```
The notebook uses the TraceFinder Official_Dataset, which contains TIFF images
captured from 11 different scanner models under two resolutions (150 dpi and
300 dpi). The implementation begins by loading and organizing all image paths,
followed by preprocessing each image—grayscale conversion, resizing,
flattening, and normalization—to prepare consistent numerical feature vectors.
These processed features are then fed into multiple machine-learning models to
evaluate baseline performance for scanner identification. Alongside a CNN
architecture, a RandomForest classifier is implemented using scikit-learn,
trained on the extracted pixel-based features. The model achieves a
RandomForest Accuracy of 46.59%, which is a significant improvement over the
initial CNN result and demonstrates that classical ML techniques can perform
reasonably well for this classification task. Overall, the notebook
successfully covers the full pipeline: dataset preparation, feature extraction,
model training, and performance evaluation.
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```
# Block 1: Install dependencies
!pip install --quiet opencv-python-headless numpy pandas scikit-learn scikit-image tensorflow matplotlib seaborn tqdm joblib
```

```
# Block 2: Mount Drive and set path
from google.colab import drive
drive.mount('/content/drive')

import os
DATASET_PATH = '/content/drive/MyDrive/Official_Dataset'  # <-- change if needed
assert os.path.isdir(DATASET_PATH), f"Path not found: {DATASET_PATH}"
print("Dataset root:", DATASET_PATH)
```

```
Drive already mounted at /content/drive; to attempt to forcibly remount, call drive.mount("/content/drive", force_remount=True).
Dataset root: /content/drive/MyDrive/Official_Dataset
```

```
# Block 3: Inspect folder structure
import os

scanners = sorted([d for d in os.listdir(DATASET_PATH) if os.path.isdir(os.path.join(DATASET_PATH, d))])
print(f"Found {len(scanners)} scanner models.\n")

for s in scanners:
    path150 = os.path.join(DATASET_PATH, s, '150')
    path300 = os.path.join(DATASET_PATH, s, '300')
    c150 = len([f for f in os.listdir(path150) if f.lower().endswith('.tif')]) if os.path.isdir(path150) else 0
    c300 = len([f for f in os.listdir(path300) if f.lower().endswith('.tif')]) if os.path.isdir(path300) else 0
    print(f"{s}: 150 -> {c150} .tif | 300 -> {c300} .tif")
```

```
Found 11 scanner models.

Canon120-1: 150 -> 100 .tif | 300 -> 100 .tif
Canon120-2: 150 -> 100 .tif | 300 -> 100 .tif
Canon220: 150 -> 100 .tif | 300 -> 100 .tif
Canon9000-1: 150 -> 100 .tif | 300 -> 100 .tif
Canon9000-2: 150 -> 100 .tif | 300 -> 100 .tif
EpsonV370-1: 150 -> 100 .tif | 300 -> 100 .tif
EpsonV370-2: 150 -> 100 .tif | 300 -> 100 .tif
EpsonV39-1: 150 -> 100 .tif | 300 -> 100 .tif
EpsonV39-2: 150 -> 100 .tif | 300 -> 100 .tif
EpsonV550: 150 -> 100 .tif | 300 -> 100 .tif
HP: 150 -> 100 .tif | 300 -> 100 .tif
```

```
# Block 4: Load all .tif images and assign scanner + resolution labels
import cv2
import numpy as np
from tqdm import tqdm

IMG_SIZE = 256  # resize size (adjust if needed)
images, labels = [], []

