EEE385L_dataset

May 17, 2025

[1]:
```
from google.colab import drive
drive.mount('/content/drive')
```

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

1 Setup & Load Metadata

[2]:
```
import os
import pandas as pd
import numpy as np
from sklearn.utils.class_weight import compute_class_weight
import matplotlib.pyplot as plt


# Paths
EXCEL_PATH = "/content/drive/MyDrive/EEE385L/correctSheetlast.xlsx"
IMG_DIR = "/content/drive/MyDrive/EEE385L/mammograms"

# Load required columns only
cols_needed = ['Assesment', 'Image path']
df = pd.read_excel(EXCEL_PATH, usecols=cols_needed)

# Clean column names and values
df.columns = df.columns.str.strip()
df['Assesment'] = df['Assesment'].astype(str).str.strip().str.upper()
df['Image path'] = df['Image path'].astype(str).str.strip()

# Verify
print(" Metadata preview")
print(df.head())
print("\nUnique BI-RADS in 'Assesment':", df['Assesment'].unique())
```

```
 Metadata preview
  Assesment                        Image path
0   BIRAD 2   BIRAD 2/2019_BC007741_ CC_R.dcm
1   BIRAD 2  BIRAD 2/2019_BC007741_ MLO_R.dcm
```

```
2   BIRAD 2   BIRAD 2/2019_BC007741_ CC_L.dcm
3   BIRAD 2  BIRAD 2/2019_BC007741_ MLO_L.dcm
4   BIRAD 2   BIRAD 2/2019_BC005401_ CC_R.dcm

Unique BI-RADS in 'Assesment': ['BIRAD 2' 'BIRAD 3' 'BIRAD 1' 'BIRAD 4' 'BIRAD
5' 'NAN']
```

[3]:

```
import pandas as pd

EXCEL_PATH = "/content/drive/MyDrive/EEE385L/correctSheetlast.xlsx"

# Load full Excel file (no usecols restriction)
raw_df = pd.read_excel(EXCEL_PATH)

# Show original column names
print("Original columns from Excel:")
print(list(raw_df.columns))
```

```
Original columns from Excel:
['Study date', 'PatientID', 'Patient age ', 'Breast  type', 'Breast view',
'Percentage of\n grandular tissue(density)', 'Assesment', 'Image path']
```

[4]:

```
# Strip spaces and newlines from column names
raw_df.columns = raw_df.columns.str.strip().str.replace('\n', ' ', regex=True)

# Just keep relevant columns
cols_needed = ['Assesment', 'Image path']
df = raw_df[cols_needed].copy()

# Clean values inside the selected columns
df['Assesment'] = df['Assesment'].astype(str).str.strip().str.upper()
df['Image path'] = df['Image path'].astype(str).str.strip()

# Verify
print(" Cleaned Metadata Preview:")
print(df.head())
print("\nUnique BI-RADS in 'Assesment':", df['Assesment'].unique())
```

```
 Cleaned Metadata Preview:
  Assesment                        Image path
0   BIRAD 2   BIRAD 2/2019_BC007741_ CC_R.dcm
1   BIRAD 2  BIRAD 2/2019_BC007741_ MLO_R.dcm
2   BIRAD 2   BIRAD 2/2019_BC007741_ CC_L.dcm
3   BIRAD 2  BIRAD 2/2019_BC007741_ MLO_L.dcm
4   BIRAD 2   BIRAD 2/2019_BC005401_ CC_R.dcm

Unique BI-RADS in 'Assesment': ['BIRAD 2' 'BIRAD 3' 'BIRAD 1' 'BIRAD 4' 'BIRAD
5' 'NAN']
```

2 Extract BI-RADS Labels & Filter

[5]:
```
# Extract numeric BI-RADS value
df['BI-RADS_num'] = df['Assesment'].str.extract(r'(\d)').astype(float)

# Filter to keep only BIRADS 1,3,4,5 (drop 2)
valid_birads = [1, 3, 4, 5]
df = df[df['BI-RADS_num'].isin(valid_birads)].copy()

# Map to class labels
label_map = {1: 0, 3: 1, 4: 2, 5: 3}
df['label'] = df['BI-RADS_num'].map(label_map)

# Verify
print("Label distribution")
print(df['label'].value_counts())
```

```
Label distribution
label
0    1884
1     290
2      72
3      22
Name: count, dtype: int64
```

