```
import qc
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sb
from sklearn.preprocessing import LabelEncoder, StandardScaler
from sklearn.model selection import train test split, StratifiedKFold,
cross val score
from sklearn.calibration import CalibratedClassifierCV
from imblearn.over sampling import SMOTE
from sklearn.neighbors import KNeighborsClassifier
from sklearn.mixture import GaussianMixture
from catboost import CatBoostClassifier, Pool
from sklearn.metrics import accuracy score, precision score,
recall score, fl score, confusion matrix, classification report,
adjusted rand score
import torch
from sklearn.linear model import LogisticRegression
import torch.nn as nn
import torch.optim as optim
import torch.nn.functional as F
from torch.utils.data import DataLoader, TensorDataset
from sklearn.inspection import permutation importance
import shap
import warnings
import seaborn as sns
from sklearn.model selection import GridSearchCV
warnings.filterwarnings("ignore")
sb.set(rc={'figure.figsize': (12,7)})
gc.enable()
gc.collect()
18607
```

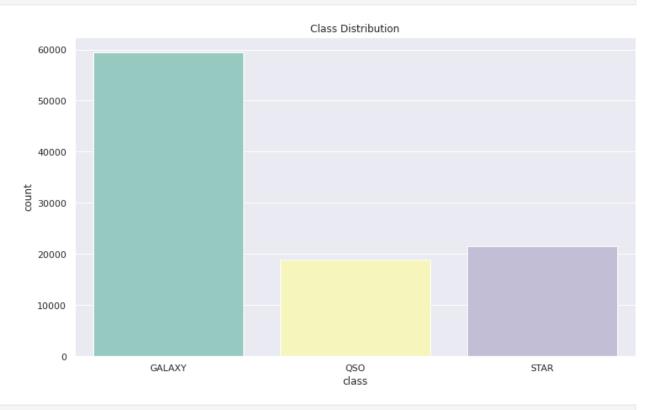
Load dataset

```
def rem_outliers(df):
    s1 = df.shape
    for i in df.select_dtypes(include='number').columns:
        qt1 = df[i].quantile(0.25)
        qt3 = df[i].quantile(0.75)
        iqr = qt3 - qt1
        lower = qt1 - (1.5 * iqr)
        upper = qt3 + (1.5 * iqr)
```

```
min in = df[df[i] < lower].index
        \max in = df[df[i] > upper].index
        df.drop(min in, inplace=True)
        df.drop(max in, inplace=True)
    s2 = df.shape
    outliers = s1[0] - s2[0]
    return outliers
def print_metrics(y_true, y_pred, dataset_name, model_name):
    print(f"\n{model_name} on {dataset_name}:")
    print(f"Accuracy: {accuracy_score(y_true, y_pred) * 100:.2f}%")
    print(f"Precision: {precision score(y true, y pred,
average='macro'):.2f}")
    print(f"Recall: {recall score(y true, y pred,
average='macro'):.2f}")
    print(f"F1-Score: {f1_score(y_true, y_pred,
average='macro'):.2f}")
    print(f"Confusion Matrix:\n{confusion matrix(y true, y pred)}")
class HybridNN(nn.Module):
    def init (self, input size, num classes):
        super(HybridNN, self). init ()
        self.fc1 = nn.Linear(input size, 128)
        self.bn1 = nn.BatchNorm1d(128)
        self.relu = nn.ReLU()
        self.dropout = nn.Dropout(0.5)
        self.fc2 = nn.Linear(128, 64)
        self.bn2 = nn.BatchNorm1d(64)
        self.fc3 = nn.Linear(64, num classes)
    def forward(self, x):
        x = self.fc1(x)
        x = self.bn1(x)
        x = self.relu(x)
        x = self.dropout(x)
        x = self.fc2(x)
        x = self.bn2(x)
        x = self.relu(x)
        x = self.fc3(x)
        return x
star = pd.read_csv('/kaggle/input/stellar-classification-dataset-
sdss17/star classification.csv')
print("First few rows:")
print(star.head())
print("Class Distribution:")
print(star["class"].value counts(normalize=True) * 100)
sb.countplot(x=star["class"], palette="Set3")
plt.title("Class Distribution")
```

```
plt.show()
outliers removed = rem outliers(star)
print(f"Number of outliers deleted: {outliers removed}")
for col in ['u', 'g', 'r', 'i', 'z']:
    star[f'redshift {col}'] = star['redshift'] * star[col]
columns_to_drop = ['run_ID', 'rerun_ID', 'cam_col', 'field_ID',
'spec_obj_ID', 'fiber_ID', 'obj_ID']
star.drop(columns=columns_to_drop, axis=1, inplace=True)
le = LabelEncoder()
star["class"] = le.fit transform(star["class"])
X = star.drop('class', axis=1)
y = star['class']
X_train_val, X_test, y_train_val, y_test = train_test_split(X, y,
test size=0.2, random state=42)
X_train, X_val, y_train, y_val = train_test_split(X_train_val,
y train val, test size=0.25, random state=42)
sc = StandardScaler()
X train scaled = pd.DataFrame(sc.fit transform(X train),
columns=X train.columns, index=X train.index)
X val scaled = pd.DataFrame(sc.transform(X val),
columns=X val.columns, index=X val.index)
X test scaled = pd.DataFrame(sc.transform(X test),
columns=X test.columns, index=X test.index)
oversampler = SMOTE(random state=1)
X train smote, y train smote =
oversampler.fit resample(X train scaled, y train)
qc.collect()
First few rows:
                     alpha
                                 delta
         obj ID
0 1.237661e+18 135.689107 32.494632 23.87882 22.27530 20.39501
1 1.237665e+18 144.826101 31.274185 24.77759 22.83188 22.58444
2 1.237661e+18 142.188790 35.582444 25.26307 22.66389 20.60976
3 1.237663e+18 338.741038 -0.402828 22.13682 23.77656 21.61162
4 1.237680e+18 345.282593 21.183866 19.43718 17.58028 16.49747
                    z run ID rerun ID cam col field ID
```

