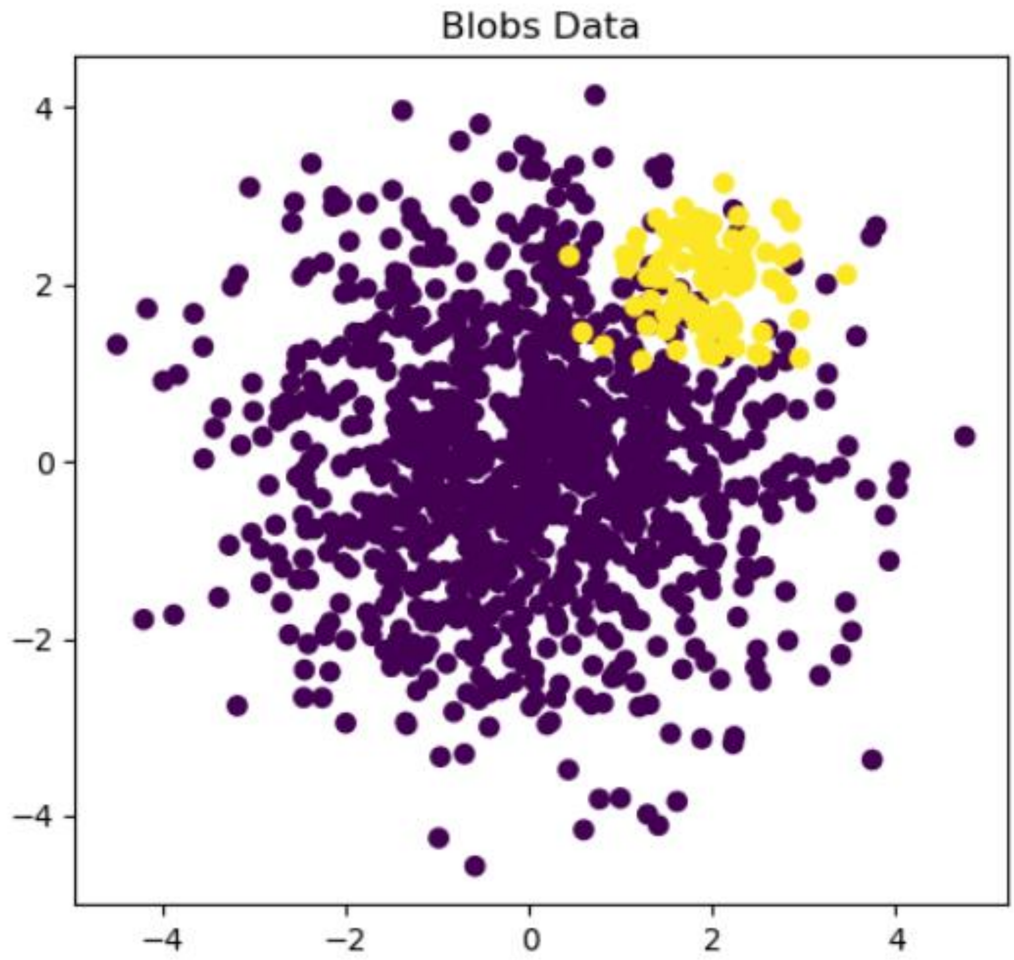
3. With the above input dataset here is the combined code in addition to that I created a graph to visualize both datasets for proper understanding.

