```
import pandas as pd
import numpy as np
import os
import matplotlib.pyplot as plt
import seaborn as sns
import matplotlib.patches as patches
from sklearn.metrics import precision_recall_curve,
average_precision_score
from sklearn.preprocessing import LabelEncoder
from torchvision import transforms
from PIL import Image
from tqdm import tqdm
import shutil
from sklearn.metrics import roc_curve, auc
import torch
import torch.nn as nn
import torch.optim as optim
from torchvision import transforms, models
from torch.utils.data import Dataset, DataLoader, random_split
from sklearn.metrics import confusion_matrix, ConfusionMatrixDisplay

test_base_dir ="/kaggle/input/gtsrb-german-traffic-sign"

# File paths for CSV files

test_csv_path = '/kaggle/input/gtsrb-german-traffic-sign/Test.csv'

# Load CSV files
test_df = pd.read_csv(test_csv_path)

# Load CSV files
test_df = pd.read_csv(test_csv_path)

# Custom Dataset Class
class CustomDataset(Dataset):
    def __init__(self, dataframe, base_dir, transform=None):
        self.dataframe = dataframe
        self.base_dir = base_dir
        self.transform = transform

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

    def __getitem__(self, idx):
        # Concatenate base directory with relative image path
        img_path = os.path.join(self.base_dir,
str(self.dataframe.iloc[idx, -1]))
        label = int(self.dataframe.iloc[idx, -2])  # Ensure this is
the correct column for labels
        try:
```

```python
            image = Image.open(img_path).convert("RGB")
        except FileNotFoundError:
            raise ValueError(f"Image not found: {img_path}")
        if self.transform:
            image = self.transform(image)
        return image, label


test_transforms = transforms.Compose([
    transforms.Resize((224, 224)),
    transforms.ToTensor(),
    transforms.Normalize(mean=[0.485, 0.456, 0.406], std=[0.229,
0.224, 0.225]),
])

# Create Datasets
test_dataset = CustomDataset(test_df, test_base_dir,
transform=test_transforms)

# Create Data Loaders
test_loader = DataLoader(test_dataset, batch_size=1, shuffle=False)

print(f"Total images in test dataset: {len(test_dataset)}")
```

```
Total images in test dataset: 12630
```

```python
# Load the trained model
model_path =
"/kaggle/input/theiss_model/pytorch/default/1/mobilenet_v2_traffic_sig
ns.pth"  # Replace with the path to your saved model
device = torch.device("cuda" if torch.cuda.is_available() else "cpu")

# Reconstruct the model architecture
model =
models.mobilenet_v2(weights=models.MobileNet_V2_Weights.IMAGENET1K_V1)
model.classifier[1] = nn.Linear(model.last_channel, 43)  # 43 classes
in your dataset
model.load_state_dict(torch.load(model_path))
model = model.to(device)
model.eval()  # Set the model to evaluation mode
```

```
<ipython-input-10-29859e955a0a>:8: FutureWarning: You are using
`torch.load` with `weights_only=False` (the current default value),
which uses the default pickle module implicitly. It is possible to
construct malicious pickle data which will execute arbitrary code
during unpickling (See
https://github.com/pytorch/pytorch/blob/main/SECURITY.md#untrusted-
models for more details). In a future release, the default value for
`weights_only` will be flipped to `True`. This limits the functions
that could be executed during unpickling. Arbitrary objects will no
longer be allowed to be loaded via this mode unless they are
```

```
explicitly allowlisted by the user via
`torch.serialization.add_safe_globals`. We recommend you start setting
`weights_only=True` for any use case where you don't have full control
of the loaded file. Please open an issue on GitHub for any issues
related to this experimental feature.
  model.load_state_dict(torch.load(model_path))

MobileNetV2(
  (features): Sequential(
    (0): Conv2dNormActivation(
      (0): Conv2d(3, 32, kernel_size=(3, 3), stride=(2, 2),
padding=(1, 1), bias=False)
      (1): BatchNorm2d(32, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
      (2): ReLU6(inplace=True)
    )
    (1): InvertedResidual(
      (conv): Sequential(
        (0): Conv2dNormActivation(
          (0): Conv2d(32, 32, kernel_size=(3, 3), stride=(1, 1),
padding=(1, 1), groups=32, bias=False)
          (1): BatchNorm2d(32, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
          (2): ReLU6(inplace=True)
        )
        (1): Conv2d(32, 16, kernel_size=(1, 1), stride=(1, 1),
bias=False)
        (2): BatchNorm2d(16, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
      )
    )
    (2): InvertedResidual(
      (conv): Sequential(
        (0): Conv2dNormActivation(
          (0): Conv2d(16, 96, kernel_size=(1, 1), stride=(1, 1),
bias=False)
          (1): BatchNorm2d(96, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
          (2): ReLU6(inplace=True)
        )
        (1): Conv2dNormActivation(
          (0): Conv2d(96, 96, kernel_size=(3, 3), stride=(2, 2),
padding=(1, 1), groups=96, bias=False)
          (1): BatchNorm2d(96, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
          (2): ReLU6(inplace=True)
        )
        (2): Conv2d(96, 24, kernel_size=(1, 1), stride=(1, 1),
bias=False)
        (3): BatchNorm2d(24, eps=1e-05, momentum=0.1, affine=True,
```

```
track_running_stats=True)
      )
    )
    (3): InvertedResidual(
      (conv): Sequential(
        (0): Conv2dNormActivation(
          (0): Conv2d(24, 144, kernel_size=(1, 1), stride=(1, 1),
bias=False)
          (1): BatchNorm2d(144, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
          (2): ReLU6(inplace=True)
        )
        (1): Conv2dNormActivation(
          (0): Conv2d(144, 144, kernel_size=(3, 3), stride=(1, 1),
padding=(1, 1), groups=144, bias=False)
          (1): BatchNorm2d(144, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
          (2): ReLU6(inplace=True)
        )
        (2): Conv2d(144, 24, kernel_size=(1, 1), stride=(1, 1),
bias=False)
        (3): BatchNorm2d(24, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
      )
    )
    (4): InvertedResidual(
      (conv): Sequential(
        (0): Conv2dNormActivation(
          (0): Conv2d(24, 144, kernel_size=(1, 1), stride=(1, 1),
bias=False)
          (1): BatchNorm2d(144, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
          (2): ReLU6(inplace=True)
        )
        (1): Conv2dNormActivation(
          (0): Conv2d(144, 144, kernel_size=(3, 3), stride=(2, 2),
padding=(1, 1), groups=144, bias=False)
          (1): BatchNorm2d(144, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
          (2): ReLU6(inplace=True)
        )
        (2): Conv2d(144, 32, kernel_size=(1, 1), stride=(1, 1),
bias=False)
        (3): BatchNorm2d(32, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
      )
    )
    (5): InvertedResidual(
      (conv): Sequential(
```

```
        (0): Conv2dNormActivation(
          (0): Conv2d(32, 192, kernel_size=(1, 1), stride=(1, 1),
bias=False)
          (1): BatchNorm2d(192, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
          (2): ReLU6(inplace=True)
        )
        (1): Conv2dNormActivation(
          (0): Conv2d(192, 192, kernel_size=(3, 3), stride=(1, 1),
padding=(1, 1), groups=192, bias=False)
          (1): BatchNorm2d(192, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
          (2): ReLU6(inplace=True)
        )
        (2): Conv2d(192, 32, kernel_size=(1, 1), stride=(1, 1),
bias=False)
        (3): BatchNorm2d(32, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
      )
    )
    (6): InvertedResidual(
      (conv): Sequential(
        (0): Conv2dNormActivation(
          (0): Conv2d(32, 192, kernel_size=(1, 1), stride=(1, 1),
bias=False)
          (1): BatchNorm2d(192, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
          (2): ReLU6(inplace=True)
        )
        (1): Conv2dNormActivation(
          (0): Conv2d(192, 192, kernel_size=(3, 3), stride=(1, 1),
padding=(1, 1), groups=192, bias=False)
          (1): BatchNorm2d(192, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
          (2): ReLU6(inplace=True)
        )
        (2): Conv2d(192, 32, kernel_size=(1, 1), stride=(1, 1),
bias=False)
        (3): BatchNorm2d(32, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
      )
    )
    (7): InvertedResidual(
      (conv): Sequential(
        (0): Conv2dNormActivation(
          (0): Conv2d(32, 192, kernel_size=(1, 1), stride=(1, 1),
bias=False)
          (1): BatchNorm2d(192, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
```

```
          (2): ReLU6(inplace=True)
        )
        (1): Conv2dNormActivation(
          (0): Conv2d(192, 192, kernel_size=(3, 3), stride=(2, 2),
padding=(1, 1), groups=192, bias=False)
          (1): BatchNorm2d(192, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
          (2): ReLU6(inplace=True)
        )
        (2): Conv2d(192, 64, kernel_size=(1, 1), stride=(1, 1),
bias=False)
        (3): BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
      )
    )
    (8): InvertedResidual(
      (conv): Sequential(
        (0): Conv2dNormActivation(
          (0): Conv2d(64, 384, kernel_size=(1, 1), stride=(1, 1),
bias=False)
          (1): BatchNorm2d(384, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
          (2): ReLU6(inplace=True)
        )
        (1): Conv2dNormActivation(
          (0): Conv2d(384, 384, kernel_size=(3, 3), stride=(1, 1),
padding=(1, 1), groups=384, bias=False)
          (1): BatchNorm2d(384, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
          (2): ReLU6(inplace=True)
        )
        (2): Conv2d(384, 64, kernel_size=(1, 1), stride=(1, 1),
bias=False)
        (3): BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
      )
    )
    (9): InvertedResidual(
      (conv): Sequential(
        (0): Conv2dNormActivation(
          (0): Conv2d(64, 384, kernel_size=(1, 1), stride=(1, 1),
bias=False)
          (1): BatchNorm2d(384, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
          (2): ReLU6(inplace=True)
        )
        (1): Conv2dNormActivation(
          (0): Conv2d(384, 384, kernel_size=(3, 3), stride=(1, 1),
padding=(1, 1), groups=384, bias=False)
```

```
          (1): BatchNorm2d(384, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
          (2): ReLU6(inplace=True)
        )
        (2): Conv2d(384, 64, kernel_size=(1, 1), stride=(1, 1),
bias=False)
        (3): BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
      )
    )
    (10): InvertedResidual(
      (conv): Sequential(
        (0): Conv2dNormActivation(
          (0): Conv2d(64, 384, kernel_size=(1, 1), stride=(1, 1),
bias=False)
          (1): BatchNorm2d(384, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
          (2): ReLU6(inplace=True)
        )
        (1): Conv2dNormActivation(
          (0): Conv2d(384, 384, kernel_size=(3, 3), stride=(1, 1),
padding=(1, 1), groups=384, bias=False)
          (1): BatchNorm2d(384, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
          (2): ReLU6(inplace=True)
        )
        (2): Conv2d(384, 64, kernel_size=(1, 1), stride=(1, 1),
bias=False)
        (3): BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
      )
    )
    (11): InvertedResidual(
      (conv): Sequential(
        (0): Conv2dNormActivation(
          (0): Conv2d(64, 384, kernel_size=(1, 1), stride=(1, 1),
bias=False)
          (1): BatchNorm2d(384, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
          (2): ReLU6(inplace=True)
        )
        (1): Conv2dNormActivation(
          (0): Conv2d(384, 384, kernel_size=(3, 3), stride=(1, 1),
padding=(1, 1), groups=384, bias=False)
          (1): BatchNorm2d(384, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
          (2): ReLU6(inplace=True)
        )
        (2): Conv2d(384, 96, kernel_size=(1, 1), stride=(1, 1),
```

```
bias=False)
        (3): BatchNorm2d(96, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
      )
    )
    (12): InvertedResidual(
      (conv): Sequential(
        (0): Conv2dNormActivation(
          (0): Conv2d(96, 576, kernel_size=(1, 1), stride=(1, 1),
bias=False)
          (1): BatchNorm2d(576, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
          (2): ReLU6(inplace=True)
        )
        (1): Conv2dNormActivation(
          (0): Conv2d(576, 576, kernel_size=(3, 3), stride=(1, 1),
padding=(1, 1), groups=576, bias=False)
          (1): BatchNorm2d(576, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
          (2): ReLU6(inplace=True)
        )
        (2): Conv2d(576, 96, kernel_size=(1, 1), stride=(1, 1),
bias=False)
        (3): BatchNorm2d(96, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
      )
    )
    (13): InvertedResidual(
      (conv): Sequential(
        (0): Conv2dNormActivation(
          (0): Conv2d(96, 576, kernel_size=(1, 1), stride=(1, 1),
bias=False)
          (1): BatchNorm2d(576, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
          (2): ReLU6(inplace=True)
        )
        (1): Conv2dNormActivation(
          (0): Conv2d(576, 576, kernel_size=(3, 3), stride=(1, 1),
padding=(1, 1), groups=576, bias=False)
          (1): BatchNorm2d(576, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
          (2): ReLU6(inplace=True)
        )
        (2): Conv2d(576, 96, kernel_size=(1, 1), stride=(1, 1),
bias=False)
        (3): BatchNorm2d(96, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
      )
    )
```

```
    (14): InvertedResidual(
      (conv): Sequential(
        (0): Conv2dNormActivation(
          (0): Conv2d(96, 576, kernel_size=(1, 1), stride=(1, 1),
bias=False)
          (1): BatchNorm2d(576, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
          (2): ReLU6(inplace=True)
        )
        (1): Conv2dNormActivation(
          (0): Conv2d(576, 576, kernel_size=(3, 3), stride=(2, 2),
padding=(1, 1), groups=576, bias=False)
          (1): BatchNorm2d(576, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
          (2): ReLU6(inplace=True)
        )
        (2): Conv2d(576, 160, kernel_size=(1, 1), stride=(1, 1),
bias=False)
        (3): BatchNorm2d(160, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
      )
    )
    (15): InvertedResidual(
      (conv): Sequential(
        (0): Conv2dNormActivation(
          (0): Conv2d(160, 960, kernel_size=(1, 1), stride=(1, 1),
bias=False)
          (1): BatchNorm2d(960, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
          (2): ReLU6(inplace=True)
        )
        (1): Conv2dNormActivation(
          (0): Conv2d(960, 960, kernel_size=(3, 3), stride=(1, 1),
padding=(1, 1), groups=960, bias=False)
          (1): BatchNorm2d(960, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
          (2): ReLU6(inplace=True)
        )
        (2): Conv2d(960, 160, kernel_size=(1, 1), stride=(1, 1),
bias=False)
        (3): BatchNorm2d(160, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
      )
    )
    (16): InvertedResidual(
      (conv): Sequential(
        (0): Conv2dNormActivation(
          (0): Conv2d(160, 960, kernel_size=(1, 1), stride=(1, 1),
bias=False)
```

```
          (1): BatchNorm2d(960, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
          (2): ReLU6(inplace=True)
        )
        (1): Conv2dNormActivation(
          (0): Conv2d(960, 960, kernel_size=(3, 3), stride=(1, 1),
padding=(1, 1), groups=960, bias=False)
          (1): BatchNorm2d(960, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
          (2): ReLU6(inplace=True)
        )
        (2): Conv2d(960, 160, kernel_size=(1, 1), stride=(1, 1),
bias=False)
        (3): BatchNorm2d(160, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
      )
    )
    (17): InvertedResidual(
      (conv): Sequential(
        (0): Conv2dNormActivation(
          (0): Conv2d(160, 960, kernel_size=(1, 1), stride=(1, 1),
bias=False)
          (1): BatchNorm2d(960, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
          (2): ReLU6(inplace=True)
        )
        (1): Conv2dNormActivation(
          (0): Conv2d(960, 960, kernel_size=(3, 3), stride=(1, 1),
padding=(1, 1), groups=960, bias=False)
          (1): BatchNorm2d(960, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
          (2): ReLU6(inplace=True)
        )
        (2): Conv2d(960, 320, kernel_size=(1, 1), stride=(1, 1),
bias=False)
        (3): BatchNorm2d(320, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
      )
    )
    (18): Conv2dNormActivation(
      (0): Conv2d(320, 1280, kernel_size=(1, 1), stride=(1, 1),
bias=False)
      (1): BatchNorm2d(1280, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
      (2): ReLU6(inplace=True)
    )
  )
  (classifier): Sequential(
    (0): Dropout(p=0.2, inplace=False)
    (1): Linear(in_features=1280, out_features=43, bias=True)
```

```
    )
)

def test_model(model, test_loader, device):
    """
    Test the model and return accuracy, labels, and predictions.

    Args:
        model (torch.nn.Module): The model to test.
        test_loader (torch.utils.data.DataLoader): DataLoader for the
test dataset.
        device (torch.device): The device to perform testing on (CPU
or GPU).

    Returns:
        tuple: A tuple containing accuracy, all true labels, and all
predicted labels.
    """
    model.eval()
    correct = 0
    total = 0
    all_labels = []
    all_predictions = []

    with torch.no_grad():
        for images, labels in tqdm(test_loader, desc="Testing"):
            images, labels = images.to(device), labels.to(device)
            outputs = model(images)
            _, predicted = outputs.max(1)
            total += labels.size(0)
            correct += predicted.eq(labels).sum().item()

            # Collect all labels and predictions for confusion matrix
            all_labels.extend(labels.cpu().numpy())
            all_predictions.extend(predicted.cpu().numpy())

    accuracy = 100. * correct / total
    print(f"Test Accuracy: {accuracy:.2f}%")

    return accuracy, all_labels, all_predictions

ccuracy, all_labels, all_predictions = test_model(model, test_loader,
device)

Testing: 100%|██████████| 12630/12630 [04:06<00:00, 51.28it/s]

Test Accuracy: 95.61%
```

