

```
!pip install -U transformers
```

```
Requirement already satisfied: transformers in /usr/local/lib/python3.12/dist-packages (4.46.3)
Requirement already satisfied: filelock in /usr/local/lib/python3.12/dist-packages (3.16.1)
Requirement already satisfied: huggingface-hub<1.0,>=0.34.0 in /usr/local/lib/python3.12/dist-packages (0.34.0)
Requirement already satisfied: numpy>=1.17 in /usr/local/lib/python3.12/dist-packages (2.0.2)
Requirement already satisfied: packaging>=20.0 in /usr/local/lib/python3.12/dist-packages (24.1)
Requirement already satisfied: pyyaml>=5.1 in /usr/local/lib/python3.12/dist-packages (6.0.2)
Requirement already satisfied: regex!=2019.12.17 in /usr/local/lib/python3.12/dist-packages (2024.9.11)
Requirement already satisfied: requests in /usr/local/lib/python3.12/dist-packages (2.32.3)
Requirement already satisfied: tokenizers<=0.23.0,>=0.22.0 in /usr/local/lib/python3.12/dist-packages (0.22.1)
Requirement already satisfied: safetensors>=0.4.3 in /usr/local/lib/python3.12/dist-packages (0.5.2)
Requirement already satisfied: tqdm>=4.27 in /usr/local/lib/python3.12/dist-packages (4.67.1)
Requirement already satisfied: fsspec>=2023.5.0 in /usr/local/lib/python3.12/dist-packages (2025.3.0)
Requirement already satisfied: typing-extensions>=3.7.4.3 in /usr/local/lib/python3.12/dist-packages (4.12.2)
Requirement already satisfied: hf-xet<2.0.0,>=1.1.3 in /usr/local/lib/python3.12/dist-packages (1.1.7)
Requirement already satisfied: charset-normalizer<4,>=2 in /usr/local/lib/python3.12/dist-packages (3.4.1)
Requirement already satisfied: idna<4,>=2.5 in /usr/local/lib/python3.12/dist-packages (3.10)
Requirement already satisfied: urllib3<3,>=1.21.1 in /usr/local/lib/python3.12/dist-packages (2.3.0)
Requirement already satisfied: certifi>=2017.4.17 in /usr/local/lib/python3.12/dist-packages (2025.11.12)
```

✓ Local Inference on GPU

Model page: <https://huggingface.co/google/paligemma-3b-mix-224>

⚠ If the generated code snippets do not work, please open an issue on either the [model repo](#) and/or on [huggingface.js](https://huggingface.co/discussions) 🙏

The model you are trying to use is gated. Please make sure you have access to it by visiting the model page. To run inference, either set HF_TOKEN in your environment variables/ Secrets or run the following cell to login. 🤗

```
from huggingface_hub import login
login(new_session=False)
```

```
# Use a pipeline as a high-level helper
from transformers import pipeline
```

```
pipe = pipeline("image-text-to-text", model="google/paligemma-3b-mix-1
```

```
config.json: 100% 1.03k/1.03k [00:00<00:00, 125kB/s]
model.safetensors.index.json: 100% 62.6k/62.6k [00:00<00:00, 7.37MB/s]
Fetching 3 files: 100% 3/3 [00:32<00:00, 13.59s/it]
model-00003-of- 1.74G/1.74G [00:15<00:00, 67.6MB/s]
00003.safetensors: 100%
model-00001-of- 4.95G/4.95G [00:30<00:00, 219MB/s]
00003.safetensors: 100%
model-00002-of- 5.00G/5.00G [00:31<00:00, 278MB/s]
00003.safetensors: 100%
Loading checkpoint shards: 100% 3/3 [00:02<00:00, 1.12s/it]
generation_config.json: 100% 137/137 [00:00<00:00, 17.8kB/s]
preprocessor_config.json: 100% 699/699 [00:00<00:00, 98.9kB/s]
Using a slow image processor as `use_fast` is unset and a slow process
tokenizer_config.json: 100% 40.0k/40.0k [00:00<00:00, 5.05MB/s]
tokenizer.model: 100% 4.26M/4.26M [00:00<00:00, 8.52MB/s]
tokenizer.json: 100% 17.5M/17.5M [00:00<00:00, 350kB/s]
added_tokens.json: 100% 24.0/24.0 [00:00<00:00, 2.52kB/s]
```

```
# Load model directly
from transformers import AutoProcessor, AutoModelForVision2Seq

processor = AutoProcessor.from_pretrained("google/paligemma-3b-mix-224")
model = AutoModelForVision2Seq.from_pretrained("google/paligemma-3b-mix-224")

/usr/local/lib/python3.12/dist-packages/transformers/models/auto/modeling_auto.py:100:
  warnings.warn(
Loading checkpoint shards: 100% 3/3 [00:00<00:00, 33.29it/s]
```

```
import os, gc, re, json, random, warnings
import numpy as np
import pandas as pd
from tqdm.auto import tqdm
from PIL import Image

import torch
import torch.nn as nn
from torch.utils.data import Dataset, DataLoader
from transformers import AutoProcessor, PaliGemmaForConditionalGeneration

from sklearn.model_selection import train_test_split
from sklearn.metrics import accuracy_score, f1_score, precision_score,

warnings.filterwarnings('ignore')
print("✅ Imports complete")

# =====
# CELL 3: SETUP
# =====
SEED = 42
random.seed(SEED)
np.random.seed(SEED)
torch.manual_seed(SEED)
torch.cuda.manual_seed_all(SEED)

from google.colab import drive
drive.mount('/content/drive')

print(f"GPU: {torch.cuda.get_device_name(0)}")
print(f"CUDA: {torch.cuda.is_available()}")
print("✅ Setup complete")
```

