Downloading & Extracting CASIA-2 Dataset

```
# STEP 1: Download CASIA-2 from Kaggle in Google Colab
from google.colab import files
import os
print("Please upload your Kaggle API JSON file (kaggle.json):")
uploaded = files.upload() # Upload your kaggle.json here
# Move the file to the proper place
!mkdir -p ~/.kaggle
!cp kaggle.json ~/.kaggle/
!chmod 600 ~/.kaggle/kaggle.json
# Download and unzip the CASIA-2 dataset (may take some time, ~3GB)
!kaggle datasets download divg07/casia-20-image-tampering-detection-dataset --unzip -p ./casia2
# Verify the folder structure
print("\nCASIA-2 Dataset folder structure (showing top levels):")
for root, dirs, files in os.walk('./casia2'):
    level = root.replace('./casia2', '').count(os.sep)
    indent = ' ' * 4 * (level)
    print(f"\{indent\}\{os.path.basename(root)\}/")
    if level > 2:
    for f in files[:5]: # Show first 5 files per folder
       print(f"{subindent}{f}")
→ Please upload your Kaggle API JSON file (kaggle.json):
     Choose Files kaggle.json
     • kaggle.json(application/json) - 64 bytes, last modified: 6/21/2025 - 100% done
     Saving kaggle.json to kaggle.json
     Dataset URL: <a href="https://www.kaggle.com/datasets/divg07/casia-20-image-tampering-detection-dataset">https://www.kaggle.com/datasets/divg07/casia-20-image-tampering-detection-dataset</a>
     License(s): unknown
     Downloading casia-20-image-tampering-detection-dataset.zip to ./casia2
      98% 2.52G/2.56G [00:03<00:00, 676MB/s]
     100% 2.56G/2.56G [00:03<00:00, 824MB/s]
     CASIA-2 Dataset folder structure (showing top levels):
     casia2/
         CASIA2
                 Tp_S_NNN_S_N_pla20052_pla20052_01952.tif
                 Tp_D_NNN_S_N_nat00059_nat00059_00666.tif
                 Tp S NNN S B arc20092 arc20092 02407.tif
                 Tp_D_NRN_M_N_nat10143_nat00095_12035.jpg
                 Tp_S_NNN_S_N_arc10001_arc10001_20012.jpg
             CASIA 2 Groundtruth/
                 Tp_S_NRN_S_N_arc00010_arc00010_01109_gt.png
                 Tp_S_NNN_S_N_ind00044_ind00044_01334_gt.png
                 Tp_D_NRD_S_N_ani00041_ani00040_00161_gt.png
                  Tp_D_NRN_S_N_cha00035_cha00040_00355_gt.png
                  Tp_S_NNN_S_N_arc20095_arc20095_02409_gt.png
                 Au sec 30533.jpg
                 Au_art_30093.jpg
                 Au_pla_30586.jpg
                 Au_art_30237.jpg
```

Data Preparation - Split into train, val, test

```
import os
import random
import shutil
from collections import Counter

# Define paths
base_dir = 'casia2/CASIA2'
split_dir = 'casia2/split'
class_names = ['Tp', 'Au']

# Split proportions
train_pct, val_pct, test_pct = 0.7, 0.15, 0.15
random.seed(42)

# Create split directories
for split in ['train', 'val', 'test']:
```

```
TOI. CT2 TIL CT422 Halle2:
       os.makedirs(os.path.join(split_dir, split, cls), exist_ok=True)
# Split and copy images
split_counts = {split: Counter() for split in ['train', 'val', 'test']}
for cls in class_names:
    img_dir = os.path.join(base_dir, cls)
   img_files = [f for f in os.listdir(img_dir) if f.lower().endswith(('.jpg', '.jpeg', '.png', '.tif'))]
    random.shuffle(img_files)
   n_total = len(img_files)
   n_train = int(n_total * train_pct)
   n_val = int(n_total * val_pct)
   n_test = n_total - n_train - n_val
   splits = [
        ('train', img_files[:n_train]),
        ('val', img_files[n_train:n_train+n_val]),
        ('test', img_files[n_train+n_val:])
   1
    for split, files in splits:
       for f in files:
           src = os.path.join(img_dir, f)
            dst = os.path.join(split_dir, split, cls, f)
            shutil.copy2(src, dst)
            split_counts[split][cls] += 1
# Print summary table
import pandas as pd
summary_df = pd.DataFrame(split_counts).T
summary_df.columns = ['Tampered (Tp)', 'Authentic (Au)']
summary_df['Total'] = summary_df['Tampered (Tp)'] + summary_df['Authentic (Au)']
print("\nDataset Split Summary:")
display(summary_df)
# Show some sample images
import matplotlib.pyplot as plt
from PIL import Image
def show_samples(split, cls, n=3):
    img_dir = os.path.join(split_dir, split, cls)
    img_files = random.sample(os.listdir(img_dir), min(n, len(os.listdir(img_dir))))
    plt.figure(figsize=(12, 3))
    for i, f in enumerate(img files):
        img = Image.open(os.path.join(img_dir, f))
       plt.subplot(1, n, i+1)
       plt.imshow(img)
       plt.axis('off')
       plt.title(f"{split}/{cls}\n{f}")
    plt.show()
print("Sample Tampered (Tp) images from train split:")
show_samples('train', 'Tp')
print("Sample Authentic (Au) images from train split:")
show_samples('train', 'Au')
```