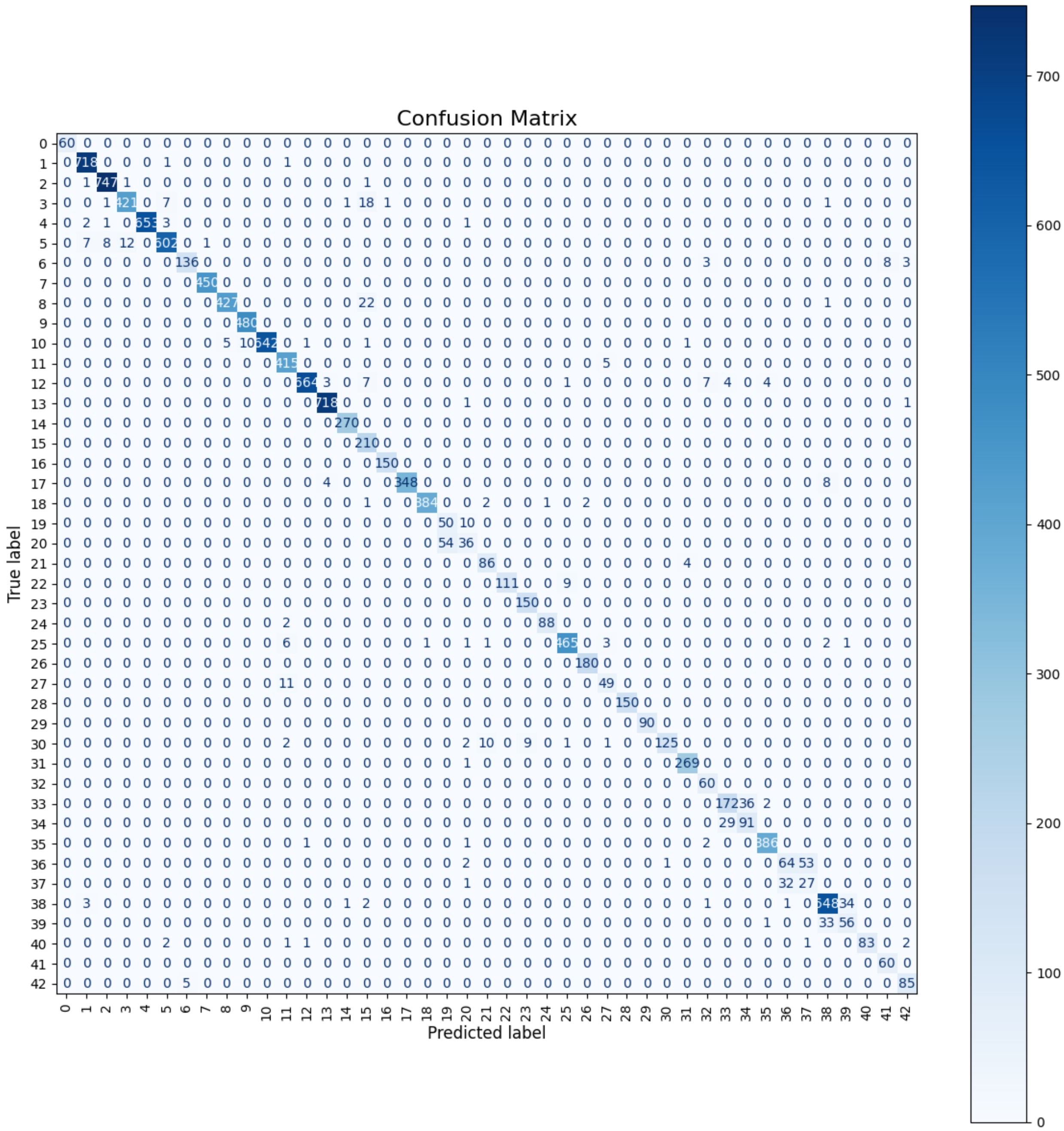
```python
def predict(model, image, device):
    image = image.to(device)

    with torch.no_grad():
        output = model(image.unsqueeze(0))  # Add batch dimension
        probabilities = torch.nn.functional.softmax(output, dim=1)
        confidence, predicted = probabilities.max(1)

    result = {
        "predicted_class": predicted.item(),
        "confidence": confidence.item()
    }

    return result

image_path = "/kaggle/input/gtsrb-german-traffic-sign/Test/00000.png"
# Replace with your image path
image = Image.open(image_path).convert("RGB")
transform = transforms.Compose([
    transforms.Resize((224, 224)),
    transforms.ToTensor(),
    transforms.Normalize(mean=[0.485, 0.456, 0.406], std=[0.229,
0.224, 0.225]),
])
image_tensor = transform(image)

# Perform prediction
result = predict(model, image_tensor, device)

# Print the result
print("predicted_class:", result["predicted_class"])
print("confidence:", result["confidence"])
```

```
predicted_class: 16
confidence: 1.0
```

```python
import pandas as pd
from sklearn.metrics import confusion_matrix, ConfusionMatrixDisplay
import matplotlib.pyplot as plt

def plot_and_save_confusion_matrix(all_labels, all_predictions,
filename="confusion_matrix.csv"):
    """
    Plot and save the confusion matrix using true and predicted
labels.

    Args:
        all_labels (list): True labels.
        all_predictions (list): Predicted labels.
        filename (str): Filename to save the confusion matrix.
    """
```

```
    class_names = [str(i) for i in range(43)]  # Generate class names
from 0 to 42
    cm = confusion_matrix(all_labels, all_predictions)

    # Save confusion matrix to CSV
    pd.DataFrame(cm).to_csv(filename, index=False, header=False)
    print(f"Confusion matrix saved as {filename}")

    # Plotting the confusion matrix
    disp = ConfusionMatrixDisplay(confusion_matrix=cm,
display_labels=class_names)
    fig, ax = plt.subplots(figsize=(12, 12))
    disp.plot(cmap=plt.cm.Blues, ax=ax, xticks_rotation='vertical')
    plt.title("Confusion Matrix", fontsize=16)
    plt.xlabel("Predicted label", fontsize=12)
    plt.ylabel("True label", fontsize=12)
    plt.tight_layout()
    plt.show()

plot_and_save_confusion_matrix(all_labels, all_predictions)
```