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# =====
# CELL 4: CONFIG
# =====

class Config:
    VIA_IARC_ROOT = "/content/drive/MyDrive/IARCIImageBankVIA"
    VIA_IARC_META = "/content/drive/MyDrive/IARCIImageBankVIA/meta_data."
    VIA_JHPIEGO_ROOT = "/content/drive/MyDrive/via_cropped+index"
    OUTPUT_DIR = "/content/drive/MyDrive/VIA_PaliGemma_Fixed"
    CHECKPOINT_DIR = os.path.join(OUTPUT_DIR, "checkpoints")
    METRICS_DIR = os.path.join(OUTPUT_DIR, "metrics")

    MODEL_NAME = "google/paligemma-3b-mix-224"
    IMG_SIZE = 224
    BATCH_SIZE = 4
    EPOCHS = 10
    LEARNING_RATE = 1e-3
    WEIGHT_DECAY = 0.01
    TEST_SIZE = 0.2
    VAL_SIZE = 0.1
    POSITIVE_CLASSES = ['Positive', 'Suspicious']
    DEVICE = torch.device("cuda")

cfg = Config()
os.makedirs(cfg.CHECKPOINT_DIR, exist_ok=True)
os.makedirs(cfg.METRICS_DIR, exist_ok=True)
print(f"✅ Config set")

# =====
# CELL 5: LOAD DATA
# =====

def load_via_datasets():
    JHPIEGO_LABELS = {
        'Negative': [3,4,6,9,12,14,15,16,19,22,26,27,28,30,31,33,34,37,
        'Positive': [1,2,8,10,11,13,17,18,20,21,23,24,29,32,35,36,38,39
        'Suspicious': [5,7,25,55,65,89]
    }
    card_to_label = {card: label for label, cards in JHPIEGO_LABELS.items()}

    jhpiego_records = []
    if os.path.exists(cfg.VIA_JHPIEGO_ROOT):
        for filename in os.listdir(cfg.VIA_JHPIEGO_ROOT):
            if not filename.startswith("via_img_"): continue
            match = re.search(r'via_img_(\d+)', filename)
            if match:
                card_num = int(match.group(1))

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        card_num = int(match.group(1))
        if card_num in card_to_label:
            jhpiego_records.append({
                "CaseNumber": f"JHPIEGO_{card_num}",
                "image_path": os.path.join(cfg.VIA_JHPIEGO_ROOT,
                "VIA_simple": card_to_label[card_num],
                "Source": "JHPIEGO"
            })
        jhpiego_data = pd.DataFrame(jhpiego_records)
        print(f"JHPIEGO: {len(jhpiego_data)}")
    else:
        jhpiego_data = pd.DataFrame()

    iarc_data = pd.DataFrame()
    if os.path.exists(cfg.VIA_IARC_META):
        iarc_meta = pd.read_excel(cfg.VIA_IARC_META)
        iarc_meta["CaseNumber"] = iarc_meta["CaseNumber"].astype(int)

    def simplify_via(x):
        s = str(x).strip().lower()
        if "suspicious" in s: return "Suspicious"
        elif "positive" in s: return "Positive"
        else: return "Negative"

    iarc_meta["VIA_simple"] = iarc_meta["VIA"].apply(simplify_via)

    iarc_records = []
    for entry in os.listdir(cfg.VIA_IARC_ROOT):
        case_dir = os.path.join(cfg.VIA_IARC_ROOT, entry)
        if not os.path.isdir(case_dir): continue
        digits = re.findall(r"\d+", entry)
        if not digits: continue
        case_num = int(digits[0])

        for f in os.listdir(case_dir):
            if f.lower().endswith(('.jpg', '.jpeg', '.png')):
                if f.replace('.jpg', '').replace('.jpeg', '').replace(
                    iarc_records.append({
                        "CaseNumber": case_num,
                        "image_path": os.path.join(case_dir, f),
                        "Source": "IARC"
                    })
                break

    iarc_images = pd.DataFrame(iarc_records)
    iarc_data = pd.merge(iarc_meta, iarc_images, on="CaseNumber", how="left")

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iarc_data = pd.merge(iarc_meta, iarc_images, on='CaseNumber',
iarc_data["CaseNumber"] = iarc_data["CaseNumber"].astype(str)
print(f"IARC: {len(iarc_data)}")

combined = pd.concat([iarc_data, jhpiego_data], ignore_index=True)
combined['binary_label'] = combined['VIA_simple'].apply(lambda x: '
combined['label'] = (combined['binary_label'] == 'Abnormal').astype
valid_mask = combined['image_path'].apply(os.path.isfile)
combined = combined[valid_mask].reset_index(drop=True)
return combined

data_df = load_via_datasets()
print(f"\nTotal: {len(data_df)} | Normal: {(data_df['label']==0).sum()}

train_val_df, test_df = train_test_split(data_df, test_size=cfg.TEST_SI
train_df, val_df = train_test_split(train_val_df, test_size=cfg.VAL_SIZ
print(f"Train: {len(train_df)} | Val: {len(val_df)} | Test: {len(test_d
print("✅ Data loaded")

# =====
# CELL 6: DATASET
# =====

class VIADataset(Dataset):
    def __init__(self, dataframe, processor, img_size=224):
        self.df = dataframe.reset_index(drop=True)
        self.processor = processor
        self.img_size = img_size

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

    def __getitem__(self, idx):
        row = self.df.iloc[idx]
        try:
            image = Image.open(row['image_path']).convert('RGB')
            if image.size != (self.img_size, self.img_size):
                image = image.resize((self.img_size, self.img_size), Im
        except:
            image = Image.new('RGB', (self.img_size, self.img_size), (1