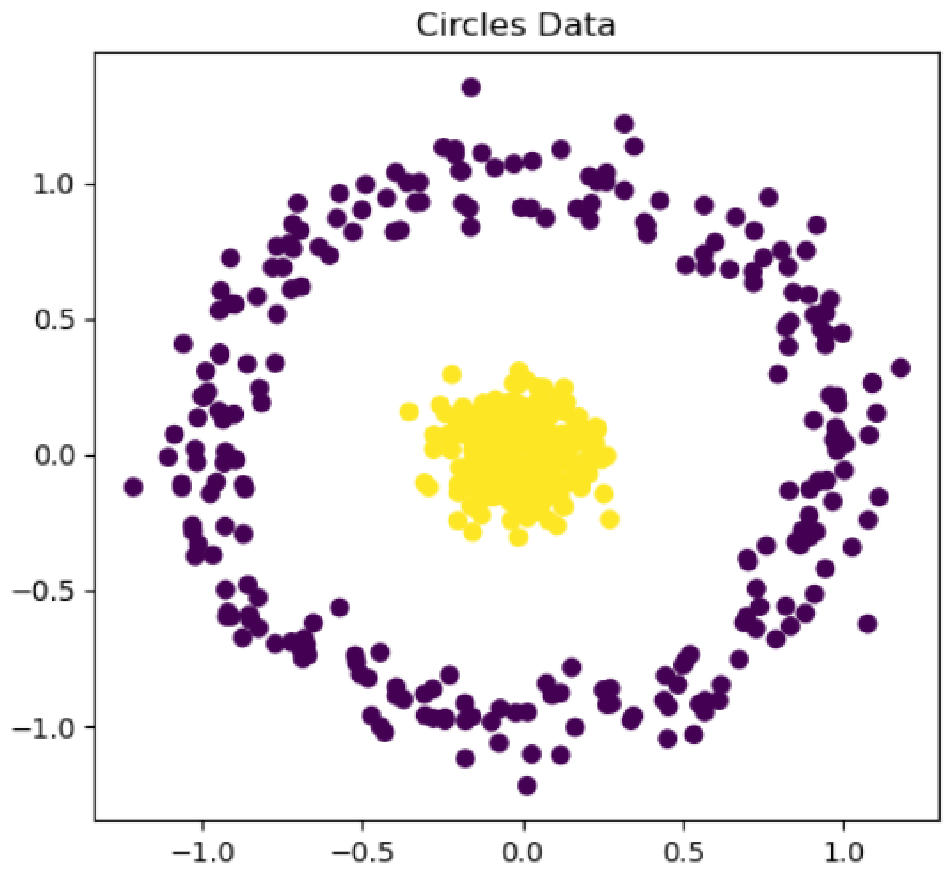
```python
import numpy as np
import matplotlib.pyplot as plt
from sklearn.datasets import make_blobs, make_circles

# Blobs data
n_samples_1 = 1000
n_samples_2 = 100
centers = [[0.0, 0.0], [2.0, 2.0]]
clusters_std = [1.5, 0.5]
X_blobs, y_blobs = make_blobs(n_samples=[n_samples_1, n_samples_2],
                              centers=centers,
                              cluster_std=clusters_std,
                              random_state=0, shuffle=False)

# Circles data
X_circles, y_circles = make_circles(500, factor=0.1, noise=0.1)

# Visualize the datasets
plt.figure(figsize=(12, 5))
plt.subplot(1, 2, 1)
plt.scatter(X_blobs[:, 0], X_blobs[:, 1], c=y_blobs, cmap='viridis')
plt.title('Blobs Data')
plt.subplot(1, 2, 2)
plt.scatter(X_circles[:, 0], X_circles[:, 1], c=y_circles, cmap='viridis')
plt.title('Circles Data')
plt.show()
```


Blobs Data
4
2
0
−2
−4
−4
−2
0
2
4


Circles Data
1.0
0.5
0.0
−0.5
−1.0
−1.0
−0.5
0.0
0.5
1.0

4. In the next step, Divide data for the training, control, and test samples. Control sample used for the hyperparameters setting. Test sample use for the final evaluation of the model quality. Here is the input code.

```
from sklearn.model_selection import train_test_split

# Blobs data split
X_train_blobs, X_temp_blobs, y_train_blobs, y_temp_blobs = train_test_split(X_blobs, y_blobs, test_size=0.4, random_state=0)
X_control_blobs, X_test_blobs, y_control_blobs, y_test_blobs = train_test_split(X_temp_blobs, y_temp_blobs, test_size=0.5, random_state=0)

# Circles data split
X_train_circles, X_temp_circles, y_train_circles, y_temp_circles = train_test_split(X_circles, y_circles, test_size=0.4, random_state=0)
X_control_circles, X_test_circles, y_control_circles, y_test_circles = train_test_split(X_temp_circles, y_temp_circles, test_size=0.5, random_state=0)
```

5. Create NN models with the usage of MLPClassifier. Data should be scaled. The same scaling method should be applied to the training, control, and test data set. For MLPClassifier try to find the best value of the hyperparameters.

```
from sklearn.neural_network import MLPClassifier
from sklearn.preprocessing import StandardScaler

# Scaling
scaler_blobs = StandardScaler().fit(X_train_blobs)
X_train_blobs_scaled = scaler_blobs.transform(X_train_blobs)
X_control_blobs_scaled = scaler_blobs.transform(X_control_blobs)
X_test_blobs_scaled = scaler_blobs.transform(X_test_blobs)

scaler_circles = StandardScaler().fit(X_train_circles)
X_train_circles_scaled = scaler_circles.transform(X_train_circles)
X_control_circles_scaled = scaler_circles.transform(X_control_circles)
X_test_circles_scaled = scaler_circles.transform(X_test_circles)
```

6. Create different architectures of the NN by variation of the hidden_layer_sizes. Use early_stopping=True.Show lost functions at the first and last iterations for each variant.

```
# MLP Classifier with hyperparameter tuning
mlp_blobs = MLPClassifier(hidden_layer_sizes=(50,), max_iter=1000, early_stopping=True, random_state=0)
mlp_blobs.fit(X_train_blobs_scaled, y_train_blobs)

mlp_circles = MLPClassifier(hidden_layer_sizes=(50,), max_iter=1000, early_stopping=True, random_state=0)
mlp_circles.fit(X_train_circles_scaled, y_train_circles)
```