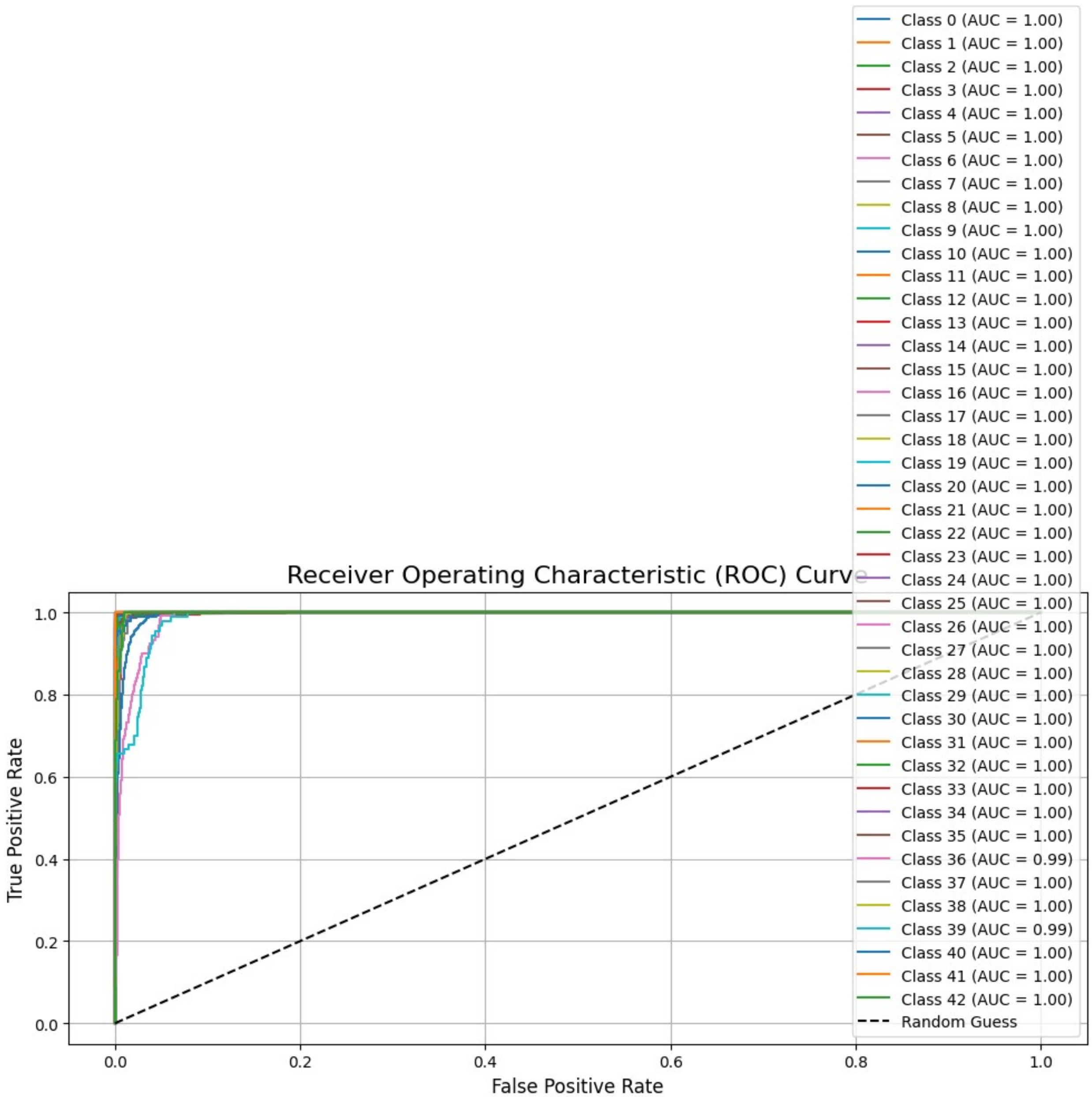
```
Confusion matrix saved as confusion_matrix.csv
```




```
def plot_roc_curve(model, test_loader, device, num_classes=43):
    """
    Plot the ROC curve for a multi-class classification model.

    Args:
        model (torch.nn.Module): The trained model.
        test_loader (torch.utils.data.DataLoader): DataLoader for the
test dataset.
        device (torch.device): The device to perform testing on (CPU
or GPU).
```

```python
        num_classes (int): The number of classes in the dataset.
    """
    model.eval()
    all_labels = []
    all_outputs = []

    # Collect predictions and true labels
    with torch.no_grad():
        for images, labels in tqdm(test_loader, desc="Calculating ROC"):
            images, labels = images.to(device), labels.to(device)
            outputs = model(images)
            all_labels.extend(labels.cpu().numpy())
            all_outputs.extend(outputs.cpu().numpy())

    all_labels = np.array(all_labels)
    all_outputs = np.array(all_outputs)

    # Compute ROC curve and AUC for each class
    fpr = {}
    tpr = {}
    roc_auc = {}

    for i in range(num_classes):
        true_binary = (all_labels == i).astype(int)  # Convert labels to binary for each class
        fpr[i], tpr[i], _ = roc_curve(true_binary, all_outputs[:, i])
        roc_auc[i] = auc(fpr[i], tpr[i])

    # Plot ROC curve for each class
    plt.figure(figsize=(10, 8))
    for i in range(num_classes):
        plt.plot(fpr[i], tpr[i], label=f"Class {i} (AUC = {roc_auc[i]:.2f})")

    # Plot the diagonal line
    plt.plot([0, 1], [0, 1], 'k--', label="Random Guess")

    plt.title("Receiver Operating Characteristic (ROC) Curve", fontsize=16)
    plt.xlabel("False Positive Rate", fontsize=12)
    plt.ylabel("True Positive Rate", fontsize=12)
    plt.legend(loc="lower right")
    plt.grid()
    plt.tight_layout()
    plt.show()

plot_roc_curve(model, test_loader, device, num_classes=43)
```

```
Calculating ROC: 100%|██████████| 12630/12630 [02:21<00:00, 89.07it/s]
```