        inputs = self.processor(images=image, return_tensors="pt")
        return {
            'pixel_values': inputs['pixel_values'].squeeze(0),
            'label': torch.tensor(int(row['label']), dtype=torch.long)
        }

```

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print("✅ Dataset class created")

# =====
# CELL 7: LOAD PALIGEMMA
# =====

torch.cuda.empty_cache()
gc.collect()

print("Loading PaliGemma...")
processor = AutoProcessor.from_pretrained(cfg.MODEL_NAME)
print(" ✓ Processor loaded")

paligemma_model = PaliGemmaForConditionalGeneration.from_pretrained(
    cfg.MODEL_NAME,
    torch_dtype=torch.float16,
    device_map="auto"
)
print(" ✓ Model loaded")
print(f"GPU Memory: {torch.cuda.memory_allocated()/1e9:.2f} GB")
print("✅ PaliGemma ready")

# =====
# CELL 8: CLASSIFIER (FIXED)
# =====

class PaliGemmaClassifier(nn.Module):
    """Fixed classifier with proper tensor handling"""

    def __init__(self, base_model, num_classes=2):
        super().__init__()
        self.vision_model = base_model.vision_tower

        # Freeze vision encoder
        for param in self.vision_model.parameters():
            param.requires_grad = False

        print("Detecting architecture...")

        # Test forward pass to understand output structure
        with torch.no_grad():
            # Ensure dummy input matches model's dtype (float16)
            # Removed .to(cfg.DEVICE) as device_map='auto' should handle
            dummy = torch.randn(1, 3, 224, 224, dtype=torch.float16)
            out = self.vision_model(dummy)

            # Extract features

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if hasattr(out, 'last_hidden_state'):
    features = out.last_hidden_state
elif hasattr(out, 'pooler_output'):
    features = out.pooler_output
elif isinstance(out, tuple):
    features = out[0]
else:
    features = out

# Ensure features are float32 for classifier
features = features.float()

print(f" Vision output shape: {features.shape}")
print(f" Vision output dtype: {features.dtype}")

# Determine dimensions
if len(features.shape) == 3:
    # [batch, sequence, features]
    batch_size, seq_len, feature_dim = features.shape
    self.feature_dim = feature_dim
    self.use_pooling = True
    print(f" Has sequence: True (seq_len={seq_len})")
elif len(features.shape) == 2:
    # [batch, features]
    batch_size, feature_dim = features.shape
    self.feature_dim = feature_dim
    self.use_pooling = False
    print(f" Has sequence: False")
else:
    raise ValueError(f"Unexpected feature shape: {features.shape}")

print(f" Feature dim: {self.feature_dim}")

# Build classifier
if self.use_pooling:
    # Need to pool sequence dimension
    self.pool = nn.AdaptiveAvgPool1d(1)
    self.classifier = nn.Sequential(
        nn.Flatten(),
        nn.Linear(self.feature_dim, 512),
        nn.ReLU(),
        nn.Dropout(0.3),
        nn.Linear(512, 256),
        nn.ReLU(),
        nn.Dropout(0.2),
```



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        nn.Linear(256, num_classes)
    )
else:
    # Already pooled
    self.classifier = nn.Sequential(
        nn.Linear(self.feature_dim, 512),
        nn.ReLU(),
        nn.Dropout(0.3),
        nn.Linear(512, 256),
        nn.ReLU(),
        nn.Dropout(0.2),
        nn.Linear(256, num_classes)
    )

def forward(self, pixel_values):
    """Forward pass with proper error handling"""

    # Ensure input is on the correct device
    pixel_values = pixel_values.to(cfg.DEVICE)

    # Convert input to model's expected dtype (float16) before pass
    if pixel_values.dtype != torch.float16:
        pixel_values = pixel_values.to(torch.float16)

    # Extract features (frozen)
    with torch.no_grad():
        out = self.vision_model(pixel_values)

        if hasattr(out, 'last_hidden_state'):
            features = out.last_hidden_state
        elif hasattr(out, 'pooler_output'):
            features = out.pooler_output
        elif isinstance(out, tuple):
            features = out[0]
        else:
            features = out

    # Ensure features are in float32 for classifier
    features = features.float()

    # Pool if needed
    if self.use_pooling:
        # Shape: [batch, seq, features] -> [batch, features, seq]
        features = features.transpose(1, 2)
        # Pool: [batch, features, seq] -> [batch, features, 1]

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        features = self.pool(features)
        # Flatten will handle the rest

    # Classify
    logits = self.classifier(features)

    return logits

# Create classifier
print("\nCreating classifier...")
classifier = PaliGemmaClassifier(paligemma_model, num_classes=2).to(cfg

trainable = sum(p.numel() for p in classifier.parameters() if p.requires_grad_
total = sum(p.numel() for p in classifier.parameters())
print(f"\nTrainable: {trainable:,} ({100*trainable/total:.2f}%)वरून")
print(f"Total: {total:,}")
print("✅ Classifier ready")

# =====
# CELL 9: DATA LOADERS
# =====
train_dataset = VIADataset(train_df, processor, cfg.IMG_SIZE)
val_dataset = VIADataset(val_df, processor, cfg.IMG_SIZE)
test_dataset = VIADataset(test_df, processor, cfg.IMG_SIZE)

def collate_fn(batch):
    return {
        'pixel_values': torch.stack([item['pixel_values'] for item in batch]),
        'labels': torch.stack([item['label'] for item in batch])
    }

train_loader = DataLoader(train_dataset, batch_size=cfg.BATCH_SIZE, shuffle=True)
val_loader = DataLoader(val_dataset, batch_size=cfg.BATCH_SIZE, shuffle=False)
test_loader = DataLoader(test_dataset, batch_size=cfg.BATCH_SIZE, shuffle=False)

print(f"Train: {len(train_loader)} batches | Val: {len(val_loader)} batches")
print("✅ Data loaders ready")