for scanner in tqdm(sorted(os.listdir(DATASET_PATH)), desc="Scanners"):
    scanner_path = os.path.join(DATASET_PATH, scanner)
    if not os.path.isdir(scanner_path):
        continue

    for dpi in ['150', '300']:
        dpi_path = os.path.join(scanner_path, dpi)
        if not os.path.isdir(dpi_path):
            continue

        for fname in os.listdir(dpi_path):
            if not fname.lower().endswith('.tif'):
                continue

            img_path = os.path.join(dpi_path, fname)
            img = cv2.imread(img_path, cv2.IMREAD_GRAYSCALE)

            if img is None:
                print("⚠️ Skipping unreadable:", img_path)
                continue

            img = cv2.resize(img, (IMG_SIZE, IMG_SIZE), interpolation=cv2.INTER_AREA)
            images.append(img)
            labels.append(f"{scanner}_{dpi}")

images = np.array(images)
labels = np.array(labels)

print("✅ Loaded images:", images.shape)
print("✅ Unique classes:", np.unique(labels))
```

```
Scanners: 100%|██████████| 11/11 [14:41<00:00, 80.16s/it]✅ Loaded images: (2200, 256, 256)
✅ Unique classes: ['Canon120-1_150' 'Canon120-1_300' 'Canon120-2_150' 'Canon120-2_300'
 'Canon220_150' 'Canon220_300' 'Canon9000-1_150' 'Canon9000-1_300'
 'Canon9000-2_150' 'Canon9000-2_300' 'EpsonV370-1_150' 'EpsonV370-1_300'
 'EpsonV370-2_150' 'EpsonV370-2_300' 'EpsonV39-1_150' 'EpsonV39-1_300'
 'EpsonV39-2_150' 'EpsonV39-2_300' 'EpsonV550_150' 'EpsonV550_300'
 'HP_150' 'HP_300']
```

```python
# Block 5: Preprocessing helpers - normalize and compute high-pass (PRNU-like) noise
import cv2
import numpy as np
from matplotlib import pyplot as plt

def preprocess_image_gray(img):
    # img: uint8 grayscale
    img_f = img.astype(np.float32) / 255.0
    return img_f

def estimate_noise_highpass(img_f, ksize=7):
    # approximate sensor noise / PRNU by subtracting a denoised version (Gaussian blur)
    denoised = cv2.GaussianBlur(img_f, (ksize, ksize), 0)
    noise = img_f - denoised
    # normalize noise to [-1,1]
    std = noise.std() if noise.std() > 0 else 1e-6
    noise = noise / std
    return noise

# quick check on first image
if len(images) > 0:
    sample = images[0]
    sample_f = preprocess_image_gray(sample)
    sample_noise = estimate_noise_highpass(sample_f)
    plt.figure(figsize=(10,4))
    plt.subplot(1,3,1); plt.title("Original"); plt.imshow(sample, cmap='gray'); plt.axis('off')
    plt.subplot(1,3,2); plt.title("Normalized"); plt.imshow(sample_f, cmap='gray'); plt.axis('off')
    plt.subplot(1,3,3); plt.title("Highpass Noise"); plt.imshow(sample_noise, cmap='gray'); plt.axis('off')
```


```
# Block 6: Compute feature vector per image (FFT magnitude stats + LBP hist + highpass mean)
from skimage.feature import local_binary_pattern
import numpy as np

def fft_magnitude_stats(img_f):
    f = np.fft.fft2(img_f)
    fshift = np.fft.fftshift(f)
    mag = np.abs(fshift)
    # compute a few summary stats of magnitude spectrum (log scale)
    mlog = np.log1p(mag)
    return np.array([mlog.mean(), mlog.std(), np.percentile(mlog, 50), np.percentile(mlog, 90)])