7. Make predictions based on the NN models.

```
# Predictions
y_pred_train_blobs = mlp_blobs.predict(X_train_blobs_scaled)
y_pred_test_blobs = mlp_blobs.predict(X_test_blobs_scaled)

y_pred_train_circles = mlp_circles.predict(X_train_circles_scaled)
y_pred_test_circles = mlp_circles.predict(X_test_circles_scaled)
```

8. Evaluate the quality of the NN models based on accuracy, confusion matrix, precision, recall, F1 score, ROC curve, AUC. Make conclusions.

```python
from sklearn.metrics import accuracy_score, confusion_matrix, precision_score, recall_score, f1_score, roc_curve, auc

def evaluate_model(y_true, y_pred):
    accuracy = accuracy_score(y_true, y_pred)
    precision = precision_score(y_true, y_pred)
    recall = recall_score(y_true, y_pred)
    f1 = f1_score(y_true, y_pred)
    conf_matrix = confusion_matrix(y_true, y_pred)

    return accuracy, precision, recall, f1, conf_matrix

# Blobs data evaluation
accuracy_blobs_train, precision_blobs_train, recall_blobs_train, f1_blobs_train, conf_matrix_blobs_train = evaluate_model(y_train_blobs, y_pred_train_blc
accuracy_blobs_test, precision_blobs_test, recall_blobs_test, f1_blobs_test, conf_matrix_blobs_test = evaluate_model(y_test_blobs, y_pred_test_blobs)

# Circles data evaluation
accuracy_circles_train, precision_circles_train, recall_circles_train, f1_circles_train, conf_matrix_circles_train = evaluate_model(y_train_circles, y_pr
accuracy_circles_test, precision_circles_test, recall_circles_test, f1_circles_test, conf_matrix_circles_test = evaluate_model(y_test_circles, y_pred_tes

# Display the results
print("Blobs Data - Train Accuracy:", accuracy_blobs_train)
print("Blobs Data - Test Accuracy:", accuracy_blobs_test)
print("Circles Data - Train Accuracy:", accuracy_circles_train)
print("Circles Data - Test Accuracy:", accuracy_circles_test)
```

```
Blobs Data - Train Accuracy: 0.9212121212121213
Blobs Data - Test Accuracy: 0.8863636363636364
Circles Data - Train Accuracy: 0.5233333333333333
Circles Data - Test Accuracy: 0.43
```

Analysis table for different hidden layers and selecting best value for our model for both test and train factor.

Hidden Layer Size	Blobs Data - Train Accuracy	Blobs Data - Test Accuracy	Circles Data - Train Accuracy	Circles Data - Test Accuracy
50	0.9212	0.8864	0.5233	0.4300
60	0.9227	0.8864	0.936	0.91
70	0.9212	0.8864	0.6200	0.6700
80	0.9212	0.8864	0.6200	0.6700

Conclusion

As it is clear that with hidden layer size 60 gives better accuracy for both the data set. Moreover, it is equally noticed that the hidden layer for dataset blobs actually does not create a huge impact in most of the cases it is actually at the same time circle data is highly impacted by this moreover for circle data more we are increasing the hidden layer sizes the more accuracy for train and test is reducing.

Finally input code is.

```python
# MLP Classifier with hyperparameter tuning
mlp_blobs = MLPClassifier(hidden_layer_sizes=(60,), max_iter=1000, early_stopping=True, random_state=0)
mlp_blobs.fit(X_train_blobs_scaled, y_train_blobs)

mlp_circles = MLPClassifier(hidden_layer_sizes=(60,), max_iter=1000, early_stopping=True, random_state=0)
mlp_circles.fit(X_train_circles_scaled, y_train_circles)
```

```python
# Predictions
y_pred_train_blobs = mlp_blobs.predict(X_train_blobs_scaled)
y_pred_test_blobs = mlp_blobs.predict(X_test_blobs_scaled)

y_pred_train_circles = mlp_circles.predict(X_train_circles_scaled)
y_pred_test_circles = mlp_circles.predict(X_test_circles_scaled)
```

```python
from sklearn.metrics import accuracy_score, confusion_matrix, precision_score, recall_score, f1_score, roc_curve, auc

def evaluate_model(y_true, y_pred):
    accuracy = accuracy_score(y_true, y_pred)
    precision = precision_score(y_true, y_pred)
    recall = recall_score(y_true, y_pred)
    f1 = f1_score(y_true, y_pred)
    conf_matrix = confusion_matrix(y_true, y_pred)

    return accuracy, precision, recall, f1, conf_matrix

# Blobs data evaluation
accuracy_blobs_train, precision_blobs_train, recall_blobs_train, f1_blobs_train, conf_matrix_blobs_train = evaluate_model(y_train_blobs, y_pred_train_blc
accuracy_blobs_test, precision_blobs_test, recall_blobs_test, f1_blobs_test, conf_matrix_blobs_test = evaluate_model(y_test_blobs, y_pred_test_blobs)

# Circles data evaluation
accuracy_circles_train, precision_circles_train, recall_circles_train, f1_circles_train, conf_matrix_circles_train = evaluate_model(y_train_circles, y_pr
accuracy_circles_test, precision_circles_test, recall_circles_test, f1_circles_test, conf_matrix_circles_test = evaluate_model(y_test_circles, y_pred_tes

# Display the results
print("Blobs Data - Train Accuracy:", accuracy_blobs_train)
print("Blobs Data - Test Accuracy:", accuracy_blobs_test)
print("Circles Data - Train Accuracy:", accuracy_circles_train)
print("Circles Data - Test Accuracy:", accuracy_circles_test)
```

