Downloading CASIA-2 & verifying the folder structure

```
# STEP 1: Download CASIA-2 from Kaggle and print folder structure

from google.colab import files
import os

print("Please upload your Kaggle API JSON file (kaggle.json):")
uploaded = files.upload()  # Upload kaggle.json when prompted

# Move to Kaggle location and set permissions
!mkdir -p ~/.kaggle
!cp kaggle.json ~/.kaggle/
!chmod 600 ~/.kaggle/kaggle.json

# Download and unzip the CASIA-2 dataset (about 3GB)
!kaggle datasets download divg07/casia-20-image-tampering-detection-dataset --unzip -p ./casia2

# Print the folder structure (top 2 levels)
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:
        continue  # To avoid printing thousands of files
    subindent = ' ' * 4 * (level + 1)
    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 No file chosen  Upload widget is only available when the cell has been executed in the current browser session. Please rerun this cell to enable.
Saving kaggle.json to kaggle.json
Dataset URL: https://www.kaggle.com/datasets/divg07/casia-20-image-tampering-detection-dataset
License(s): unknown
Downloading casia-20-image-tampering-detection-dataset.zip to ./casia2
 98% 2.51G/2.56G [00:03<00:00, 740MB/s]
100% 2.56G/2.56G [00:03<00:00, 817MB/s]

CASIA-2 Dataset folder structure (showing top levels):
casia2/
    CASIA2/
        Tp/
            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/
            Au_sec_30533.jpg
            Au_art_30093.jpg
            Au_pla_30586.jpg
            Au_art_30237.jpg
            Au_art_30032.jpg
```

Data Preparation

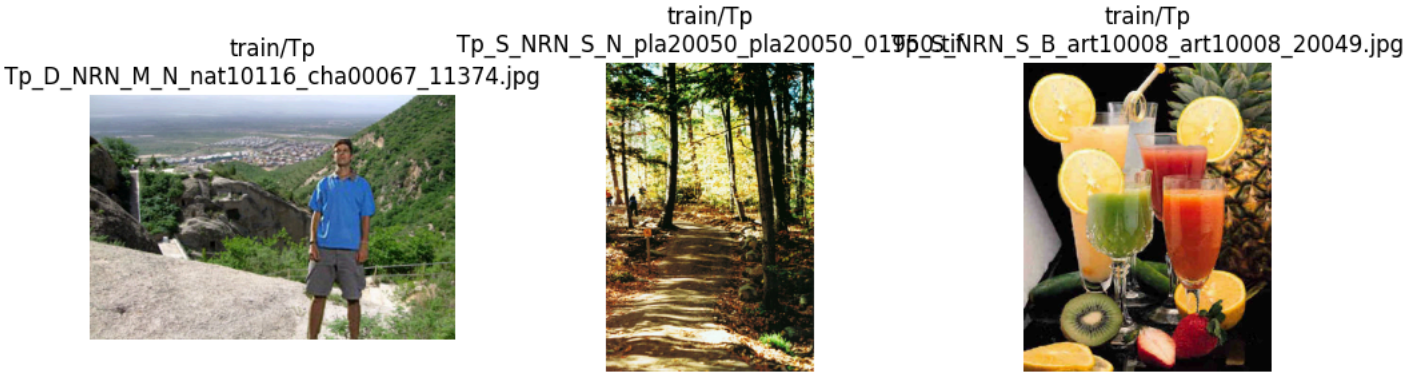
```
import os
import random
import shutil
from collections import Counter
import pandas as pd
import matplotlib.pyplot as plt
from PIL import Image

# 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']:
    for cls in class_names:
        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:])
    ]

    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
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 sample images
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)	Authentic (Au)	Total
train	3586	5205	8791
val	768	1115	1883
test	769	1117	1886

Sample Tampered (Tp) images from train split:



Sample Authentic (Au) images from train split:

Dataloaders and Transforms for ResNet-50