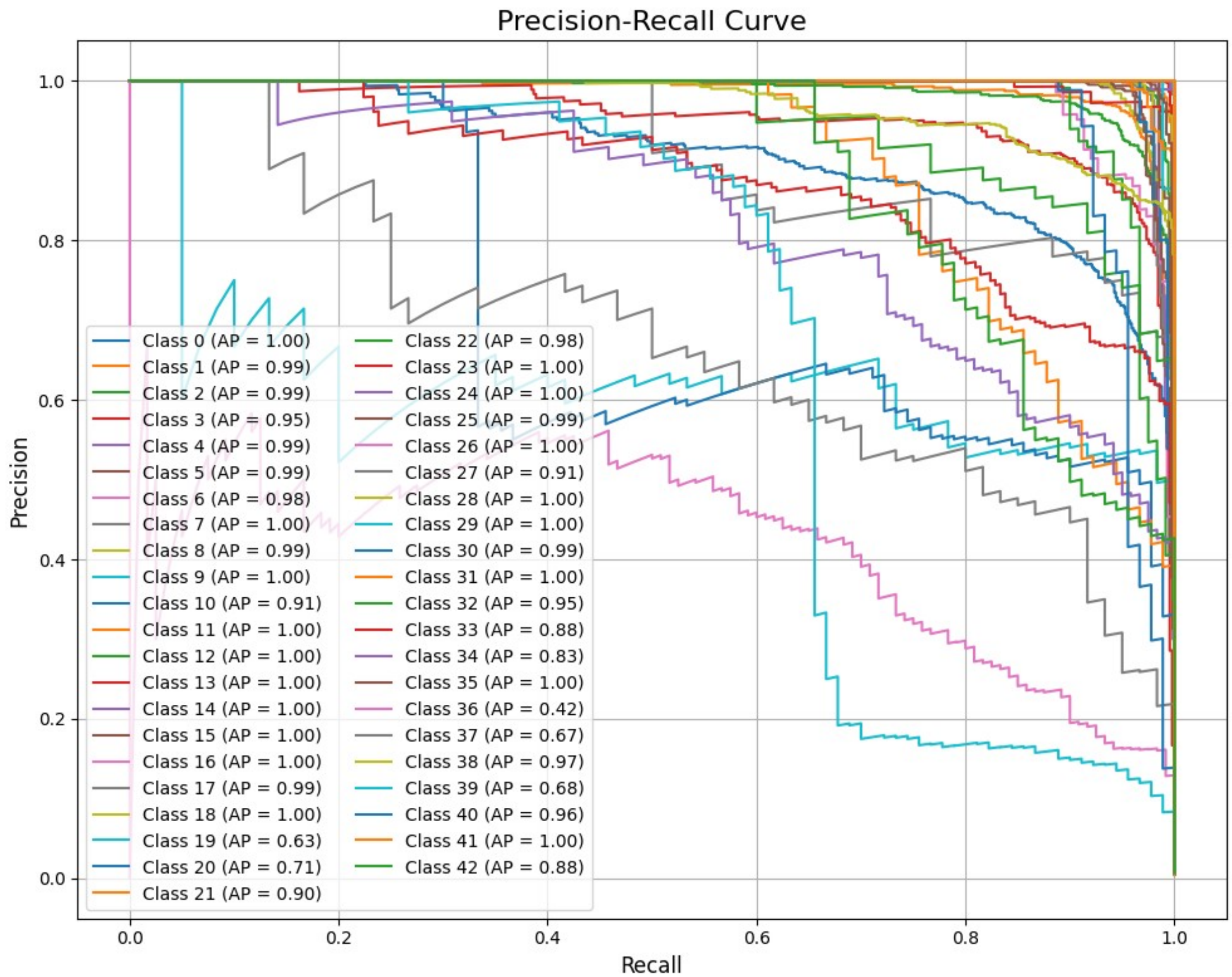



```
from sklearn.metrics import precision_recall_curve,
average_precision_score
import matplotlib.pyplot as plt
import numpy as np

def plot_precision_recall_curve(model, test_loader, device,
num_classes=43):
    """
    Plot the Precision-Recall curve for a multi-class classification
model.

    Args:
```

```
        model (torch.nn.Module): The trained model.
        test_loader (torch.utils.data.DataLoader): DataLoader for the
test dataset.
        device (torch.device): The device to perform testing on (CPU
or GPU).
        num_classes (int): The number of classes in the dataset.
    """
    model.eval()
    all_labels = []
    all_outputs = []

    # Collect predictions and true labels
    with torch.no_grad():
        for images, labels in tqdm(test_loader, desc="Calculating
Precision-Recall"):
            images, labels = images.to(device), labels.to(device)
            outputs = model(images)
            all_labels.extend(labels.cpu().numpy())
            all_outputs.extend(outputs.cpu().numpy())

    all_labels = np.array(all_labels)
    all_outputs = np.array(all_outputs)

    # Compute Precision-Recall curve and Average Precision for each
class
    precision = {}
    recall = {}
    average_precision = {}

    for i in range(num_classes):
        true_binary = (all_labels == i).astype(int)  # Convert labels
to binary for each class
        precision[i], recall[i], _ =
precision_recall_curve(true_binary, all_outputs[:, i])
        average_precision[i] = average_precision_score(true_binary,
all_outputs[:, i])

    # Plot Precision-Recall curve for each class
    plt.figure(figsize=(10, 8))
    for i in range(num_classes):
        plt.plot(recall[i], precision[i], label=f"Class {i} (AP =
{average_precision[i]:.2f})")

    plt.title("Precision-Recall Curve", fontsize=16)
    plt.xlabel("Recall", fontsize=12)
    plt.ylabel("Precision", fontsize=12)
    plt.legend(loc="lower left", fontsize=10, ncol=2)
    plt.grid()
    plt.tight_layout()
    plt.show()
```

```
plot_precision_recall_curve(model, test_loader, device,
num_classes=43)
```

