Multimodal Classification Pipeline for ECG Data using ML and LSTM Models

Import Libraries:

[ ]:
```
# Data manipulation and visualization
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns

# Scikit-learn: preprocessing, decomposition, splitting, and metrics
from sklearn.preprocessing import MinMaxScaler, label_binarize
from sklearn.decomposition import PCA
from sklearn.model_selection import train_test_split, GridSearchCV
from sklearn.linear_model import LogisticRegression
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import (accuracy_score, classification_report,␣
 ↪confusion_matrix,
                             roc_auc_score, roc_curve, auc,␣
 ↪precision_recall_curve,
                             average_precision_score)

# TensorFlow/Keras for deep learning
import tensorflow as tf
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense, LSTM, Dropout
from tensorflow.keras.callbacks import EarlyStopping
from tensorflow.keras.utils import to_categorical

# IPython for DataFrame display
from IPython.display import display

sns.set(style="whitegrid")
plt.rcParams['figure.figsize'] = (10, 6)
```

Data Loading:

[ ]:
```
from google.colab import drive
drive.mount('/content/drive')
```

```
# Define file paths
train_path = "/content/drive/My Drive/ECG_Dataset/mitbih_train.csv"

# Load CSV files
df_train = pd.read_csv(train_path, header=None)

# Display first few rows of dataset
print("First few rows of the training dataset:")
display(df_train.head())
```

```
Mounted at /content/drive
First few rows of the training dataset:
```

```
        0         1         2         3         4         5         6    \
0  0.977941  0.926471  0.681373  0.245098  0.154412  0.191176  0.151961
1  0.960114  0.863248  0.461538  0.196581  0.094017  0.125356  0.099715
2  1.000000  0.659459  0.186486  0.070270  0.070270  0.059459  0.056757
3  0.925414  0.665746  0.541436  0.276243  0.196133  0.077348  0.071823
4  0.967136  1.000000  0.830986  0.586854  0.356808  0.248826  0.145540

        7         8         9    …  178  179  180  181  182  183  184  185  \
0  0.085784  0.058824  0.049020  …  0.0  0.0  0.0  0.0  0.0  0.0  0.0  0.0
1  0.088319  0.074074  0.082621  …  0.0  0.0  0.0  0.0  0.0  0.0  0.0  0.0
2  0.043243  0.054054  0.045946  …  0.0  0.0  0.0  0.0  0.0  0.0  0.0  0.0
3  0.060773  0.066298  0.058011  …  0.0  0.0  0.0  0.0  0.0  0.0  0.0  0.0
4  0.089202  0.117371  0.150235  …  0.0  0.0  0.0  0.0  0.0  0.0  0.0  0.0

   186  187
0  0.0  0.0
1  0.0  0.0
2  0.0  0.0
3  0.0  0.0
4  0.0  0.0

[5 rows x 188 columns]
```

Categorization of Data:

[ ]:
```
# --- Missing Values ---
# missing values in data
missing_train = pd.DataFrame(df_train.isnull().sum(), columns=["Missing␣
 ↪Values"])

print("Missing values in training data:")
display(missing_train)
```

```
Missing values in training data:

     Missing Values
0                 0
```

```
1                 0
2                 0
3                 0
4                 0
..              ...
183               0
184               0
185               0
186               0
187               0

[188 rows x 1 columns]
```

```
[ ]: # --- Data Types ---
dtypes_train = pd.DataFrame(df_train.dtypes, columns=["Data Type"])
print("\nTraining data types:")
display(dtypes_train)
```

```
Training data types:

    Data Type
0     float64
1     float64
2     float64
3     float64
4     float64
..        ...
183   float64
184   float64
185   float64
186   float64
187   float64

[188 rows x 1 columns]
```

```
[ ]: # --- Descriptive Statistics ---
desc_train = df_train.describe().T
print("\nDescriptive Statistics of Training Data:")
display(desc_train)
```

```
Descriptive Statistics of Training Data:

       count      mean       std  min       25%       50%       75%  max
0    87554.0  0.890360  0.240909  0.0  0.921922  0.991342  1.000000  1.0
1    87554.0  0.758160  0.221813  0.0  0.682486  0.826013  0.910506  1.0
2    87554.0  0.423972  0.227305  0.0  0.250969  0.429472  0.578767  1.0
3    87554.0  0.219104  0.206878  0.0  0.048458  0.166000  0.341727  1.0
4    87554.0  0.201127  0.177058  0.0  0.082329  0.147878  0.258993  1.0
```

```
..        …        …        …   …       …        …        …   …
183   87554.0   0.003471   0.036255   0.0   0.000000   0.000000   0.000000   1.0
184   87554.0   0.003221   0.034789   0.0   0.000000   0.000000   0.000000   1.0
185   87554.0   0.002945   0.032865   0.0   0.000000   0.000000   0.000000   1.0
186   87554.0   0.002807   0.031924   0.0   0.000000   0.000000   0.000000   1.0
187   87554.0   0.473376   1.143184   0.0   0.000000   0.000000   0.000000   4.0

[188 rows x 8 columns]
```

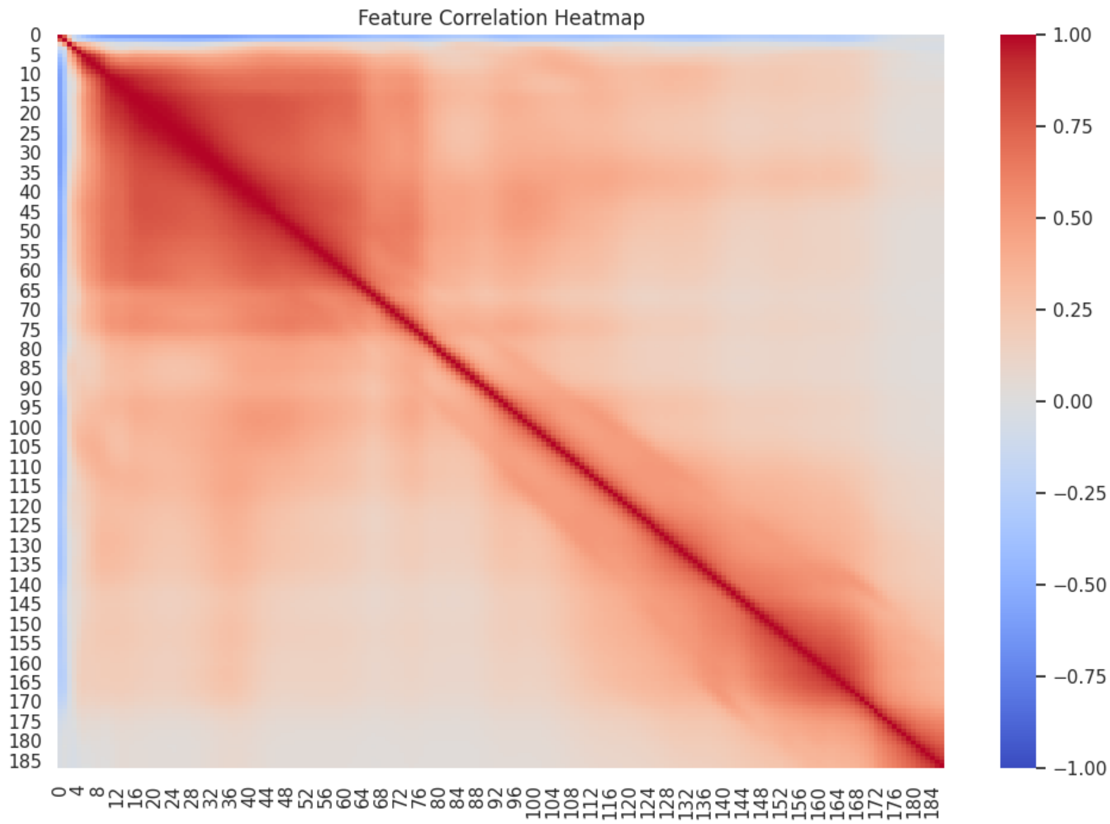
Visualize Class Distribution:

[ ]:
```python
# Class distribution
plt.figure()
sns.countplot(x=df_train.iloc[:, -1])
plt.title("Class Distribution in Training Data")
plt.xlabel("Class Labels")
plt.ylabel("Count")
plt.show()
```

Compute and Visualize the Correlation Matrix:

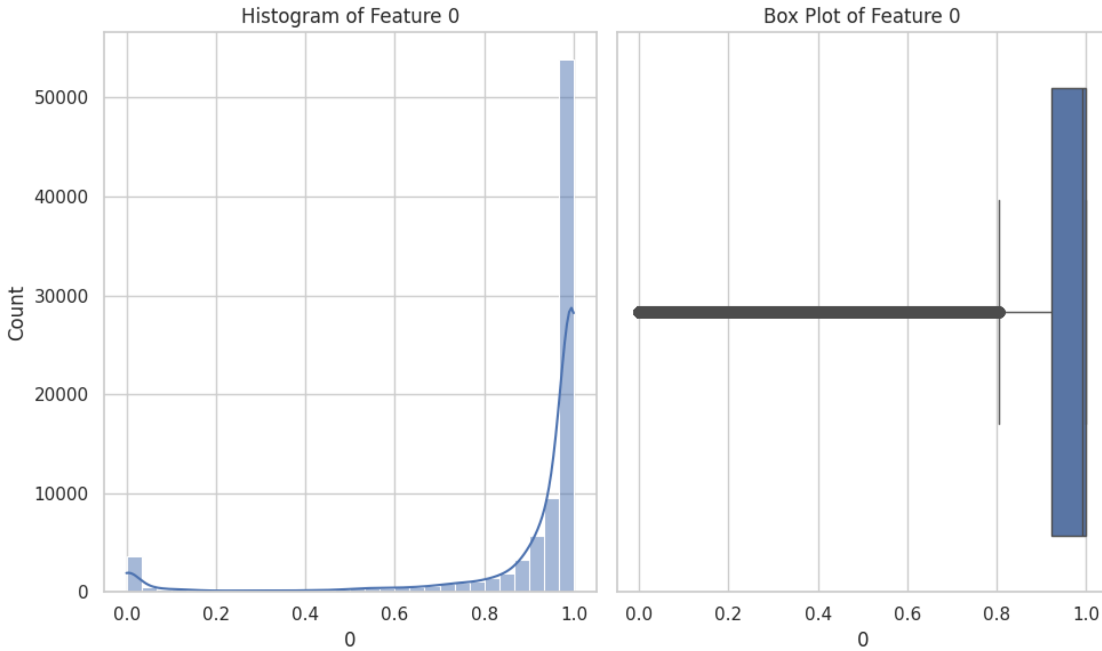
[ ]:
```python
# Correlation matrix
correlation_matrix = df_train.iloc[:, :-1].corr()
plt.figure(figsize=(12, 8))
sns.heatmap(correlation_matrix, cmap="coolwarm", vmin=-1, vmax=1, annot=False)
```

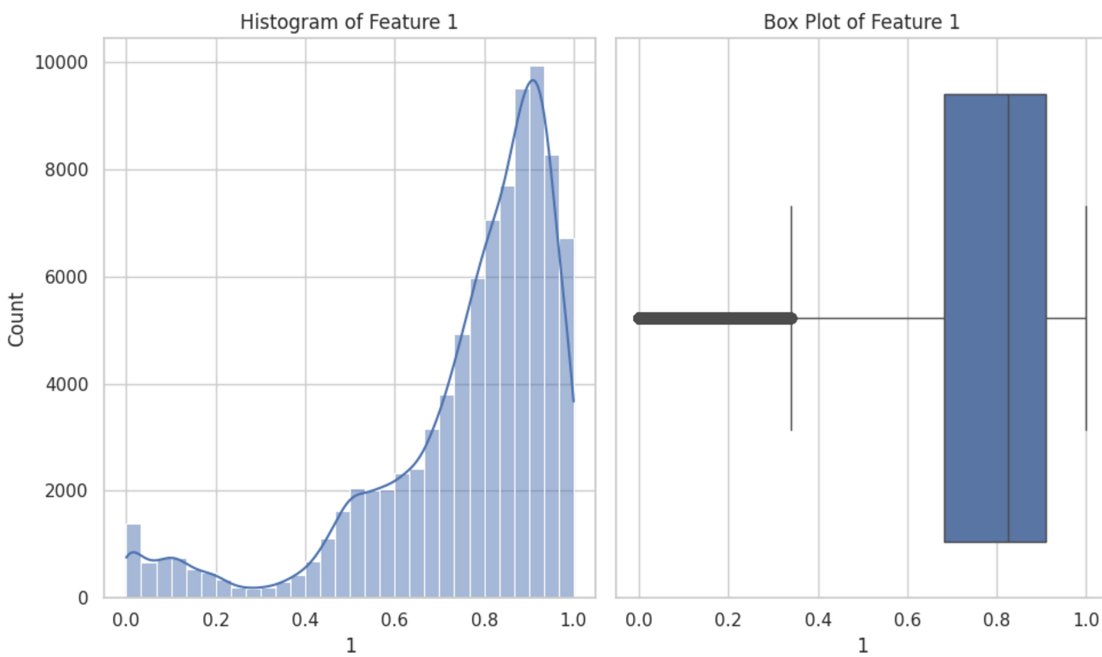
```
plt.title("Feature Correlation Heatmap")
plt.show()
```