spec_obj_ID	\				
0 19.16573 6.543777e+18	18.79371	3606	301	2	79
1 21.16812	21.61427	4518	301	5	119
1.176014e+19 2 19.34857	18.94827	3606	301	2	120
5.152200e+18		3000	301		120
3 20.50454 1.030107e+19	19.25010	4192	301	3	214
4 15.97711	15.54461	8102	301	3	137
6.891865e+18					
0 GALAXY 0 1 GALAXY 0 2 GALAXY 0 3 GALAXY 0 4 GALAXY 0 Class Distri GALAXY 59 STAR 21	.634794 58 .779136 104 .644195 49 .932346 99 .116123 69 bution: .445 .594	mate MJD 812 56354 445 58158 576 55592 149 58039 121 56187	fiber_ID 171 427 299 775 842		
QSO 18 Name: class,	.961 dtype: floa	at64			



Number of outliers deleted: 14266

Models

```
param grid knn = \{'n neighbors': [3, 5, 7, 10]\}
knn = KNeighborsClassifier()
grid search knn = GridSearchCV(knn, param grid knn, cv=5,
scoring='accuracy')
grid search knn.fit(X train smote, y train smote)
best knn = grid search_knn.best_estimator_
print(f"Best KNN parameters: {grid search knn.best params }")
y val pred knn = best knn.predict(X val scaled)
print_metrics(y_val, y_val_pred_knn, "Validation Set", "KNN")
y test pred knn = best knn.predict(X test scaled)
print metrics(y test, y test pred knn, "Test Set", "KNN")
gc.collect()
Best KNN parameters: {'n neighbors': 3}
KNN on Validation Set:
Accuracy: 94.17%
Precision: 0.90
Recall: 0.94
F1-Score: 0.92
Confusion Matrix:
[[10428
         485
                226]
 [ 214 1741
                  71
  65 2 3979]]
KNN on Test Set:
Accuracy: 94.44%
Precision: 0.90
Recall: 0.94
F1-Score: 0.92
Confusion Matrix:
[[10417
        447
                2431
   183 1692
                  71
[
    69 4 4085]]
408
bic = []
for n in range(1, 11):
    gmm = GaussianMixture(n components=n, random state=42)
    gmm.fit(X train smote)
    bic.append(gmm.bic(X train smote))
optimal n = np.argmin(bic) + 1
```

```
qmm = GaussianMixture(n components=optimal n, random state=42)
gmm.fit(X train smote)
clusters val = gmm.predict(X val scaled)
ari = adjusted rand score(y val, clusters val)
print(f"GMM Optimal Components: {optimal n}, Adjusted Rand Index on
Validation Set: {ari:.4f}")
clusters test = gmm.predict(X test scaled)
ari_test = adjusted_rand_score(y_test, clusters_test)
print(f"GMM Adjusted Rand Index on Test Set: {ari test:.4f}")
qc.collect()
GMM Optimal Components: 10, Adjusted Rand Index on Validation Set:
GMM Adjusted Rand Index on Test Set: 0.2661
23
param grid catboost = {
    'depth': [4, 6, 8],
    'learning rate': [0.01, 0.05, 0.1],
    'l2 leaf reg': [1, 3, 5]
catboost = CatBoostClassifier(task type='GPU' if
torch.cuda.is available() else 'CPU', verbose=0)
grid search catboost = GridSearchCV(catboost, param grid catboost,
cv=5, scoring='accuracy')
grid search catboost.fit(X train smote, y train smote)
best catboost = grid search catboost.best estimator
print(f"Best CatBoost parameters:
{grid search catboost best params }")
catboost probs train = best catboost.predict proba(X train smote)
catboost probs val = best catboost.predict proba(X val scaled)
catboost probs test = best catboost.predict proba(X test scaled)
y val pred catboost = best catboost.predict(X val scaled)
print metrics(y val, y val pred catboost, "Validation Set",
"CatBoost")
gc.collect()
Best CatBoost parameters: {'depth': 8, 'l2 leaf reg': 1,
'learning rate': 0.1}
CatBoost on Validation Set:
Accuracy: 97.21%
Precision: 0.95
Recall: 0.96
F1-Score: 0.96
Confusion Matrix:
[[10853
         236
                 501
```

```
[ 182 1778 2]
[ 9 0 4037]]
24
```