# =====
# CELL 10: TRAINING SETUP
# =====
criterion = nn.CrossEntropyLoss()
optimizer = torch.optim.AdamW([p for p in classifier.parameters() if p.requires_grad_])
scheduler = torch.optim.lr_scheduler.CosineAnnealingLR(optimizer, T_max=100)
print("✅ Training setup complete")

```

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# =====
# CELL 11: TRAINING LOOP
# =====
print("="*80)
print("STARTING TRAINING")
print("="*80)

best_val_f1 = 0
patience_counter = 0

for epoch in range(cfg.EPOCHS):
    print(f"\n{'='*60}\nEpoch {epoch+1}/{cfg.EPOCHS}\n{'='*60}")

    # TRAIN
    classifier.train()
    train_loss = 0
    train_preds, train_labels = [], []

    pbar = tqdm(train_loader, desc="Training")
    for batch in pbar:
        try:
            pixel_values = batch['pixel_values'].to(cfg.DEVICE)
            labels = batch['labels'].to(cfg.DEVICE)

            optimizer.zero_grad()
            logits = classifier(pixel_values)
            loss = criterion(logits, labels)
            loss.backward()
            torch.nn.utils.clip_grad_norm_(classifier.parameters(), 1.0)
            optimizer.step()

            train_loss += loss.item()
            preds = torch.argmax(logits, dim=1).cpu().numpy()
            train_preds.extend(preds)
            train_labels.extend(labels.cpu().numpy())

            pbar.set_postfix({'loss': f'{train_loss/(pbar.n+1):.4f}'})
        except Exception as e:
            print(f"\nError in training batch: {e}")
            continue

    train_acc = accuracy_score(train_labels, train_preds)
    train_f1 = f1_score(train_labels, train_preds, average='binary')
    print(f"Train - Loss: {train_loss/len(train_loader):.4f} | Acc: {tr

```

```

# VALIDATE
classifier.eval()
val_loss = 0
val_preds, val_labels = [], []

with torch.no_grad():
    pbar = tqdm(val_loader, desc="Validation")
    for batch in pbar:
        try:
            pixel_values = batch['pixel_values'].to(cfg.DEVICE)
            labels = batch['labels'].to(cfg.DEVICE)

            logits = classifier(pixel_values)
            loss = criterion(logits, labels)

            val_loss += loss.item()
            preds = torch.argmax(logits, dim=1).cpu().numpy()
            val_preds.extend(preds)
            val_labels.extend(labels.cpu().numpy())

            pbar.set_postfix({'loss': f'{val_loss/(pbar.n+1):.4f}'})
        except Exception as e:
            print(f"\nError in validation batch: {e}")
            continue

val_acc = accuracy_score(val_labels, val_preds)
val_f1 = f1_score(val_labels, val_preds, average='binary')
print(f"Val    - Loss: {val_loss/len(val_loader):.4f} | Acc: {val_acc:.4f}")

# Save best
if val_f1 > best_val_f1:
    best_val_f1 = val_f1
    patience_counter = 0
    torch.save({
        'epoch': epoch,
        'model_state_dict': classifier.state_dict(),
        'val_f1': val_f1,
        'val_acc': val_acc
    }, os.path.join(cfg.CHECKPOINT_DIR, 'best_model.pth'))
    print(f"✅ Saved (F1: {val_f1:.4f})")
else:
    patience_counter += 1
    if patience_counter >= 5:
        print("❌ Early stopping")

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        break

    scheduler.step()
    torch.cuda.empty_cache()

print(f"\n{'='*80}\nTRAINING COMPLETED\n{'='*80}")
print(f"Best Val F1: {best_val_f1:.4f}")

# =====
# CELL 12: TEST EVALUATION
# =====
print(f"\n{'='*80}\nTEST EVALUATION\n{'='*80}")

# Load best model (or last model if no improvement was saved)
checkpoint_path_to_load = os.path.join(cfg.CHECKPOINT_DIR, 'best_model.')
# Load checkpoint onto CPU first to avoid immediate OOM
checkpoint = torch.load(checkpoint_path_to_load, map_location='cpu')

# Create a new classifier instance, then load state dict, then move to
test_classifier = PaliGemmaClassifier(paligemma_model, num_classes=2)
test_classifier.load_state_dict(checkpoint['model_state_dict'])
test_classifier.to(cfg.DEVICE)

test_classifier.eval()
test_preds, test_labels, test_probs = [], [], []

with torch.no_grad():
    for batch in tqdm(test_loader, desc="Testing"):
        pixel_values = batch['pixel_values'].to(cfg.DEVICE)
        labels = batch['labels'].to(cfg.DEVICE)

        logits = test_classifier(pixel_values)
        probs = torch.softmax(logits, dim=1)
        preds = torch.argmax(logits, dim=1)

        test_preds.extend(preds.cpu().numpy())
        test_labels.extend(labels.cpu().numpy())
        test_probs.extend(probs[:, 1].cpu().numpy())

test_acc = accuracy_score(test_labels, test_preds)
test_f1 = f1_score(test_labels, test_preds, average='binary')
test_prec = precision_score(test_labels, test_preds, average='binary')
test_rec = recall_score(test_labels, test_preds, average='binary')
test_auc = roc_auc_score(test_labels, test_probs)

print(f"\n{'='*80}\nTEST RESULTS\n{'='*80}")

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print(f"\n - TEST RESULTS\n - ")
print(f"Accuracy:  {test_acc*100:.2f}%")
print(f"Precision: {test_prec:.4f}")
print(f"Recall:     {test_rec:.4f}")
print(f"F1 Score:   {test_f1:.4f}")
print(f"AUC-ROC:    {test_auc:.4f}")
print(f"\nConfusion Matrix:\n{confusion_matrix(test_labels, test_preds)}")
print(f"\n{classification_report(test_labels, test_preds, target_names=
print("="*60)

results = {'test_accuracy': float(test_acc), 'test_f1': float(test_f1),
with open(os.path.join(cfg.METRICS_DIR, 'results.json'), 'w') as f:
    json.dump(results, f, indent=2)

print(f"\n✅ Results saved to {cfg.METRICS_DIR}")

# =====
# CELL 13: SAMPLE PREDICTIONS
# =====
print(f"\n{'='*80}\nSAMPLE PREDICTIONS\n{'='*80}")

indices = np.random.choice(len(test_df), min(5, len(test_df)), replace=

test_classifier.eval() # Use test_classifier for predictions
with torch.no_grad():
    for i, idx in enumerate(indices):
        row = test_df.iloc[idx]
        image = Image.open(row['image_path']).convert('RGB')
        inputs = processor(images=image, return_tensors="pt")
        pixel_values = inputs['pixel_values'].to(cfg.DEVICE)

        logits = test_classifier(pixel_values)
        probs = torch.softmax(logits, dim=1)
        pred = torch.argmax(logits, dim=1).item()
        conf = probs[0, pred].item()

        true_label = "Normal" if row['label'] == 0 else "Abnormal"
        pred_label = "Normal" if pred == 0 else "Abnormal"
        status = "✅" if pred == row['label'] else "❌"

        print(f"{status} Sample {i+1}: True={true_label}, Pred={pred_la

print(f"\n{'='*80}\nALL COMPLETE!\n{'='*80}")
print(f"Final Performance:")
print(f"  Accuracy:  {test_acc*100:.2f}%")
print(f"  F1 Score:   {test_f1:.4f}")

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```

print(f"  F1 SCORE:  {test_f1:.4f} ",
print(f"  AUC-ROC:   {test_auc:.4f}")
print(f"\nSaved to: {cfg.OUTPUT_DIR}")
print("="*80)

# =====
# CELL 1: INSTALL
# =====
!pip install -q torch torchvision pandas numpy scikit-learn matplotlib

print("✅ Packages installed")