```
import torch
from torchvision import datasets, transforms

IMG_SIZE = 224  # Standard for ResNet-50
BATCH_SIZE = 16

# Data transforms (ResNet-50 uses ImageNet stats)
data_transforms = {
    'train': transforms.Compose([
        transforms.Resize((IMG_SIZE, IMG_SIZE)),
        transforms.RandomHorizontalFlip(),
        transforms.RandomRotation(10),
        transforms.ToTensor(),
        transforms.Normalize([0.485, 0.456, 0.406],
                             [0.229, 0.224, 0.225])
    ]),
    'val': transforms.Compose([
        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])
    ]),
}

# ImageFolder assumes structure: split_dir/train/Tp, split_dir/train/Au, etc.
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)
print("Device:", device)
```

```
Class Names: ['Au', 'Tp']
Device: cuda
```

Model Setup – ResNet-50 for binary classification

```
import torchvision.models as models
import torch.nn as nn

# Load pre-trained ResNet-50
model = models.resnet50(pretrained=True)

# Replace the final fully connected layer for 2 classes
num_ftrs = model.fc.in_features
model.fc = nn.Linear(num_ftrs, 2)  # 2 output classes: Au, Tp

# Move model to device (GPU if available)
model = model.to(device)

print("ResNet-50 binary classification model ready.")
```

```
/usr/local/lib/python3.11/dist-packages/torchvision/models/_utils.py:208: UserWarning: The parameter 'pretrained' is deprecated since 0.13 and may be r
  warnings.warn(
/usr/local/lib/python3.11/dist-packages/torchvision/models/_utils.py:223: UserWarning: Arguments other than a weight enum or `None` for 'weights' are d
  warnings.warn(msg)
Downloading: "https://download.pytorch.org/models/resnet50-0676ba61.pth" to /root/.cache/torch/hub/checkpoints/resnet50-0676ba61.pth
100%|██████████| 97.8M/97.8M [00:00<00:00, 203MB/s]
ResNet-50 binary classification model ready.
```

Loss, Optimizer, Scheduler setup for ResNet-50

```
import torch.optim as optim
import torch.nn as nn

# Loss function
criterion = nn.CrossEntropyLoss()

# Optimizer (Adam is robust for fine-tuning)
optimizer = optim.Adam(model.parameters(), lr=1e-4)

# Learning rate scheduler (optional but helps reduce LR after some epochs)
scheduler = optim.lr_scheduler.StepLR(optimizer, step_size=5, gamma=0.5)

print("Loss, optimizer, and scheduler set up.")
```

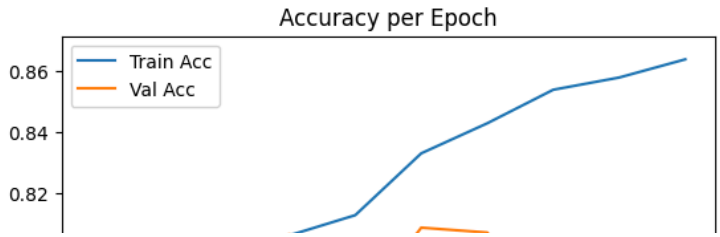
```
Loss, optimizer, and scheduler set up.
```

Training Loop with Learning Curves

```
import time
import copy
import matplotlib.pyplot as plt
import pandas as pd

num_epochs = 10  # You can increase this for longer training

train_acc_history = []
val_acc_history = []
train_loss_history = []
val_loss_history = []
history_table = []

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())
            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 learning curves
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()

# Show table
history_df = pd.DataFrame(history_table)
print("\nEpoch-wise Training/Validation History:")
from IPython.display import display
display(history_df)
```

```
Epoch 1/10
--------------------
Train Loss: 0.5595 Acc: 0.7123
Val Loss: 0.4603 Acc: 0.7929

Epoch 2/10
--------------------
Train Loss: 0.4842 Acc: 0.7648
Val Loss: 0.4613 Acc: 0.7934

Epoch 3/10
--------------------
Train Loss: 0.4445 Acc: 0.7918
Val Loss: 0.4541 Acc: 0.7897

Epoch 4/10
--------------------
Train Loss: 0.4194 Acc: 0.8063
Val Loss: 0.4269 Acc: 0.8067