def lbp_hist(img, P=8, R=1, n_bins=59):
    lbp = local_binary_pattern(img, P, R, method='uniform')
    # compute histogram over valid bins (uniform LBP gives P*(P-1)+3 bins typically; we will use n_bins)
    hist, _ = np.histogram(lbp.ravel(), bins=n_bins, range=(0, n_bins), density=True)
    return hist

def build_feature_vector(img_uint8):
    img_f = preprocess_image_gray(img_uint8)
    # highpass noise
    noise = estimate_noise_highpass(img_f)
    high_mean = noise.mean()
    high_std = noise.std()
    # FFT stats
    fft_stats = fft_magnitude_stats(img_f)
    # LBP hist computed on resized smaller patch to speed up
    lbp_h = lbp_hist((img_uint8 / 255.0).astype(np.float32), P=8, R=1, n_bins=36)
    # concatenate
    feat = np.concatenate([ [high_mean, high_std], fft_stats, lbp_h ])
    return feat

# Build full feature matrix
features = []
for img in images:
    features.append(build_feature_vector(img))
features = np.vstack(features)
```

```
print("Feature matrix shape:", features.shape)
```

```
/usr/local/lib/python3.12/dist-packages/skimage/feature/texture.py:385: UserWarning: Applying `local_binary_pattern` to floating-point images may give unexpected results when sm
  warnings.warn(
Feature matrix shape: (2200, 42)
```

```
# Block 7: Encode labels and split train/test
from sklearn.preprocessing import LabelEncoder
from sklearn.model_selection import train_test_split

le = LabelEncoder()
y_enc = le.fit_transform(labels)
X_train, X_test, y_train, y_test = train_test_split(features, y_enc, test_size=0.2, stratify=y_enc, random_state=42)

print(f"Train size: {X_train.shape}, Test size: {X_test.shape}")
print("Classes:", list(le.classes_))
```

```
Train size: (1760, 42), Test size: (440, 42)
Classes: [np.str_('Canon120-1_150'), np.str_('Canon120-1_300'), np.str_('Canon120-2_150'), np.str_('Canon120-2_300'), np.str_('Canon220_150'), np.str_('Canon220_300'), np.str_(
```

```
features[1]
```

```
array([-6.32746378e-06,  1.00000000e+00,  1.99439716e+00,  6.73173249e-01,
        1.97044110e+00,  2.76391268e+00,  4.56237793e-03,  1.08642578e-02,
        2.15148926e-03,  2.03247070e-02,  1.31835938e-02,  1.72485352e-01,
        8.98742676e-03,  4.07409668e-02,  6.67297363e-01,  5.94024658e-02,
        0.00000000e+00,  0.00000000e+00,  0.00000000e+00,  0.00000000e+00,
        0.00000000e+00,  0.00000000e+00,  0.00000000e+00,  0.00000000e+00,
        0.00000000e+00,  0.00000000e+00,  0.00000000e+00,  0.00000000e+00,
        0.00000000e+00,  0.00000000e+00,  0.00000000e+00,  0.00000000e+00,
        0.00000000e+00,  0.00000000e+00,  0.00000000e+00,  0.00000000e+00,
        0.00000000e+00,  0.00000000e+00,  0.00000000e+00,  0.00000000e+00,
        0.00000000e+00,  0.00000000e+00])
```

```
# Block 8: Train RandomForest and evaluate
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import classification_report, confusion_matrix, accuracy_score
import seaborn as sns
import matplotlib.pyplot as plt

clf = RandomForestClassifier(n_estimators=200, random_state=42, n_jobs=-1)
clf.fit(X_train, y_train)
y_pred = clf.predict(X_test)