Dataset Split Summary:

	Tampered	(Tp)	Authenti	ic (Au)	Total	
train		3586		5205	8791	ılı
val		768		1115	1883	+/
test		769		1117	1886	
Sample	Tampered	(Tp)	images f	rom trai	n split:	

train/Tp train/Tp Tp S NRN S N pla20050 pla20050 01950StiNRN S B art10008 art10008 20049.jpg train/Tp









Sample Authentic (Au) images from train split:

train/Au Au_sec_20062.jpg





train/Au Au_nat_30142.jpg



Next steps: (Generate code with summary_df) (View recommended plots) New interactive sheet

VGG-19 Model Training

```
import torch
from torchvision import datasets, transforms
IMG_SIZE = 224 # Standard for VGG-19
BATCH_SIZE = 16
data_transforms = {
    'train': transforms.Compose([
       transforms.Resize((IMG_SIZE, IMG_SIZE)),
        transforms. Random Horizontal Flip(),\\
        transforms.RandomRotation(10),
        transforms.ToTensor(),
        transforms.Normalize([0.485, 0.456, 0.406],
                             [0.229, 0.224, 0.225])
    'val': transforms.Compose([
        {\tt transforms.Resize((IMG\_SIZE,\ IMG\_SIZE)),}
        transforms.ToTensor(),
        transforms.Normalize([0.485, 0.456, 0.406],
                             [0.229, 0.224, 0.225])
    ]),
     'test': transforms.Compose([
        transforms.Resize((IMG_SIZE, IMG_SIZE)),
        transforms.ToTensor(),
        transforms.Normalize([0.485, 0.456, 0.406],
                             [0.229, 0.224, 0.225])
    ]),
image_datasets = {x: datasets.ImageFolder(os.path.join(split_dir, x),
                                           data_transforms[x])
                  for x in ['train', 'val', 'test']}
dataloaders = {x: torch.utils.data.DataLoader(image_datasets[x], batch_size=BATCH_SIZE,
```

```
shuffle=True if x == 'train' else False, num_workers=2)
                         for x in ['train', 'val', 'test']}
class_names = image_datasets['train'].classes
device = torch.device("cuda" if torch.cuda.is_available() else "cpu")
print("Class Names:", class_names)
→ Class Names: ['Au', 'Tp']
import torchvision.models as models
import torch.nn as nn
model = models.vgg19_bn(pretrained=True)
num_ftrs = model.classifier[6].in_features
model.classifier[6] = nn.Linear(num_ftrs, 2) # 2 classes: Tp, Au
model = model.to(device)
yusr/local/lib/python3.11/dist-packages/torchvision/models/_utils.py:208: UserWarning: The parameter 'pretrained' is deprecated sinc
            warnings.warn(
        /usr/local/lib/python3.11/dist-packages/torchvision/models/_utils.py:223: UserWarning: Arguments other than a weight enum or `None`
           warnings.warn(msg)
        Downloading: "https://download.pytorch.org/models/vgg19_bn-c79401a0.pth" to /root/.cache/torch/hub/checkpoints/vgg19_bn-c79401a0.pth
100%| $\frac{1}{2} \frac{1}{2} \frac{1}{2
import torch.optim as optim
criterion = nn.CrossEntropyLoss()
optimizer = optim.Adam(model.parameters(), lr=1e-4)
scheduler = optim.lr_scheduler.StepLR(optimizer, step_size=5, gamma=0.5)
import time
import copy
import matplotlib.pyplot as plt
num_epochs = 10
train_acc_history = []
val acc history = []
train_loss_history = []
val_loss_history = []
best_model_wts = copy.deepcopy(model.state_dict())
best_acc = 0.0
for epoch in range(num_epochs):
  print(f"\nEpoch {epoch+1}/{num_epochs}")
     print("-" ** 20)
for phase in ['train', 'val']:
····if phase == 'train':
....model.train()
····else:
model.eval()
 running_loss = 0.0
running_corrects = 0
for inputs, labels in dataloaders[phase]:
.....inputs, labels = inputs.to(device), labels.to(device)
····optimizer.zero_grad()
....with torch.set_grad_enabled(phase == 'train'):
outputs = model(inputs)
preds = torch.max(outputs, 1)
loss = criterion(outputs, labels)
·····if phase == 'train':
 ·····loss.backward()
optimizer.step()
running loss += loss.item() * inputs.size(0)
running_corrects += torch.sum(preds == labels.data)
epoch_loss = running_loss / len(image_datasets[phase])
epoch_acc = running_corrects.double() / len(image_datasets[phase])
print(f"{phase.capitalize()} Loss: {epoch_loss:.4f} Acc: {epoch_acc:.4f}")
····if phase == 'train':
train_loss_history.append(epoch_loss)
```