Epoch 5/10
--------------------
Train Loss: 0.4044 Acc: 0.8129
Val Loss: 0.4673 Acc: 0.7807

Epoch 6/10
--------------------
Train Loss: 0.3539 Acc: 0.8330
Val Loss: 0.4394 Acc: 0.8088

Epoch 7/10
--------------------
Train Loss: 0.3377 Acc: 0.8428
Val Loss: 0.4618 Acc: 0.8072

Epoch 8/10
--------------------
Train Loss: 0.3177 Acc: 0.8537
Val Loss: 0.4710 Acc: 0.7785

Epoch 9/10
--------------------
Train Loss: 0.3109 Acc: 0.8577
Val Loss: 0.4722 Acc: 0.8062

Epoch 10/10
--------------------
Train Loss: 0.2966 Acc: 0.8636
Val Loss: 0.5142 Acc: 0.7801
```



Evaluation & Metrics Table

```
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

# Evaluate on the test set
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())

# Basic 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]
true_negatives = cm[0,0]
true_positives = cm[1,1]
false_positives = cm[0,1]

# Number of parameters
param_count = sum(p.numel() for p in model.parameters())

# FLOPs (MACs) using ptflops (install if needed)
try:
    !pip install ptflops --quiet
    from ptflops import get_model_complexity_info
    macs, params = get_model_complexity_info(model, (3, 224, 224), as_strings=False, print_per_layer_stat=False)
    flops = macs  # MACs ~= FLOPs for this purpose
except Exception:
    flops = 'N/A (install ptflops)'

# Inference time (ms per image, averaged over 50 runs)
n_runs = 50
sample = torch.rand(1, 3, 224, 224).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 diff (between classwise accs)
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", "True Negatives", "True Positives", "False Positives",
        "Parameter Count", "FLOPs (MACs)",
        "Inference Time (ms)", "Mean IOU (%)", "Mean Accuracy Diff", "p-value (t-test)"
    ],
    "Value": [
        f"{acc:.4f}", f"{prec:.4f}", f"{rec:.4f}", f"{f1:.4f}",
        false_negatives, true_negatives, true_positives, false_positives,
        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:")
from IPython.display import display
display(metrics_table)

# Display confusion matrix
print("\nConfusion Matrix (Rows: True, Columns: Predicted):")
print(cm)
```

```
     ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 363.4/363.4 MB 3.4 MB/s eta 0:00:00
     ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 13.8/13.8 MB 130.2 MB/s eta 0:00:00
     ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 24.6/24.6 MB 101.6 MB/s eta 0:00:00
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```

Full Metrics Table:

	Metric	Value
0	Accuracy	0.7990
1	Precision	0.6982
2	Recall	0.8934
3	F1 Score	0.7838
4	False Negatives	82
5	True Negatives	820
6	True Positives	687
7	False Positives	297
8	Parameter Count	23,512,130
9	FLOPs (MACs)	4,130,392,066
10	Inference Time (ms)	7.19
11	Mean IOU (%)	66.42
12	Mean Accuracy Diff	0.1593
13	p-value (t-test)	1.928e-12

```
Confusion Matrix (Rows: True, Columns: Predicted):
[[820 297]
 [ 82 687]]
```

