```
# Install necessary libraries
!pip install transformers tqdm seaborn matplotlib scikit-learn

from sklearn.metrics import confusion_matrix, roc_curve, auc, precision_recall_curve
from sklearn.preprocessing import label_binarize

# Import necessary libraries
import torch
from torch.utils.data import Dataset, DataLoader
from torch import nn
from transformers import BertTokenizer, BertForSequenceClassification, AdamW, get_linear_schedule_with_warmup
from tqdm import tqdm
import pandas as pd
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import LabelEncoder, label_binarize
from sklearn.metrics import confusion_matrix, roc_curve, auc, precision_recall_curve
import seaborn as sns
import matplotlib.pyplot as plt
import numpy as np

# Check if GPU is available and set the device
device = torch.device("cuda" if torch.cuda.is_available() else "cpu")
print(f"Using device: {device}")

# Load your dataset (you can upload your CSV to Colab)
from google.colab import files
uploaded = files.upload()

# Load the dataset (replace 'your_file.csv' with the actual filename after uploading)
df = pd.read_csv('MN-DS-news-classification_combined.csv', encoding='ISO-8859-1')

# Preprocess the data: Select relevant columns, clean up missing values, and encode labels
df = df[['title', 'category_level_1']].dropna()

# Encode the labels into numerical format
label_encoder = LabelEncoder()
df['label'] = label_encoder.fit_transform(df['category_level_1'])

# Plot class distribution
def plot_class_distribution(df, label_encoder):
    plt.figure(figsize=(10, 5))
    sns.countplot(x=df['category_level_1'])
    plt.title('Class Distribution')
    plt.xticks(rotation=45)
    plt.show()

plot_class_distribution(df, label_encoder)

# Split the data into training and validation sets
train_texts, val_texts, train_labels, val_labels = train_test_split(
    df['title'].tolist(), df['label'].tolist(), test_size=0.2, random_state=42
)

# Define a Dataset class for PyTorch
class NewsDataset(Dataset):
    def __init__(self, texts, labels, tokenizer, max_len):
        self.texts = texts
        self.labels = labels
        self.tokenizer = tokenizer
        self.max_len = max_len

    def __len__(self):
        return len(self.texts)

    def __getitem__(self, idx):
        text = self.texts[idx]
        label = self.labels[idx]
        encoding = self.tokenizer.encode_plus(
            text,
            add_special_tokens=True,
            max_length=self.max_len,
            return_token_type_ids=False,
            padding='max_length',
            truncation=True
```

```
            truncation=True,
            return_attention_mask=True,
            return_tensors='pt',
        )

        return {
            'input_ids': encoding['input_ids'].flatten(),
            'attention_mask': encoding['attention_mask'].flatten(),
            'labels': torch.tensor(label, dtype=torch.long)