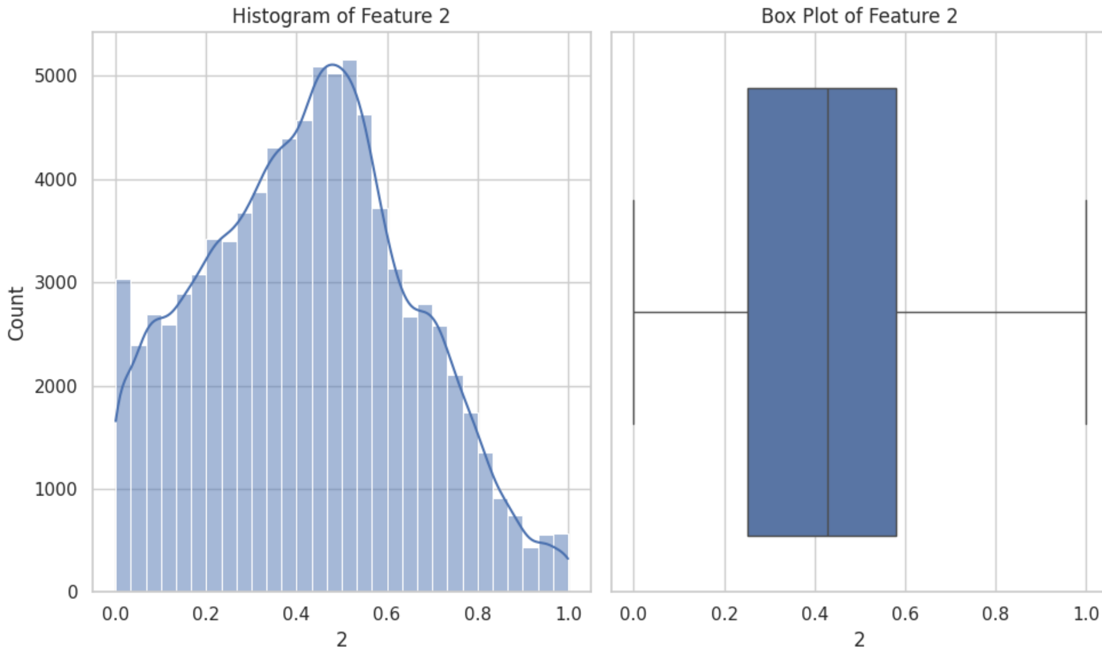


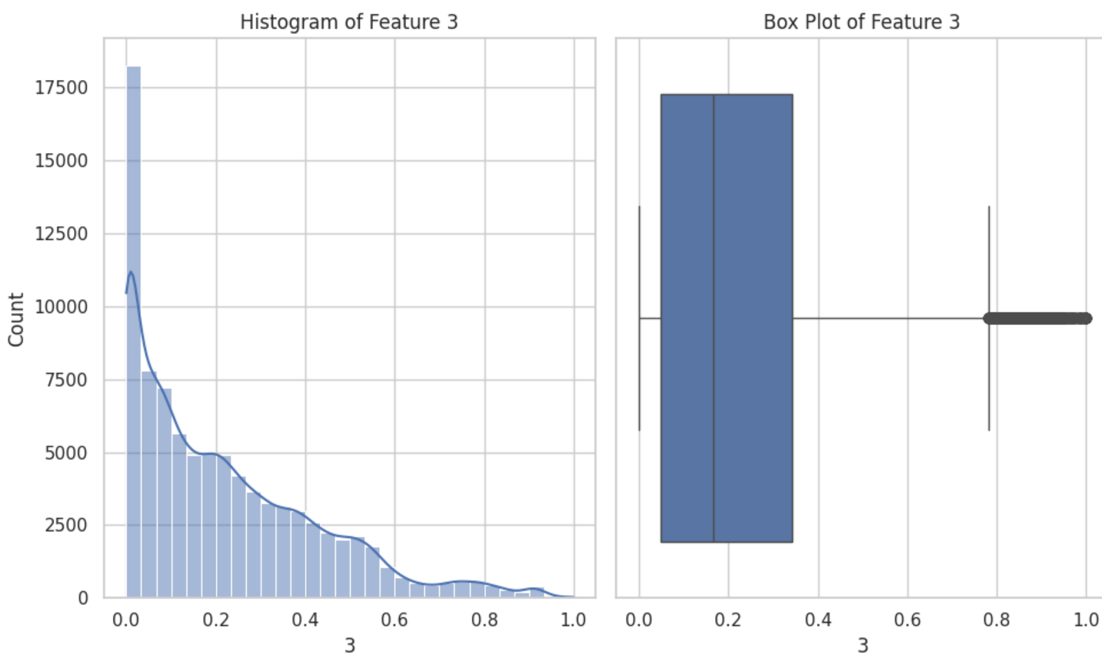
Additional Visualizations for Feature Distributions:

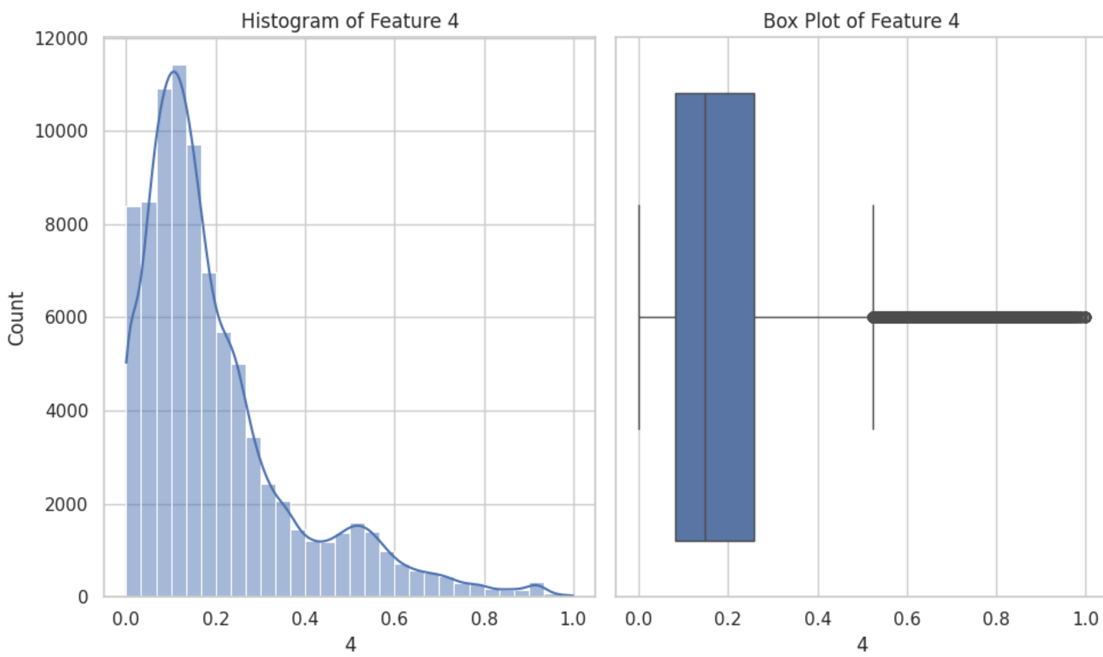
[ ]:
```
selected_features = [0, 1, 2, 3, 4]
for feature in selected_features:
    plt.figure()
    plt.subplot(1, 2, 1)
    sns.histplot(df_train[feature], bins=30, kde=True)
    plt.title(f"Histogram of Feature {feature}")

    plt.subplot(1, 2, 2)
    sns.boxplot(x=df_train[feature])
    plt.title(f"Box Plot of Feature {feature}")

    plt.tight_layout()
    plt.show()
```