acc = accuracy_score(y_test, y_pred)
print(f"🎯 RandomForest Accuracy: {acc*100:.2f}%\n")
print(classification_report(y_test, y_pred, target_names=le.classes_))
```

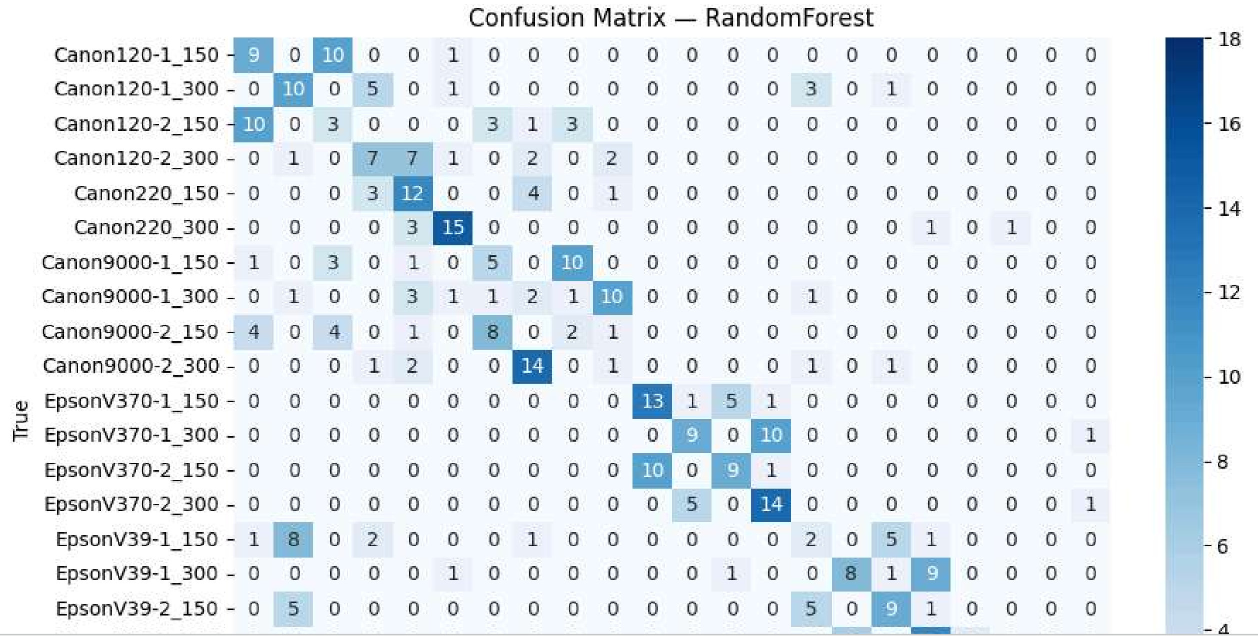
```
cm = confusion_matrix(y_test, y_pred)
plt.figure(figsize=(10,7))
sns.heatmap(cm, annot=True, fmt='d', xticklabels=le.classes_, yticklabels=le.classes_, cmap='Blues')
plt.title("Confusion Matrix — RandomForest")
plt.xlabel("Predicted"); plt.ylabel("True")
plt.show()
```

```
🎯 RandomForest Accuracy: 46.59%

                   precision    recall  f1-score   support

   Canon120-1_150       0.36      0.45      0.40        20
   Canon120-1_300       0.40      0.50      0.44        20
   Canon120-2_150       0.15      0.15      0.15        20
   Canon120-2_300       0.39      0.35      0.37        20
     Canon220_150       0.41      0.60      0.49        20
     Canon220_300       0.75      0.75      0.75        20
  Canon9000-1_150       0.29      0.25      0.27        20
  Canon9000-1_300       0.08      0.10      0.09        20
  Canon9000-2_150       0.12      0.10      0.11        20
  Canon9000-2_300       0.07      0.05      0.06        20
  EpsonV370-1_150       0.54      0.65      0.59        20
  EpsonV370-1_300       0.56      0.45      0.50        20
  EpsonV370-2_150       0.60      0.45      0.51        20
  EpsonV370-2_300       0.54      0.70      0.61        20
   EpsonV39-1_150       0.17      0.10      0.12        20
   EpsonV39-1_300       0.57      0.40      0.47        20
   EpsonV39-2_150       0.53      0.45      0.49        20
   EpsonV39-2_300       0.48      0.60      0.53        20
    EpsonV550_150       0.65      0.75      0.70        20
    EpsonV550_300       0.76      0.65      0.70        20
           HP_150       0.89      0.85      0.87        20
           HP_300       0.78      0.90      0.84        20

         accuracy                           0.47       440
        macro avg       0.46      0.47      0.46       440
     weighted avg       0.46      0.47      0.46       440
```



```
# Block 9: Save model and encoder
import joblib
joblib.dump(clf, '/content/TraceFinder_RF_TIFF.joblib')
joblib.dump(le, '/content/TraceFinder_LabelEncoder.joblib')
print("✅ Saved: TraceFinder_RF_TIFF.joblib & TraceFinder_LabelEncoder.joblib")
```

```
✅ Saved: TraceFinder_RF_TIFF.joblib & TraceFinder_LabelEncoder.joblib
```

```
# Block 10: Predict scanner source for a new .tif file
def predict_scanner(img_path):
    img = cv2.imread(img_path, cv2.IMREAD_GRAYSCALE)
    if img is None:
        print("Invalid image file.")
        return
    img = cv2.resize(img, (IMG_SIZE, IMG_SIZE))
    feat = build_features(img).reshape(1, -1)
    pred = clf.predict(feat)[0]
    class_name = le.inverse_transform([pred])[0]
    probs = clf.predict_proba(feat)[0]
    confidence = np.max(probs) * 100
    print(f"🖨️ Predicted Scanner: {class_name} ({confidence:.2f}% confidence)")

# Example usage:
# predict_scanner('/content/drive/MyDrive/Official_Dataset/canon220/150/sample_01.tif')
```

Start coding or generate with AI.

