Downloading & Extracting CoMoFoD Dataset

```
# STEP 1: Download & Extract CoMoFoD from Kaggle

from google.colab import files
import os

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

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

# Download and unzip the CoMoFoD dataset
!kaggle datasets download tusharchauhan1898/comofod --unzip -p ./comofod

# Print the top-level folder structure to verify
print("\nCoMoFoD Dataset folder structure (showing top levels):")
for root, dirs, files in os.walk('./comofod'):
    level = root.replace('./comofod', '').count(os.sep)
    indent = ' ' * 4 * (level)
    print(f"{indent}{os.path.basename(root)}/")
    if level > 2:
        continue  # Skip deep subfolders for brevity
    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 kaggle.json
• kaggle.json(application/json) - 64 bytes, last modified: 6/22/2025 - 100% done
Saving kaggle.json to kaggle.json
Dataset URL: https://www.kaggle.com/datasets/tusharchauhan1898/comofod
License(s): unknown
Downloading comofod.zip to ./comofod
100% 2.98G/2.99G [00:04<00:00, 509MB/s]
100% 2.99G/2.99G [00:05<00:00, 639MB/s]

CoMoFoD Dataset folder structure (showing top levels):
comofod/
    CoMoFoD_small_v2/
        129_O_CA1.png
        163_O_NA3.png
        095_F_CR1.png
        038_M.png
```

Data Preparation

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

# Paths
base_dir = 'comofod/CoMoFoD_small_v2'
split_dir = 'comofod/split'
os.makedirs(split_dir, exist_ok=True)

# Classify: '_F_' in filename = Tampered (Tp), '_O_' or '_M' = Authentic (Au)
def is_tp(filename): return '_F_' in filename or '_F.' in filename or filename.startswith('F_') or '_F' in filename
def is_au(filename): return '_O_' in filename or '_O.' in filename or filename.startswith('O_') or '_O' in filename or '_M' in filename

all_files = [f for f in os.listdir(base_dir) if f.lower().endswith(('.jpg', '.jpeg', '.png'))]
tp_files = [f for f in all_files if is_tp(f)]
au_files = [f for f in all_files if is_au(f)]

print(f"Tamp.: {len(tp_files)} | Authentic: {len(au_files)} | Total: {len(all_files)}")

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

splits = {'train': {}, 'val': {}, 'test': {}}
class_names = ['Tp', 'Au']
```

```
for cls, files in zip(class_names, [tp_files, au_files]):
    n_total = len(files)
    random.shuffle(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'][cls] = files[:n_train]
    splits['val'][cls] = files[n_train:n_train+n_val]
    splits['test'][cls] = files[n_train+n_val:]
    # Copy files to split folders
    for split in ['train', 'val', 'test']:
        target_dir = os.path.join(split_dir, split, cls)
        os.makedirs(target_dir, exist_ok=True)
        for f in splits[split][cls]:
            shutil.copy2(os.path.join(base_dir, f), os.path.join(target_dir, f))

# Print summary as a table
summary_df = pd.DataFrame({split: {cls: len(splits[split][cls]) for cls in class_names} for split in ['train', 'val', 'test']}).T
summary_df['Total'] = summary_df['Tp'] + summary_df['Au']
summary_df.columns = ['Tampered (Tp)', 'Authentic (Au)', 'Total']
print("\nDataset Split Summary:")
from IPython.display import display
display(summary_df)

# Show sample images for both classes
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')
```

```
Tamp.: 5000 | Authentic: 5200 | Total: 10400
```

Dataset Split Summary:

	Tampered (Tp)	Authentic (Au)	Total
train	3500	3639	7139
val	750	780	1530
test	750	781	1531

Sample Tampered (Tp) images from train split:

Sample Authentic (Au) images from train split:

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

Dataloaders & Transforms for ResNet-50 on CoMoFoD

```
import torch
from torchvision import datasets, transforms

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

# Image transforms: use 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])
    ]),
}

# Create datasets and dataloaders
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)

# Modify the classifier for 2 output classes (Tampered, Authentic)
num_ftrs = model.fc.in_features
model.fc = nn.Linear(num_ftrs, 2)  # Two classes: Tp, Au