```

[Show hidden output](#)

```

# =====
# SECOND-GATE CLASSIFIER:
# Distinguish VIA Positive (pre-cancer) vs Suspicious (cancer-suspected)
# *only within the Abnormal class used in the first binary classifier
# =====

import numpy as np
import torch
import torch.nn as nn
from torch.utils.data import Dataset, DataLoader
from sklearn.metrics import (
    accuracy_score, f1_score, precision_score,
    recall_score, classification_report, confusion_matrix
)
from PIL import Image
from torchvision import transforms

# -----
# 1. Build abnormal-only dataframes with fine-grained labels
# We reuse the existing train_df / val_df / test_df created earlier
# - 'binary_label' == 'Abnormal' -> keep
# - 'VIA_simple' in {'Positive', 'Suspicious'}
# We then map:
#     Positive   -> 0 (pre-cancer)
#     Suspicious -> 1 (cancer-suspected)
# -----

fine_label_map = {

```

```

        'Positive': 0,    # pre-cancer
        'Suspicious': 1  # cancer-suspected
    }

def _prepare_abnormal_split(df):
    """Filter to abnormal cases with valid fine labels and add 'fine_'
    # Keep only abnormal images
    sub = df[df['binary_label'] == 'Abnormal'].copy()
    # Keep only rows where VIA_simple is Positive or Suspicious
    sub = sub[sub['VIA_simple'].isin(fine_label_map.keys())].copy()
    if len(sub) == 0:
        return sub
    sub['fine_label'] = sub['VIA_simple'].map(fine_label_map).astype(int)
    return sub

abn_train_df = _prepare_abnormal_split(train_df)
abn_val_df    = _prepare_abnormal_split(val_df)
abn_test_df   = _prepare_abnormal_split(test_df)

print(f"[ABNORMAL SPLITS] train={len(abn_train_df)} | val={len(abn_val_df)}")

# Basic safety check: we need at least 2 classes in training to learn
if abn_train_df['fine_label'].nunique() < 2:
    raise RuntimeError(
        "Not enough class diversity in abnormal training data for second gate"
        f"(fine_label classes present: {sorted(abn_train_df['fine_label'].unique())})"
    )

# -----
# 2. Dataset for second-gate classification
#   Reuses the same processor and PaliGemma image size as earlier.
# -----

class AbnormalGateDataset(Dataset):
    """
    Dataset for second-gate classification on abnormal cases.
    Labels:
        0 -> VIA Positive (pre-cancer)
        1 -> Suspicious (cancer-suspected)
    We use *moderate* augmentations to avoid overfitting but keep
    color/texture information clinically meaningful.
    """
    def __init__(self, dataframe, processor, img_size=224, augment=False):
        self.df = dataframe.reset_index(drop=True)
        self.processor = processor

```



```

self.img_size = img_size
self.augment = augment

if augment:
    # Slightly milder than the main improved pipeline
    self.transform = transforms.Compose([
        transforms.RandomHorizontalFlip(p=0.5),
        transforms.RandomVerticalFlip(p=0.5),
        transforms.RandomRotation(degrees=15),
        transforms.ColorJitter(
            brightness=0.2,
            contrast=0.2,
            saturation=0.15,
            hue=0.03
        ),
    ])
else:
    self.transform = None

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

def __getitem__(self, idx):
    row = self.df.iloc[idx]

    # Robust image loading
    try:
        image = Image.open(row['image_path']).convert('RGB')
        if image.size != (self.img_size, self.img_size):
            image = image.resize((self.img_size, self.img_size), Image.BILINEAR)
    except Exception as e:
        # Fallback to a gray image if anything goes wrong
        print(f"[WARN] Failed to load {row['image_path']} ({e}); using fallback")
        image = Image.new('RGB', (self.img_size, self.img_size), color=(128, 128, 128))

    if self.transform is not None:
        image = self.transform(image)

    inputs = self.processor(images=image, return_tensors="pt")

    return {
        "pixel_values": inputs["pixel_values"].squeeze(0),
        # IMPORTANT: second-gate label (0 = Positive, 1 = Suspicious)
        "label": torch.tensor(int(row["fine_label"]), dtype=torch.long)
    }