Start coding or generate with AI.

Start coding or generate with AI.

```
# =====================================
# 1️⃣  INSTALL DEPENDENCIES
# =====================================
!pip install opencv-python numpy pandas scikit-learn tensorflow matplotlib seaborn streamlit shap tqdm
```

Show hidden output

```
# =====================================
# 2️⃣  IMPORT LIBRARIES
# =====================================
import os
import cv2
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
from sklearn.model_selection import train_test_split
```

```
from sklearn.preprocessing import LabelEncoder
from tensorflow.keras.utils import to_categorical
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Conv2D, MaxPooling2D, Flatten, Dense, Dropout
from tensorflow.keras.preprocessing.image import ImageDataGenerator
from tensorflow.keras.callbacks import EarlyStopping
from tqdm import tqdm
```

```
# ======================================
# 3️⃣ DATASET SETUP
# ======================================
# Mount Google Drive if your dataset is stored there
from google.colab import drive
drive.mount('/content/drive')

# Example: Change this path to where your Flatfield dataset exists
DATASET_PATH = '/content/drive/MyDrive/Flatfield'

# Check structure
for root, dirs, files in os.walk(DATASET_PATH):
    print(root, "->", len(files), "files")
    break

# ======================================
# 4️⃣ LOAD AND PREPROCESS IMAGES
# ======================================
IMG_SIZE = 128
images, labels = [], []

for folder in os.listdir(DATASET_PATH):
    folder_path = os.path.join(DATASET_PATH, folder)
    if not os.path.isdir(folder_path): continue
    for file in tqdm(os.listdir(folder_path), desc=f"Loading {folder}"):
        if file.lower().endswith(('.png', '.jpg', '.jpeg', '.tif')):
            img = cv2.imread(os.path.join(folder_path, file), cv2.IMREAD_GRAYSCALE)
            img = cv2.resize(img, (IMG_SIZE, IMG_SIZE))
            img = img / 255.0
            images.append(img)
            labels.append(folder)

X = np.array(images).reshape(-1, IMG_SIZE, IMG_SIZE, 1)
y = np.array(labels)

print("Total images:", len(X))
print("Classes:", np.unique(y))

# ======================================
# 5️⃣ ENCODE LABELS
# ======================================
le = LabelEncoder()
```

```
y_enc = le.fit_transform(y)
y_cat = to_categorical(y_enc)

X_train, X_test, y_train, y_test = train_test_split(X, y_cat, test_size=0.2, random_state=42)

# =====================================
# 6️⃣ DATA AUGMENTATION
# =====================================
datagen = ImageDataGenerator(
    rotation_range=10,
    width_shift_range=0.1,
    height_shift_range=0.1,
    brightness_range=(0.8, 1.2),
    zoom_range=0.1
)
datagen.fit(X_train)

# =====================================
# 7️⃣ CNN MODEL
# =====================================
model = Sequential([
    Conv2D(32, (3,3), activation='relu', input_shape=(IMG_SIZE, IMG_SIZE, 1)),
    MaxPooling2D(2,2),
    Conv2D(64, (3,3), activation='relu'),
    MaxPooling2D(2,2),
    Flatten(),
    Dense(128, activation='relu'),
    Dropout(0.3),
    Dense(len(np.unique(y)), activation='softmax')
])