# Move model to device (GPU/CPU)
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 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/resnet50-0676ba61.pth" to /root/.cache/torch/hub/checkpoints/resnet50-0676ba61.pth
100%|██████████| 97.8M/97.8M [00:00<00:00, 199MB/s]
ResNet-50 binary classification model ready.
```

Loss, Optimizer, Scheduler setup

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

# Loss function: CrossEntropyLoss for binary classification
criterion = nn.CrossEntropyLoss()

# Optimizer: Adam (good for fine-tuning, you can switch to SGD if you wish)
optimizer = optim.Adam(model.parameters(), lr=1e-4)

# Scheduler: Reduce learning rate by half every 5 epochs
scheduler = optim.lr_scheduler.StepLR(optimizer, step_size=5, gamma=0.5)

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

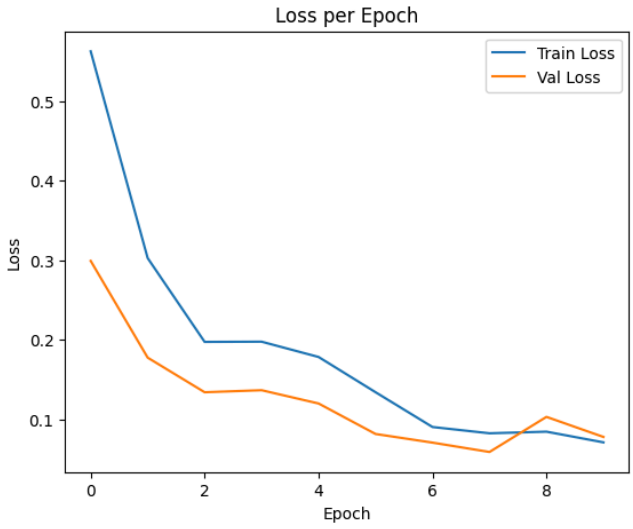
```
Loss, optimizer, and scheduler set up.
```

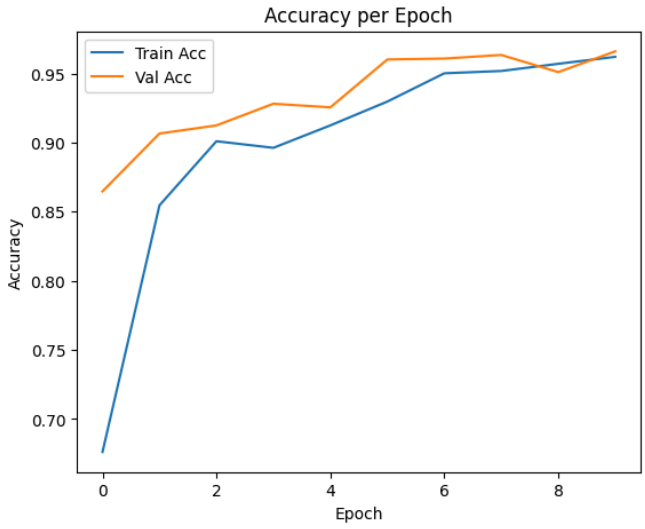
Training Loop with Learning Curves

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

num_epochs = 10  # Adjust as needed

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: 0.5624 Acc: 0.6761
Val Loss: 0.2992 Acc: 0.8647

Epoch 2/10
--------------------
Train Loss: 0.3027 Acc: 0.8546
Val Loss: 0.1777 Acc: 0.9065

Epoch 3/10
--------------------
Train Loss: 0.1975 Acc: 0.9010
Val Loss: 0.1342 Acc: 0.9124

Epoch 4/10
--------------------
Train Loss: 0.1977 Acc: 0.8962
Val Loss: 0.1368 Acc: 0.9281

Epoch 5/10
--------------------
Train Loss: 0.1785 Acc: 0.9125
Val Loss: 0.1201 Acc: 0.9255

Epoch 6/10
--------------------
Train Loss: 0.1343 Acc: 0.9297
Val Loss: 0.0818 Acc: 0.9601

Epoch 7/10
--------------------
Train Loss: 0.0906 Acc: 0.9501
Val Loss: 0.0710 Acc: 0.9608

Epoch 8/10
--------------------
Train Loss: 0.0827 Acc: 0.9518
Val Loss: 0.0592 Acc: 0.9634

Epoch 9/10
--------------------
Train Loss: 0.0847 Acc: 0.9570
Val Loss: 0.1033 Acc: 0.9510

Epoch 10/10
--------------------
Train Loss: 0.0713 Acc: 0.9620
Val Loss: 0.0781 Acc: 0.9660
```