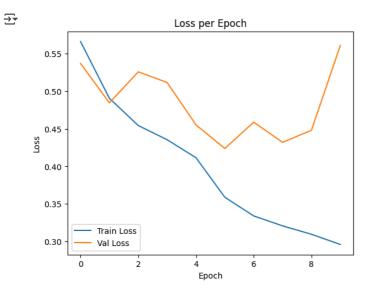
```
train_acc_history.append(epoch_acc.item())
scheduler.step()
····else:
val_loss_history.append(epoch_loss)
val_acc_history.append(epoch_acc.item())
·····best_acc:
best_acc = epoch_acc
best_model_wts = copy.deepcopy(model.state_dict())
model.load_state_dict(best_model_wts)
→*
    Epoch 1/10
    Train Loss: 0.5662 Acc: 0.7113
    Val Loss: 0.5370 Acc: 0.7302
    Epoch 2/10
    Train Loss: 0.4905 Acc: 0.7657
    Val Loss: 0.4845 Acc: 0.7754
    Epoch 3/10
    Train Loss: 0.4543 Acc: 0.7910
    Val Loss: 0.5258 Acc: 0.7148
    Epoch 4/10
    Train Loss: 0.4354 Acc: 0.7997
    Val Loss: 0.5116 Acc: 0.7552
    Epoch 5/10
    Train Loss: 0.4114 Acc: 0.8139
    Val Loss: 0.4551 Acc: 0.7881
    Epoch 6/10
    Train Loss: 0.3587 Acc: 0.8346
    Val Loss: 0.4237 Acc: 0.8062
    Epoch 7/10
    Train Loss: 0.3339 Acc: 0.8437
    Val Loss: 0.4588 Acc: 0.7918
    Epoch 8/10
    Train Loss: 0.3207 Acc: 0.8492
    Val Loss: 0.4319 Acc: 0.8136
    Epoch 9/10
    Train Loss: 0.3094 Acc: 0.8591
    Val Loss: 0.4480 Acc: 0.8083
    Epoch 10/10
    Train Loss: 0.2959 Acc: 0.8601
    Val Loss: 0.5610 Acc: 0.7897
    <All keys matched successfully>
import pandas as pd
history_table = []
# Log train/val for table after both phases
history table.append({
   "Epoch": epoch + 1,
   "Train Loss": train_loss_history[-1],
   "Train Acc": train_acc_history[-1],
   "Val Loss": val_loss_history[-1],
    "Val Acc": val_acc_history[-1]
})
# Convert to DataFrame and show
history_df = pd.DataFrame(history_table)
print("\nEpoch-wise Training/Validation History:")
display(history_df)
```