Histogram of Feature 0
Box Plot of Feature 0
Count
0
50000
40000
30000
20000
10000
0.0
0.2
0.4
0.6
0.8
1.0


Histogram of Feature 1
Box Plot of Feature 1
Count
1
10000
8000
6000
4000
2000
0.0
0.2
0.4
0.6
0.8
1.0


Histogram of Feature 2
Box Plot of Feature 2
Count
5000
4000
3000
2000
1000
0
0.0
0.2
0.4
0.6
0.8
1.0
2


Histogram of Feature 3
Box Plot of Feature 3
Count
17500
15000
12500
10000
7500
5000
2500
0
0.0
0.2
0.4
0.6
0.8
1.0
3



Data Cleaning

```
[ ]: # Remove duplicate rows
initial_rows = df_train.shape[0]
df_train = df_train.drop_duplicates()
final_rows = df_train.shape[0]
print(f"Removed {initial_rows - final_rows} duplicate rows from training data.")


def remove_outliers(df, column, factor=1.5):
    Q1 = df[column].quantile(0.25)
    Q3 = df[column].quantile(0.75)
    IQR = Q3 - Q1
    lower_bound = Q1 - factor * IQR
    upper_bound = Q3 + factor * IQR
    return df[(df[column] >= lower_bound) & (df[column] <= upper_bound)]

df_train = remove_outliers(df_train, 0)
print(f"Training data shape after outlier removal: {df_train.shape}")
```

```
Removed 0 duplicate rows from training data.
Training data shape after outlier removal: (75393, 188)
```

Data Scaling(Normalization)

```
[ ]: # Separate features and target from raw DataFrames
X_train = df_train.iloc[:, :-1]
```

```
y_train = df_train.iloc[:, -1]

# Normalize features using MinMaxScaler
scaler = MinMaxScaler()
X_train_scaled = scaler.fit_transform(X_train)

df_train_scaled = pd.DataFrame(X_train_scaled, columns=X_train.columns)
df_train_scaled['target'] = y_train.values

print("First few rows of the normalized training data:")
display(df_train_scaled.head())
```

```
First few rows of the normalized training data:

          0         1         2         3         4         5         6  \
0  0.977941  0.926471  0.681373  0.245098  0.154412  0.191176  0.151961
1  0.960114  0.863248  0.461538  0.196581  0.094017  0.125356  0.099715
2  1.000000  0.659459  0.186486  0.070270  0.070270  0.059459  0.056757
3  0.925414  0.665746  0.541436  0.276243  0.196133  0.077348  0.071823
4  0.967136  1.000000  0.830986  0.586854  0.356808  0.248826  0.145540

          7         8         9  …  178  179  180  181  182  183  184  185  \
0  0.085784  0.058824  0.049020  …  0.0  0.0  0.0  0.0  0.0  0.0  0.0  0.0
1  0.088319  0.074074  0.082621  …  0.0  0.0  0.0  0.0  0.0  0.0  0.0  0.0
2  0.043243  0.054054  0.045946  …  0.0  0.0  0.0  0.0  0.0  0.0  0.0  0.0
3  0.060773  0.066298  0.058011  …  0.0  0.0  0.0  0.0  0.0  0.0  0.0  0.0
4  0.089202  0.117371  0.150235  …  0.0  0.0  0.0  0.0  0.0  0.0  0.0  0.0

   186  target
0  0.0     0.0
1  0.0     0.0
2  0.0     0.0
3  0.0     0.0
4  0.0     0.0

[5 rows x 188 columns]
```

Feature Engineering

[ ]:
```
# Apply PCA to reduce dimensionality
pca = PCA(n_components=50)
X_train_pca = pca.fit_transform(X_train_scaled)

df_train_pca = pd.DataFrame(X_train_pca, columns=[f"PC{i+1}" for i in␣
 ↪range(X_train_pca.shape[1])])
df_train_pca['target'] = y_train.values

print("Shape of PCA-transformed training data:", df_train_pca.shape)
```

```
Shape of PCA-transformed training data: (87554, 51)
```

[ ]:
```python
# Use normalized data for modeling
X_train_full = df_train_scaled.drop('target', axis=1)
y_train_full = df_train_scaled['target']

# Split into training (80%) and validation (20%) sets
X_train_split, X_val_split, y_train_split, y_val_split = train_test_split(
    X_train_full, y_train_full, test_size=0.2, random_state=42,␣
 ↪stratify=y_train_full
)

print("Training set shape:", X_train_split.shape)
print("Validation set shape:", X_val_split.shape)
```

```
Training set shape: (70043, 187)
Validation set shape: (17511, 187)
```

Logistic Regression with GridSearchCV

[ ]:
```python
param_grid_lr = {
    'C': [0.01, 0.1, 1, 10],
    'solver': ['liblinear', 'saga'],
    'penalty': ['l2']
}

lr = LogisticRegression(max_iter=1000)
grid_lr = GridSearchCV(lr, param_grid_lr, cv=5, scoring='accuracy', n_jobs=-1)
grid_lr.fit(X_train_split, y_train_split)

print("Best parameters for Logistic Regression:", grid_lr.best_params_)
y_val_pred_lr = grid_lr.predict(X_val_split)
accuracy_lr = accuracy_score(y_val_split, y_val_pred_lr)
print("Validation Accuracy for Logistic Regression:", accuracy_lr)
```

```
Best parameters for Logistic Regression: {'C': 10, 'penalty': 'l2', 'solver':
'saga'}
Validation Accuracy for Logistic Regression: 0.9530472843026726
```