Tensor prepping

```
X train nn = np.hstack((X train smote, catboost probs train))
X_{val_nn} = np.hstack((X_{val_scaled}, catboost_probs val))
X_test_nn = np.hstack((X_test_scaled, cathoost_probs_test))
X_train_tensor = torch.tensor(X_train_nn, dtype=torch.float32)
y_train_tensor = torch.tensor(y_train_smote.values, dtype=torch.long)
X val tensor = torch.tensor(X val nn, dtype=torch.float32)
v val tensor = torch.tensor(v val.values, dtype=torch.long)
X_test_tensor = torch.tensor(X_test_nn, dtype=torch.float32)
y test tensor = torch.tensor(y test.values, dtype=torch.long)
train dataset = TensorDataset(X train tensor, y train tensor)
val dataset = TensorDataset(X val tensor, y val tensor)
test dataset = TensorDataset(X test tensor, y test tensor)
train loader = DataLoader(train dataset, batch size=64, shuffle=True)
val loader = DataLoader(val dataset, batch size=64, shuffle=False)
test loader = DataLoader(test dataset, batch size=64, shuffle=False)
device = torch.device('cuda' if torch.cuda.is available() else 'cpu')
input size = X train nn.shape[1]
nn model = HybridNN(input size=input size, num classes=3).to(device)
criterion = nn.CrossEntropyLoss()
optimizer = optim.Adam(nn model.parameters(), lr=0.001)
best val loss = float('inf')
patience = 5
counter = 0
for epoch in range(100):
    nn model.train()
    for X_batch, y_batch in train_loader:
        X batch, y batch = X batch.to(device), y batch.to(device)
        optimizer.zero grad()
        outputs = nn model(X batch)
        loss = criterion(outputs, y batch)
        loss.backward()
        optimizer.step()
    nn model.eval()
    val loss = 0
    with torch.no grad():
        for X val batch, y val batch in val loader:
```

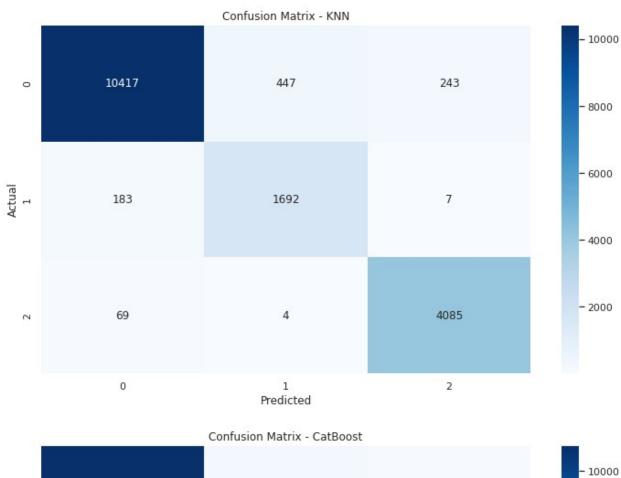
```
X val batch, y val batch = X val batch.to(device),
y val batch.to(device)
            val outputs = nn model(X val batch)
            val loss += criterion(val outputs, y val batch).item()
    val loss /= len(val loader)
    print(f'Epoch {epoch+1}, Validation Loss: {val loss:.4f}')
    if val loss < best val loss:</pre>
        best_val_loss = val_loss
        counter = 0
        torch.save(nn model.state dict(), 'best nn model.pt')
    else:
        counter += 1
        if counter >= patience:
            print("Early stopping")
            break
nn model.load state dict(torch.load('best nn model.pt'))
gc.collect()
Epoch 1, Validation Loss: 0.1594
Epoch 2, Validation Loss: 0.1619
Epoch 3, Validation Loss: 0.1533
Epoch 4, Validation Loss: 0.1537
Epoch 5, Validation Loss: 0.1575
Epoch 6, Validation Loss: 0.1736
Epoch 7, Validation Loss: 0.1540
Epoch 8, Validation Loss: 0.1513
Epoch 9, Validation Loss: 0.1672
Epoch 10, Validation Loss: 0.1579
Epoch 11, Validation Loss: 0.1571
Epoch 12, Validation Loss: 0.1924
Epoch 13, Validation Loss: 0.1802
Early stopping
35
```