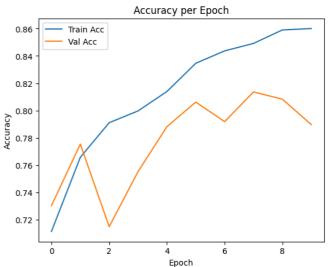
```
Epoch-wise Training/Validation History:
                                                             \blacksquare
         Epoch Train Loss Train Acc Val Loss Val Acc
                  0.295886
                            0.860084 0.56097 0.789697
            10
                                                             +/
import pandas as pd
history_table = []
for epoch in range(num_epochs):
    # ... your existing loop code ...
    for phase in ['train', 'val']:
        # ... phase logic ...
        # [After computing epoch_loss and epoch_acc]
        if phase == 'train':
            train_loss_history.append(epoch_loss)
            train_acc_history.append(epoch_acc.item())
            scheduler.step()
        else:
            val_loss_history.append(epoch_loss)
            val_acc_history.append(epoch_acc.item())
            if epoch_acc > best_acc:
                best_acc = epoch_acc
                best_model_wts = copy.deepcopy(model.state_dict())
    # Log to table after both phases
    history_table.append({
        "Epoch": epoch + 1,
        "Train Loss": train_loss_history[-1],
        "Train Acc": train_acc_history[-1],
        "Val Loss": val_loss_history[-1],
        "Val Acc": val_acc_history[-1]
    })
model.load_state_dict(best_model_wts)
# Show as DataFrame
history df = pd.DataFrame(history table)
print("\nEpoch-wise Training/Validation History:")
display(history_df)
Epoch-wise Training/Validation History:
                                                             \blacksquare
         Epoch Train Loss Train Acc Val Loss Val Acc
                   0.56097
                             0.789697
                                         0.56097 0.789697
      1
             2
                   0.56097
                             0.789697
                                         0.56097 0.789697
                             0.789697
      2
             3
                   0.56097
                                         0.56097 0.789697
      3
             4
                   0.56097
                             0.789697
                                         0.56097 0.789697
      4
             5
                   0.56097
                             0.789697
                                         0.56097 0.789697
                             0.789697
                                         0.56097 0.789697
             6
                   0.56097
      6
             7
                   0.56097
                             0.789697
                                         0.56097 0.789697
             8
                   0.56097
                             0.789697
                                         0.56097 0.789697
      8
             9
                   0.56097
                             0.789697
                                         0.56097 0.789697
      9
            10
                   0.56097
                             0.789697
                                         0.56097 0.789697
 Next steps: ( Generate code with history_df

    View recommended plots

                                                                          New interactive sheet
plt.figure(figsize=(14, 5))
plt.subplot(1,2,1)
plt.plot(train_loss_history, label='Train Loss')
plt.plot(val_loss_history, label='Val Loss')
plt.title('Loss per Epoch')
plt.xlabel('Epoch')
plt.ylabel('Loss')
plt.legend()
plt.subplot(1,2,2)
plt.plot(train_acc_history, label='Train Acc')
plt.plot(val_acc_history, label='Val Acc')
plt.title('Accuracy per Epoch')
plt.xlabel('Epoch')
plt.ylabel('Accuracy')
```

plt.legend()
plt.show()





```
from \ sklearn.metrics \ import \ accuracy\_score, \ precision\_score, \ recall\_score, \ f1\_score, \ confusion\_matrix
model.eval()
all_preds, all_labels = [], []
with torch.no_grad():
    for inputs, labels in dataloaders['test']:
       inputs, labels = inputs.to(device), labels.to(device)
        outputs = model(inputs)
        _, preds = torch.max(outputs, 1)
        all_preds.extend(preds.cpu().numpy())
        all_labels.extend(labels.cpu().numpy())
test_acc = accuracy_score(all_labels, all_preds)
test_prec = precision_score(all_labels, all_preds)
test_rec = recall_score(all_labels, all_preds)
test_f1 = f1_score(all_labels, all_preds)
cm = confusion_matrix(all_labels, all_preds)
print(f"Test Accuracy: {test_acc:.4f}")
print(f"Test Precision: {test_prec:.4f}")
print(f"Test Recall: {test_rec:.4f}")
print(f"Test F1 Score: {test_f1:.4f}")
print("Confusion Matrix:\n", cm)
→ Test Accuracy: 0.8086
     Test Precision: 0.7213
     Test Recall: 0.8648
     Test F1 Score: 0.7865
     Confusion Matrix:
      [[860 257]
      [104 665]]
import pandas as pd
metrics_table = pd.DataFrame({
    "Metric": [
        "Test Accuracy",
        "Test Precision",
        "Test Recall",
        "Test F1 Score",
        "False Negatives",
        "True Negatives",
        "True Positives",
        "False Positives"
    ],
    "Value": [
        f"{test_acc:.4f}",
        f"{test_prec:.4f}",
        f"{test_rec:.4f}",
        f"{test_f1:.4f}",
```