Random Forest

[ ]:
```python
# Initialize Random Forest Classifier
rf_model = RandomForestClassifier(n_estimators=100, class_weight="balanced",␣
 ↪random_state=42)


rf_model.fit(X_train_split, y_train_split)

# Predict on validation data
```

```
y_pred_rf = rf_model.predict(X_val_split)

print("Random Forest Performance:")
print(classification_report(y_val_split, y_pred_rf))
```

```
Random Forest Performance:
              precision    recall  f1-score   support

         0.0       0.98      1.00      0.99     13122
         1.0       0.98      0.63      0.77       390
         2.0       0.98      0.84      0.90       596
         3.0       0.81      0.62      0.70       112
         4.0       1.00      0.94      0.97       859

    accuracy                           0.98     15079
   macro avg       0.95      0.80      0.86     15079
weighted avg       0.98      0.98      0.97     15079
```

Data prepration for LSTM

[ ]:
```
n_timesteps = X_train_full.shape[1]

# Reshape for LSTM: (samples, timesteps, features)
X_train_lstm = X_train_split.values.reshape(-1, n_timesteps, 1)
X_val_lstm = X_val_split.values.reshape(-1, n_timesteps, 1)

num_classes = len(np.unique(y_train_full))
y_train_cat = to_categorical(y_train_split, num_classes)
y_val_cat = to_categorical(y_val_split, num_classes)
```

LSTM with Early Stopping

[ ]:
```
# Building LSTM model
lstm_model = Sequential([
    LSTM(64, return_sequences=True, input_shape=(n_timesteps, 1)),
    Dropout(0.2),
    LSTM(64),
    Dropout(0.2),
    Dense(64, activation="relu"),
    Dense(num_classes, activation="softmax")  # num_classes output classes
])

# Compiling model
lstm_model.compile(optimizer="adam", loss="categorical_crossentropy",␣
 ↪metrics=["accuracy"])

# Set up EarlyStopping
```

```python
early_stop = EarlyStopping(monitor='val_loss', patience=5,␣
↪restore_best_weights=True)

# Training the LSTM model
history = lstm_model.fit(
    X_train_lstm,
    y_train_cat,
    validation_data=(X_val_lstm, y_val_cat),
    epochs=20,
    batch_size=32,
    callbacks=[early_stop]
)
```

```
/usr/local/lib/python3.11/dist-packages/keras/src/layers/rnn/rnn.py:200:
UserWarning: Do not pass an `input_shape`/`input_dim` argument to a layer. When
using Sequential models, prefer using an `Input(shape)` object as the first
layer in the model instead.
  super().__init__(**kwargs)
```

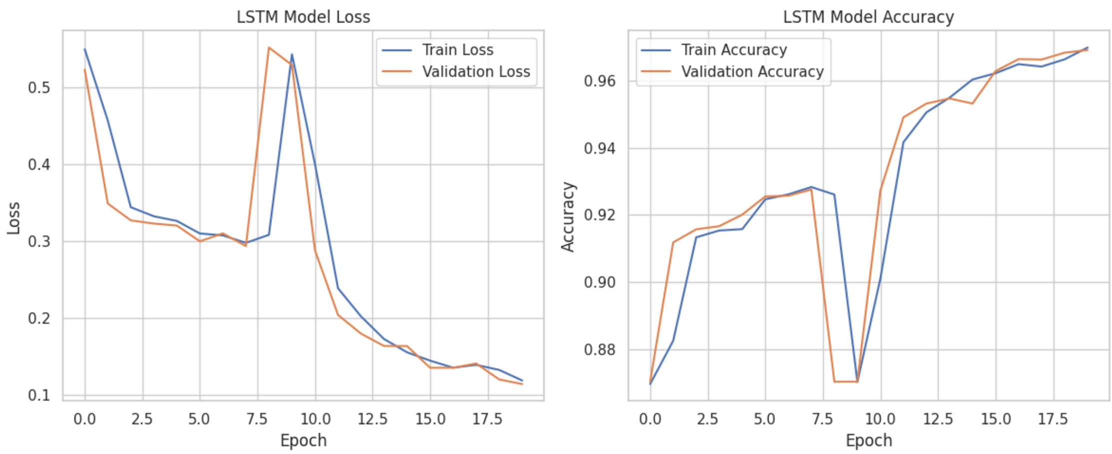
```
Epoch 1/20
1885/1885            409s 214ms/step
- accuracy: 0.8662 - loss: 0.5926 - val_accuracy: 0.8702 - val_loss: 0.5233
Epoch 2/20
1885/1885            457s 222ms/step
- accuracy: 0.8731 - loss: 0.5082 - val_accuracy: 0.9118 - val_loss: 0.3491
Epoch 3/20
1885/1885            417s 221ms/step
- accuracy: 0.9116 - loss: 0.3514 - val_accuracy: 0.9157 - val_loss: 0.3272
Epoch 4/20
1885/1885            442s 222ms/step
- accuracy: 0.9158 - loss: 0.3330 - val_accuracy: 0.9166 - val_loss: 0.3230
Epoch 5/20
1885/1885            444s 222ms/step
- accuracy: 0.9168 - loss: 0.3235 - val_accuracy: 0.9201 - val_loss: 0.3204
Epoch 6/20
1885/1885            443s 223ms/step
- accuracy: 0.9238 - loss: 0.3121 - val_accuracy: 0.9255 - val_loss: 0.2999
Epoch 7/20
1885/1885            445s 225ms/step
- accuracy: 0.9255 - loss: 0.3114 - val_accuracy: 0.9257 - val_loss: 0.3103
Epoch 8/20
1885/1885            439s 223ms/step
- accuracy: 0.9276 - loss: 0.3021 - val_accuracy: 0.9276 - val_loss: 0.2937
Epoch 9/20
1885/1885            440s 222ms/step
- accuracy: 0.9290 - loss: 0.2934 - val_accuracy: 0.8702 - val_loss: 0.5521
Epoch 10/20
1885/1885            440s 221ms/step
```

```
- accuracy: 0.8705 - loss: 0.5454 - val_accuracy: 0.8702 - val_loss: 0.5293
Epoch 11/20
1885/1885                442s 221ms/step
- accuracy: 0.8795 - loss: 0.4843 - val_accuracy: 0.9273 - val_loss: 0.2882
Epoch 12/20
1885/1885                444s 222ms/step
- accuracy: 0.9399 - loss: 0.2484 - val_accuracy: 0.9491 - val_loss: 0.2041
Epoch 13/20
1885/1885                427s 214ms/step
- accuracy: 0.9500 - loss: 0.2098 - val_accuracy: 0.9532 - val_loss: 0.1797
Epoch 14/20
1885/1885                456s 222ms/step
- accuracy: 0.9540 - loss: 0.1767 - val_accuracy: 0.9548 - val_loss: 0.1637
Epoch 15/20
1885/1885                427s 214ms/step
- accuracy: 0.9600 - loss: 0.1543 - val_accuracy: 0.9532 - val_loss: 0.1636
Epoch 16/20
1885/1885                459s 223ms/step
- accuracy: 0.9613 - loss: 0.1477 - val_accuracy: 0.9629 - val_loss: 0.1353
Epoch 17/20
1885/1885                439s 221ms/step
- accuracy: 0.9638 - loss: 0.1391 - val_accuracy: 0.9665 - val_loss: 0.1353
Epoch 18/20
1885/1885                442s 221ms/step
- accuracy: 0.9655 - loss: 0.1346 - val_accuracy: 0.9664 - val_loss: 0.1409
Epoch 19/20
1885/1885                442s 222ms/step
- accuracy: 0.9646 - loss: 0.1381 - val_accuracy: 0.9684 - val_loss: 0.1201
Epoch 20/20
1885/1885                442s 221ms/step
- accuracy: 0.9706 - loss: 0.1173 - val_accuracy: 0.9692 - val_loss: 0.1141
```