And final output is:-

```
Blobs Data - Train Accuracy: 0.9212121212121213
Blobs Data - Test Accuracy: 0.8818181818181818
Circles Data - Train Accuracy: 0.9366666666666666
Circles Data - Test Accuracy: 0.91
```

9. Create Ensembles of models with the usage of the Random Forest Classifier. Consider different values of max_depth of max_features bootstrap,n_estimators Additionally use VotingClassifier to consider different voting and weights.

```python
from sklearn.ensemble import RandomForestClassifier, VotingClassifier

# Random Forest Classifier
rf_blobs = RandomForestClassifier(n_estimators=100, max_depth=5, random_state=0)
rf_blobs.fit(X_train_blobs_scaled, y_train_blobs)

rf_circles = RandomForestClassifier(n_estimators=100, max_depth=5, random_state=0)
rf_circles.fit(X_train_circles_scaled, y_train_circles)

# Voting Classifier
voting_clf_blobs = VotingClassifier(estimators=[('mlp', mlp_blobs), ('rf', rf_blobs)], voting='hard')
voting_clf_blobs.fit(X_train_blobs_scaled, y_train_blobs)

voting_clf_circles = VotingClassifier(estimators=[('mlp', mlp_circles), ('rf', rf_circles)], voting='hard')
voting_clf_circles.fit(X_train_circles_scaled, y_train_circles)
```

```python
# Evaluate Random Forest with different hyperparameters
rf_blobs = RandomForestClassifier(n_estimators=50, max_depth=5, random_state=0)
rf_blobs.fit(X_train_blobs_scaled, y_train_blobs)

rf_blobs = RandomForestClassifier(n_estimators=200, max_depth=5, random_state=0)
rf_blobs.fit(X_train_blobs_scaled, y_train_blobs)

# Voting Classifier
voting_clf_blobs = VotingClassifier(estimators=[('mlp', mlp_blobs), ('rf', rf_blobs)], voting='hard')
voting_clf_blobs.fit(X_train_blobs_scaled, y_train_blobs)

voting_clf_circles = VotingClassifier(estimators=[('mlp', mlp_circles), ('rf', rf_circles)], voting='hard')
voting_clf_circles.fit(X_train_circles_scaled, y_train_circles)

# Compare their performances
y_pred_rf_blobs = rf_blobs.predict(X_test_blobs_scaled)
y_pred_rf_blobs = rf_blobs.predict(X_test_blobs_scaled)

accuracy_rf_blobs = accuracy_score(y_test_blobs, y_pred_rf_blobs)
accuracy_rf_blobs = accuracy_score(y_test_blobs, y_pred_rf_blobs)

print("Random Forest Estimators - Test Accuracy:", accuracy_rf_blobs)
print("Random Forest  Estimators - Test Accuracy:", accuracy_rf_blobs)
```

```
Random Forest Estimators - Test Accuracy: 0.9681818181818181
Random Forest  Estimators - Test Accuracy: 0.9681818181818181
```

```
VotingClassifier
VotingClassifier(estimators=[('mlp',
                              MLPClassifier(early_stopping=True,
                                            hidden_layer_sizes=(60,),
                                            max_iter=1000, random_state=0)),
                             ('rf',
                              RandomForestClassifier(max_depth=5,
                                                     random_state=0))])
        mlp                      rf
  ▸ MLPClassifier    ▸ RandomForestClassifier
```

Here is the the analysis table where a comparison is made by changing the different values of n_eatimators and max_depth and trying to find the best model for RandomForestClassifier.

Model Configuration	Random Forest - Test Accuracy
n_estimators=200, max_depth=5	0.9682
n_estimators=200, max_depth=6	0.9591
n_estimators=50, max_depth=5	0.9636
n_estimators=100, max_depth=5	0.9682
n_estimators=100, max_depth=6	0.9591

As we can see the best n_estimators=100, max_depth=5 so further models have been created using this below are the input code and output.