cm[1,0],

cm[0,0],

False Negatives

True Negatives

```
6/22/25, 12:02 AM

cm[1,
cm[0,
]
})
```

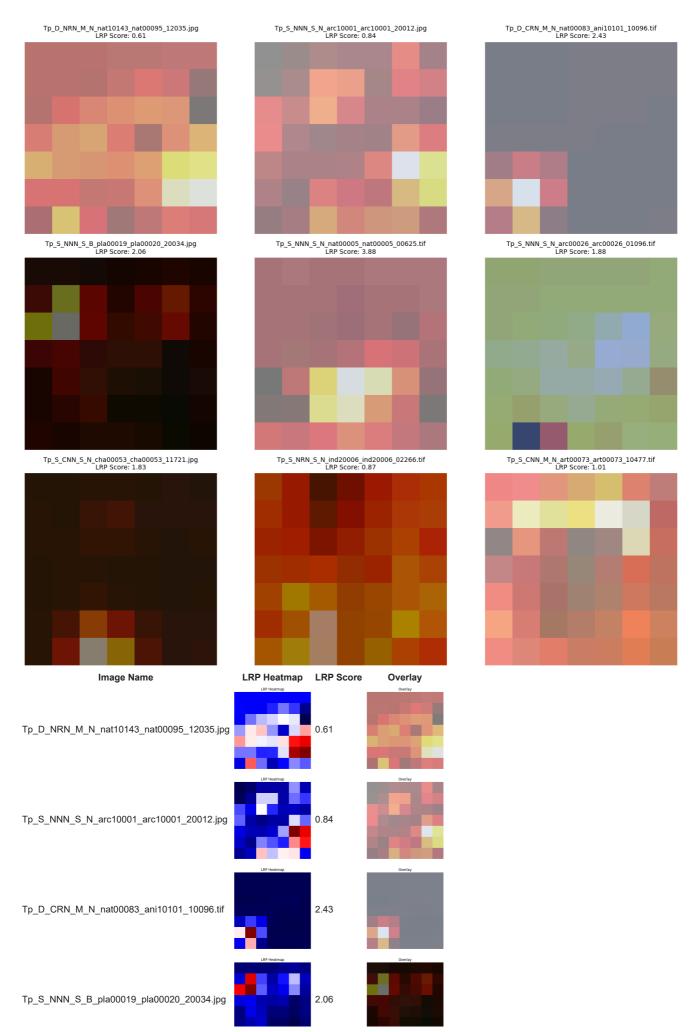
```
# True Positives
        cm[1,1],
                    # False Positives
        cm[0,1]
print("\nTest Set Metrics Table:")
display(metrics_table)
₹
     Test Set Metrics Table:
                Metric Value
                                 Ħ
          Test Accuracy 0.8086
                                 11.
          Test Precision 0.7213
      1
             Test Recall 0.8648
      2
      3
          Test F1 Score 0.7865
      4 False Negatives
                           104
        True Negatives
                           860
          True Positives
                           665
         False Positives
                           257
 Next steps: (Generate code with metrics_table ) ( View recommended plots
                                                                            New interactive sheet
import torch
import numpy as np
import pandas as pd
from \ sklearn.metrics \ import \ confusion\_matrix, \ precision\_score, \ recall\_score, \ f1\_score, \ accuracy\_score, \ jaccard\_score
from scipy.stats import ttest ind
import time
# If not already defined:
# all_labels = ground truth labels (list)
# all preds = predicted labels (list)
# Main Metrics
acc = accuracy_score(all_labels, all_preds)
prec = precision_score(all_labels, all_preds)
rec = recall_score(all_labels, all_preds)
f1 = f1_score(all_labels, all_preds)
cm = confusion_matrix(all_labels, all_preds)
false_negatives = cm[1,0]
# Number of parameters
param_count = sum(p.numel() for p in model.parameters())
# FLOPs calculation (using ptflops, install if needed)
    !pip install ptflops --quiet
    from ptflops import get_model_complexity_info
    macs, params = get_model_complexity_info(model, (3, IMG_SIZE, IMG_SIZE), as_strings=False, print_per_layer_stat=False)
    flops = macs # MACs ~= FLOPs for this purpose
except Exception:
    flops = 'N/A (install ptflops)'
# Inference time (average per image)
n_runs = 50
sample = torch.rand(1, 3, IMG_SIZE, IMG_SIZE).to(device)
start = time.time()
with torch.no_grad():
    for _ in range(n_runs):
         = model(sample)
elapsed = (time.time() - start) / n_runs * 1000 # ms per image
# IOU (mean per class, Jaccard index)
iou = jaccard_score(all_labels, all_preds, average=None)
mean_iou = np.mean(iou) * 100 # %
# Mean accuracy difference (abs diff between classwise acc)
cm = confusion_matrix(all_labels, all_preds)
class_accs = cm.diagonal() / cm.sum(axis=1)
mean_acc_diff = np.abs(class_accs[0] - class_accs[1])
# p-value (t-test between predicted and true labels)
tstat, pval = ttest_ind(all_labels, all_preds)
# Tabulate all results
```