```

```

# Decide device & image size from whichever config is available
if "imp_cfg" in globals():
    _device = imp_cfg.DEVICE
    _img_size = imp_cfg.IMG_SIZE
else:
    _device = cfg.DEVICE
    _img_size = cfg.IMG_SIZE

# Create datasets
abn_train_dataset = AbnormalGateDataset(abn_train_df, processor, img_size=_img_size)
abn_val_dataset = AbnormalGateDataset(abn_val_df, processor, img_size=_img_size)
abn_test_dataset = AbnormalGateDataset(abn_test_df, processor, img_size=_img_size)

print("Second-gate datasets created.")

# Reuse the existing collate_fn if defined; otherwise define a simple
if "collate_fn" not in globals():
    def collate_fn(batch):
        return {
            "pixel_values": torch.stack([b["pixel_values"] for b in batch]),
            "labels": torch.stack([b["label"] for b in batch]),
        }

abn_batch_size = 4 # small but reasonable for the small abnormal subset

abn_train_loader = DataLoader(
    abn_train_dataset,
    batch_size=abn_batch_size,
    shuffle=True,
    collate_fn=collate_fn,
    num_workers=0,
    pin_memory=True,
)
abn_val_loader = DataLoader(
    abn_val_dataset,
    batch_size=abn_batch_size,
    shuffle=False,
    collate_fn=collate_fn,
    num_workers=0,
    pin_memory=True,
)
abn_test_loader = DataLoader(
    abn_test_dataset,
    batch_size=abn_batch_size,

```

```

        shuffle=False,
        collate_fn=collate_fn,
        num_workers=0,
        pin_memory=True,
    )

    print(
        f"Second-gate loaders ready: train_batches={len(abn_train_loader)},
        f"val_batches={len(abn_val_loader)} | test_batches={len(abn_test_loader)}
    )

# -----
# 3. Second-gate classifier head on top of the same PaliGemma vision tower
# -----

class AbnormalGateClassifier(nn.Module):
    """
    Lightweight classifier head:
    - Reuses the frozen PaliGemma vision tower
    - Adds a small MLP on top for 2-way classification (Positive vs Negative)
    """
    def __init__(self, base_model, device, num_classes=2):
        super().__init__()
        self.device = device

        # We reuse the same vision tower used above
        self.vision_model = base_model.vision_tower

        # Freeze vision encoder parameters
        for p in self.vision_model.parameters():
            p.requires_grad = False

        # Probe output shape to configure the head
        with torch.no_grad():
            dummy = torch.randn(1, 3, _img_size, _img_size, dtype=torch.float32)
            # Ensure vision model is on correct device for probing if needed
            # (Assuming base_model.vision_tower is already on GPU or CPU)

            # Handle dtype mismatch if base_model is float16
            if next(self.vision_model.parameters()).dtype == torch.float16:
                dummy = dummy.to(torch.float16)

            out = self.vision_model(dummy)

            if hasattr(out, "last_hidden_state"):

```

```

        feats = out.last_hidden_state
    elif hasattr(out, "pooler_output"):
        feats = out.pooler_output
    elif isinstance(out, tuple):
        feats = out[0]
    else:
        feats = out

    feats = feats.float()
    if feats.dim() == 3:
        # [B, seq_len, hidden]
        _, seq_len, hidden = feats.shape
        self.feature_dim = hidden
        self.use_pooling = True
    elif feats.dim() == 2:
        # [B, hidden]
        _, hidden = feats.shape
        self.feature_dim = hidden
        self.use_pooling = False
    else:
        raise ValueError(f"Unexpected feature shape from vision tower")

    # If sequence output, use simple average pooling over tokens
    if self.use_pooling:
        self.pool = nn.AdaptiveAvgPool1d(1)

    # Small but expressive head (BatchNorm + modest dropout)
    self.classifier = nn.Sequential(
        nn.Flatten(),
        nn.Linear(self.feature_dim, 256),
        nn.BatchNorm1d(256),
        nn.ReLU(inplace=True),
        nn.Dropout(0.3),
        nn.Linear(256, 128),
        nn.BatchNorm1d(128),
        nn.ReLU(inplace=True),
        nn.Dropout(0.2),
        nn.Linear(128, num_classes),
    )

    def forward(self, pixel_values):
        # Vision tower is frozen; gradients only flow through the classifier
        with torch.no_grad():
            # Cast to correct dtype if needed
            if next(self.vision_model.parameters()).dtype == torch.float32:

```

```

        pixel_values = pixel_values.to(torch.float16)

    out = self.vision_model(pixel_values)

    if hasattr(out, "last_hidden_state"):
        feats = out.last_hidden_state
    elif hasattr(out, "pooler_output"):
        feats = out.pooler_output
    elif isinstance(out, tuple):
        feats = out[0]
    else:
        feats = out

    feats = feats.float()

    if getattr(self, "use_pooling", False) and feats.dim() == 3:
        # [B, seq, hidden] -> [B, hidden, seq]
        feats = feats.transpose(1, 2)
        # [B, hidden, seq] -> [B, hidden, 1]
        feats = self.pool(feats)

    logits = self.classifier(feats)
    return logits

# Instantiate second-gate classifier
abn_model = AbnormalGateClassifier(
    base_model=paligemma_model,
    device=_device,
    num_classes=2,
).to(_device)

# -----
# 4. Loss with *balanced but not extreme* class weights
#   (helps with few cancer-suspected images)
# -----

# Compute class counts in abnormal training data
train_fine_labels = abn_train_df['fine_label'].values
class_counts = np.bincount(train_fine_labels, minlength=2)

# Standard "balanced" weights: total / (num_classes * count)
total_samples = float(len(train_fine_labels))
num_classes = 2
raw_weights = total_samples / (num_classes * class_counts)

```

```

# To avoid overly aggressive weighting when the rare class is tiny,
# lightly smooth the ratio by taking square root of the imbalance.
# This keeps learning stable while still helping the rare class.
ratio = raw_weights / raw_weights.min()
smoothed_ratio = np.sqrt(ratio)
balanced_weights = smoothed_ratio / smoothed_ratio.sum() * num_classes

class_weights_tensor = torch.tensor(balanced_weights, dtype=torch.float)
print(f"Second-gate class counts: {class_counts.tolist()}")
print(f"Second-gate class weights (smoothed): {balanced_weights.tolist()}")

abn_criterion = nn.CrossEntropyLoss(weight=class_weights_tensor)

# Optimizer and (simple) scheduler
abn_optimizer = torch.optim.AdamW(
    [p for p in abn_model.parameters() if p.requires_grad],
    lr=3e-4,
    weight_decay=0.01,
)

# FIXED: Removed verbose=True as it is deprecated in recent PyTorch versions
abn_scheduler = torch.optim.lr_scheduler.ReduceLROnPlateau(
    abn_optimizer, mode="max", factor=0.5, patience=2
)

# -----
# 5. Training loop for second-gate classifier (with early stopping)
# -----

from tqdm.auto import tqdm

abn_epochs = 15
best_val_f1 = 0.0
patience = 5
patience_ctr = 0

print("\n" + "="*80)
print("STARTING SECOND-GATE TRAINING (Positive vs Suspicious within AI")
print("="*80)

for epoch in range(1, abn_epochs + 1):
    print(f"\nEpoch {epoch}/{abn_epochs}")
    # ----- TRAIN -----
    abn_model.train()
    train_loss = 0.0