10. Create Ensembles Random forest
    a. For base_estimator use one/several models with tge basic parameters. Compare different Ensembles which differs only with the hyperparameters.
    b. Create graphs for dependencies of n_estimators for Ensembles and individual models.

```
# Random Forest Classifier
rf_blobs = RandomForestClassifier(n_estimators=100, max_depth=5, random_state=0)
rf_blobs.fit(X_train_blobs_scaled, y_train_blobs)

rf_circles = RandomForestClassifier(n_estimators=100, max_depth=5, random_state=0)
rf_circles.fit(X_train_circles_scaled, y_train_circles)

# Voting Classifier
voting_clf_blobs = VotingClassifier(estimators=[('mlp', mlp_blobs), ('rf', rf_blobs)], voting='soft')
voting_clf_blobs.fit(X_train_blobs_scaled, y_train_blobs)

voting_clf_circles = VotingClassifier(estimators=[('mlp', mlp_circles), ('rf', rf_circles)], voting='soft')
voting_clf_circles.fit(X_train_circles_scaled, y_train_circles)
```

```
# Voting Classifier
voting_clf_blobs = VotingClassifier(estimators=[('mlp', mlp_blobs), ('rf', rf_blobs)], voting='soft')
voting_clf_blobs.fit(X_train_blobs_scaled, y_train_blobs)

voting_clf_circles = VotingClassifier(estimators=[('mlp', mlp_circles), ('rf', rf_circles)], voting='soft')
voting_clf_circles.fit(X_train_circles_scaled, y_train_circles)


def plot_decision_boundary(clf, X, y, title):
    x_min, x_max = X[:, 0].min() - 1, X[:, 0].max() + 1
    y_min, y_max = X[:, 1].min() - 1, X[:, 1].max() + 1
    xx, yy = np.meshgrid(np.arange(x_min, x_max, 0.1),
                         np.arange(y_min, y_max, 0.1))
    Z = clf.predict(np.c_[xx.ravel(), yy.ravel()])
    Z = Z.reshape(xx.shape)
    plt.contourf(xx, yy, Z, alpha=0.8)
    plt.scatter(X[:, 0], X[:, 1], c=y, edgecolor='k', s=20)
    plt.title(title)from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import accuracy_score
```

```
from sklearn.ensemble import VotingClassifier
# Voting ensemble based on the best NN model
voting_clf_best_blobs = VotingClassifier(estimators=[('mlp', mlp_blobs), ('rf', rf_blobs_200)], voting='soft')
voting_clf_best_blobs.fit(X_train_blobs_scaled, y_train_blobs)

# Predictions and evaluation
y_pred_voting_best_blobs = voting_clf_best_blobs.predict(X_test_blobs_scaled)
accuracy_voting_best_blobs = accuracy_score(y_test_blobs, y_pred_voting_best_blobs)

print("Voting Classifier (Best NN + RF) - Test Accuracy:", accuracy_voting_best_blobs)
```

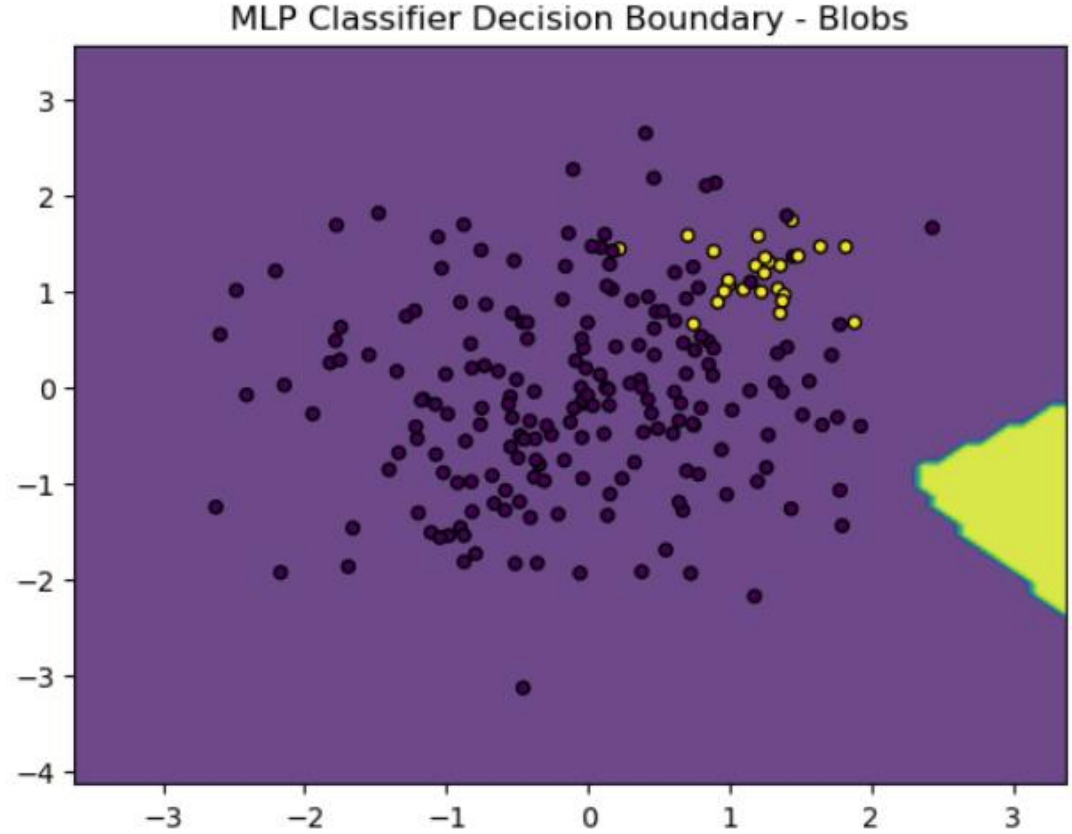
Voting Classifier (Best NN + RF) - Test Accuracy: 0.9545454545454546