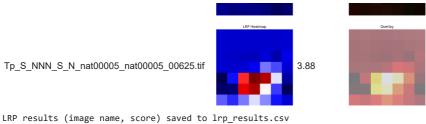
```
metrics_table = pd.DataFrame({
    "Metric": [
         "Accuracy", "Precision", "Recall", "F1 Score",
        "False Negatives", "Parameter Count", "FLOPs (MACs)",
"Inference Time (ms)", "Mean IOU (%)", "Mean Accuracy Diff", "p-value (t-test)"
    ٦,
    "Value": [
        f"{acc:.4f}", f"{prec:.4f}", f"{rec:.4f}", f"{f1:.4f}",
        false_negatives, f"{param_count:,}", flops if isinstance(flops, str) else f"{flops:,}",
f"{elapsed:.2f}", f"{mean_iou:.2f}", f"{mean_acc_diff:.4f}", f"{pval:.4g}"
})
print("\nFull Metrics Table:")
display(metrics_table)
→
                                                     363.4/363.4 MB 3.1 MB/s eta 0:00:00
                                                    - 13.8/13.8 MB 123.1 MB/s eta 0:00:00
                                                     24.6/24.6 MB 98.4 MB/s eta 0:00:00
                                                     883.7/883.7 kB 59.2 MB/s eta 0:00:00
                                                     664.8/664.8 MB 1.7 MB/s eta 0:00:00
                                                    - 211.5/211.5 MB 11.7 MB/s eta 0:00:00
                                                     56.3/56.3 MB 43.1 MB/s eta 0:00:00
                                                    - 127.9/127.9 MB 19.4 MB/s eta 0:00:00
                                                     207.5/207.5 MB 4.0 MB/s eta 0:00:00
                                                    - 21.1/21.1 MB 108.3 MB/s eta 0:00:00
     Full Metrics Table:
                                                丽
                     Metric
                                       Value
       0
                    Accuracy
                                      0.8086
                                                ıl.
       1
                    Precision
                                      0.7213
       2
                       Recall
                                      0.8648
       3
                    F1 Score
                                      0.7865
                                         104
              False Negatives
       4
             Parameter Count
                                 139,589,442
       5
       6
               FLOPs (MACs) 19.714.552.834
       7
          Inference Time (ms)
                                        2.84
       8
               Mean IOU (%)
                                       67.62
           Mean Accuracy Diff
                                      0.0948
       9
      10
               p-value (t-test)
                                   5.278e-07
 Next steps: ( Generate code with metrics_table
                                                  View recommended plots
                                                                                 New interactive sheet
LRP explainability
!pip install captum --quiet
\overline{\mathbf{x}}
                                                      - 61.0/61.0 kB 2.8 MB/s eta 0:00:00
                                                    - 1.4/1.4 MB 25.8 MB/s eta 0:00:00
                                                    - 18.3/18.3 MB 114.5 MB/s eta 0:00:00
     ERROR: pip's dependency resolver does not currently take into account all the packages that are installed. This behaviour is the sou
     thinc 8.3.6 requires numpy<3.0.0,>=2.0.0, but you have numpy 1.26.4 which is incompatible.
from captum.attr import LayerDeepLift
import matplotlib.pyplot as plt
import numpy as np
import pandas as pd
import os
# Choose sample images: 9 from tampered test set
N GRID = 9
N_TABLE = 5
tampered_test_dir = os.path.join(split_dir, 'test', 'Tp')
tampered_imgs = [f for f in os.listdir(tampered_test_dir) if f.lower().endswith(('.jpg', '.jpeg', '.png', '.tif'))]
sample_files = tampered_imgs[:max(N_GRID, N_TABLE)]