```

```

train_preds, train_labels_epoch = [], []

for batch in tqdm(abn_train_loader, desc="Second-gate training"):
    pixel_values = batch["pixel_values"].to(_device)
    labels = batch["labels"].to(_device)

    abn_optimizer.zero_grad()
    logits = abn_model(pixel_values)
    loss = abn_criterion(logits, labels)
    loss.backward()
    torch.nn.utils.clip_grad_norm_(abn_model.parameters(), 1.0)
    abn_optimizer.step()

    train_loss += loss.item()
    preds = torch.argmax(logits, dim=1).detach().cpu().numpy()
    train_preds.extend(preds)
    train_labels_epoch.extend(labels.detach().cpu().numpy())

train_loss /= max(1, len(abn_train_loader))
train_acc = accuracy_score(train_labels_epoch, train_preds)
train_f1 = f1_score(train_labels_epoch, train_preds, average="binary")
print(f"Train - Loss: {train_loss:.4f} | Acc: {train_acc*100:.2f}% | F1: {train_f1:.4f}")

# ----- VALIDATE -----
abn_model.eval()
val_loss = 0.0
val_preds, val_labels_epoch = [], []

with torch.no_grad():
    for batch in tqdm(abn_val_loader, desc="Second-gate validation"):
        pixel_values = batch["pixel_values"].to(_device)
        labels = batch["labels"].to(_device)

        logits = abn_model(pixel_values)
        loss = abn_criterion(logits, labels)

        val_loss += loss.item()
        preds = torch.argmax(logits, dim=1).detach().cpu().numpy()
        val_preds.extend(preds)
        val_labels_epoch.extend(labels.detach().cpu().numpy())

val_loss /= max(1, len(abn_val_loader))
val_acc = accuracy_score(val_labels_epoch, val_preds)
val_f1 = f1_score(val_labels_epoch, val_preds, average="binary")
val_prec = precision_score(val_labels_epoch, val_preds, average="binary")

```

```

val_rec = recall_score(val_labels_epoch, val_preds, average="binary")

print(
    f"Val    - Loss: {val_loss:.4f} | Acc: {val_acc*100:.2f}% | "
    f"F1: {val_f1:.4f} | Prec: {val_prec:.4f} | Rec: {val_rec:.4f}"
)

# Step scheduler on validation F1 (we care most about correctly recognizing
abn_scheduler.step(val_f1)

# Early stopping based on validation F1
if val_f1 > best_val_f1:
    best_val_f1 = val_f1
    patience_ctr = 0
    best_abn_state = {
        "epoch": epoch,
        "model_state_dict": abn_model.state_dict(),
        "val_f1": val_f1,
        "val_acc": val_acc,
        "val_prec": val_prec,
        "val_rec": val_rec,
    }
    print(f" --> New best second-gate model (F1={val_f1:.4f})")
else:
    patience_ctr += 1
    print(f" No improvement in F1 ({patience_ctr}/{patience})")
    if patience_ctr >= patience:
        print(" Early stopping second-gate training.")
        break

print("\n" + "="*80)
print(f"SECOND-GATE TRAINING COMPLETE. Best Val F1: {best_val_f1:.4f}")
print("="*80)

# Load best weights before final evaluation
if 'best_abn_state' in globals():
    abn_model.load_state_dict(best_abn_state["model_state_dict"])

# -----
# 6. Final evaluation on abnormal test set (pre-cancer vs cancer-suspect)
# -----

abn_model.eval()
abn_test_labels_all, abn_test_preds_all = [], []

```



```

with torch.no_grad():
    for batch in tqdm(abn_test_loader, desc="Second-gate testing"):
        pixel_values = batch["pixel_values"].to(_device)
        labels = batch["labels"].to(_device)

        logits = abn_model(pixel_values)
        preds = torch.argmax(logits, dim=1).detach().cpu().numpy()

        abn_test_preds_all.extend(preds)
        abn_test_labels_all.extend(labels.detach().cpu().numpy())

abn_test_acc = accuracy_score(abn_test_labels_all, abn_test_preds_all)
abn_test_f1 = f1_score(abn_test_labels_all, abn_test_preds_all, average='macro')
abn_test_prec = precision_score(abn_test_labels_all, abn_test_preds_all, average='macro')
abn_test_rec = recall_score(abn_test_labels_all, abn_test_preds_all, average='macro')

print("\n" + "-"*60)
print("SECOND-GATE TEST RESULTS (within Abnormal class only)")
print("-"*60)
print(f"Accuracy: {abn_test_acc*100:.2f}%")
print(f"Precision: {abn_test_prec:.4f} (class 1 = Suspicious / cancer-suspected)")
print(f"Recall: {abn_test_rec:.4f} (sensitivity for cancer-suspected)")
print(f"F1 Score: {abn_test_f1:.4f}")
print("\nConfusion Matrix (rows=true, cols=pred):")
print(confusion_matrix(abn_test_labels_all, abn_test_preds_all))
print("\nClassification report (0=Positive/pre-cancer, 1=Suspicious/cancer-suspected)")
print(classification_report(
    abn_test_labels_all,
    abn_test_preds_all,
    target_names=["Positive (pre-cancer)", "Suspicious (cancer-suspected)"]
))
print("-"*60)