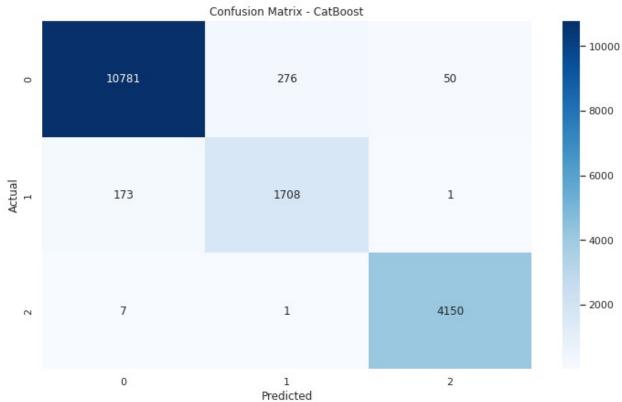
Evals and plots

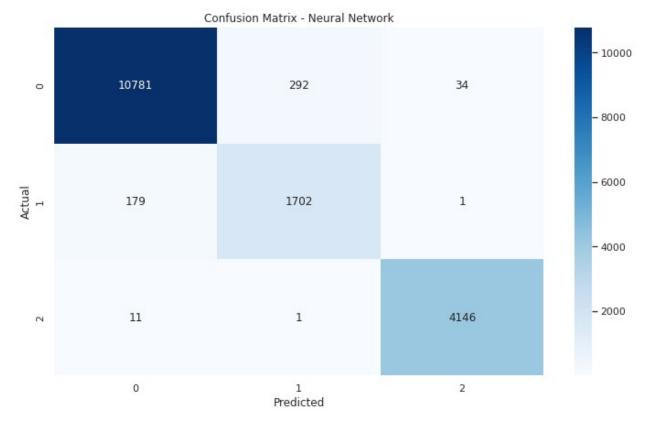
```
nn_model.eval()
nn_probs_val = []
with torch.no_grad():
    for X_val_batch, _ in val_loader:
        X_val_batch = X_val_batch.to(device)
        outputs = nn_model(X_val_batch)
        probs = torch.softmax(outputs, dim=1).cpu().numpy()
        nn_probs_val.append(probs)
nn_probs_val = np.vstack(nn_probs_val)
```

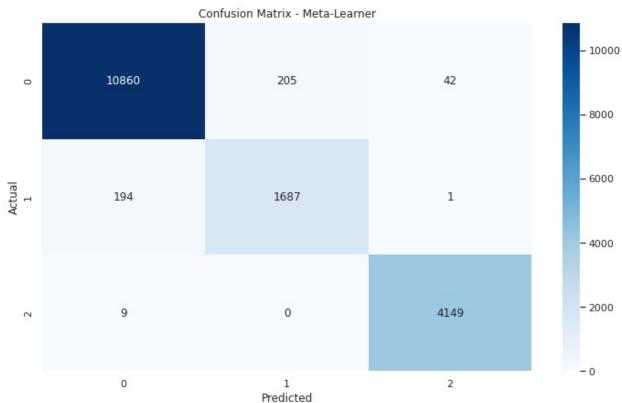
```
knn probs val = best knn.predict proba(X val scaled)
meta features val = np.hstack((catboost probs val, nn probs val,
knn probs val))
meta learner = LogisticRegression()
meta learner.fit(meta features val, y val)
nn probs test = []
with torch.no grad():
    for X_test_batch, _ in test_loader:
        X test batch = X test batch.to(device)
        outputs = nn model(X test batch)
        probs = torch.softmax(outputs, dim=1).cpu().numpy()
        nn_probs_test.append(probs)
nn probs test = np.vstack(nn probs test)
knn probs test = best knn.predict proba(X test scaled)
meta features test = np.hstack((catboost probs test, nn probs test,
knn probs test))
y_test_pred_meta = meta_learner.predict(meta_features_test)
print_metrics(y_test, y_test_pred_meta, "Test Set", "Meta-Learner")
gc.collect()
Meta-Learner on Test Set:
Accuracy: 97.37%
Precision: 0.95
Recall: 0.96
F1-Score: 0.96
Confusion Matrix:
[[10860 205
                 421
[ 194 1687
                  1]
  9 0 414911
ſ
24
y test pred catboost = best catboost.predict(X test scaled)
print_metrics(y_test, y_test_pred_catboost, "Test Set", "CatBoost")
v test pred nn = []
with torch.no grad():
    for X_test_batch, _ in test_loader:
        X test batch = X test batch.to(device)
        outputs = nn_model(X_test_batch)
        _, predicted = torch.max(outputs.data, 1)
        y_test_pred_nn.extend(predicted.cpu().numpy())
print metrics(y test, y test pred nn, "Test Set", "Neural Network")
cm knn = confusion matrix(y_test, y_test_pred_knn)
sb.heatmap(cm_knn, annot=True, fmt='d', cmap='Blues')
plt.title('Confusion Matrix - KNN')
plt.xlabel('Predicted')
```

```
plt.ylabel('Actual')
plt.show()
cm catboost = confusion_matrix(y_test, y_test_pred_catboost)
sb.heatmap(cm catboost, annot=True, fmt='d', cmap='Blues')
plt.title('Confusion Matrix - CatBoost')
plt.xlabel('Predicted')
plt.ylabel('Actual')
plt.show()
cm nn = confusion matrix(y test, y test pred nn)
sb.heatmap(cm nn, annot=True, fmt='d', cmap='Blues')
plt.title('Confusion Matrix - Neural Network')
plt.xlabel('Predicted')
plt.ylabel('Actual')
plt.show()
cm meta = confusion matrix(y test, y test pred meta)
sb.heatmap(cm meta, annot=True, fmt='d', cmap='Blues')
plt.title('Confusion Matrix - Meta-Learner')
plt.xlabel('Predicted')
plt.ylabel('Actual')
plt.show()
gc.collect()
CatBoost on Test Set:
Accuracy: 97.04%
Precision: 0.94
Recall: 0.96
F1-Score: 0.95
Confusion Matrix:
                 501
[[10781 276
[ 173 1708
                  11
  7 1 4150]]
Neural Network on Test Set:
Accuracy: 96.98%
Precision: 0.94
Recall: 0.96
F1-Score: 0.95
Confusion Matrix:
[[10781 292
                 341
 [ 179 1702
                  11
     11
        1 4146]]
```