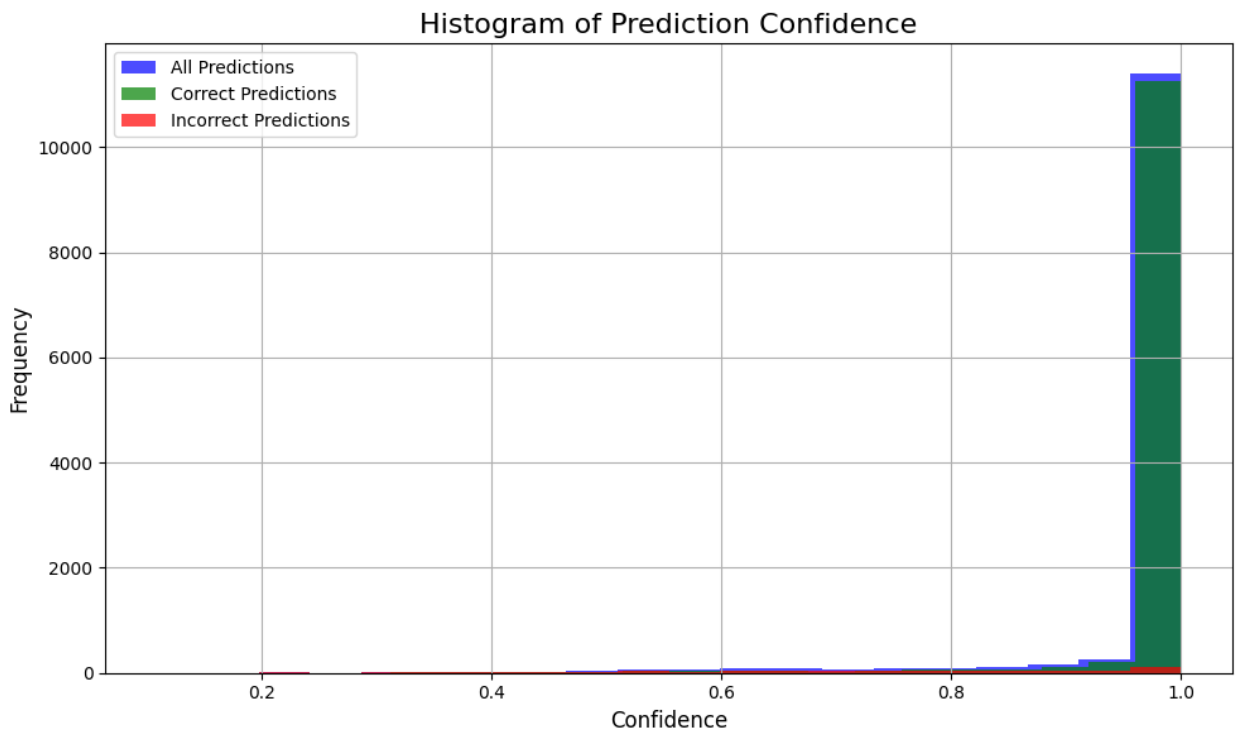
```
Calculating Precision-Recall: 100%|██████████| 12630/12630
[02:15<00:00, 93.00it/s]
```




```python
def plot_prediction_confidence(model, test_loader, device,
num_bins=10):
    """
    Plot a histogram of prediction confidence for the test dataset.

    Args:
        model (torch.nn.Module): The trained model.
        test_loader (torch.utils.data.DataLoader): DataLoader for the
test dataset.
        device (torch.device): Device to perform testing on (CPU or
GPU).
        num_bins (int): Number of bins for the histogram.
    """
```

```
    model.eval()
    confidences = []
    correct_predictions = []
    incorrect_predictions = []

    with torch.no_grad():
        for images, labels in tqdm(test_loader, desc="Calculating Confidence"):
            images, labels = images.to(device), labels.to(device)
            outputs = model(images)
            probabilities = torch.nn.functional.softmax(outputs, dim=1)
            max_confidence, predicted = probabilities.max(1)

            confidences.extend(max_confidence.cpu().numpy())
            correct_predictions.extend(max_confidence[labels == predicted].cpu().numpy())
            incorrect_predictions.extend(max_confidence[labels != predicted].cpu().numpy())

    # Plot histogram
    plt.figure(figsize=(10, 6))
    plt.hist(confidences, bins=num_bins, alpha=0.7, label="All Predictions", color="blue")
    plt.hist(correct_predictions, bins=num_bins, alpha=0.7, label="Correct Predictions", color="green")
    plt.hist(incorrect_predictions, bins=num_bins, alpha=0.7, label="Incorrect Predictions", color="red")
    plt.title("Histogram of Prediction Confidence", fontsize=16)
    plt.xlabel("Confidence", fontsize=12)
    plt.ylabel("Frequency", fontsize=12)
    plt.legend()
    plt.grid(True)
    plt.tight_layout()
    plt.show()

plot_prediction_confidence(model, test_loader, device, num_bins=20)
```