        }

# Initialize the tokenizer (using BERT for demonstration)
tokenizer = BertTokenizer.from_pretrained('bert-base-uncased')

# Set maximum length for tokenized sequences
MAX_LEN = 128

# Create DataLoader for training and validation
train_dataset = NewsDataset(train_texts, train_labels, tokenizer, MAX_LEN)
val_dataset = NewsDataset(val_texts, val_labels, tokenizer, MAX_LEN)

train_loader = DataLoader(train_dataset, batch_size=16, shuffle=True)
val_loader = DataLoader(val_dataset, batch_size=16)

# Define a basic model using BERT for sequence classification
class NewsClassifier(nn.Module):
    def __init__(self, n_classes):
        super(NewsClassifier, self).__init__()
        self.bert = BertForSequenceClassification.from_pretrained('bert-base-uncased', num_labels=n_classes)

    def forward(self, input_ids, attention_mask):
        return self.bert(input_ids=input_ids, attention_mask=attention_mask)

# Get the number of classes
num_classes = df['label'].nunique()

# Instantiate the model
model = NewsClassifier(num_classes).to(device)

# Set up the optimizer and learning rate scheduler
optimizer = AdamW(model.parameters(), lr=2e-5, correct_bias=False)
total_steps = len(train_loader) * 3  # 3 epochs

scheduler = get_linear_schedule_with_warmup(
    optimizer, num_warmup_steps=0, num_training_steps=total_steps
)

# Define loss function (CrossEntropyLoss is used for classification tasks)
loss_fn = nn.CrossEntropyLoss().to(device)

# Training function
def train_epoch(model, data_loader, loss_fn, optimizer, device, scheduler):
    model.train()
    losses = 0
    correct_predictions = 0

    for d in tqdm(data_loader, desc="Training"):
        input_ids = d["input_ids"].to(device)
        attention_mask = d["attention_mask"].to(device)
        labels = d["labels"].to(device)

        optimizer.zero_grad()

        outputs = model(input_ids=input_ids, attention_mask=attention_mask)
        logits = outputs.logits
        _, preds = torch.max(logits, dim=1)
        loss = loss_fn(logits, labels)

        loss.backward()
        optimizer.step()
        scheduler.step()

        correct_predictions += torch.sum(preds == labels)
        losses += loss.item()

    return correct_predictions.double() / len(data_loader.dataset), losses / len(data_loader)
```

```python
    return correct_predictions.double() / len(data_loader.dataset), losses / len(data_loader)

# Evaluation function
def eval_model(model, data_loader, loss_fn, device):
    model.eval()
    losses = 0
    correct_predictions = 0

    with torch.no_grad():
        for d in tqdm(data_loader, desc="Validation"):
            input_ids = d["input_ids"].to(device)
            attention_mask = d["attention_mask"].to(device)
            labels = d["labels"].to(device)

            outputs = model(input_ids=input_ids, attention_mask=attention_mask)