# Helper to preprocess image to tensor
from PIL import Image
from torchvision import transforms
vgg19_transform = transforms.Compose([
    transforms.Resize((IMG SIZE. IMG SIZE)).
```

```
transforms.ToTensor(),
    transforms.Normalize([0.485, 0.456, 0.406],
                        [0.229, 0.224, 0.225])
1)
def load_tensor(img_path):
    img = Image.open(img_path).convert("RGB")
    return vgg19_transform(img).unsqueeze(0).to(device)
# LRP via LayerDeepLift on the last conv layer
lrp = LayerDeepLift(model, model.features[-1])
img_names, lrp_scores, lrp_heatmaps, overlays = [], [], []
for fname in sample_files:
   img_path = os.path.join(tampered_test_dir, fname)
    input_tensor = load_tensor(img_path)
    input_tensor.requires_grad_()
    output = model(input_tensor)
   pred = torch.argmax(output, dim=1).item()
    # Attribution (LRP)
   attributions = lrp.attribute(input_tensor, target=pred)
    attr_map = attributions.squeeze().detach().cpu().numpy()
    attr_map = np.sum(attr_map, axis=0) # sum over channels
    score = np.sum(np.abs(attr_map))
   lrp_scores.append(score)
    img names.append(fname)
    lrp_heatmaps.append(attr_map)
   # Overlay
    img_np = input_tensor.squeeze().permute(1,2,0).detach().cpu().numpy()
    img_disp = np.clip(img_np * [0.229, 0.224, 0.225] + [0.485, 0.456, 0.406], 0, 1)
    attr_norm = (attr_map - attr_map.min()) / (attr_map.max() - attr_map.min() + 1e-8)
    overlays.append((img_disp, attr_norm))
# --- 3x3 Grid Display ---
fig, axs = plt.subplots(3, 3, figsize=(15, 15))
for i in range(min(N_GRID, len(sample_files))):
    row, col = divmod(i, 3)
    img_disp, attr_norm = overlays[i]
    axs[row, col].imshow(img_disp)
    axs[row, col].imshow(attr_norm, cmap='hot', alpha=0.4)
   axs[row, col].set_title(f"{img_names[i]}\nLRP Score: {lrp_scores[i]:.2f}", fontsize=10)
   axs[row, col].axis('off')
for i in range(len(sample_files), 9):
   row, col = divmod(i, 3)
    axs[row, col].axis('off')
plt.suptitle("LRP Overlays for Tampered Images (3x3 Grid)", fontsize=16)
plt.tight_layout(rect=[0, 0, 1, 0.96])
plt.show()
# --- Tabular Display of 5 Images ---
import io, base64
from PIL import Image
from IPython.display import display, HTML
def arr_to_img(arr):
    arr = (arr * 255).astype(np.uint8)
    return Image.fromarray(arr)
def fig2img(fig):
   buf = io.BytesIO()
    fig.savefig(buf, format='png', bbox_inches='tight')
    buf, seek(0)
    img = Image.open(buf)
   return img
def img_to_html(img):
   buf = io.BytesIO()
    img.save(buf, format='PNG')
    data = base64.b64encode(buf.read()).decode('utf-8')
    return f'<img src="data:image/png;base64,{data}" width="120"/>'
rows = []
for i in range(N_TABLE):
   # Original
    img_disp, attr_norm = overlays[i]
    img_disp_255 = (img_disp * 255).astype(np.uint8)
    orig_pil = Image.fromarray(img_disp_255)
    # Heatmap
```

```
Tigi, axi = pit.suppiots()
   ax1.imshow(lrp_heatmaps[i], cmap='seismic')
   ax1.axis('off')
   ax1.set_title('LRP Heatmap')
   lrp_heatmap_img = fig2img(fig1)
   plt.close(fig1)
   # Overlay
   fig2, ax2 = plt.subplots()
   ax2.imshow(img_disp)
   ax2.imshow(attr_norm, cmap='hot', alpha=0.4)
   ax2.axis('off')
   ax2.set_title('Overlay')
   overlay_img_pil = fig2img(fig2)
   plt.close(fig2)
   row html = f"""
   {img_names[i]}
       {img_to_html(lrp_heatmap_img)}
       {lrp_scores[i]:.2f}
       {img_to_html(overlay_img_pil)}
   rows.append(row_html)
table_html = f"""
Image Name
      LRP Heatmap
       LRP Score
      Overlay
   {''.join(rows)}
display(HTML(table_html))
# --- Save results to CSV ---
csv_df = pd.DataFrame({
   'Image Name': img_names[:N_TABLE],
   'LRP Score': lrp_scores[:N_TABLE]
})
csv_df.to_csv("lrp_results.csv", index=False)
print("LRP results (image name, score) saved to lrp_results.csv")
```