3 Construct Valid Image Paths (.jpg) and Filter

[6]:
```
import glob

# Check for any JPGs
found_files = glob.glob('/content/drive/MyDrive/EEE385L/mammograms/**/*.jpg',␣
↪recursive=True)
print(f" Total JPGs found: {len(found_files)}")
print(found_files[:5])  # Show a few
```

```
 Total JPGs found: 2378
['/content/drive/MyDrive/EEE385L/mammograms/BIRAD 1/2016_BC017021_ MLO_R.jpg',
'/content/drive/MyDrive/EEE385L/mammograms/BIRAD 1/2017_BC003381_ CC_R.jpg',
'/content/drive/MyDrive/EEE385L/mammograms/BIRAD 1/2017_BC015881_ CC_L.jpg',
'/content/drive/MyDrive/EEE385L/mammograms/BIRAD 1/2016_BC016243_ MLO_R.jpg',
'/content/drive/MyDrive/EEE385L/mammograms/BIRAD 1/2017_BC0020541_ CC_R.jpg']
```

[7]:
```
# Show actual column names from Excel
print("Original columns:", df.columns.tolist())

# Clean column names
df.columns = df.columns.str.strip()
```

```
# Re-check after stripping
print("Cleaned columns:", df.columns.tolist())
```

```
Original columns: ['Assesement', 'Image path', 'BI-RADS_num', 'label']
Cleaned columns: ['Assesement', 'Image path', 'BI-RADS_num', 'label']
```

[8]:
```
# Use the correct column name after cleaning
df['Image path'] = df['Image path'].astype(str).str.strip().str.replace('.dcm',␣
↪'.jpg')
```

[9]:
```
import os

# Update paths to .jpg and construct full paths
df['Image path'] = df['Image path'].astype(str).str.strip().str.replace('.dcm',␣
↪'.jpg')
df['image_full_path'] = df['Image path'].apply(lambda p: os.path.join(IMG_DIR,␣
↪p))

# Keep only valid paths (file exists)
df = df[df['image_full_path'].apply(os.path.exists)].copy()

print(f"Total valid images found: {len(df)}")
df[['label', 'image_full_path']].head()
```