            logits = outputs.logits
            _, preds = torch.max(logits, dim=1)
            loss = loss_fn(logits, labels)

            correct_predictions += torch.sum(preds == labels)
            losses += loss.item()

    return correct_predictions.double() / len(data_loader.dataset), losses / len(data_loader)

# Plotting training and validation accuracy and loss
def plot_training_history(history):
    epochs = range(1, len(history['train_acc']) + 1)

    # Plot training & validation accuracy
    plt.figure(figsize=(12, 5))

    plt.subplot(1, 2, 1)
    plt.plot(epochs, history['train_acc'], label='Training Accuracy')
    plt.plot(epochs, history['val_acc'], label='Validation Accuracy')
    plt.title('Training and Validation Accuracy')
    plt.xlabel('Epochs')
    plt.ylabel('Accuracy')
    plt.legend()

    # Plot training & validation loss
    plt.subplot(1, 2, 2)
    plt.plot(epochs, history['train_loss'], label='Training Loss')
    plt.plot(epochs, history['val_loss'], label='Validation Loss')
    plt.title('Training and Validation Loss')
    plt.xlabel('Epochs')
    plt.ylabel('Loss')
    plt.legend()

    plt.show()

# Training the model for 3 epochs
history = {'train_acc': [], 'train_loss': [], 'val_acc': [], 'val_loss': []}
epochs = 3

for epoch in range(epochs):
    print(f"Epoch {epoch + 1}/{epochs}")

    # Train
    train_acc, train_loss = train_epoch(model, train_loader, loss_fn, optimizer, device, scheduler)
    train_acc = train_acc.cpu().item()  # Move accuracy to CPU and convert to Python float
    train_loss = float(train_loss)  # Ensure the loss is a float

    # Validate
    val_acc, val_loss = eval_model(model, val_loader, loss_fn, device)
    val_acc = val_acc.cpu().item()  # Move accuracy to CPU and convert to Python float
    val_loss = float(val_loss)  # Ensure the loss is a float

    # Append the metrics to the history dictionary
    history['train_acc'].append(train_acc)
    history['train_loss'].append(train_loss)
    history['val_acc'].append(val_acc)
    history['val_loss'].append(val_loss)

    print(f"Train loss: {train_loss}, Train accuracy: {train_acc}")
    print(f"Validation loss: {val_loss}, Validation accuracy: {val_acc}")
```

```
# Plot the training history
plot_training_history(history)

# Plot confusion matrix
def plot_confusion_matrix(model, data_loader, label_encoder, device):
    model.eval()
    all_preds = []
    all_labels = []

    with torch.no_grad():
        for d in data_loader:
            input_ids = d["input_ids"].to(device)
            attention_mask = d["attention_mask"].to(device)
            labels = d["labels"].to(device)

            outputs = model(input_ids=input_ids, attention_mask=attention_mask)
            logits = outputs.logits
            _, preds = torch.max(logits, dim=1)

            all_preds.extend(preds.cpu().numpy())