Epoch-wise Training/Validation History:

	Epoch	Train Loss	Train Acc	Val Loss	Val Acc
0	1	0.562409	0.676145	0.299196	0.864706
1	2	0.302717	0.854601	0.177701	0.906536
2	3	0.197474	0.900967	0.134242	0.912418
3	4	0.197738	0.896204	0.136784	0.928105
4	5	0.178533	0.912453	0.120113	0.925490
5	6	0.134269	0.929682	0.081811	0.960131
6	7	0.090570	0.950133	0.070962	0.960784

7	8	0.082691	0.951814	0.059212	0.963399
8	9	0.084718	0.956997	0.103304	0.950980
9	10	0.071294	0.962040	0.078091	0.966013

Next steps: Generate code with `history_df` View recommended plots New interactive sheet

Evaluation & Metrics Table

```
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
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)
```

```
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```

Full Metrics Table:

	Metric	Value
0	Accuracy	0.9686
1	Precision	1.0000
2	Recall	0.9360
3	F1 Score	0.9669
4	False Negatives	48
5	True Negatives	781
6	True Positives	702
7	False Positives	0
8	Parameter Count	23,512,130
9	FLOPs (MACs)	4,130,392,066
10	Inference Time (ms)	7.02
11	Mean IOU (%)	93.90
12	Mean Accuracy Diff	0.0640
13	p-value (t-test)	0.0824

```
Confusion Matrix (Rows: True, Columns: Predicted):
[[781   0]
 [ 48 702]]
```

Next steps: Generate code with `metrics_table` View recommended plots New interactive sheet

LRP Explainability

```
!pip install captum --quiet

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

# Parameters
IMG_SIZE = 224
N_GRID = 9
N_TABLE = 5
tp_dir = os.path.join(split_dir, 'test', 'Tp')
tp_imgs = [f for f in os.listdir(tp_dir) if f.lower().endswith(('.jpg', '.jpeg', '.png'))]
sample_files = tp_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 block for LRP (ResNet-50: layer4)
lrp = LayerDeepLift(model, model.layer4)

img_names, lrp_scores, lrp_heatmaps, overlays = [], [], [], []

for fname in sample_files:
    img_path = os.path.join(tp_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_resnet50_comofod.csv", index=False)
    print("LRP results (image name, score) saved to lrp_results_resnet50_comofod.csv")
```