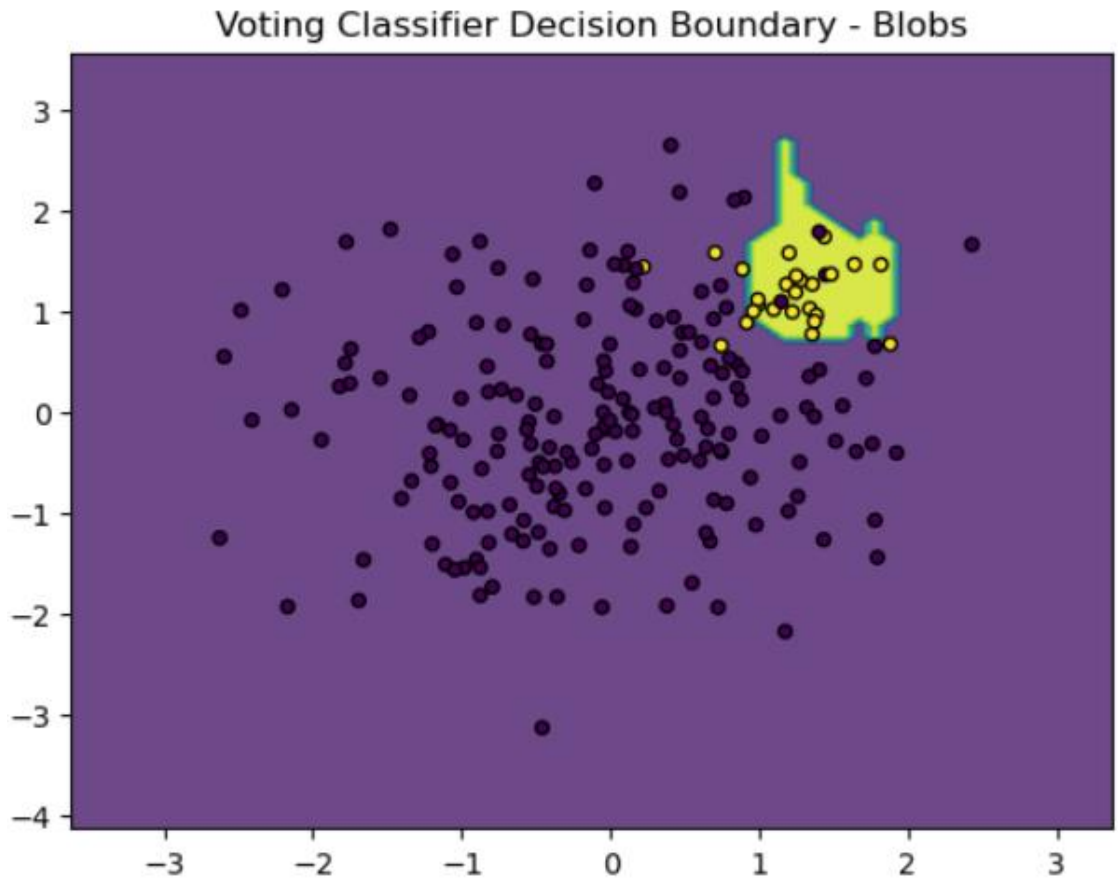
```
import numpy as np
import matplotlib.pyplot as plt

def plot_decision_boundary(clf, X, y, title):
    x_min, x_max = X[:, 0].min() - 1, X[:, 0].max() + 1
    y_min, y_max = X[:, 1].min() - 1, X[:, 1].max() + 1
    xx, yy = np.meshgrid(np.arange(x_min, x_max, 0.1),
                         np.arange(y_min, y_max, 0.1))
    Z = clf.predict(np.c_[xx.ravel(), yy.ravel()])
    Z = Z.reshape(xx.shape)
    plt.contourf(xx, yy, Z, alpha=0.8)
    plt.scatter(X[:, 0], X[:, 1], c=y, edgecolor='k', s=20)
    plt.title(title)
    plt.show()

# Plot decision boundaries
plot_decision_boundary(mlp_blobs, X_test_blobs_scaled, y_test_blobs, "MLP Classifier Decision Boundary - Blobs")
plot_decision_boundary(voting_clf_best_blobs, X_test_blobs_scaled, y_test_blobs, "Voting Classifier Decision Boundary - Blobs")
```