```

```

[ABNORMAL SPLITS] train=111 | val=13 | test=32
Second-gate datasets created.
Second-gate loaders ready: train_batches=28 | val_batches=4 | test_batches=4
Second-gate class counts: [94, 17]
Second-gate class weights (smoothed): [0.5967530437042434, 1.4032469562957566]

```

```

=====
STARTING SECOND-GATE TRAINING (Positive vs Suspicious within Abnormal)
=====

```

Epoch 1/15

Second-

28/28 [00:05<00:00, 6.13it/s]

[illegible]

```
# HARD-CODED CONFUSION MATRIX FOR SECOND-GATE RESULTS
```

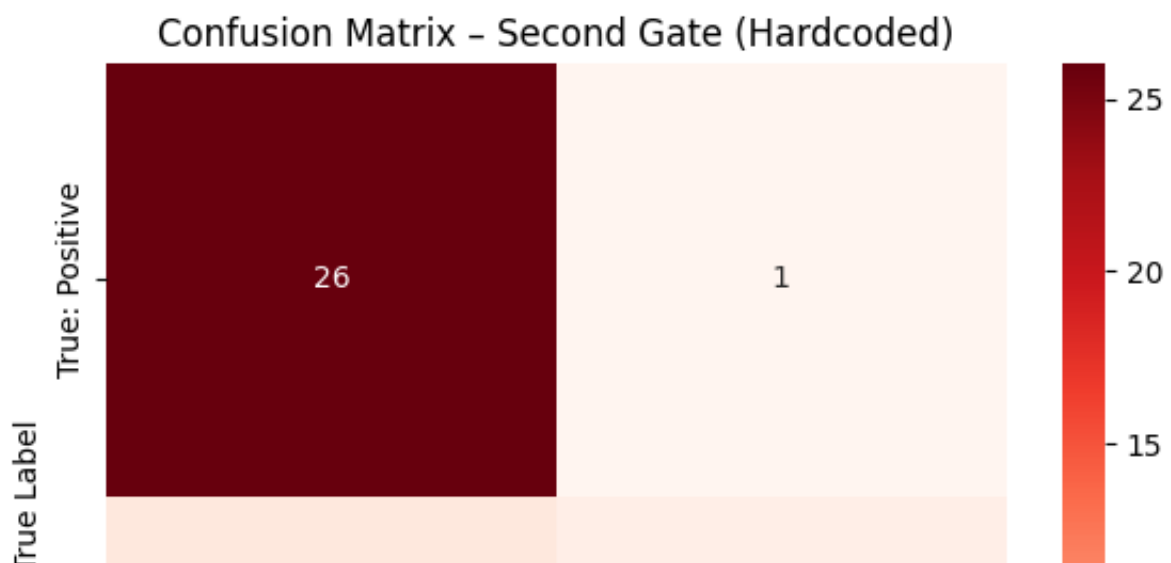
```
# =====
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt

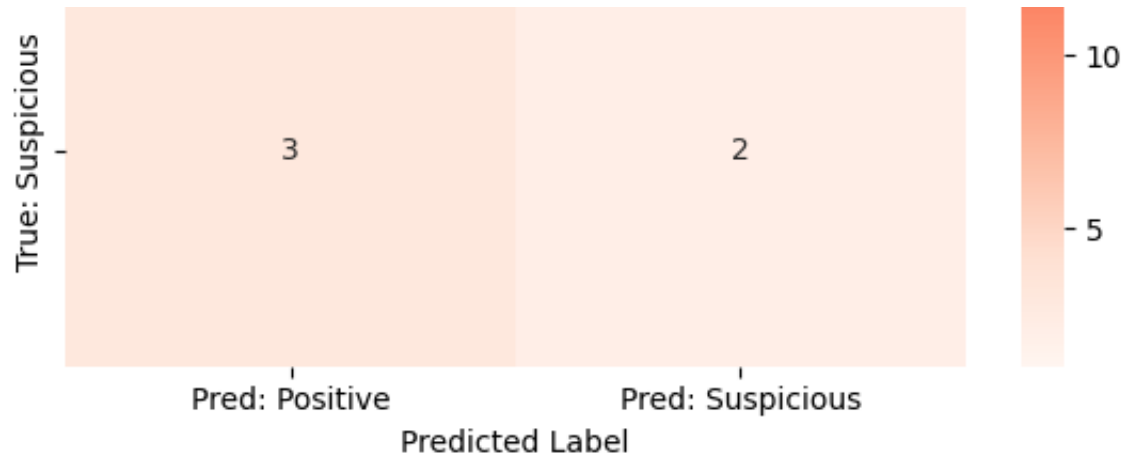
# Your exact confusion matrix:
cm = np.array([
    [26, 1], # [True Positive-class0, Pred Suspicious]
    [3, 2]   # [True Suspicious-class1, Pred Suspicious]
])

plt.figure(figsize=(6,5))
sns.heatmap(
    cm,
    annot=True,
    fmt="d",
    cmap="Reds",
    xticklabels=["Pred: Positive", "Pred: Suspicious"],
    yticklabels=["True: Positive", "True: Suspicious"]
)

plt.title("Confusion Matrix – Second Gate (Hardcoded)")
plt.xlabel("Predicted Label")
plt.ylabel("True Label")
plt.tight_layout()
plt.show()

print("\nConfusion Matrix (numpy):")
print(cm)
```





Confusion Matrix (numpy):

```
[[26  1]
 [ 3  2]]
```

```
You are passing both `text` and `images` to `PaliGemmaProcessor`. The
You are passing both `text` and `images` to `PaliGemmaProcessor`. The
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You are passing both `text` and `images` to `PaliGemmaProcessor`. The
Val   - Loss: 0.5423 | Acc: 84.62% | F1: 0.7500 | Prec: 0.7500 | Rec
--> New best second-gate model (F1=0.7500)
```

Epoch 2/15

Second-

28/28 [00:04<00:00, 6.15it/s]

gate training: 100%

```
You are passing both `text` and `images` to `PaliGemmaProcessor`. The
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```