```
     ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 61.0/61.0 kB 2.8 MB/s eta 0:00:00
     ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 1.4/1.4 MB 26.1 MB/s eta 0:00:00
     ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 18.3/18.3 MB 96.6 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
thinc 8.3.6 requires numpy<3.0.0,>=2.0.0, but you have numpy 1.26.4 which is incompatible.
```

LRP Overlays for Tampered Images (3x3 Grid)

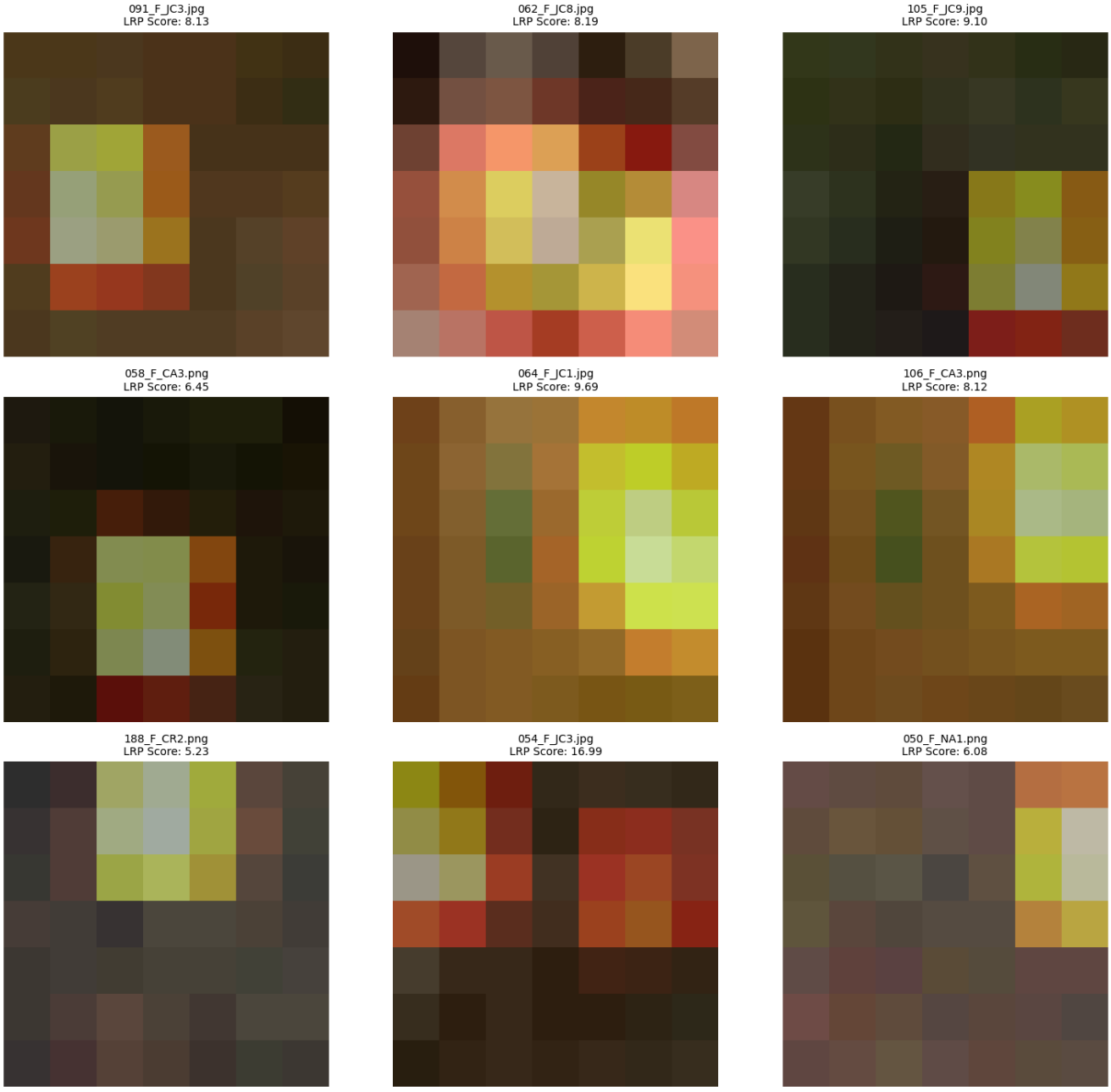
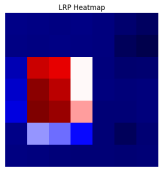
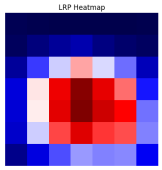
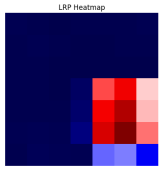
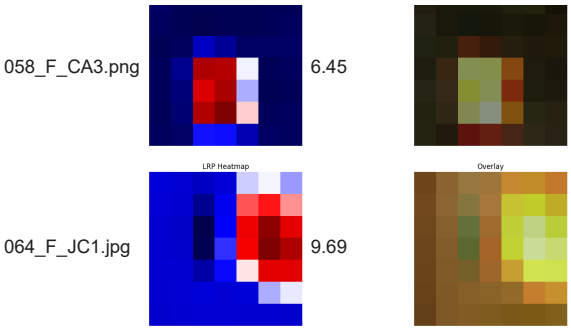


Image Name	LRP Heatmap	LRP Score	Overlay
091_F_JC3.jpg		8.13	
062_F_JC8.jpg		8.19	
105_F_JC9.jpg		9.10	