LSTM history

[ ]:
```
plt.figure(figsize=(12, 5))

# Loss plot
plt.subplot(1, 2, 1)
plt.plot(history.history['loss'], label='Train Loss')
plt.plot(history.history['val_loss'], label='Validation Loss')
plt.title('LSTM Model Loss')
plt.xlabel('Epoch')
plt.ylabel('Loss')
plt.legend()

# Accuracy plot
plt.subplot(1, 2, 2)
plt.plot(history.history['accuracy'], label='Train Accuracy')
```

```python
plt.plot(history.history['val_accuracy'], label='Validation Accuracy')
plt.title('LSTM Model Accuracy')
plt.xlabel('Epoch')
plt.ylabel('Accuracy')
plt.legend()

plt.tight_layout()
plt.show()

# Extract final training and validation accuracy and loss values
final_train_accuracy = history.history['accuracy'][-1] * 100
final_val_accuracy = history.history['val_accuracy'][-1] * 100

final_train_loss = history.history['loss'][-1]
final_val_loss = history.history['val_loss'][-1]

final_train_loss_pct = final_train_loss * 100
final_val_loss_pct = final_val_loss * 100

# Create a summary DataFrame for Accuracy
accuracy_summary = pd.DataFrame({
    'Phase': ['Training Accuracy', 'Validation Accuracy'],
    'Accuracy (%)': [final_train_accuracy, final_val_accuracy]
})

print("Final Accuracy Summary:")
display(accuracy_summary)

# Create a summary DataFrame for Loss
loss_summary = pd.DataFrame({
    'Phase': ['Training Loss', 'Validation Loss'],
    'Loss Value': [final_train_loss, final_val_loss],
    'Loss (%)': [final_train_loss_pct, final_val_loss_pct]
})

print("Final Loss Summary:")
display(loss_summary)
```




```
Final Accuracy Summary:

                 Phase  Accuracy (%)
0    Training Accuracy     96.997380
1  Validation Accuracy     96.922874
```

```
Final Loss Summary:

             Phase  Loss Value   Loss (%)
0    Training Loss    0.118750  11.875039
1  Validation Loss    0.114145  11.414526
```

Defining Top-k Accuracy Function

```
[ ]: def top_k_accuracy(y_true, y_prob, k=5):
         top_k_preds = np.argsort(y_prob, axis=1)[:, -k:]
         return np.mean([1 if y_true.values[i] in top_k_preds[i] else 0 for i in␣
      ↪range(len(y_true))])
```

LR

```
[ ]: # --- Logistic Regression Metrics Evaluation and Display as DataFrames ---

     # Predictions and predicted probabilities
     y_val_pred_lr = grid_lr.predict(X_val_split)
     y_val_prob_lr = grid_lr.predict_proba(X_val_split)

     # Compute the classification report
     lr_report = classification_report(y_val_split, y_val_pred_lr, output_dict=True)
     lr_report_df = pd.DataFrame(lr_report).transpose()
     print("Logistic Regression Classification Report:")
     display(lr_report_df)

     # Compute overall accuracy
```

```python
accuracy_lr = accuracy_score(y_val_split, y_val_pred_lr)

classes = np.unique(y_val_split)
y_val_onehot = label_binarize(y_val_split, classes=classes)

# Compute ROC AUC Score (macro average, one-vs-rest)
roc_auc_lr = roc_auc_score(y_val_onehot, y_val_prob_lr, average="macro",␣
↪multi_class="ovr")

# Compute AUPR for each class and then macro average
aupr_scores_lr = []
for i in range(len(classes)):
    precision, recall, _ = precision_recall_curve(y_val_onehot[:, i],␣
↪y_val_prob_lr[:, i])

    sorted_indices = np.argsort(recall)
    recall_sorted = recall[sorted_indices]
    precision_sorted = precision[sorted_indices]
    aupr = auc(recall_sorted, precision_sorted)
    aupr_scores_lr.append(aupr)
macro_aupr_lr = np.mean(aupr_scores_lr)

# Compute Top-5 Accuracy (mAP)
top5_map_lr = top_k_accuracy(y_val_split, y_val_prob_lr, k=5)

summary_lr = pd.DataFrame({
    'Metric': ['Accuracy', 'ROC AUC (macro, OVR)', 'Macro AUPR', 'Top-5 mAP'],
    'Value': [accuracy_lr, roc_auc_lr, macro_aupr_lr, top5_map_lr]
})
print("Overall Logistic Regression Performance Metrics:")
display(summary_lr)


aupr_scores_lr_df = pd.DataFrame({
    'Class': classes,
    'AUPR': aupr_scores_lr
})
print("AUPR Scores for Each Class:")
display(aupr_scores_lr_df)
```

```
Logistic Regression Classification Report:

              precision    recall  f1-score       support
0.0            0.958226  0.992913  0.975261  13122.000000
1.0            0.882845  0.541026  0.670906    390.000000
2.0            0.858491  0.610738  0.713725    596.000000
3.0            0.459016  0.250000  0.323699    112.000000
4.0            0.974934  0.860303  0.914038    859.000000
```

```
accuracy       0.953047  0.953047  0.953047      0.953047
macro avg      0.826702  0.650996  0.719526  15079.000000
weighted avg   0.949578  0.953047  0.948725  15079.000000
```

```
Overall Logistic Regression Performance Metrics:
```

```
                 Metric     Value
0              Accuracy  0.953047
1  ROC AUC (macro, OVR)  0.945421
2            Macro AUPR  0.743697
3             Top-5 mAP  1.000000
```

```
AUPR Scores for Each Class:
```

```
   Class      AUPR
0    0.0  0.983444
1    1.0  0.621228
2    2.0  0.786060
3    3.0  0.392902
4    4.0  0.934850
```