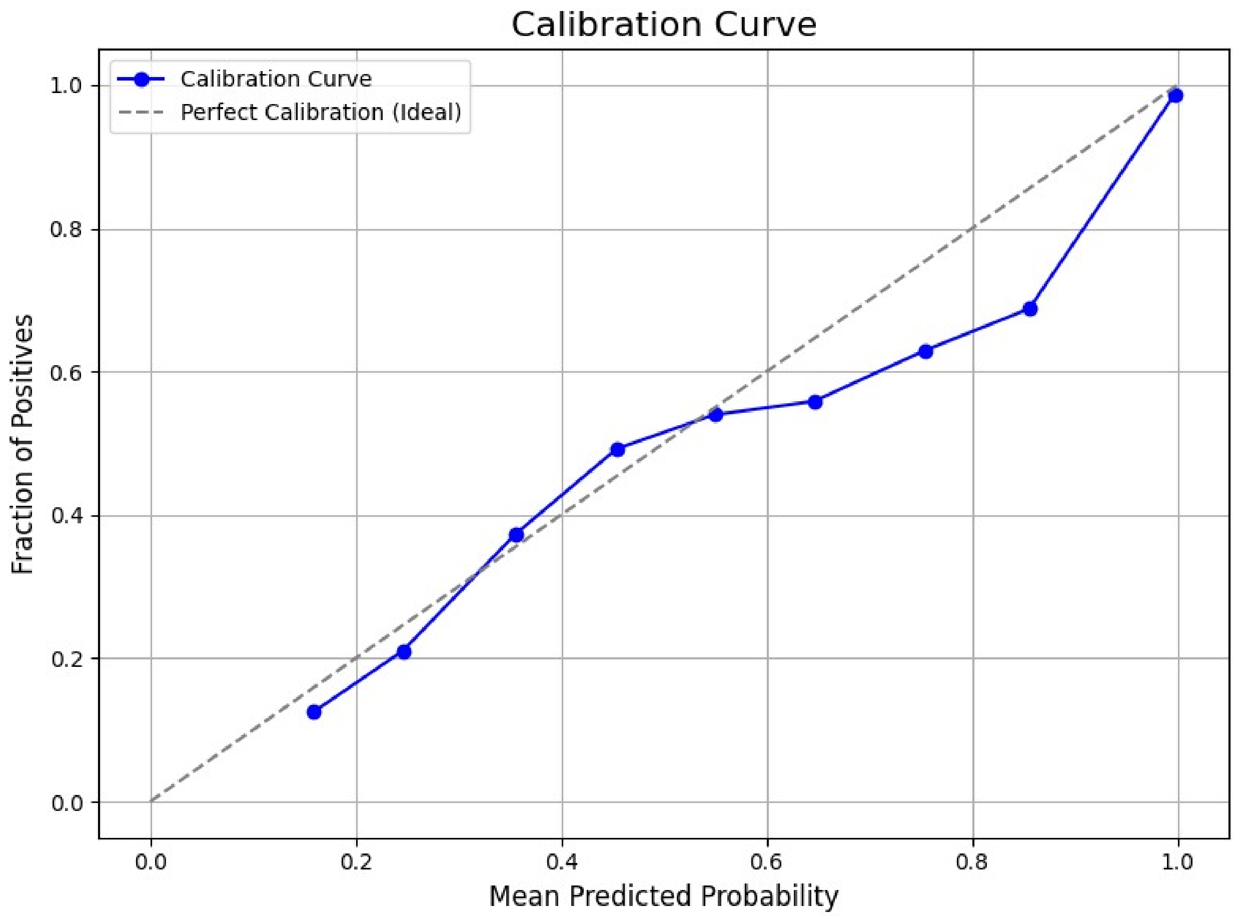
```
Calculating Confidence: 100%|██████████| 12630/12630 [02:19<00:00, 90.33it/s]
```




```
from sklearn.calibration import calibration_curve
import matplotlib.pyplot as plt

def plot_calibration_curve(model, test_loader, device, num_bins=10):
    """
    Plot a calibration curve to evaluate the reliability of the
model's confidence scores.

    Args:
        model (torch.nn.Module): The trained model.
        test_loader (torch.utils.data.DataLoader): DataLoader for the
test dataset.
        device (torch.device): Device to perform testing on (CPU or
GPU).
        num_bins (int): Number of bins for calibration.
    """
    model.eval()
    all_labels = []
    all_confidences = []
    all_predictions = []

    # Collect predictions and confidences
    with torch.no_grad():
        for images, labels in tqdm(test_loader, desc="Calculating
Calibration Data"):
            images, labels = images.to(device), labels.to(device)
            outputs = model(images)
```