            all_labels.extend(labels.cpu().numpy())

    # Create confusion matrix
    cm = confusion_matrix(all_labels, all_preds)

    # Plot the confusion matrix
    plt.figure(figsize=(10, 7))
    sns.heatmap(cm, annot=True, fmt='d', cmap='Blues', xticklabels=label_encoder.classes_, yticklabels=label_encoder.classes_)
    plt.xlabel('Predicted')
    plt.ylabel('Actual')
    plt.title('Confusion Matrix')
    plt.show()

# Call the function to plot confusion matrix after validation
plot_confusion_matrix(model, val_loader, label_encoder, device)

# Plot ROC Curve for Binary/Multiclass Classification
def plot_roc_curve(model, data_loader, device, num_classes):
    model.eval()
    all_preds = []
    all_labels = []

    with torch.no_grad():
        for d in data_loader:
            input_ids = d["input_ids"].to(device)
            attention_mask = d["attention_mask"].to(device)
            labels = d["labels"].to(device)

            outputs = model(input_ids=input_ids, attention_mask=attention_mask)
            logits = outputs.logits

            # Calculate probabilities
            probs = torch.nn.functional.softmax(logits, dim=1)

            all_preds.extend(probs.cpu().numpy())
            all_labels.extend(labels.cpu().numpy())

    # Convert to numpy arrays for easier handling
    all_preds = np.array(all_preds)
    all_labels = np.array(all_labels)

   # Plot ROC Curve for Binary/Multiclass Classification
def plot_roc_curve(model, data_loader, device, num_classes):
    model.eval()
    all_preds = []
    all_labels = []

    with torch.no_grad():
        for d in data_loader:
            input_ids = d["input_ids"].to(device)
            attention_mask = d["attention_mask"].to(device)
            labels = d["labels"].to(device)

            outputs = model(input_ids=input_ids, attention_mask=attention_mask)
            logits = outputs.logits
```

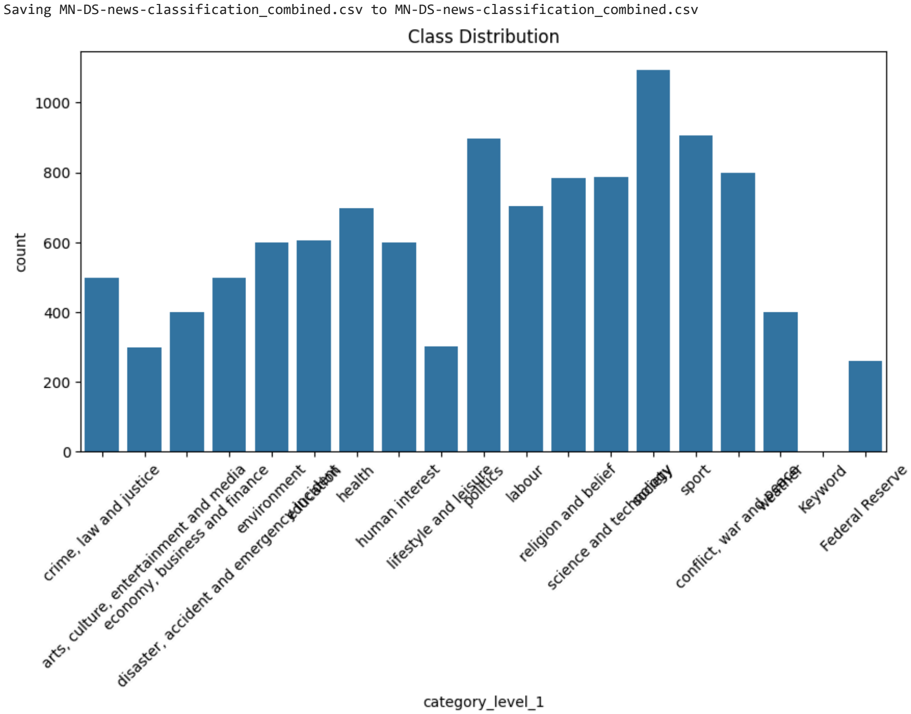
```
            # Calculate probabilities
            probs = torch.nn.functional.softmax(logits, dim=1)

            all_preds.extend(probs.cpu().numpy())
            all_labels.extend(labels.cpu().numpy())

    # Convert to numpy arrays for easier handling
    all_preds = np.array(all_preds)
    all_labels = np.array(all_labels)

    # Plot ROC curves for each class
    plt.figure(figsize=(10, 7))
    for i in range(num_classes):
        fpr, tpr, _ = roc_curve(label_binarize(all_labels, classes=range(num_classes))[:, i], all_preds[:, i])
        roc_auc = auc(fpr, tpr)
        plt.plot(fpr, tpr, label=f'Class {i} (AUC = {roc_auc:.2f})')

    plt.plot([0, 1], [0, 1], 'k--')
    plt.xlim([0.0, 1.0])
    plt.ylim([0.0, 1.05])
    plt.xlabel('False Positive Rate')
    plt.ylabel('True Positive Rate')
    plt.title('ROC Curve for Multiclass Classification')
    plt.legend(loc="lower right")
    plt.show()