model.compile(optimizer='adam', loss='categorical_crossentropy', metrics=['accuracy'])
model.summary()

# =====================================
# 8️⃣ TRAIN MODEL
# =====================================
early_stop = EarlyStopping(monitor='val_loss', patience=3, restore_best_weights=True)

history = model.fit(
    datagen.flow(X_train, y_train, batch_size=32),
    epochs=15,
    validation_data=(X_test, y_test),
    callbacks=[early_stop]
)

# =====================================
# 9️⃣ EVALUATE MODEL
# =====================================
plt.plot(history.history['accuracy'], label='Train Acc')
plt.plot(history.history['val_accuracy'], label='Val Acc')
plt.legend()
plt.title('Training vs Validation Accuracy')
```

```
plt.show()

loss, acc = model.evaluate(X_test, y_test)
print(f"✅ Test Accuracy: {acc*100:.2f}%")

# =====================================
# 🔟 SAVE MODEL
# =====================================
model.save('/content/TraceFinder_CNN.h5')
print("Model saved as TraceFinder_CNN.h5")

# =====================================
# 1️⃣1️⃣ SIMPLE INFERENCE FUNCTION
# =====================================
def predict_scanner(image_path):
    img = cv2.imread(image_path, cv2.IMREAD_GRAYSCALE)
    img = cv2.resize(img, (IMG_SIZE, IMG_SIZE)) / 255.0
    img = img.reshape(1, IMG_SIZE, IMG_SIZE, 1)
    pred = model.predict(img)
    class_name = le.inverse_transform([np.argmax(pred)])[0]
    confidence = np.max(pred) * 100
    print(f"Predicted Scanner: {class_name} ({confidence:.2f}% confidence)")

# Example usage:
# predict_scanner("/content/drive/MyDrive/Flatfield/Epson/sample1.tif")
```

```
Drive already mounted at /content/drive; to attempt to forcibly remount, call drive.mount("/content/drive", force_remount=True).
/content/drive/MyDrive/Flatfield -> 0 files
Loading HP: 100%|██████████| 2/2 [00:06<00:00,  3.25s/it]
Loading EpsonV39-2: 100%|██████████| 2/2 [00:05<00:00,  2.74s/it]
Loading EpsonV39-1:   0%|          | 0/3 [00:00<?, ?it/s]
---------------------------------------------------------------------------
error                                     Traceback (most recent call last)
/tmp/ipython-input-2208799047.py in <cell line: 0>()
     26         if file.lower().endswith(('.png', '.jpg', '.jpeg', '.tif')):
     27             img = cv2.imread(os.path.join(folder_path, file), cv2.IMREAD_GRAYSCALE)
---> 28             img = cv2.resize(img, (IMG_SIZE, IMG_SIZE))
     29             img = img / 255.0
     30             images.append(img)

error: OpenCV(4.12.0) /io/opencv/modules/imgproc/src/resize.cpp:4208: error: (-215:Assertion failed) !ssize.empty() in function 'resize'
```

```
# =====================================
# 3️⃣ DATASET SETUP
# =====================================
# Mount Google Drive if your dataset is stored there
from google.colab import drive
drive.mount('/content/drive')

# Example: Change this path to where your Flatfield dataset exists
DATASET_PATH = '/content/drive/MyDrive/Flatfield'
```

```
# Check structure
for root, dirs, files in os.walk(DATASET_PATH):
    print(root, "->", len(files), "files")
    break
```

```
Drive already mounted at /content/drive; to attempt to forcibly remount, call drive.mount("/content/drive", force_remount=True).