RF

[ ]:
```
# --- Random Forest Metrics Evaluation and Display as DataFrames ---

# Predictions and predicted probabilities for Random Forest
y_val_pred_rf = rf_model.predict(X_val_split)
y_val_prob_rf = rf_model.predict_proba(X_val_split)

# Generate classification report as a dictionary
rf_report = classification_report(y_val_split, y_val_pred_rf, output_dict=True)
rf_report_df = pd.DataFrame(rf_report).transpose()
print("\nRandom Forest Classification Report:")
display(rf_report_df)

# Compute overall accuracy
accuracy_rf = accuracy_score(y_val_split, y_val_pred_rf)

# ROC AUC Score
roc_auc_rf = roc_auc_score(y_val_onehot, y_val_prob_rf, average="macro",␣
 ↪multi_class="ovr")

# Compute AUPR for each class with sorted recall for proper AUC calculation
aupr_scores_rf = []
for i in range(len(classes)):
    precision, recall, _ = precision_recall_curve(y_val_onehot[:, i],␣
 ↪y_val_prob_rf[:, i])
    sorted_indices = np.argsort(recall)
    recall_sorted = recall[sorted_indices]
    precision_sorted = precision[sorted_indices]
```

```
    aupr = auc(recall_sorted, precision_sorted)
    aupr_scores_rf.append(aupr)
macro_aupr_rf = np.mean(aupr_scores_rf)

# Compute Top-5 mAP (top-5 accuracy)
top5_map_rf = top_k_accuracy(y_val_split, y_val_prob_rf, k=5)

# Create a summary DataFrame for overall metrics
summary_rf = pd.DataFrame({
    'Metric': ['Accuracy', 'ROC AUC (macro, OVR)', 'Macro AUPR', 'Top-5 mAP'],
    'Value': [accuracy_rf, roc_auc_rf, macro_aupr_rf, top5_map_rf]
})
print("Overall Random Forest Performance Metrics:")
display(summary_rf)

# Create a DataFrame for AUPR scores per class
aupr_scores_rf_df = pd.DataFrame({
    'Class': classes,
    'AUPR': aupr_scores_rf
})
print("Random Forest AUPR Scores for Each Class:")
display(aupr_scores_rf_df)
```

Random Forest Classification Report:

	precision	recall	f1-score	support
0.0	0.976162	0.998628	0.987267	13122.000000
1.0	0.976285	0.633333	0.768274	390.000000
2.0	0.978389	0.835570	0.901357	596.000000
3.0	0.811765	0.616071	0.700508	112.000000
4.0	0.996287	0.937136	0.965807	859.000000
accuracy	0.976391	0.976391	0.976391	0.976391
macro avg	0.947778	0.804148	0.864643	15079.000000
weighted avg	0.976179	0.976391	0.974855	15079.000000

Overall Random Forest Performance Metrics:

	Metric	Value
0	Accuracy	0.976391
1	ROC AUC (macro, OVR)	0.993818
2	Macro AUPR	0.932766
3	Top-5 mAP	1.000000

Random Forest AUPR Scores for Each Class:

	Class	AUPR
0	0.0	0.999095
1	1.0	0.897132
2	2.0	0.976879

```
3    3.0   0.795239
4    4.0   0.995485
```

LSTM

```
[ ]: # --- LSTM Model Metrics Evaluation and Display as DataFrames ---

# Get predictions and predicted probabilities for LSTM
y_val_pred_lstm_prob = lstm_model.predict(X_val_lstm)
y_val_pred_lstm = np.argmax(y_val_pred_lstm_prob, axis=1)

# Generate classification report and convert it to a DataFrame
print("\nLSTM Model Classification Report:")
lstm_report = classification_report(y_val_split, y_val_pred_lstm,␣
 ↪output_dict=True)
lstm_report_df = pd.DataFrame(lstm_report).transpose()
display(lstm_report_df)

# Calculate overall accuracy
accuracy_lstm = accuracy_score(y_val_split, y_val_pred_lstm)
print("LSTM Model Accuracy:", accuracy_lstm)

# Compute ROC AUC Score
roc_auc_lstm = roc_auc_score(y_val_onehot, y_val_pred_lstm_prob,␣
 ↪average="macro", multi_class="ovr")
print("LSTM Model ROC AUC (macro, OVR):", roc_auc_lstm)

# Compute AUPR for each class
aupr_scores_lstm = []
for i in range(len(classes)):
    precision, recall, _ = precision_recall_curve(y_val_onehot[:, i],␣
 ↪y_val_pred_lstm_prob[:, i])
    sorted_indices = np.argsort(recall)
    recall_sorted = recall[sorted_indices]
    precision_sorted = precision[sorted_indices]
    aupr = auc(recall_sorted, precision_sorted)
    aupr_scores_lstm.append(aupr)

macro_aupr_lstm = np.mean(aupr_scores_lstm)
print("LSTM Model Macro AUPR:", macro_aupr_lstm)

# Compute Top-5 Accuracy (mAP)
top5_map_lstm = top_k_accuracy(y_val_split, y_val_pred_lstm_prob, k=5)
print("LSTM Model Top-5 mAP:", top5_map_lstm)

#summary DataFrame for overall LSTM metrics
summary_lstm = pd.DataFrame({
    'Metric': ['Accuracy', 'ROC AUC (macro, OVR)', 'Macro AUPR', 'Top-5 mAP'],
```

```python
    'Value': [accuracy_lstm, roc_auc_lstm, macro_aupr_lstm, top5_map_lstm]
})
print("Overall LSTM Performance Metrics:")
display(summary_lstm)

#AUPR scores for each class
aupr_scores_lstm_df = pd.DataFrame({
    'Class': classes,
    'AUPR': aupr_scores_lstm
})
print("LSTM AUPR Scores for Each Class:")
display(aupr_scores_lstm_df)
```

```
472/472              34s 73ms/step

LSTM Model Classification Report:
```

	precision	recall	f1-score	support
0.0	0.979641	0.990093	0.984839	13122.000000
1.0	0.771341	0.648718	0.704735	390.000000
2.0	0.899461	0.840604	0.869037	596.000000
3.0	0.617188	0.705357	0.658333	112.000000
4.0	0.982587	0.919674	0.950090	859.000000
accuracy	0.969229	0.969229	0.969229	0.969229
macro avg	0.850044	0.820889	0.833407	15079.000000
weighted avg	0.968560	0.969229	0.968613	15079.000000

```
LSTM Model Accuracy: 0.9692287286955369
LSTM Model ROC AUC (macro, OVR): 0.9766423819858623
LSTM Model Macro AUPR: 0.8666640873982402
LSTM Model Top-5 mAP: 1.0
Overall LSTM Performance Metrics:
```