# Call the function after training
plot_roc_curve(model, val_loader, device, num_classes)
```

```
Requirement already satisfied: transformers in /usr/local/lib/python3.10/dist-packages (4.42.4)
Requirement already satisfied: tqdm in /usr/local/lib/python3.10/dist-packages (4.66.5)
Requirement already satisfied: seaborn in /usr/local/lib/python3.10/dist-packages (0.13.1)
Requirement already satisfied: matplotlib in /usr/local/lib/python3.10/dist-packages (3.7.1)
Requirement already satisfied: scikit-learn in /usr/local/lib/python3.10/dist-packages (1.3.2)
Requirement already satisfied: filelock in /usr/local/lib/python3.10/dist-packages (from transformers) (3.15.4)
Requirement already satisfied: huggingface-hub<1.0,>=0.23.2 in /usr/local/lib/python3.10/dist-packages (from transformers) (0.23.5)
Requirement already satisfied: numpy<2.0,>=1.17 in /usr/local/lib/python3.10/dist-packages (from transformers) (1.26.4)
Requirement already satisfied: packaging>=20.0 in /usr/local/lib/python3.10/dist-packages (from transformers) (24.1)
Requirement already satisfied: pyyaml>=5.1 in /usr/local/lib/python3.10/dist-packages (from transformers) (6.0.2)
Requirement already satisfied: regex!=2019.12.17 in /usr/local/lib/python3.10/dist-packages (from transformers) (2024.5.15)
Requirement already satisfied: requests in /usr/local/lib/python3.10/dist-packages (from transformers) (2.32.3)
Requirement already satisfied: safetensors>=0.4.1 in /usr/local/lib/python3.10/dist-packages (from transformers) (0.4.4)
Requirement already satisfied: tokenizers<0.20,>=0.19 in /usr/local/lib/python3.10/dist-packages (from transformers) (0.19.1)
Requirement already satisfied: pandas>=1.2 in /usr/local/lib/python3.10/dist-packages (from seaborn) (2.1.4)
Requirement already satisfied: contourpy>=1.0.1 in /usr/local/lib/python3.10/dist-packages (from matplotlib) (1.2.1)
Requirement already satisfied: cycler>=0.10 in /usr/local/lib/python3.10/dist-packages (from matplotlib) (0.12.1)
Requirement already satisfied: fonttools>=4.22.0 in /usr/local/lib/python3.10/dist-packages (from matplotlib) (4.53.1)
Requirement already satisfied: kiwisolver>=1.0.1 in /usr/local/lib/python3.10/dist-packages (from matplotlib) (1.4.5)
Requirement already satisfied: pillow>=6.2.0 in /usr/local/lib/python3.10/dist-packages (from matplotlib) (9.4.0)
Requirement already satisfied: pyparsing>=2.3.1 in /usr/local/lib/python3.10/dist-packages (from matplotlib) (3.1.2)
Requirement already satisfied: python-dateutil>=2.7 in /usr/local/lib/python3.10/dist-packages (from matplotlib) (2.8.2)
Requirement already satisfied: scipy>=1.5.0 in /usr/local/lib/python3.10/dist-packages (from scikit-learn) (1.13.1)
Requirement already satisfied: joblib>=1.1.1 in /usr/local/lib/python3.10/dist-packages (from scikit-learn) (1.4.2)
Requirement already satisfied: threadpoolctl>=2.0.0 in /usr/local/lib/python3.10/dist-packages (from scikit-learn) (3.5.0)