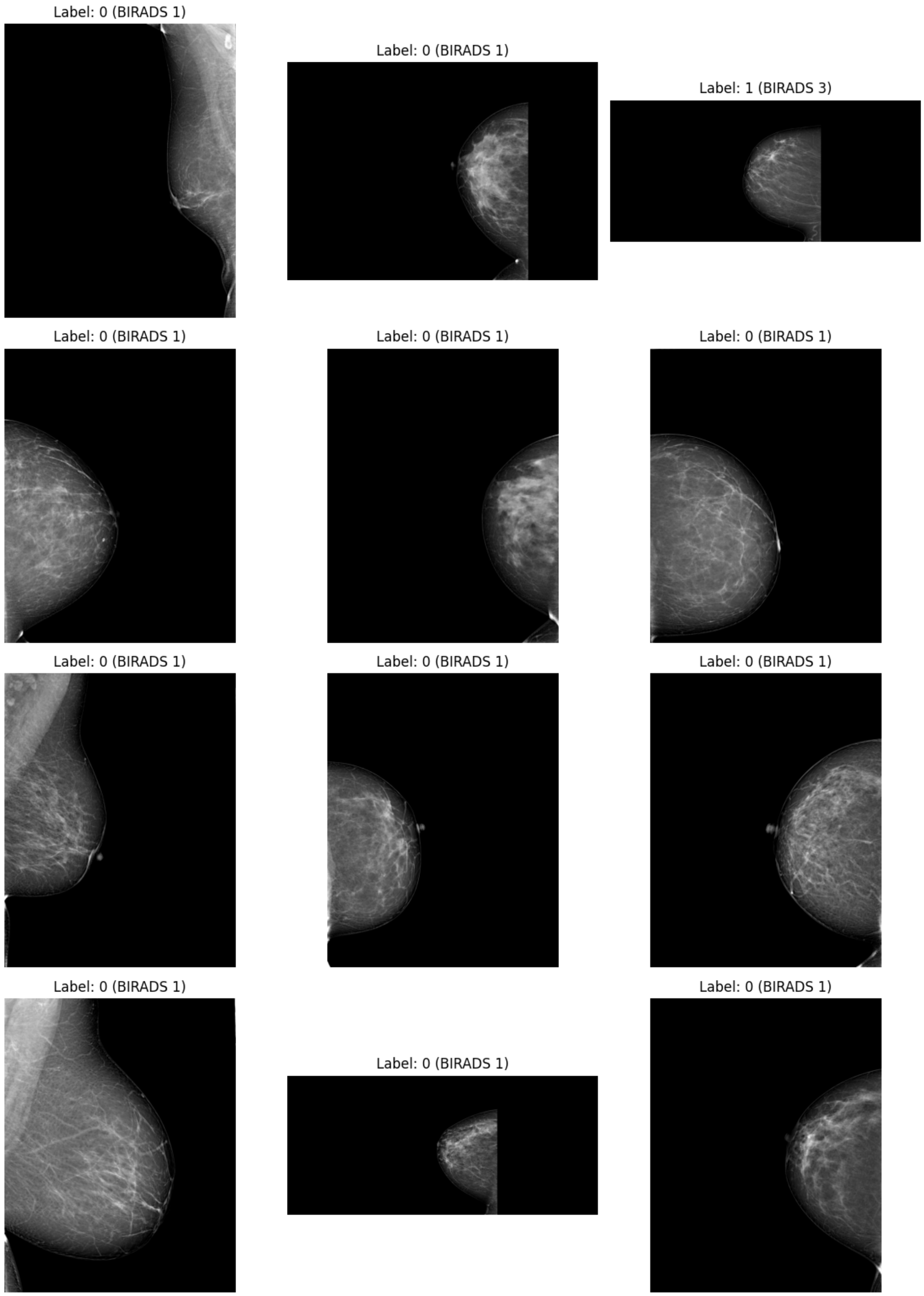
```
Total valid images found: 2206
```

[9]:

	label	image_full_path
16	1	/content/drive/MyDrive/EEE385L/mammograms/BIRA…
21	1	/content/drive/MyDrive/EEE385L/mammograms/BIRA…
22	1	/content/drive/MyDrive/EEE385L/mammograms/BIRA…
23	1	/content/drive/MyDrive/EEE385L/mammograms/BIRA…
24	1	/content/drive/MyDrive/EEE385L/mammograms/BIRA…

[10]:
```
import matplotlib.pyplot as plt
import cv2
import random

# Show 6 random samples
samples = df.sample(n=12, random_state=50)  # Random sampling

plt.figure(figsize=(12, 24))
for i, row in enumerate(samples.iterrows()):
    img = cv2.imread(row[1]['image_full_path'])
    img = cv2.cvtColor(img, cv2.COLOR_BGR2RGB)

    plt.subplot(6, 3, i + 1)
```

```
    plt.imshow(img, cmap='gray')
    plt.title(f"Label: {row[1]['label']} (BIRADS {list(label_map.
 ↪keys())[list(label_map.values()).index(row[1]['label'])]})")
    plt.axis('off')
plt.tight_layout()
plt.show()
```


Label: 0 (BIRADS 1)
Label: 0 (BIRADS 1)
Label: 1 (BIRADS 3)
Label: 0 (BIRADS 1)
Label: 0 (BIRADS 1)
Label: 0 (BIRADS 1)
Label: 0 (BIRADS 1)
Label: 0 (BIRADS 1)
Label: 0 (BIRADS 1)
Label: 0 (BIRADS 1)
Label: 0 (BIRADS 1)
Label: 0 (BIRADS 1)

[11]:

```python
# Check for the presence of label 1 (BI-RADS 3)
print("Label counts:\n", df['label'].value_counts())

# Optional: filter rows where label == 1
birads_3_samples = df[df['label'] == 1]
print(f"\n Total BI-RADS 3 (label 1) samples: {len(birads_3_samples)}")
print(birads_3_samples.head())
```

```
Label counts:
 label
0    1847
1     265
2      72
3      22
Name: count, dtype: int64

 Total BI-RADS 3 (label 1) samples: 265
   Assesment                         Image path  BI-RADS_num  label  \
16   BIRAD 3  BIRAD 3/2019_BC0022845_ MLO_L.jpg          3.0      1
21   BIRAD 3   BIRAD 3/2019_BC0026061_ CC_R.jpg          3.0      1
22   BIRAD 3  BIRAD 3/2019_BC0026061_ MLO_R.jpg          3.0      1
23   BIRAD 3   BIRAD 3/2019_BC0026061_ CC_L.jpg          3.0      1
24   BIRAD 3  BIRAD 3/2019_BC0026061_ MLO_L.jpg          3.0      1

                                      image_full_path
16  /content/drive/MyDrive/EEE385L/mammograms/BIRA…
21  /content/drive/MyDrive/EEE385L/mammograms/BIRA…
22  /content/drive/MyDrive/EEE385L/mammograms/BIRA…
23  /content/drive/MyDrive/EEE385L/mammograms/BIRA…
24  /content/drive/MyDrive/EEE385L/mammograms/BIRA…
```