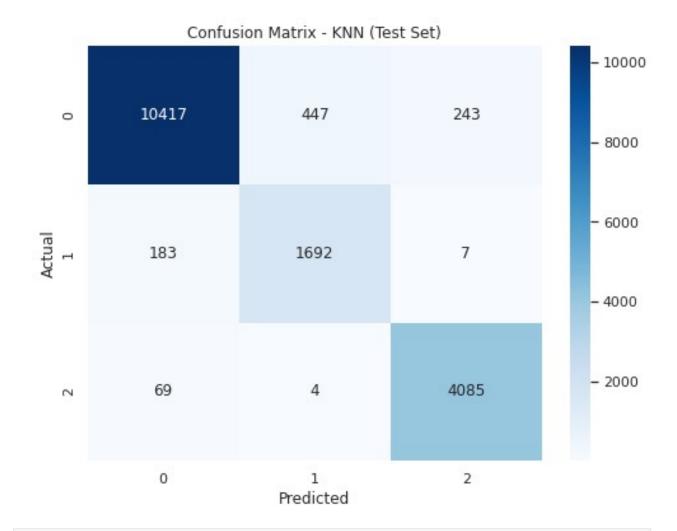




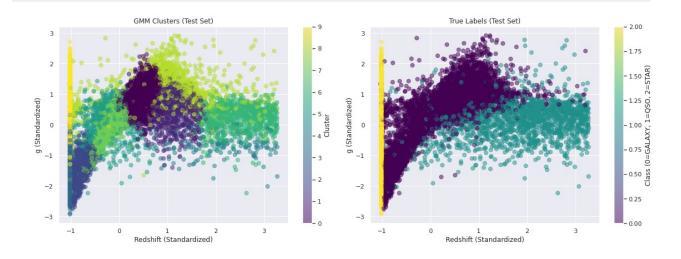


```
20776
y train pred knn = best knn.predict(X train smote)
print metrics(y train smote, y train pred knn, "Training Set", "KNN")
y val pred knn = best knn.predict(X val scaled)
print_metrics(y_val, y_val pred knn, "Validation Set", "KNN")
y test pred knn = best knn.predict(X test scaled)
print_metrics(y_test, y_test_pred_knn, "Test Set", "KNN")
cm knn = confusion matrix(y test, y test pred knn)
plt.figure(figsize=(8, 6))
sb.heatmap(cm knn, annot=True, fmt='d', cmap='Blues')
plt.title('Confusion Matrix - KNN (Test Set)')
plt.xlabel('Predicted')
plt.ylabel('Actual')
plt.show()
clusters train = qmm.predict(X train smote)
ari_train = adjusted_rand_score(y_train_smote, clusters_train)
print(f"\nGMM on Training Set: Adjusted Rand Index = {ari train:.4f}")
clusters val = gmm.predict(X val scaled)
ari val = adjusted rand score(y val, clusters val)
print(f"GMM on Validation Set: Adjusted Rand Index = {ari val:.4f}")
clusters test = qmm.predict(X test scaled)
ari_test = adjusted_rand_score(y_test, clusters_test)
print(f"GMM on Test Set: Adjusted Rand Index = {ari test:.4f}")
X test df = pd.DataFrame(X test scaled, columns=X test.columns)
plt.figure(figsize=(16, 6))
plt.subplot(1, 2, 1)
plt.scatter(X test df['redshift'], X test df['g'], c=clusters test,
cmap='viridis', s=\overline{50}, alpha=0.5)
plt.title('GMM Clusters (Test Set)')
plt.xlabel('Redshift (Standardized)')
plt.ylabel('g (Standardized)')
plt.colorbar(label='Cluster')
plt.subplot(1, 2, 2)
plt.scatter(X test df['redshift'], X test df['g'], c=y test,
cmap='viridis', s=50, alpha=0.5)
plt.title('True Labels (Test Set)')
plt.xlabel('Redshift (Standardized)')
plt.ylabel('g (Standardized)')
plt.colorbar(label='Class (0=GALAXY, 1=QSO, 2=STAR)')
```

```
plt.tight_layout()
plt.show()
gc.collect()
KNN on Training Set:
Accuracy: 98.48%
Precision: 0.99
Recall: 0.98
F1-Score: 0.98
Confusion Matrix:
[[31939 903 497]
    98 33237
                 41
[
    18 1 33320]]
KNN on Validation Set:
Accuracy: 94.17%
Precision: 0.90
Recall: 0.94
F1-Score: 0.92
Confusion Matrix:
[[10428 485 226]
[ 214 1741
                 7]
    65 2 3979]]
[
KNN on Test Set:
Accuracy: 94.44%
Precision: 0.90
Recall: 0.94
F1-Score: 0.92
Confusion Matrix:
[[10417 447 243]
[ 183 1692
                 7]
    69
        4 4085]]
```