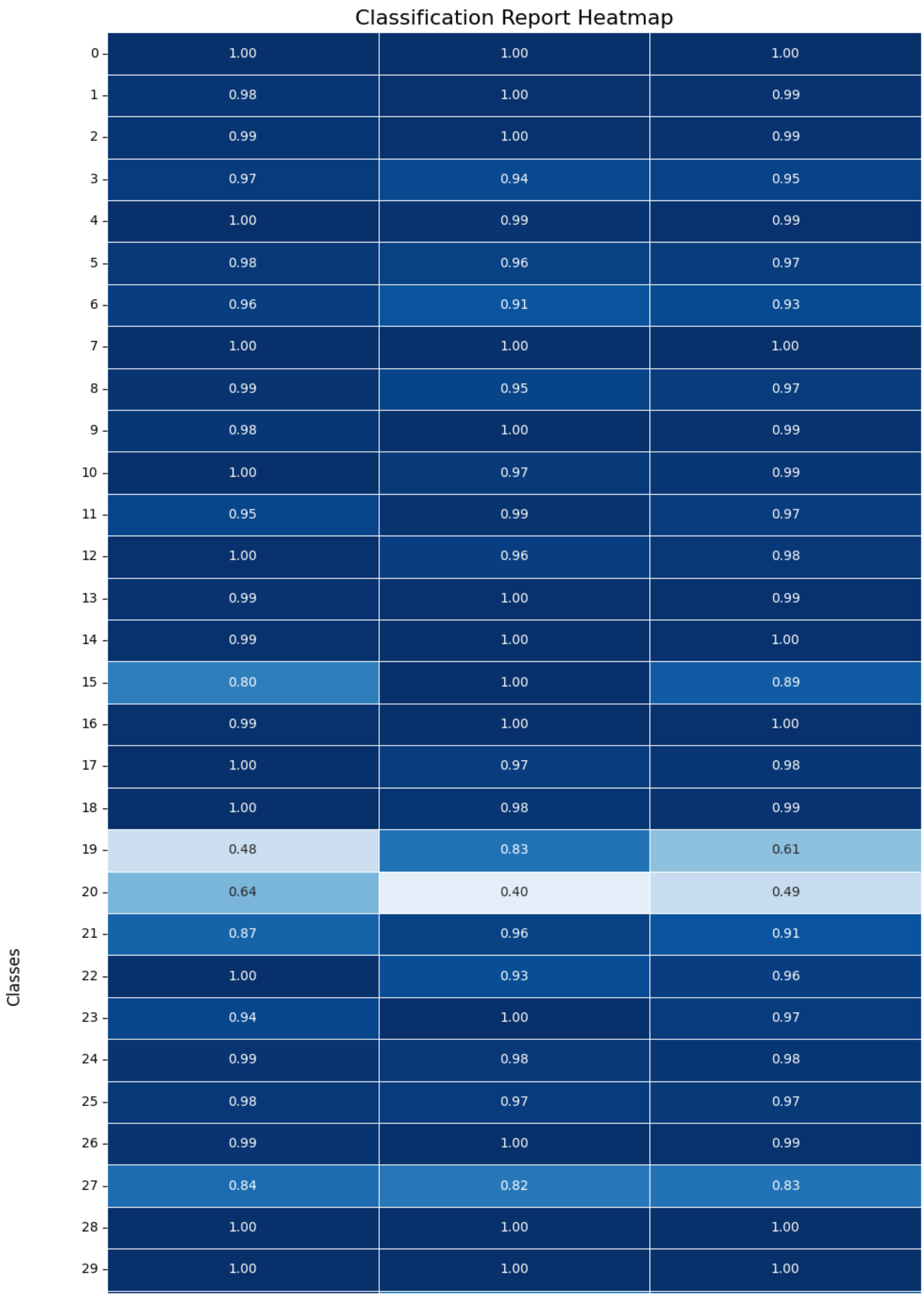
```
            probabilities = torch.nn.functional.softmax(outputs,
dim=1)
            max_confidence, predicted = probabilities.max(1)

            all_confidences.extend(max_confidence.cpu().numpy())
            all_labels.extend(labels.cpu().numpy())
            all_predictions.extend(predicted.cpu().numpy())

    # Binarize the predictions for calibration_curve
    true_labels = (np.array(all_labels) ==
np.array(all_predictions)).astype(int)
    confidences = np.array(all_confidences)

    # Compute calibration curve
    prob_true, prob_pred = calibration_curve(true_labels, confidences,
n_bins=num_bins, strategy='uniform')

    # Plot calibration curve
    plt.figure(figsize=(8, 6))
    plt.plot(prob_pred, prob_true, marker='o', label="Calibration
Curve", color="blue")
    plt.plot([0, 1], [0, 1], 'k--', label="Perfect Calibration
(Ideal)", color="gray")
    plt.title("Calibration Curve", fontsize=16)
    plt.xlabel("Mean Predicted Probability", fontsize=12)
    plt.ylabel("Fraction of Positives", fontsize=12)
    plt.legend()
    plt.grid()
    plt.tight_layout()
    plt.show()

plot_calibration_curve(model, test_loader, device, num_bins=10)
```

```
Calculating Calibration Data: 100%|██████████| 12630/12630
[02:16<00:00, 92.28it/s]
<ipython-input-23-035aff4a45d5>:41: UserWarning: color is redundantly
defined by the 'color' keyword argument and the fmt string "k--" (->
color='k'). The keyword argument will take precedence.
  plt.plot([0, 1], [0, 1], 'k--', label="Perfect Calibration (Ideal)",
color="gray")
```




```
from sklearn.metrics import classification_report
import seaborn as sns
import matplotlib.pyplot as plt
import pandas as pd

def plot_classification_report(model, test_loader, device,
class_names):
    """
    Visualize the classification report as a heatmap.

    Args:
        model (torch.nn.Module): The trained model.
        test_loader (torch.utils.data.DataLoader): DataLoader for the
test dataset.
        device (torch.device): Device to perform testing on (CPU or
GPU).
        class_names (list): List of class names corresponding to the
dataset labels.
    """
    model.eval()
    all_labels = []
```

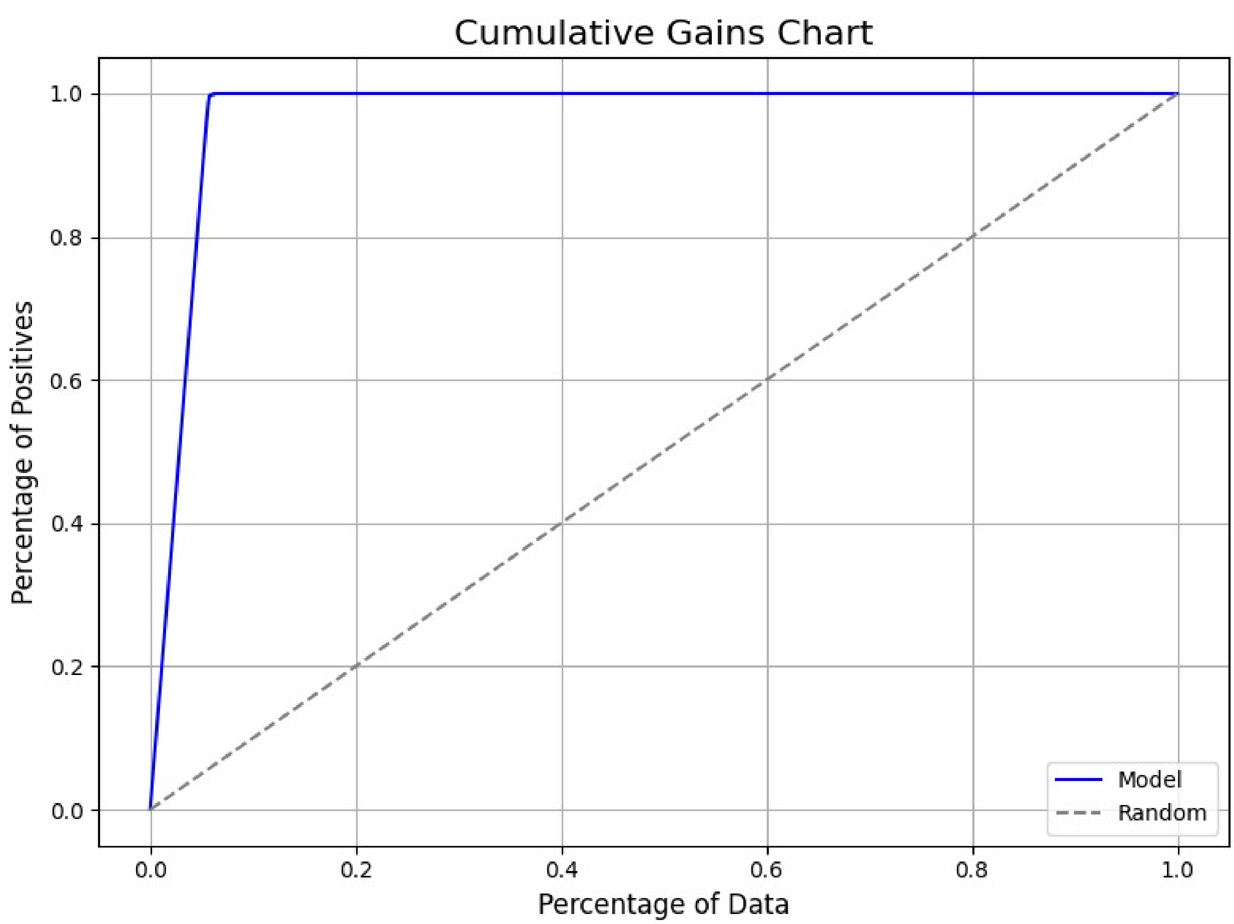
```
    all_predictions = []

    # Collect predictions and true labels
    with torch.no_grad():
        for images, labels in tqdm(test_loader, desc="Calculating 
Classification Report Data"):
            images, labels = images.to(device), labels.to(device)
            outputs = model(images)
            _, predicted = outputs.max(1)
            all_labels.extend(labels.cpu().numpy())
            all_predictions.extend(predicted.cpu().numpy())

    # Generate classification report
    report = classification_report(all_labels, all_predictions, 
target_names=class_names, output_dict=True)

    # Convert to DataFrame for better visualization
    report_df = pd.DataFrame(report).transpose()

    # Plot heatmap
    plt.figure(figsize=(10, len(class_names) // 2))
    sns.heatmap(report_df.iloc[:-1, :-1], annot=True, cmap="Blues", 
fmt=".2f", cbar=False, linewidths=0.5)
    plt.title("Classification Report Heatmap", fontsize=16)
    plt.xlabel("Metrics", fontsize=12)
    plt.ylabel("Classes", fontsize=12)
    plt.tight_layout()
    plt.show()

# Example class names (replace with your actual class names)
class_names = [str(i) for i in range(43)]

# Plot the classification report heatmap
plot_classification_report(model, test_loader, device, class_names)

Calculating Classification Report Data: 100%|██████████| 12630/12630 
[02:18<00:00, 91.04it/s]
```