4 TensorFlow Dataset & Train/Val Split

[38]:

```python
import tensorflow as tf
from sklearn.model_selection import train_test_split
from sklearn.utils.class_weight import compute_class_weight
import numpy as np

# --- Config ---
IMG_SIZE = 224
BATCH_SIZE = 32
AUTOTUNE = tf.data.AUTOTUNE

# --- Split into train and validation sets ---
from sklearn.model_selection import train_test_split
```

```
# First split: train (75%) and temp (25%)
train_df, temp_df = train_test_split(df, test_size=0.25, stratify=df['label'],␣
↪random_state=42)

# Second split: validation (15%) and test (10%)
val_df, test_df = train_test_split(temp_df, test_size=0.4,␣
↪stratify=temp_df['label'], random_state=42)

print(f" Train: {len(train_df)}, Val: {len(val_df)}, Test: {len(test_df)}")


# --- Class weights to handle imbalance ---
class_weights = compute_class_weight(
    class_weight="balanced",
    classes=np.unique(train_df['label']),
    y=train_df['label']
)
class_weights = dict(enumerate(class_weights))
print(f" Class weights: {class_weights}")
```

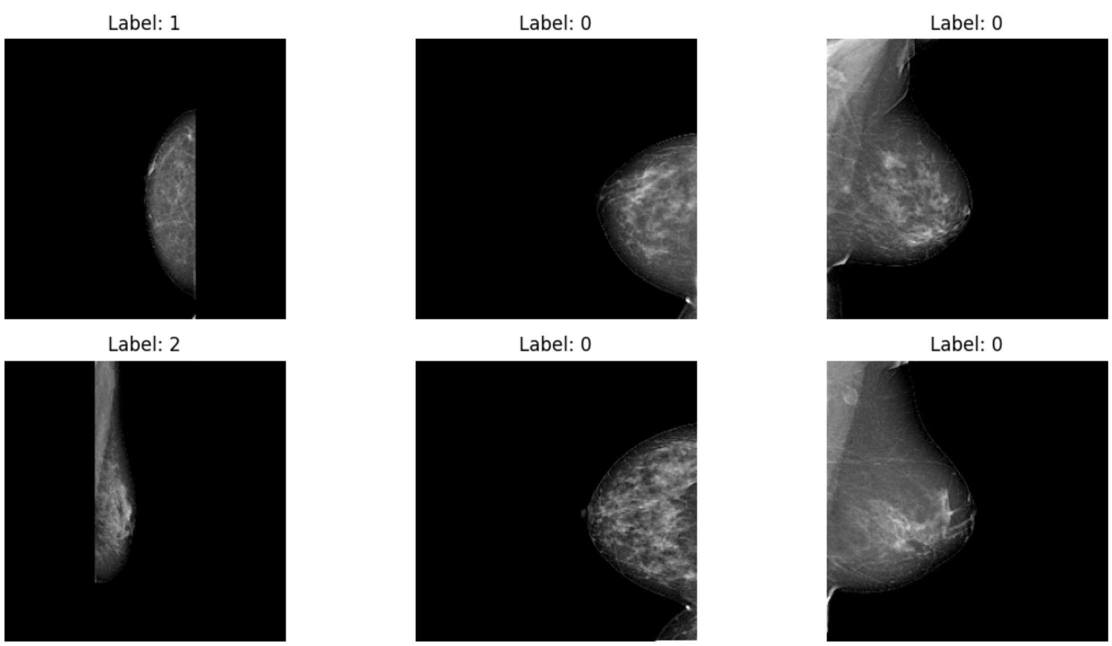
```
 Train: 1654, Val: 331, Test: 221
 Class weights: {0: np.float64(0.2985559566787004), 1:
np.float64(2.077889447236181), 2: np.float64(7.657407407407407), 3:
np.float64(25.84375)}
```