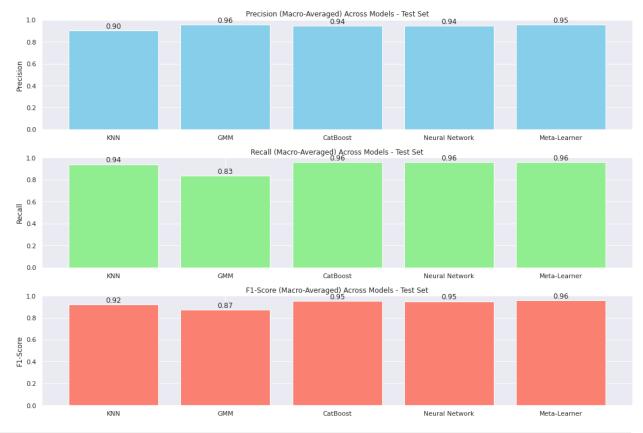


GMM on Training Set: Adjusted Rand Index = 0.3918 GMM on Validation Set: Adjusted Rand Index = 0.2644 GMM on Test Set: Adjusted Rand Index = 0.2661



```
16323
y test pred knn = best knn.predict(X test scaled)
knn precision = precision score(y test, y test pred knn,
average='macro')
knn_recall = recall_score(y_test, y_test_pred_knn, average='macro')
knn_f1 = f1_score(y_test, y_test_pred_knn, average='macro')
clusters test = gmm.predict(X test scaled)
cluster_to class = {}
for cluster in np.unique(clusters test):
    mask = clusters test == cluster
    majority class = y_test[mask].mode()[0]
    cluster to class[cluster] = majority class
y test pred gmm = np.array([cluster to class[cluster] for cluster in
clusters test1)
gmm_precision = precision_score(y_test, y_test_pred_gmm,
average='macro')
gmm_recall = recall_score(y_test, y_test_pred_gmm, average='macro')
gmm_f1 = f1_score(y_test, y_test_pred_gmm, average='macro')
y test pred catboost = best catboost.predict(X test scaled)
catboost precision = precision score(y test, y test pred catboost,
average='macro')
catboost recall = recall score(y test, y test pred catboost,
average='macro')
catboost_f1 = f1_score(y_test, y_test_pred_catboost, average='macro')
nn model.eval()
y test pred nn = []
with torch.no grad():
    for X test batch, in test loader:
        X test batch = X test batch.to(device)
        outputs = nn model(X test batch)
        _, predicted = torch.max(outputs.data, 1)
        y test pred nn.extend(predicted.cpu().numpy())
nn_precision = precision_score(y_test, y_test_pred_nn,
average='macro')
nn recall = recall score(y test, y test pred nn, average='macro')
nn f1 = f1 score(y test, y test pred nn, average='macro')
y test pred meta = meta learner.predict(meta features test)
meta precision = precision score(y test, y test pred meta,
average='macro')
meta recall = recall_score(y_test, y_test_pred_meta, average='macro')
meta_f1 = f1_score(y_test, y_test_pred_meta, average='macro')
models = ['KNN', 'GMM', 'CatBoost', 'Neural Network', 'Meta-Learner']
precisions = [knn precision, gmm precision, catboost precision,
nn_precision, meta_precision]
```

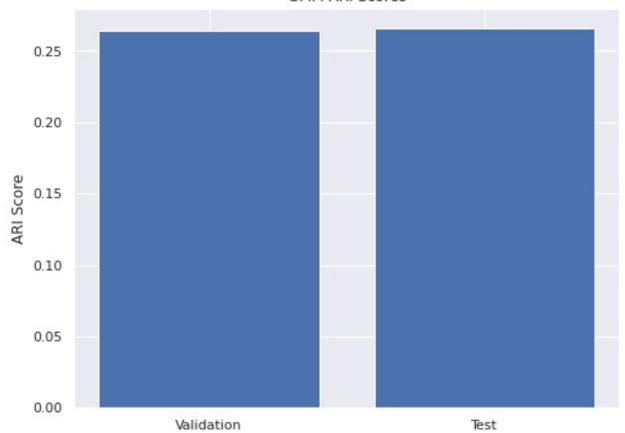
```
recalls = [knn recall, gmm recall, catboost recall, nn recall,
meta recall]
f1_scores = [knn_f1, gmm_f1, catboost_f1, nn_f1, meta_f1]
plt.figure(figsize=(15, 10))
plt.subplot(3, 1, 1)
plt.bar(models, precisions, color='skyblue')
plt.title('Precision (Macro-Averaged) Across Models - Test Set')
plt.ylabel('Precision')
plt.ylim(0, 1)
for i, v in enumerate(precisions):
    plt.text(i, v + 0.02, f'\{v:.2f\}', ha='center')
plt.subplot(3, 1, 2)
plt.bar(models, recalls, color='lightgreen')
plt.title('Recall (Macro-Averaged) Across Models - Test Set')
plt.ylabel('Recall')
plt.ylim(0, 1)
for i, v in enumerate(recalls):
    plt.text(i, v + 0.02, f'\{v:.2f\}', ha='center')
plt.subplot(3, 1, 3)
plt.bar(models, f1_scores, color='salmon')
plt.title('F1-Score (Macro-Averaged) Across Models - Test Set')
plt.ylabel('F1-Score')
plt.ylim(0, 1)
for i, v in enumerate(f1 scores):
    plt.text(i, v + 0.02, f'\{v:.2f\}', ha='center')
plt.tight layout()
plt.show()
gc.collect()
```