Requirement already satisfied: fsspec>=2023.5.0 in /usr/local/lib/python3.10/dist-packages (from huggingface-hub<1.0,>=0.23.2->transformers) (2024.6.1)
Requirement already satisfied: typing-extensions>=3.7.4.3 in /usr/local/lib/python3.10/dist-packages (from huggingface-hub<1.0,>=0.23.2->transformers) (4.12.2)
Requirement already satisfied: pytz>=2020.1 in /usr/local/lib/python3.10/dist-packages (from pandas>=1.2->seaborn) (2024.1)
Requirement already satisfied: tzdata>=2022.1 in /usr/local/lib/python3.10/dist-packages (from pandas>=1.2->seaborn) (2024.1)
Requirement already satisfied: six>=1.5 in /usr/local/lib/python3.10/dist-packages (from python-dateutil>=2.7->matplotlib) (1.16.0)
Requirement already satisfied: charset-normalizer<4,>=2 in /usr/local/lib/python3.10/dist-packages (from requests->transformers) (3.3.2)
Requirement already satisfied: idna<4,>=2.5 in /usr/local/lib/python3.10/dist-packages (from requests->transformers) (3.7)
Requirement already satisfied: urllib3<3,>=1.21.1 in /usr/local/lib/python3.10/dist-packages (from requests->transformers) (2.0.7)
Requirement already satisfied: certifi>=2017.4.17 in /usr/local/lib/python3.10/dist-packages (from requests->transformers) (2024.7.4)
Using device: cuda
```

Choose Files MN-DS-ne…ombined.csv

- **MN-DS-news-classification_combined.csv**(text/csv) - 47957005 bytes, last modified: 8/22/2024 - 100% done

```
Saving MN-DS-news-classification_combined.csv to MN-DS-news-classification_combined.csv
```




```
/usr/local/lib/python3.10/dist-packages/huggingface_hub/utils/_token.py:89: UserWarning:
The secret `HF_TOKEN` does not exist in your Colab secrets.
To authenticate with the Hugging Face Hub, create a token in your settings tab (https://huggingface.co/settings/tokens), set it as secret in your Google Colab and restart your session.
You will be able to reuse this secret in all of your notebooks.
Please note that authentication is recommended but still optional to access public models or datasets.
```

```
Please note that authentication is recommended but still optional to access public models or datasets.
  warnings.warn(
```

tokenizer_config.json: 100% 48.0/48.0 [00:00<00:00, 3.68kB/s]

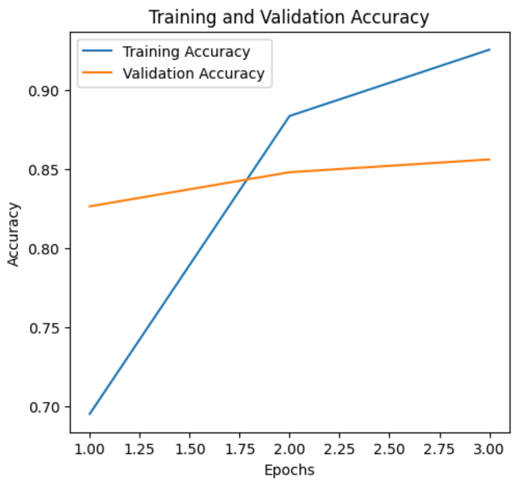
vocab.txt: 100% 232k/232k [00:00<00:00, 4.10MB/s]

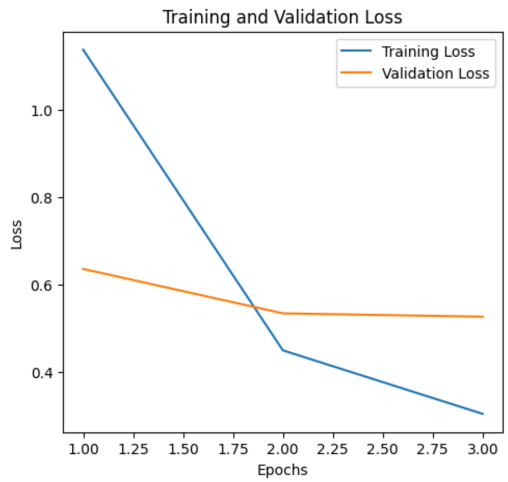
tokenizer.json: 100% 466k/466k [00:00<00:00, 19.7MB/s]

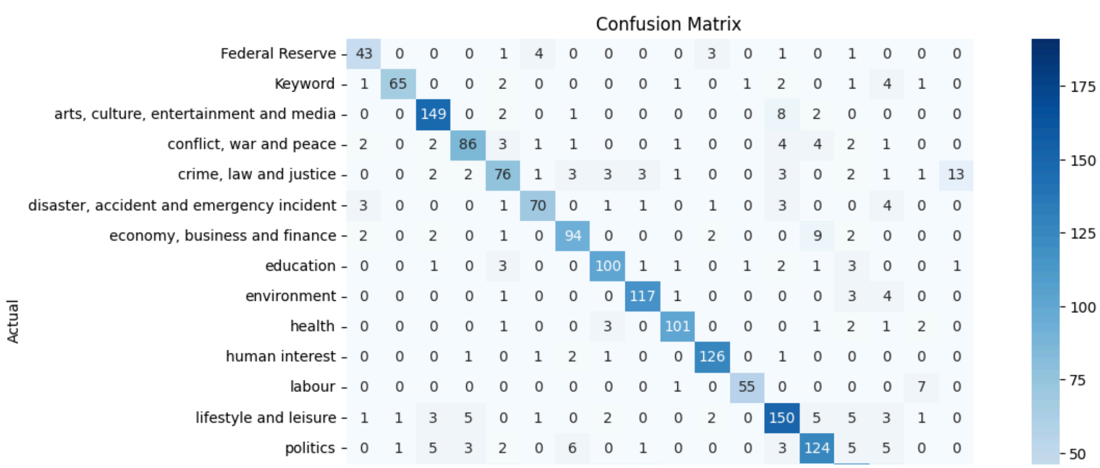
config.json: 100% 570/570 [00:00<00:00, 44.2kB/s]

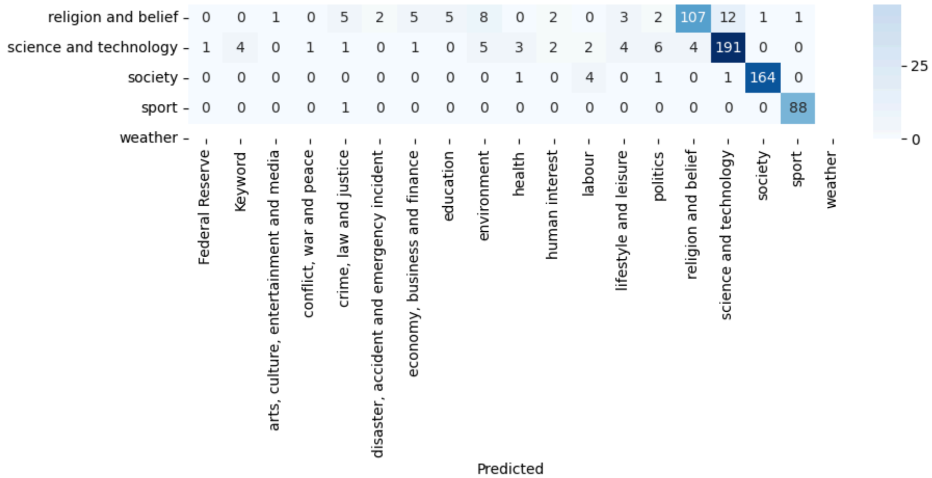
model.safetensors: 100% 440M/440M [00:02<00:00, 172MB/s]

```
Some weights of BertForSequenceClassification were not initialized from the model checkpoint at bert-base-uncased and are newly initialized: ['classifier.bias', 'classifier.weight']
You should probably TRAIN this model on a down-stream task to be able to use it for predictions and inference.