[39]:
```
import cv2

# --- Define image loading and preprocessing ---
def load_image(path, label):
    path = path.numpy().decode()
    image = cv2.imread(path)
    image = cv2.resize(image, (IMG_SIZE, IMG_SIZE))
    image = cv2.cvtColor(image, cv2.COLOR_BGR2RGB)
    image = image / 255.0  # normalize to [0,1]
    return image.astype(np.float32), np.int32(label)

def tf_wrap_load_image(path, label):
    img, lbl = tf.py_function(func=load_image, inp=[path, label], Tout=(tf.
↪float32, tf.int32))
    img.set_shape([IMG_SIZE, IMG_SIZE, 3])
    lbl.set_shape([])
    return img, lbl
```

[40]:
```
def create_dataset(dataframe, augment=False, shuffle=True):
    paths = dataframe['image_full_path'].values
    labels = dataframe['label'].values
```

```python
    ds = tf.data.Dataset.from_tensor_slices((paths, labels))
    ds = ds.map(tf_wrap_load_image, num_parallel_calls=AUTOTUNE)

    if shuffle:
        ds = ds.shuffle(buffer_size=1000)

    ds = ds.batch(BATCH_SIZE).prefetch(AUTOTUNE)
    return ds

# Create datasets
train_ds = create_dataset(train_df)
val_ds = create_dataset(val_df, shuffle=False)
```

[41]:
```python
import matplotlib.pyplot as plt

# Visualize a batch
for images, labels in train_ds.take(1):
    plt.figure(figsize=(12, 6))
    for i in range(6):
        ax = plt.subplot(2, 3, i + 1)
        plt.imshow(images[i])
        plt.title(f"Label: {labels[i].numpy()}")
        plt.axis("off")
    plt.tight_layout()
    plt.show()
```



5 Define & Train CNN Model

[43]:
```
from tensorflow.keras import layers, models
from tensorflow.keras.callbacks import EarlyStopping

# --- Define CNN model ---
model = models.Sequential([
    layers.Input(shape=(IMG_SIZE, IMG_SIZE, 3)),

    layers.Conv2D(32, (3, 3), activation='relu'),
    layers.BatchNormalization(),
    layers.MaxPooling2D(),

    layers.Conv2D(64, (3, 3), activation='relu'),
    layers.BatchNormalization(),
    layers.MaxPooling2D(),

    layers.Conv2D(128, (3, 3), activation='relu'),
    layers.BatchNormalization(),
    layers.MaxPooling2D(),

    layers.Flatten(),
    layers.Dense(256, activation='relu'),
    layers.Dropout(0.5),
    layers.Dense(4, activation='softmax')  # 4 output classes
])
```

[44]:
```
model.compile(
    optimizer='adam',
    loss='sparse_categorical_crossentropy',
    metrics=['accuracy']
)
```

[45]:
```
model.summary()
```

Model: "sequential_3"

Layer (type)	Output Shape	Param #
conv2d_9 (Conv2D)	(None, 222, 222, 32)	896
batch_normalization_6 (BatchNormalization)	(None, 222, 222, 32)	128
max_pooling2d_8 (MaxPooling2D)	(None, 111, 111, 32)	0

conv2d_10 (Conv2D)	(None, 109, 109, 64)	18,496
batch_normalization_7 (BatchNormalization)	(None, 109, 109, 64)	256
max_pooling2d_9 (MaxPooling2D)	(None, 54, 54, 64)	0
conv2d_11 (Conv2D)	(None, 52, 52, 128)	73,856
batch_normalization_8 (BatchNormalization)	(None, 52, 52, 128)	512
max_pooling2d_10 (MaxPooling2D)	(None, 26, 26, 128)	0
flatten_2 (Flatten)	(None, 86528)	0
dense_7 (Dense)	(None, 256)	22,151,424
dropout_3 (Dropout)	(None, 256)	0
dense_8 (Dense)	(None, 4)	1,028

Total params: 22,246,596 (84.86 MB)

Trainable params: 22,246,148 (84.86 MB)

Non-trainable params: 448 (1.75 KB)

[46]:

```
# Get a single batch
for images, labels in train_ds.take(1):
    preds = model(images)
    print("Predictions shape:", preds.shape)
    break
```

```
Predictions shape: (32, 4)
```