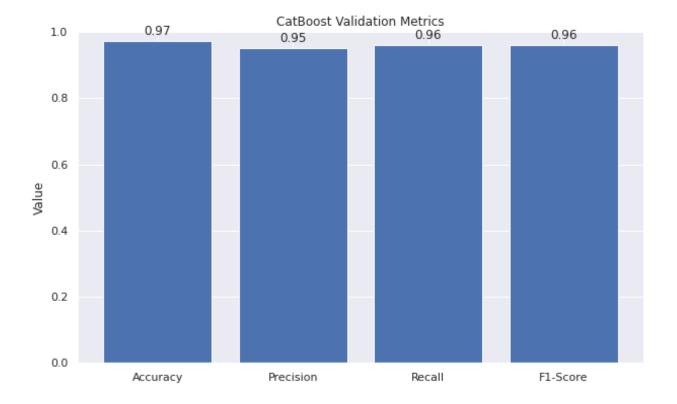


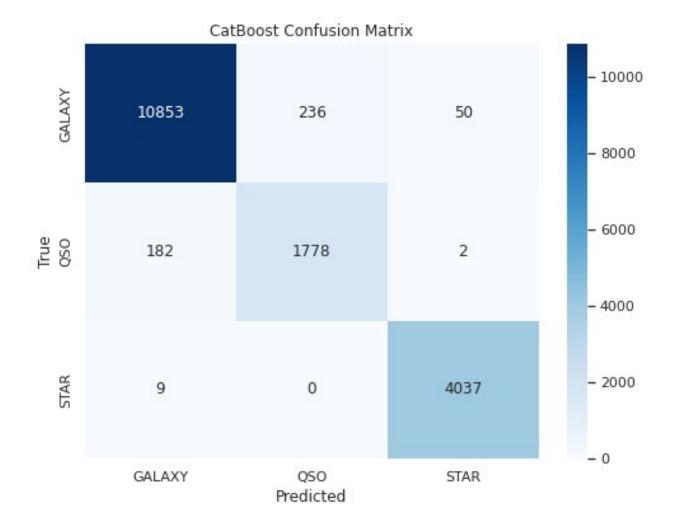
```
9073
ari val = 0.2644
ari test = 0.2661
plt.figure(figsize=(8, 6))
plt.bar(['Validation', 'Test'], [ari_val, ari_test])
plt.title('GMM ARI Scores')
plt.ylabel('ARI Score')
plt.show()
metrics = ['Accuracy', 'Precision', 'Recall', 'F1-Score']
values = [97.21 / 100, 0.95, 0.96, 0.96]
plt.figure(figsize=(10, 6))
plt.bar(metrics, values)
plt.title('CatBoost Validation Metrics')
plt.ylabel('Value')
plt.ylim(0, 1)
for i, v in enumerate(values):
    plt.text(i, v + 0.02, f'{v:.2f}', ha='center')
plt.show()
conf matrix = np.array([[10853, 236, 50], [182, 1778, 2], [9, 0,
4037]])
class_names = ['GALAXY', 'QSO', 'STAR']
plt.figure(figsize=(8, 6))
```

```
sns.heatmap(conf matrix, annot=True, fmt='d', cmap='Blues',
xticklabels=class names, yticklabels=class names)
plt.title('CatBoost Confusion Matrix')
plt.xlabel('Predicted')
plt.ylabel('True')
plt.show()
epochs = range(1, 14)
val_loss = [0.1594, 0.1619, 0.1533, 0.1537, 0.1575, 0.1736, 0.1540,
0.1513, 0.1672, 0.1579, 0.1571, 0.1924, 0.1802]
plt.figure(figsize=(10, 6))
plt.plot(epochs, val_loss, marker='o')
plt.title('Validation Loss over Epochs')
plt.xlabel('Epoch')
plt.ylabel('Loss')
plt.xticks(epochs)
plt.grid(True)
plt.show()
```