Classification Report Heatmap
Classes
0 1.00 1.00 1.00
1 0.98 1.00 0.99
2 0.99 1.00 0.99
3 0.97 0.94 0.95
4 1.00 0.99 0.99
5 0.98 0.96 0.97
6 0.96 0.91 0.93
7 1.00 1.00 1.00
8 0.99 0.95 0.97
9 0.98 1.00 0.99
10 1.00 0.97 0.99
11 0.95 0.99 0.97
12 1.00 0.96 0.98
13 0.99 1.00 0.99
14 0.99 1.00 1.00
15 0.80 1.00 0.89
16 0.99 1.00 1.00
17 1.00 0.97 0.98
18 1.00 0.98 0.99
19 0.48 0.83 0.61
20 0.64 0.40 0.49
21 0.87 0.96 0.91
22 1.00 0.93 0.96
23 0.94 1.00 0.97
24 0.99 0.98 0.98
25 0.98 0.97 0.97
26 0.99 1.00 0.99
27 0.84 0.82 0.83
28 1.00 1.00 1.00
29 1.00 1.00 1.00

```
import numpy as np
import matplotlib.pyplot as plt
from sklearn.metrics import roc_curve

def plot_cumulative_gains(model, test_loader, device):
    """
    Plot a Cumulative Gains Chart.

    Args:
        model (torch.nn.Module): The trained model.
        test_loader (torch.utils.data.DataLoader): DataLoader for the
test dataset.
        device (torch.device): Device to perform testing on (CPU or
GPU).
    """
    model.eval()
    all_labels = []
    all_probabilities = []

    # Collect true labels and model probabilities
    with torch.no_grad():
        for images, labels in tqdm(test_loader, desc="Calculating
Cumulative Gains Data"):
            images, labels = images.to(device), labels.to(device)
            outputs = model(images)
            probabilities = torch.nn.functional.softmax(outputs,
dim=1)
            all_probabilities.extend(probabilities.cpu().numpy())
            all_labels.extend(labels.cpu().numpy())

    all_labels = np.array(all_labels)
    all_probabilities = np.array(all_probabilities)

    # Assuming binary classification (adjust for multi-class if
necessary)
    positive_class = 1  # Define the positive class
    probabilities_positive = all_probabilities[:, positive_class]

    # Sort probabilities and labels together
    sorted_indices = np.argsort(probabilities_positive)[::-1]
    sorted_labels = all_labels[sorted_indices]

    # Calculate cumulative gains
    total_positives = np.sum(sorted_labels == positive_class)
    cumulative_positives = np.cumsum(sorted_labels == positive_class)
    percentage_of_data = np.arange(1, len(sorted_labels) + 1) /
len(sorted_labels)
    percentage_of_positives = cumulative_positives / total_positives

    # Plot cumulative gains
```

```
    plt.figure(figsize=(8, 6))
    plt.plot(percentage_of_data, percentage_of_positives,
label="Model", color="blue")
    plt.plot([0, 1], [0, 1], 'k--', label="Random", color="gray")
    plt.title("Cumulative Gains Chart", fontsize=16)
    plt.xlabel("Percentage of Data", fontsize=12)
    plt.ylabel("Percentage of Positives", fontsize=12)
    plt.legend()
    plt.grid()
    plt.tight_layout()
    plt.show()

plot_cumulative_gains(model, test_loader, device)
```

```
Calculating Cumulative Gains Data: 100%|██████████| 12630/12630
[02:16<00:00, 92.73it/s]
<ipython-input-27-25354360c501>:47: UserWarning: color is redundantly
defined by the 'color' keyword argument and the fmt string "k--" (->
color='k'). The keyword argument will take precedence.
  plt.plot([0, 1], [0, 1], 'k--', label="Random", color="gray")
```



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

def plot_lift_curve(model, test_loader, device):
    """
    Plot a Lift Curve.

    Args:
        model (torch.nn.Module): The trained model.
        test_loader (torch.utils.data.DataLoader): DataLoader for the
test dataset.
        device (torch.device): Device to perform testing on (CPU or
GPU).
    """
    model.eval()
    all_labels = []
    all_probabilities = []

    # Collect true labels and model probabilities
    with torch.no_grad():
        for images, labels in tqdm(test_loader, desc="Calculating Lift
Curve Data"):
            images, labels = images.to(device), labels.to(device)
            outputs = model(images)
            probabilities = torch.nn.functional.softmax(outputs,
dim=1)
            all_probabilities.extend(probabilities.cpu().numpy())
            all_labels.extend(labels.cpu().numpy())

    all_labels = np.array(all_labels)
    all_probabilities = np.array(all_probabilities)

    # Assuming binary classification (adjust for multi-class if
necessary)
    positive_class = 1  # Define the positive class
    probabilities_positive = all_probabilities[:, positive_class]

    # Sort probabilities and labels together
    sorted_indices = np.argsort(probabilities_positive)[::-1]
    sorted_labels = all_labels[sorted_indices]

    # Calculate cumulative gains
    total_positives = np.sum(sorted_labels == positive_class)
    cumulative_positives = np.cumsum(sorted_labels == positive_class)
    percentage_of_data = np.arange(1, len(sorted_labels) + 1) /
len(sorted_labels)
    lift = cumulative_positives / (percentage_of_data *
total_positives)

    # Plot lift curve
```

```
    plt.figure(figsize=(8, 6))
    plt.plot(percentage_of_data, lift, label="Model", color="blue")
    plt.axhline(1, color='gray', linestyle='--', label="Baseline
(Random)")
    plt.title("Lift Curve", fontsize=16)
    plt.xlabel("Percentage of Data", fontsize=12)
    plt.ylabel("Lift", fontsize=12)
    plt.legend()
    plt.grid()
    plt.tight_layout()
    plt.show()

plot_lift_curve(model, test_loader, device)

Calculating Lift Curve Data: 100%|██████████| 12630/12630
[02:16<00:00, 92.42it/s]
```