```
LRP results (image name, score) saved to lrp_results_resnet50_comofod.csv
```

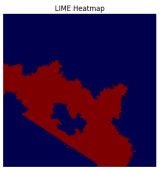
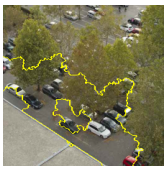
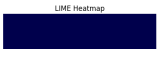
LIME Explainability

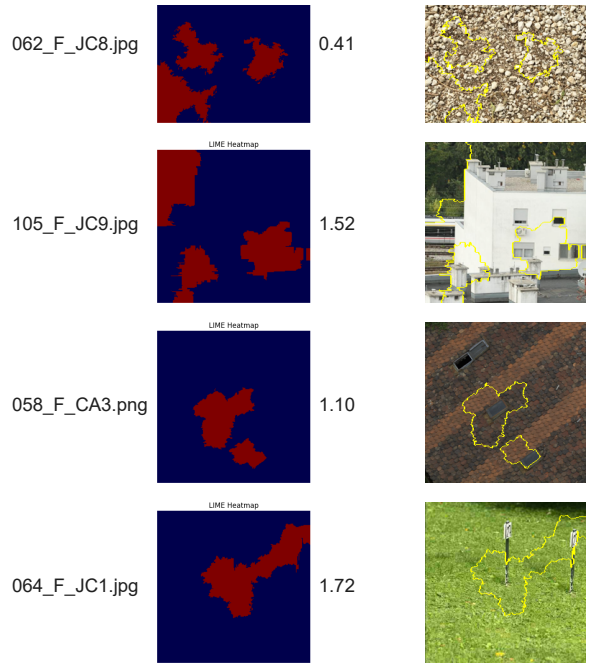
```
!pip install lime scikit-image --quiet

import numpy as np
from lime import lime_image
from skimage.segmentation import mark_boundaries
import matplotlib.pyplot as plt
import io, base64
from PIL import Image
from IPython.display import display, HTML

# Reuse variables: N_GRID, N_TABLE, img_names, sample_files, tp_dir

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

# Batch predict for LIME: ResNet 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

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

for fname in sample_files:
    img_path = os.path.join(tp_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)
    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 ---
    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):
        # 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_resnet50_comofod.csv", index=False)
    print("LIME results (image name, score) saved to lime_results_resnet50_comofod.csv")
```

```
     ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 275.7/275.7 kB 4.7 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, 315.20it/s]
100%                                                  1000/1000 [00:03<00:00, 287.05it/s]
100%                                                  1000/1000 [00:03<00:00, 313.33it/s]
100%                                                  1000/1000 [00:03<00:00, 307.50it/s]
100%                                                  1000/1000 [00:03<00:00, 312.90it/s]
100%                                                  1000/1000 [00:03<00:00, 298.13it/s]
100%                                                  1000/1000 [00:03<00:00, 314.22it/s]
100%                                                  1000/1000 [00:03<00:00, 303.96it/s]
100%                                                  1000/1000 [00:03<00:00, 291.74it/s]
```

LIME Overlays for Tampered Images (3x3 Grid)

Image Name	LIME Heatmap	LIME Score	Overlay
091_F_JC3.jpg		1.59	
			




```
LIME results (image name, score) saved to lime_results_resnet50_comofod.csv
```

Displaying LIME & LRP overlays side-by-side

```
import matplotlib.pyplot as plt

fig, axs = plt.subplots(3, 3, figsize=(15, 15))
for i in range(min(N_GRID, len(img_names))):
    row, col = divmod(i, 3)
    # LIME overlay (left)
    axs[row, col].imshow(overlays_lime[i])
    # LRP overlay (right, using overlays from LRP step)
    # Overlay: reconstruct with original image and LRP heatmap
    img_disp, attr_norm = overlays[i]
    axs[row, col].imshow(np.ones_like(img_disp), alpha=0)  # just to ensure axis is not empty
    axs[row, col].imshow(attr_norm, cmap='hot', alpha=0.4, extent=[IMG_SIZE, IMG_SIZE*2, 0, IMG_SIZE])
    # Compose both overlays as side-by-side
    combined = np.hstack([overlays_lime[i], (img_disp * 255).astype(np.uint8)])
    axs[row, col].imshow(combined)
    axs[row, col].set_title(f"{img_names[i]}\nLIME (left) | LRP (right)", fontsize=10)
    axs[row, col].axis('off')
for i in range(len(img_names), 9):
    row, col = divmod(i, 3)
    axs[row, col].axis('off')
plt.suptitle("LIME (left) vs LRP (right) Overlays for Tampered Images (3x3)", fontsize=18)
plt.tight_layout(rect=[0, 0, 1, 0.96])
plt.show()
```