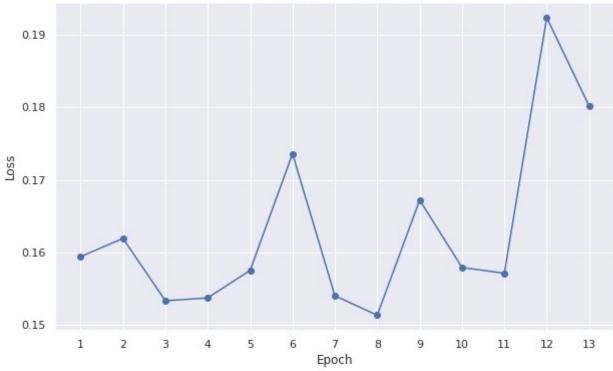
GMM ARI Scores





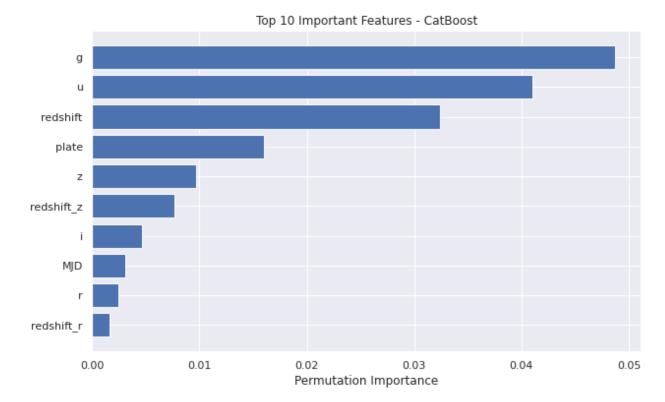




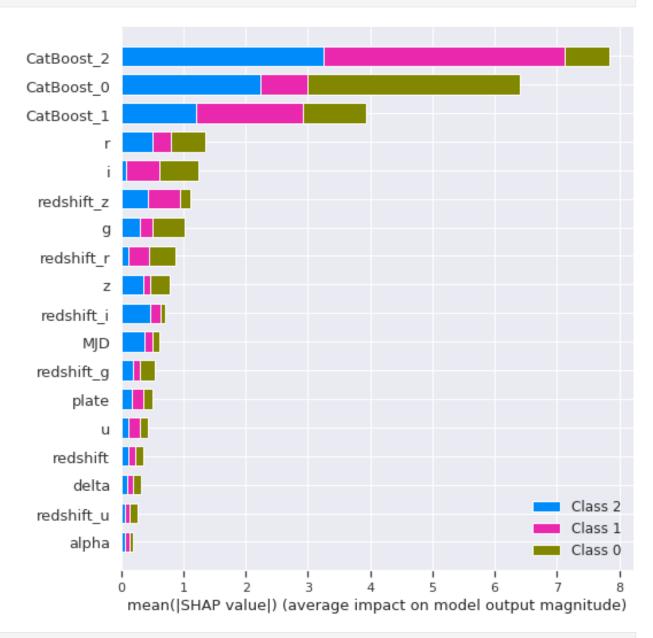


```
new data = X test.sample(5, random state=42)
new data scaled = pd.DataFrame(sc.transform(new data),
columns=new data.columns)
catboost probs new = best catboost.predict proba(new data scaled)
nn probs new = []
new tensor = torch.tensor(np.hstack((new data scaled,
catboost probs new)), dtype=torch.float32).to(device)
with torch.no grad():
    outputs = nn model(new tensor)
    nn probs new = torch.softmax(outputs, dim=1).cpu().numpy()
knn probs new = best knn.predict proba(new data scaled)
meta features new = np.hstack((catboost probs new, nn probs new,
knn probs new))
new predictions = meta learner.predict(meta features new)
new predictions labels = le.inverse transform(new predictions)
print("\nInference Pipeline Results:")
for i, pred in enumerate(new predictions labels):
    print(f"Sample {i+1}: Predicted Class = {pred}")
gc.collect()
Inference Pipeline Results:
Sample 1: Predicted Class = GALAXY
Sample 2: Predicted Class = GALAXY
```

```
Sample 3: Predicted Class = STAR
Sample 4: Predicted Class = GALAXY
Sample 5: Predicted Class = GALAXY
47
result = permutation importance(best catboost, X test scaled, y test,
n repeats=10, random state=42)
importances = result.importances mean
sorted idx = importances.argsort()[::-1]
plt.figure(figsize=(10,6))
plt.barh(X test.columns[sorted idx][:10], importances[sorted idx]
[:10])
plt.xlabel('Permutation Importance')
plt.title('Top 10 Important Features - CatBoost')
plt.gca().invert yaxis()
plt.show()
explainer = shap.KernelExplainer(lambda x: nn model(torch.tensor(x,
dtype=torch.float32).to(device)).detach().cpu().numpy(),
X train nn[:100])
shap values = explainer.shap values(X test nn[:100])
shap.summary plot(shap values, X test nn[:100],
feature names=list(X test.columns) + ['CatBoost 0', 'CatBoost 1',
'CatBoost 2'], plot type="bar")
gc.collect()
```



 $\label{localid} $$ \{ \mbox{"model_id": "2dd37b5345184bc3a32ab379dfaae569", "version_major": 2, "version_minor": 0} $$



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