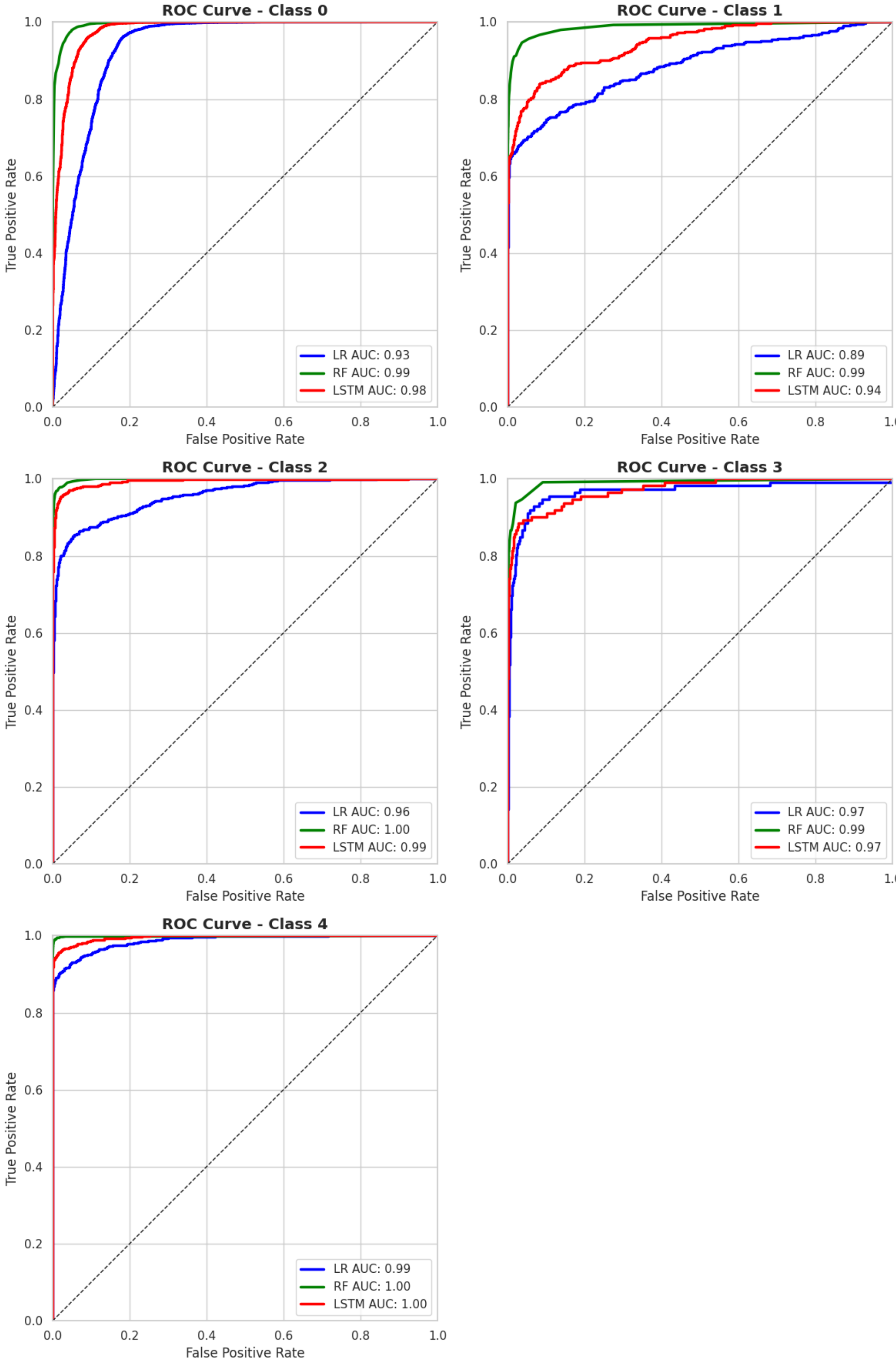
	Metric	Value
0	Accuracy	0.969229
1	ROC AUC (macro, OVR)	0.976642
2	Macro AUPR	0.866664
3	Top-5 mAP	1.000000

```
LSTM AUPR Scores for Each Class:
```

	Class	AUPR
0	0.0	0.995887
1	1.0	0.728098
2	2.0	0.944513
3	3.0	0.691998
4	4.0	0.972825

ROC curves

[ ]:
```
sns.set_style("whitegrid")

rows = (n_classes + 1) // 2
cols = 2

fig, axes = plt.subplots(rows, cols, figsize=(12, 6 * rows))
axes = axes.flatten()

for i in range(n_classes):
    fpr_lr, tpr_lr, _ = roc_curve(y_val_onehot[:, i], y_val_prob_lr[:, i])
    fpr_rf, tpr_rf, _ = roc_curve(y_val_onehot[:, i], y_val_prob_rf[:, i])
    fpr_lstm, tpr_lstm, _ = roc_curve(y_val_onehot[:, i], y_val_pred_lstm_prob[:
↪, i])

    ax = axes[i]
    ax.plot(fpr_lr, tpr_lr, label=f'LR AUC: {auc(fpr_lr, tpr_lr):.2f}',␣
↪color='blue', linewidth=2.5)
    ax.plot(fpr_rf, tpr_rf, label=f'RF AUC: {auc(fpr_rf, tpr_rf):.2f}',␣
↪color='green', linewidth=2.5)
    ax.plot(fpr_lstm, tpr_lstm, label=f'LSTM AUC: {auc(fpr_lstm, tpr_lstm):.
↪2f}', color='red', linewidth=2.5)
    ax.plot([0, 1], [0, 1], 'k--', linewidth=1)  # Diagonal reference line

    ax.set_xlim([0, 1])
    ax.set_ylim([0, 1])
    ax.set_xticks([0, 0.2, 0.4, 0.6, 0.8, 1])
    ax.set_yticks([0, 0.2, 0.4, 0.6, 0.8, 1])
    ax.set_title(f'ROC Curve - Class {i}', fontsize=14, fontweight='bold')
    ax.set_xlabel('False Positive Rate', fontsize=12)
    ax.set_ylabel('True Positive Rate', fontsize=12)
    ax.legend(loc='lower right', fontsize=11)

for j in range(n_classes, len(axes)):
    fig.delaxes(axes[j])

plt.tight_layout()
plt.show()
```


ROC Curve - Class 0
LR AUC: 0.93
RF AUC: 0.99
LSTM AUC: 0.98
ROC Curve - Class 1
LR AUC: 0.89
RF AUC: 0.99
LSTM AUC: 0.94
ROC Curve - Class 2
LR AUC: 0.96
RF AUC: 1.00
LSTM AUC: 0.99
ROC Curve - Class 3
LR AUC: 0.97
RF AUC: 0.99
LSTM AUC: 0.97
ROC Curve - Class 4
LR AUC: 0.99
RF AUC: 1.00
LSTM AUC: 1.00
True Positive Rate
False Positive Rate
0.0
0.2
0.4
0.6
0.8
1.0