LRP Overlays for Tampered Images (3x3 Grid)





Explainability with LIME

```
!pip install lime scikit-image --quiet
```

```
- 275.7/275.7 kB 6.3 MB/s eta 0:00:00
₹
       Preparing metadata (setup.py) ... done
       Building wheel for lime (setup.py) ... done
import numpy as np
import matplotlib.pyplot as plt
from lime import lime_image
from skimage.segmentation import mark_boundaries
import io, base64
from PIL import Image
from IPython.display import display, HTML
import torch
# Select images: 9 tampered test images
N GRID = 9
N_TABLE = 5
tampered_test_dir = os.path.join(split_dir, 'test', 'Tp')
tampered_imgs = [f for f in os.listdir(tampered_test_dir) if f.lower().endswith(('.jpg', '.jpeg', '.png', '.tif'))]
sample_files = tampered_imgs[:max(N_GRID, N_TABLE)]
# Transform for LIME and PIL open
def preprocess_for_lime(img_path):
    img = Image.open(img_path).convert('RGB').resize((IMG_SIZE, IMG_SIZE))
    img_np = np.array(img)
    return img_np
# LIME requires a prediction function accepting (batch of images as numpy arrays)
def batch_predict(images):
    model.eval()
    images = [torch.tensor(i.transpose((2,0,1))).float() / 255.0 for i in images]
    images = torch.stack(images)
    for i in range(3):
       images[:,i,:,:] = (images[:,i,:,:] - [0.485,0.456,0.406][i]) / [0.229,0.224,0.225][i]
    images = images.to(device)
    with torch.no_grad():
        logits = model(images)
       probs = torch.softmax(logits, dim=1).cpu().numpy()
   return probs
# For display
def fig2img(fig):
    buf = io.BytesIO()
    fig.savefig(buf, format='png', bbox_inches='tight')
    buf.seek(0)
   img = Image.open(buf)
   return img
def img_to_html(img):
   buf = io.BytesIO()
    img.save(buf, format='PNG')
   buf.seek(0)
    data = base64.b64encode(buf.read()).decode('utf-8')
   return f'<img src="data:image/png;base64,{data}" width="120"/>'
# Run LIME, save results for grid/table
explainer = lime_image.LimeImageExplainer()
img_names, lime_scores, lime_heatmaps, overlays, origs = [], [], [], []
for fname in sample_files:
    ima nath - or nath join/tamponed tost din frame)
```

```
INS_pari - 03.pari.join(rampereu_rest_uir, iname)
   img_np = preprocess_for_lime(img_path)
   explanation = explainer.explain_instance(
       img np,
       batch_predict,
       top_labels=1,
       hide color=0,
       num_samples=1000
   pred_class = explanation.top_labels[0]
   img_lime, mask_lime = explanation.get_image_and_mask(
       pred_class, positive_only=True, num_features=5, hide_rest=False
   )
   lime_score = np.sum([abs(weight) for _, weight in explanation.local_exp[pred_class]])
   lime scores.append(lime score)
   img_names.append(fname)
   lime_heatmaps.append(mask_lime)
   overlays.append(mark_boundaries(img_np, mask_lime))
   origs.append(img_np)
# --- 3x3 Grid Display ---
fig, axs = plt.subplots(3, 3, figsize=(15, 15))
for i in range(min(N_GRID, len(sample_files))):
   row, col = divmod(i, 3)
   axs[row, col].imshow(overlays[i])
   axs[row, col].set\_title(f"\{img\_names[i]\}\nLIME\ Score: \{lime\_scores[i]:.2f\}",\ fontsize=10)
   axs[row, col].axis('off')
for i in range(len(sample_files), 9):
   row, col = divmod(i, 3)
   axs[row, col].axis('off')
plt.suptitle("LIME Overlays for Tampered Images (3x3 Grid)", fontsize=16)
plt.tight_layout(rect=[0, 0, 1, 0.96])
plt.show()
# --- Tabular Display of 5 Images ---
rows = []
for i in range(N_TABLE):
   # Original
   orig_pil = Image.fromarray(origs[i])
   # LIME heatmap
   fig1, ax1 = plt.subplots()
   ax1.imshow(lime_heatmaps[i], cmap='seismic')
   ax1.axis('off')
   ax1.set_title('LIME Heatmap')
   lime_heatmap_img = fig2img(fig1)
   plt.close(fig1)
   # Overlay
   overlay_img_pil = Image.fromarray((overlays[i]*255).astype(np.uint8))
   row_html = f"""
   {img_names[i]}
       {img_to_html(lime_heatmap_img)}
       {lime_scores[i]:.2f}
       {img_to_html(overlay_img_pil)}
   rows.append(row_html)
table_html = f"""
Image Name
       LIME Heatmap
       LIME Score
       Overlay
   {''.join(rows)}
display(HTML(table_html))
# --- Save results to CSV ---
import pandas as pd
csv_df = pd.DataFrame({
    'Image Name': img_names[:N_TABLE],
    'LIME Score': lime_scores[:N_TABLE]
})
csv_df.to_csv("lime_results.csv", index=False)
print("LIME results (image name, score) saved to lime_results.csv")
```