[47]:

```
class_weight=class_weights
print(class_weights)
```

```
{0: np.float64(0.2985559566787004), 1: np.float64(2.077889447236181), 2:
np.float64(7.657407407407407), 3: np.float64(25.84375)}
```

[48]:

```
for _, labels in train_ds.take(1):
    print("Sample labels dtype:", labels.dtype)
```

```
    print("Sample labels:", labels.numpy())
    break
```

```
Sample labels dtype: <dtype: 'int32'>
Sample labels: [0 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 2 0 0 1 0 0 0 0 0 0 0 0 0]
```

[23]:
```
#  Define CNN Baseline
cnn_model = models.Sequential([
    layers.Input(shape=(224, 224, 3)),
    layers.Conv2D(32, (3, 3), activation='relu'),
    layers.MaxPooling2D(),
    layers.Conv2D(64, (3, 3), activation='relu'),
    layers.MaxPooling2D(),
    layers.Conv2D(128, (3, 3), activation='relu'),
    layers.GlobalAveragePooling2D(),
    layers.Dense(128, activation='relu'),
    layers.Dropout(0.4),
    layers.Dense(4, activation='softmax')  # 4 BI-RADS classes
])

cnn_model.compile(optimizer='adam', loss='sparse_categorical_crossentropy',␣
 ↪metrics=['accuracy'])

# Train
cnn_history = cnn_model.fit(
    train_ds,
    validation_data=val_ds,
    epochs=30,
    class_weight=class_weights,
    callbacks=[EarlyStopping(patience=5, restore_best_weights=True)]
)
```

```
Epoch 1/30
59/59               304s 5s/step -
accuracy: 0.7346 - loss: 1.2776 - val_accuracy: 0.5378 - val_loss: 1.3770
Epoch 2/30
59/59               322s 4s/step -
accuracy: 0.4564 - loss: 1.2326 - val_accuracy: 0.5136 - val_loss: 1.1090
Epoch 3/30
59/59               332s 5s/step -
accuracy: 0.3848 - loss: 0.9655 - val_accuracy: 0.4864 - val_loss: 1.1219
Epoch 4/30
59/59               314s 4s/step -
accuracy: 0.4659 - loss: 0.9571 - val_accuracy: 0.4441 - val_loss: 1.1887
Epoch 5/30
59/59               327s 5s/step -
accuracy: 0.4796 - loss: 0.9261 - val_accuracy: 0.4622 - val_loss: 1.0899
```