LRP Explainability

```
# Step 8: LRP Explainability for ResNet-50

!pip install captum --quiet

from captum.attr import LayerDeepLift
import matplotlib.pyplot as plt
import numpy as np
import pandas as pd
import os
from PIL import Image
from torchvision import transforms
import io, base64
from IPython.display import display, HTML

# Parameters
IMG_SIZE = 224
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)]

resnet_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])
])

def load_tensor(img_path):
    img = Image.open(img_path).convert("RGB")
    return resnet_transform(img).unsqueeze(0).to(device)

# Use the last conv layer for LRP
lrp = LayerDeepLift(model, model.layer4)
```

```
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)
    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 ---
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}" width="120"/>'

rows = []
for i in range(N_TABLE):
    img_disp, attr_norm = overlays[i]
    img_disp_255 = (img_disp * 255).astype(np.uint8)
    orig_pil = Image.fromarray(img_disp_255)
    # LRP heatmap
    fig1, ax1 = plt.subplots()
    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"""
    <tr>
        <td>{img_names[i]}</td>
        <td>{img_to_html(lrp_heatmap_img)}</td>
        <td>{lrp_scores[i]:.2f}</td>
        <td>{img_to_html(overlay_img_pil)}</td>
    </tr>
    """
```

```
    rows.append(row_html)

table_html = f"""
<table>
    <tr>
        <th>Image Name</th>
        <th>LRP Heatmap</th>
        <th>LRP Score</th>
        <th>Overlay</th>
    </tr>
    {''.join(rows)}
</table>
"""
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_resnet.csv", index=False)
print("LRP results (image name, score) saved to lrp_results_resnet.csv")
```

```
     ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 61.0/61.0 kB 2.8 MB/s eta 0:00:00
     ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 1.4/1.4 MB 27.6 MB/s eta 0:00:00
     ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 18.3/18.3 MB 116.7 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 source of the followir
thinc 8.3.6 requires numpy<3.0.0,>=2.0.0, but you have numpy 1.26.4 which is incompatible.
```

LIME Explainability

```
# Step 9: LIME Explainability for ResNet-50

!pip install lime scikit-image --quiet

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

# Use same images as in LRP
N_GRID = 9
N_TABLE = 5
IMG_SIZE = 224
tampered_test_dir = os.path.join(split_dir, 'test', 'Tp')
sample_files = tampered_imgs[:max(N_GRID, N_TABLE)]

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 batch predict function (ResNet-50 expects normalized tensors)
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

# Helpers for table
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}" width="120"/>'

explainer = lime_image.LimeImageExplainer()
img_names, lime_scores, lime_heatmaps, overlays_lime, origs = [], [], [], [], []

for fname in sample_files:
    img_path = os.path.join(tampered_test_dir, fname)
    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_lime.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_lime[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):
    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_lime[i]*255).astype(np.uint8))
    row_html = f"""
    <tr>
        <td>{img_names[i]}</td>
        <td>{img_to_html(lime_heatmap_img)}</td>
        <td>{lime_scores[i]:.2f}</td>
        <td>{img_to_html(overlay_img_pil)}</td>
    </tr>
    """
    rows.append(row_html)

table_html = f"""
<table>
    <tr>
        <th>Image Name</th>
        <th>LIME Heatmap</th>
        <th>LIME Score</th>
        <th>Overlay</th>
    </tr>
    {''.join(rows)}
</table>
"""
display(HTML(table_html))

# --- Save results to CSV ---
csv_df = pd.DataFrame({
    'Image Name': img_names[:N_TABLE],
    'LIME Score': lime_scores[:N_TABLE]
})
csv_df.to_csv("lime_results_resnet.csv", index=False)
print("LIME results (image name, score) saved to lime_results_resnet.csv")
```

```
     ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 275.7/275.7 kB 6.5 MB/s eta 0:00:00
  Preparing metadata (setup.py) ... done
  Building wheel for lime (setup.py) ... done
100%                                                  1000/1000 [00:03<00:00, 306.56it/s]
100%                                                  1000/1000 [00:03<00:00, 310.80it/s]
100%                                                  1000/1000 [00:03<00:00, 325.09it/s]
100%                                                  1000/1000 [00:03<00:00, 306.16it/s]
100%                                                  1000/1000 [00:03<00:00, 290.52it/s]
100%                                                  1000/1000 [00:03<00:00, 306.33it/s]
100%                                                  1000/1000 [00:03<00:00, 311.57it/s]
100%                                                  1000/1000 [00:03<00:00, 315.43it/s]
100%                                                  1000/1000 [00:03<00:00, 305.75it/s]
```

LIME Overlays for Tampered Images (3x3 Grid)