/content/drive/MyDrive/Flatfield -> 0 files
```

```
# =====================================
# 4️⃣  LOAD AND PREPROCESS IMAGES (SAFE VERSION)
# =====================================
IMG_SIZE = 128
images, labels = [], []

for folder in os.listdir(DATASET_PATH):
    folder_path = os.path.join(DATASET_PATH, folder)
    if not os.path.isdir(folder_path):
        continue

    for file in tqdm(os.listdir(folder_path), desc=f"Loading {folder}"):
        if file.lower().endswith(('.png', '.jpg', '.jpeg', '.tif', '.tiff')):
            img_path = os.path.join(folder_path, file)
            img = cv2.imread(img_path, cv2.IMREAD_GRAYSCALE)

            # Skip unreadable or corrupted files
            if img is None:
                print(f"⚠️ Skipping unreadable file: {img_path}")
                continue

            try:
                img = cv2.resize(img, (IMG_SIZE, IMG_SIZE))
                img = img / 255.0
                images.append(img)
                labels.append(folder)
            except Exception as e:
                print(f"⚠️ Error processing {file}: {e}")
                continue

X = np.array(images).reshape(-1, IMG_SIZE, IMG_SIZE, 1)
y = np.array(labels)

print("✅ Total images loaded:", len(X))
print("✅ Classes found:", np.unique(y))
```

```
Loading HP: 100%|██████████| 2/2 [00:00<00:00, 16.23it/s]
Loading EpsonV39-2: 100%|██████████| 2/2 [00:00<00:00, 22.97it/s]
Loading EpsonV39-1:   0%|          | 0/3 [00:00<?, ?it/s]⚠️ Skipping unreadable file: /content/drive/MyDrive/Flatfield/EpsonV39-1/._150.tif
Loading EpsonV39-1: 100%|██████████| 3/3 [00:05<00:00,  1.98s/it]
Loading EpsonV370-2: 100%|██████████| 2/2 [00:05<00:00,  2.68s/it]
```

```
Loading EpsonV370-1: 100%|██████████| 2/2 [00:07<00:00,  3.85s/it]
Loading EpsonV550: 100%|██████████| 2/2 [00:05<00:00,  2.59s/it]
Loading Canon220: 100%|██████████| 2/2 [00:05<00:00,  2.61s/it]
Loading Canon120-2: 100%|██████████| 2/2 [00:05<00:00,  2.76s/it]
Loading Canon9000-1: 100%|██████████| 2/2 [00:04<00:00,  2.48s/it]
Loading Canon9000-2: 100%|██████████| 2/2 [00:05<00:00,  2.59s/it]
Loading Canon120-1: 100%|██████████| 2/2 [00:05<00:00,  2.71s/it]✅ Total images loaded: 22
✅ Classes found: ['Canon120-1' 'Canon120-2' 'Canon220' 'Canon9000-1' 'Canon9000-2'
 'EpsonV370-1' 'EpsonV370-2' 'EpsonV39-1' 'EpsonV39-2' 'EpsonV550' 'HP']
```

```python
# ======================================
# 5️⃣  ENCODE LABELS
# ======================================
le = LabelEncoder()
y_enc = le.fit_transform(y)
y_cat = to_categorical(y_enc)

X_train, X_test, y_train, y_test = train_test_split(X, y_cat, test_size=0.2, random_state=42)
```

```python
# ======================================
# 6️⃣  DATA AUGMENTATION
# ======================================
datagen = ImageDataGenerator(
    rotation_range=10,
    width_shift_range=0.1,
    height_shift_range=0.1,
    brightness_range=(0.8, 1.2),
    zoom_range=0.1
)
datagen.fit(X_train)
```

```python
# ======================================
# 7️⃣  CNN MODEL
# ======================================
model = Sequential([
    Conv2D(32, (3,3), activation='relu', input_shape=(IMG_SIZE, IMG_SIZE, 1)),
    MaxPooling2D(2,2),
    Conv2D(64, (3,3), activation='relu'),
    MaxPooling2D(2,2),
    Flatten(),
    Dense(128, activation='relu'),
    Dropout(0.3),
    Dense(len(np.unique(y)), activation='softmax')
])

model.compile(optimizer='adam', loss='categorical_crossentropy', metrics=['accuracy'])