/usr/local/lib/python3.10/dist-packages/transformers/optimization.py:591: FutureWarning: This implementation of AdamW is deprecated and will be removed in a future version. Use the PyTorch implementation torch.optim.AdamW instead, or se
  warnings.warn(
Epoch 1/3
Training: 100%|██████████| 557/557 [03:07<00:00,  2.96it/s]
Validation: 100%|██████████| 140/140 [00:16<00:00,  8.64it/s]
Train loss: 1.1368510144189188, Train accuracy: 0.6953932584269663
Validation loss: 0.6351048793643713, Validation accuracy: 0.8265947888589399
Epoch 2/3
Training: 100%|██████████| 557/557 [03:09<00:00,  2.94it/s]
Validation: 100%|██████████| 140/140 [00:16<00:00,  8.56it/s]
Train loss: 0.4487701477131788, Train accuracy: 0.8837078651685394
Validation loss: 0.5335162905177899, Validation accuracy: 0.8481581311769991
Epoch 3/3
Training: 100%|██████████| 557/557 [03:08<00:00,  2.95it/s]
Validation: 100%|██████████| 140/140 [00:16<00:00,  8.67it/s]
Train loss: 0.30344499430253, Train accuracy: 0.9256179775280899
Validation loss: 0.5258766201191715, Validation accuracy: 0.8562443845462714
```

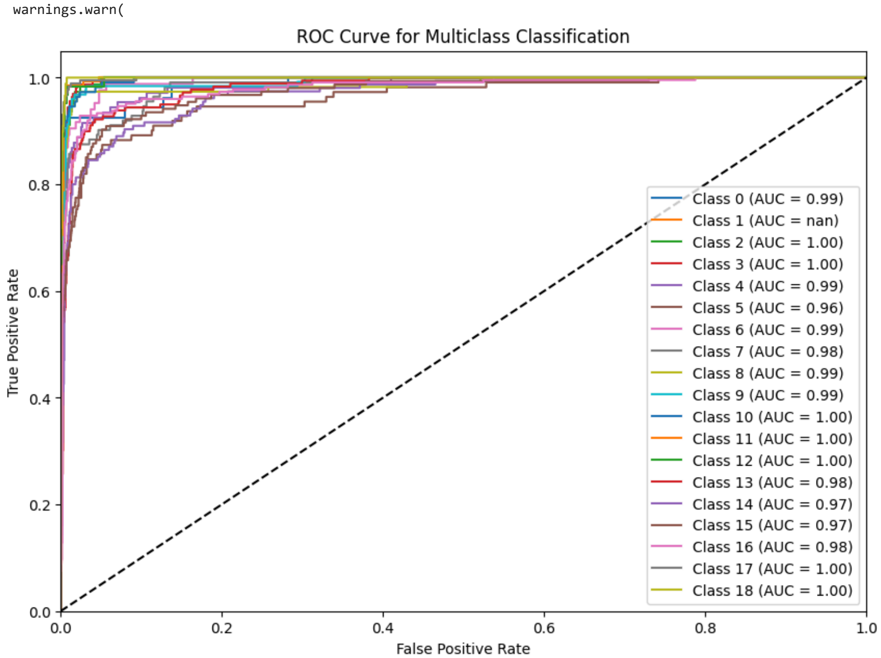









```
/usr/local/lib/python3.10/dist-packages/sklearn/metrics/_ranking.py:1133: UndefinedMetricWarning: No positive samples in y_true, true positive value should be meaningless
  warnings.warn(
```




```
# Executive Summary
# This project focused on developing and fine-tuning a news classification model using PyTorch and BERT (Bidirectional Encoder Representations from Transformers). The model was tasked with classifying news headlines into various categories ba

# Key Findings:
# Data Preprocessing and Exploration:

# The dataset consisted of news headlines and corresponding categories, which were transformed into numerical labels using LabelEncoder.
# A class distribution plot highlighted a class imbalance in the dataset, which suggested the need for careful evaluation of model performance to ensure balanced handling of all categories.
# Model Architecture:

# BERT in PyTorch: The model architecture utilized a pre-trained BERT transformer model for sequence classification, implemented using PyTorch. BERT's powerful contextual language understanding was fine-tuned to classify the headlines into di
```