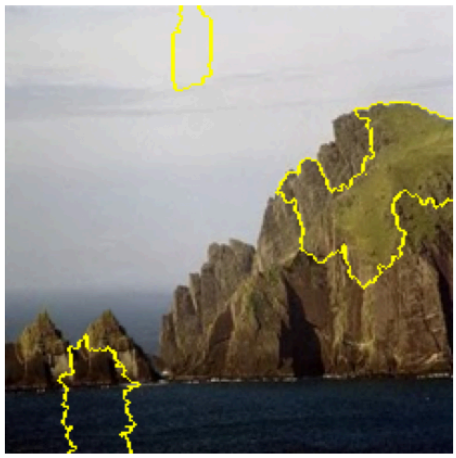
Tp_D_NRN_M_N_nat10143_nat00095_12035.jpg
LIME Score: 1.17

Tp_S_NNN_S_N_arc10001_arc10001_20012.jpg
LIME Score: 0.55

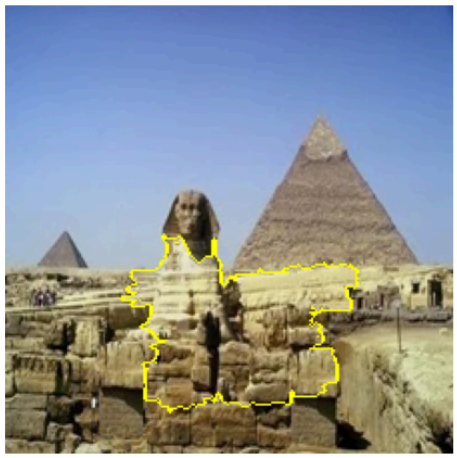
Tp_D_CRN_M_N_nat00083_ani10101_10096.tif
LIME Score: 1.13

Tp_S_NNN_S_B_pla00019_pla00020_20034.jpg
LIME Score: 0.77

Tp_S_NNN_S_N_nat00005_nat00005_00625.tif
LIME Score: 0.83



Tp_S_NNN_S_N_arc00026_arc00026_01096.tif
LIME Score: 1.08



Tp_S_CNN_S_N_cha00053_cha00053_11721.jpg
LIME Score: 0.43

Tp_S_NRN_S_N_ind20006_ind20006_02266.tif
LIME Score: 0.39

Tp_S_CNN_M_N_art00073_art00073_10477.tif
LIME Score: 1.20

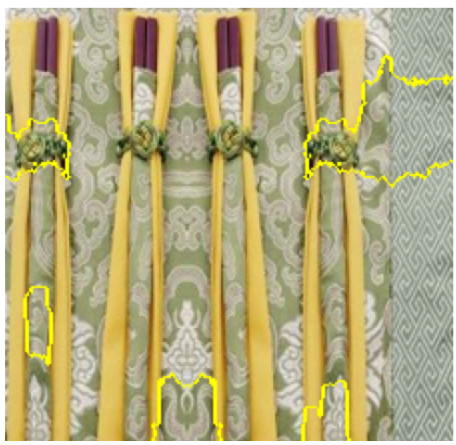
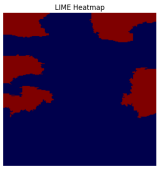
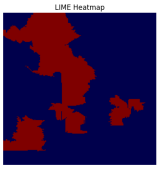
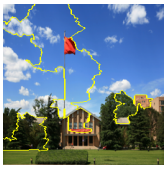
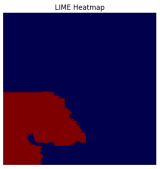
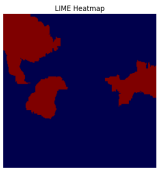
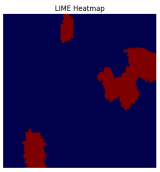
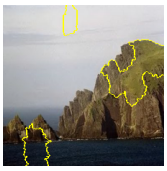


Image Name	LIME Heatmap	LIME Score	Overlay
Tp_D_NRN_M_N_nat10143_nat00095_12035.jpg		1.17	
Tp_S_NNN_S_N_arc10001_arc10001_20012.jpg		0.55	
Tp_D_CRN_M_N_nat00083_ani10101_10096.tif		1.13	
Tp_S_NNN_S_B_pla00019_pla00020_20034.jpg		0.77	
Tp_S_NNN_S_N_nat00005_nat00005_00625.tif		0.83	

LIME results (image name, score) saved to lime_results_resnet.csv

LIME & LRP Table