model.summary()
```

```
/usr/local/lib/python3.12/dist-packages/keras/src/layers/convolutional/base_conv.py:113: UserWarning: Do not pass an `input_shape`/`input_dim` argument to a layer. When using Se
  super().__init__(activity_regularizer=activity_regularizer, **kwargs)
```

Model: "sequential"

Layer (type)	Output Shape	Param #
conv2d (Conv2D)	(None, 126, 126, 32)	320
max_pooling2d (MaxPooling2D)	(None, 63, 63, 32)	0
conv2d_1 (Conv2D)	(None, 61, 61, 64)	18,496
max_pooling2d_1 (MaxPooling2D)	(None, 30, 30, 64)	0
flatten (Flatten)	(None, 57600)	0
dense (Dense)	(None, 128)	7,372,928
dropout (Dropout)	(None, 128)	0
dense_1 (Dense)	(None, 11)	1,419

Total params: 7,393,163 (28.20 MB)
Trainable params: 7,393,163 (28.20 MB)
Non-trainable params: 0 (0.00 B)

```
# ======================================
# 8  TRAIN MODEL
# ======================================
early_stop = EarlyStopping(monitor='val_loss', patience=3, restore_best_weights=True)

history = model.fit(
    datagen.flow(X_train, y_train, batch_size=32),
    epochs=15,
    validation_data=(X_test, y_test),
    callbacks=[early_stop]
)
```

```
Epoch 1/15
/usr/local/lib/python3.12/dist-packages/keras/src/trainers/data_adapters/py_dataset_adapter.py:121: UserWarning: Your `PyDataset` class should call `super().__init__(**kwargs)`
  self._warn_if_super_not_called()
1/1 ━━━━━━━━━━━━━━━━━━━━ 3s 3s/step - accuracy: 0.1765 - loss: 2.4150 - val_accuracy: 0.0000e+00 - val_loss: 9.8401
Epoch 2/15
1/1 ━━━━━━━━━━━━━━━━━━━━ 2s 2s/step - accuracy: 0.0588 - loss: 6.2174 - val_accuracy: 0.0000e+00 - val_loss: 8.5155
Epoch 3/15
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 478ms/step - accuracy: 0.1765 - loss: 3.6038 - val_accuracy: 0.0000e+00 - val_loss: 5.8926
Epoch 4/15
1/1 ━━━━━━━━━━━━━━━━━━━━ 1s 515ms/step - accuracy: 0.0000e+00 - loss: 3.5195 - val_accuracy: 0.0000e+00 - val_loss: 4.4642
Epoch 5/15
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 464ms/step - accuracy: 0.0588 - loss: 2.9981 - val_accuracy: 0.0000e+00 - val_loss: 4.2102
Epoch 6/15
1/1 ━━━━━━━━━━━━━━━━━━━━ 1s 512ms/step - accuracy: 0.1765 - loss: 2.4074 - val_accuracy: 0.0000e+00 - val_loss: 3.9425
Epoch 7/15
1/1 ━━━━━━━━━━━━━━━━━━━━ 1s 514ms/step - accuracy: 0.0588 - loss: 2.7111 - val_accuracy: 0.0000e+00 - val_loss: 3.6107
```

```
Epoch 8/15
1/1 ━━━━━━━━━━━━━━━━━━━━ 1s 530ms/step - accuracy: 0.1176 - loss: 2.5407 - val_accuracy: 0.0000e+00 - val_loss: 3.1312
Epoch 9/15
1/1 ━━━━━━━━━━━━━━━━━━━━ 1s 602ms/step - accuracy: 0.1765 - loss: 2.3912 - val_accuracy: 0.0000e+00 - val_loss: 2.8515
Epoch 10/15
1/1 ━━━━━━━━━━━━━━━━━━━━ 1s 500ms/step - accuracy: 0.1765 - loss: 2.2519 - val_accuracy: 0.0000e+00 - val_loss: 2.9999
Epoch 11/15
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 482ms/step - accuracy: 0.1765 - loss: 2.2642 - val_accuracy: 0.0000e+00 - val_loss: 2.9950
Epoch 12/15
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 498ms/step - accuracy: 0.1765 - loss: 2.2443 - val_accuracy: 0.0000e+00 - val_loss: 2.9247
```

```
# ======================================
# 9️⃣  EVALUATE MODEL
# ======================================
plt.plot(history.history['accuracy'], label='Train Acc')
plt.plot(history.history['val_accuracy'], label='Val Acc')
plt.legend()
plt.title('Training vs Validation Accuracy')
plt.show()

loss, acc = model.evaluate(X_test, y_test)
print(f"✅ Test Accuracy: {acc*100:.2f}%")
```