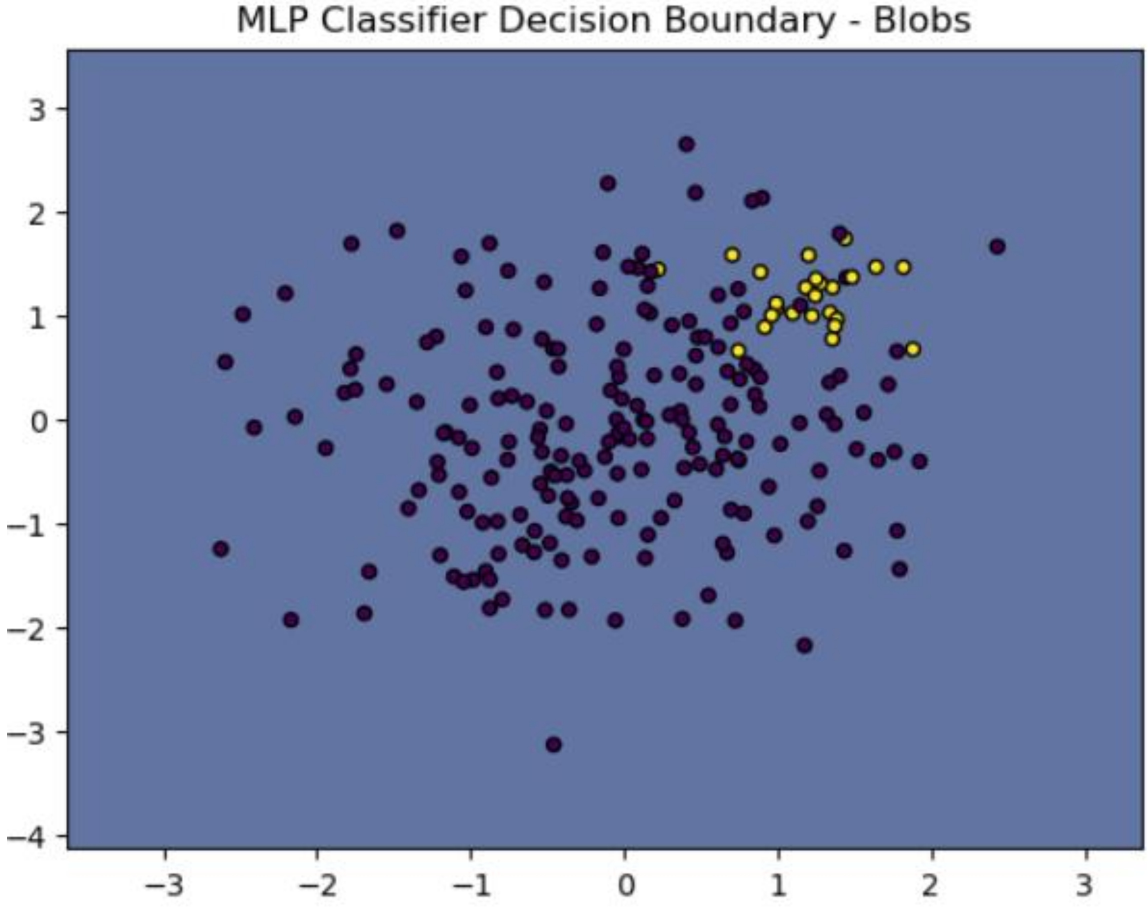
Changing the different values of the base parameter analysis of different graphs for decision boundary.

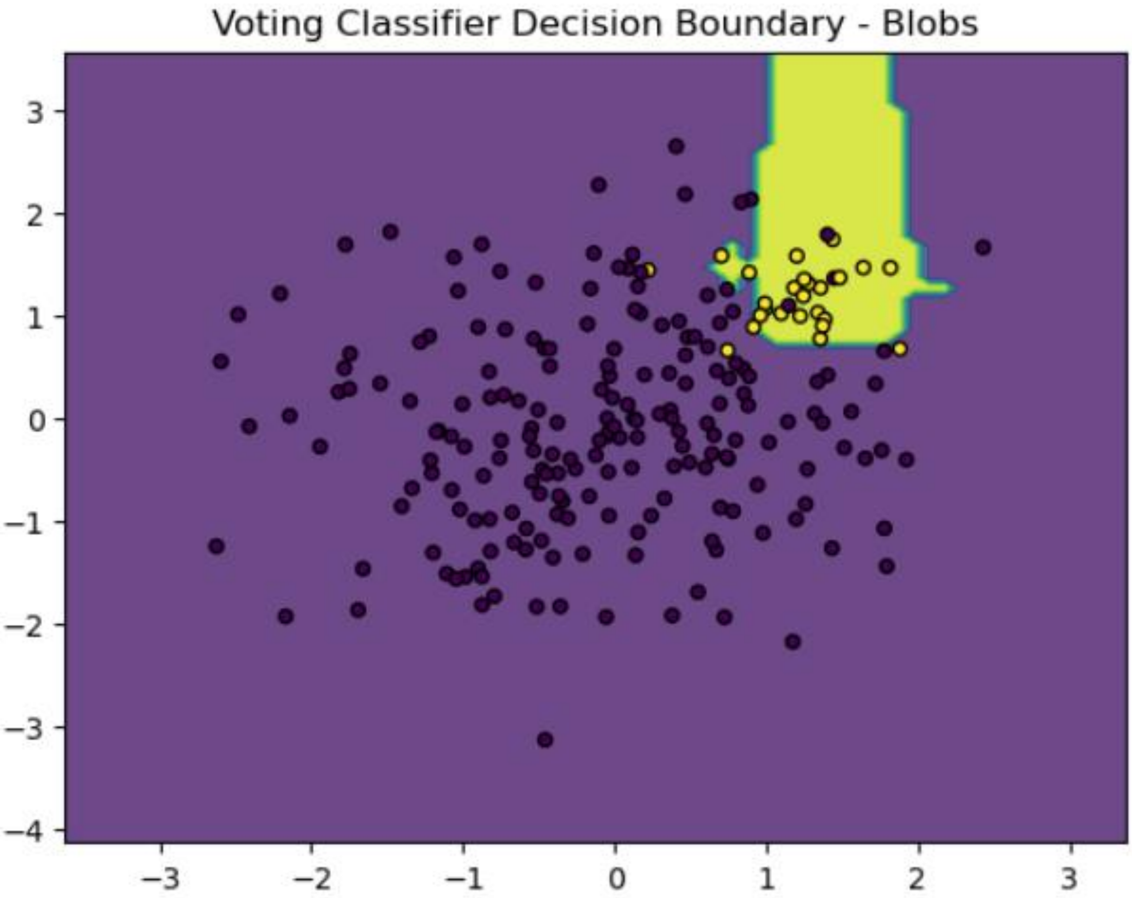




Analysis of the graph the MLP classifier has non-linear decision boundary, which might indicates good performance but also a risk of overfitting. The voting classifier combines the decisions of multiple classifiers, resulting in a potentially more balanced decision boundary that could generalize better for the data which is unseen.

2. Another Graph for Analysis.





After making certain changes in the hyperparameter we could achieve better result and making more clear results.

10. Create ensemble voting based on the best NN model from the previous stages.

    Here is the input code followed by the output.

    Voting Classifier (Best NN + RF) - Test Accuracy: 0.9681818181818181

```
from sklearn.ensemble import VotingClassifier
# Voting ensemble based on the best NN model
voting_clf_best_blobs = VotingClassifier(estimators=[('mlp', mlp_blobs), ('rf', rf_blobs_200)], voting='soft')
voting_clf_best_blobs.fit(X_train_blobs_scaled, y_train_blobs)

# Predictions and evaluation
y_pred_voting_best_blobs = voting_clf_best_blobs.predict(X_test_blobs_scaled)
accuracy_voting_best_blobs = accuracy_score(y_test_blobs, y_pred_voting_best_blobs)

print("Voting Classifier (Best NN + RF) - Test Accuracy:", accuracy_voting_best_blobs)
```

Voting Classifier (Best NN + RF) - Test Accuracy: 0.9681818181818181

11. Calculate the shift and variation for the basic model and Ensemble.

    Here is the input followed by the output.

```python
def calculate_shift_variation(y_true, y_pred_1, y_pred_2):
    shift = np.mean(y_pred_1 != y_pred_2)
    variation = np.var([y_pred_1, y_pred_2], axis=0).mean()
    return shift, variation

shift_blobs, variation_blobs = calculate_shift_variation(y_test_blobs, mlp_blobs.predict(X_test_blobs_scaled), voting_clf_best_blobs.predict(X_test_blobs

print("Shift - Blobs:", shift_blobs)
print("Variation - Blobs:", variation_blobs)
```

```
Shift - Blobs: 0.11818181818181818
Variation - Blobs: 0.029545454545454545
```

12. Analysis and conclusion drawn on the basis of shift and variation.

High Accuracy

The Voting Classifier, combining the best Neural Network (NN) and Random Forest (RF), achieved a high test accuracy of 0.9681, indicating strong performance in classifying the blobs dataset.

Low Variation

A variation of 0.02952 indicates low variability in the model's predictions, implying that the model is consistent in its decision making processs different subsets of the data.

Shift

A shift of 0.1182 suggests that the model's predictions have some deviation when compared to the actual distribution. This could be due to slight overfitting or inherent variability in the data.