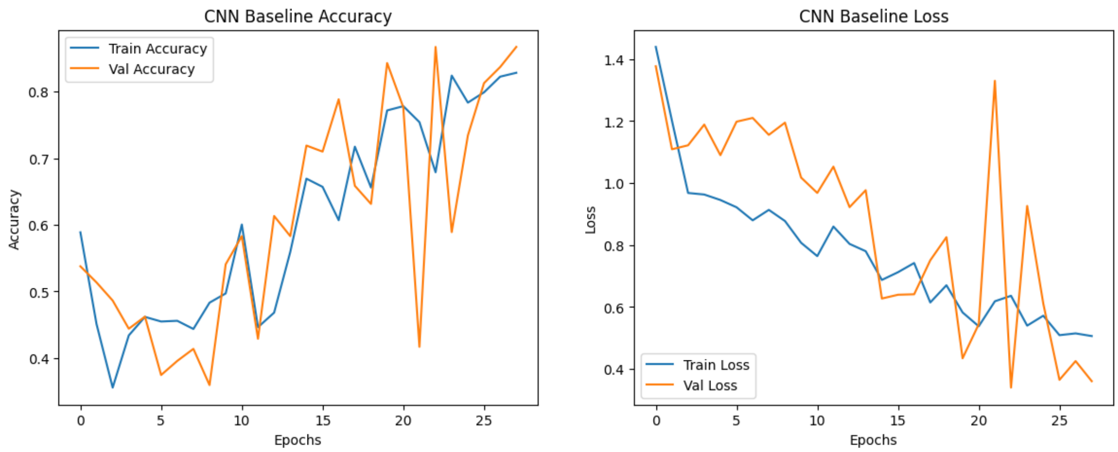
```
Epoch 6/30
59/59            310s 4s/step -
accuracy: 0.4743 - loss: 0.8443 - val_accuracy: 0.3746 - val_loss: 1.1981
Epoch 7/30
59/59            326s 4s/step -
accuracy: 0.4597 - loss: 0.8490 - val_accuracy: 0.3958 - val_loss: 1.2101
Epoch 8/30
59/59            287s 4s/step -
accuracy: 0.4845 - loss: 0.8995 - val_accuracy: 0.4139 - val_loss: 1.1555
Epoch 9/30
59/59            344s 4s/step -
accuracy: 0.4685 - loss: 0.8525 - val_accuracy: 0.3595 - val_loss: 1.1949
Epoch 10/30
59/59            304s 4s/step -
accuracy: 0.4760 - loss: 0.7658 - val_accuracy: 0.5408 - val_loss: 1.0176
Epoch 11/30
59/59            321s 4s/step -
accuracy: 0.6016 - loss: 0.7464 - val_accuracy: 0.5831 - val_loss: 0.9682
Epoch 12/30
59/59            327s 4s/step -
accuracy: 0.5242 - loss: 0.7769 - val_accuracy: 0.4290 - val_loss: 1.0529
Epoch 13/30
59/59            292s 4s/step -
accuracy: 0.4687 - loss: 0.8010 - val_accuracy: 0.6133 - val_loss: 0.9222
Epoch 14/30
59/59            317s 4s/step -
accuracy: 0.5864 - loss: 0.7428 - val_accuracy: 0.5831 - val_loss: 0.9769
Epoch 15/30
59/59            274s 4s/step -
accuracy: 0.6302 - loss: 0.7142 - val_accuracy: 0.7190 - val_loss: 0.6273
Epoch 16/30
59/59            338s 4s/step -
accuracy: 0.6522 - loss: 0.6737 - val_accuracy: 0.7100 - val_loss: 0.6396
Epoch 17/30
59/59            305s 4s/step -
accuracy: 0.6142 - loss: 0.6939 - val_accuracy: 0.7885 - val_loss: 0.6411
Epoch 18/30
59/59            326s 4s/step -
accuracy: 0.7359 - loss: 0.5765 - val_accuracy: 0.6586 - val_loss: 0.7508
Epoch 19/30
59/59            316s 4s/step -
accuracy: 0.6879 - loss: 0.6243 - val_accuracy: 0.6314 - val_loss: 0.8254
Epoch 20/30
59/59            348s 4s/step -
accuracy: 0.7410 - loss: 0.6170 - val_accuracy: 0.8429 - val_loss: 0.4345
Epoch 21/30
59/59            292s 4s/step -
accuracy: 0.7987 - loss: 0.4951 - val_accuracy: 0.7764 - val_loss: 0.5444
```

```
Epoch 22/30
59/59              331s 5s/step -
accuracy: 0.7781 - loss: 0.5189 - val_accuracy: 0.4169 - val_loss: 1.3299
Epoch 23/30
59/59              295s 4s/step -
accuracy: 0.5921 - loss: 0.7071 - val_accuracy: 0.8671 - val_loss: 0.3400
Epoch 24/30
59/59              326s 4s/step -
accuracy: 0.8486 - loss: 0.5089 - val_accuracy: 0.5891 - val_loss: 0.9262
Epoch 25/30
59/59              271s 4s/step -
accuracy: 0.7461 - loss: 0.5729 - val_accuracy: 0.7341 - val_loss: 0.6110
Epoch 26/30
59/59              326s 4s/step -
accuracy: 0.7711 - loss: 0.4997 - val_accuracy: 0.8127 - val_loss: 0.3650
Epoch 27/30
59/59              315s 4s/step -
accuracy: 0.8059 - loss: 0.5153 - val_accuracy: 0.8369 - val_loss: 0.4256
Epoch 28/30
59/59              333s 4s/step -
accuracy: 0.8339 - loss: 0.5144 - val_accuracy: 0.8671 - val_loss: 0.3607
```

[33]:

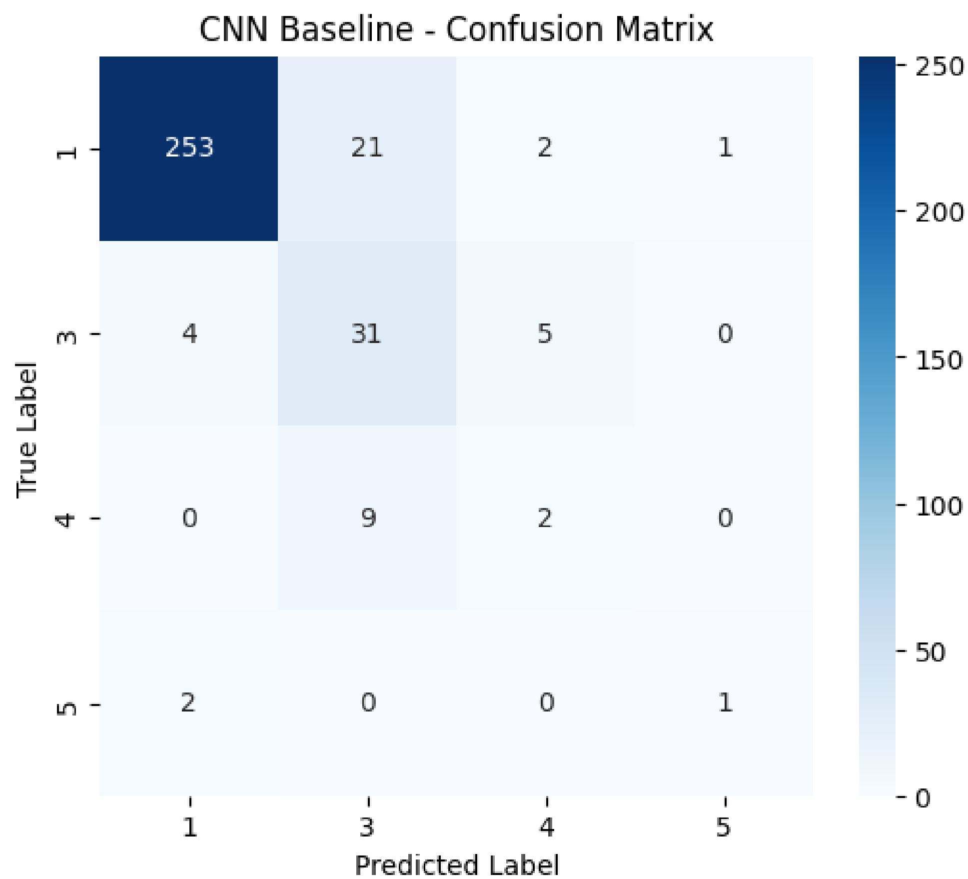
```
def plot_training_history(history, model_name="CNN"):
    acc = history.history['accuracy']
    val_acc = history.history['val_accuracy']
    loss = history.history['loss']
    val_loss = history.history['val_loss']
    epochs_range = range(len(acc))

    plt.figure(figsize=(14, 5))

    plt.subplot(1, 2, 1)
    plt.plot(epochs_range, acc, label='Train Accuracy')
    plt.plot(epochs_range, val_acc, label='Val Accuracy')
    plt.title(f'{model_name} Accuracy')
    plt.xlabel('Epochs')
    plt.ylabel('Accuracy')
    plt.legend()

    plt.subplot(1, 2, 2)
    plt.plot(epochs_range, loss, label='Train Loss')
    plt.plot(epochs_range, val_loss, label='Val Loss')
    plt.title(f'{model_name} Loss')
    plt.xlabel('Epochs')
    plt.ylabel('Loss')
    plt.legend()
```

```
    plt.show()

plot_training_history(cnn_history, model_name="CNN Baseline")
```



[34]:
```
from sklearn.metrics import classification_report, confusion_matrix
import seaborn as sns
import numpy as np

def evaluate_model(model, val_ds, name="Model"):
    y_true, y_pred = [], []
    for images, labels in val_ds:
        preds = model.predict(images)
        y_true.extend(labels.numpy())
        y_pred.extend(np.argmax(preds, axis=1))

    print(f"\n {name} - Classification Report")
    print(classification_report(y_true, y_pred, target_names=["BI-RADS 1", "3",␣
↪"4", "5"], zero_division=0))

    cm = confusion_matrix(y_true, y_pred)
    plt.figure(figsize=(6, 5))
    sns.heatmap(cm, annot=True, fmt="d", cmap="Blues",
                xticklabels=["1", "3", "4", "5"],
                yticklabels=["1", "3", "4", "5"])
    plt.title(f"{name} - Confusion Matrix")
    plt.xlabel("Predicted Label")
    plt.ylabel("True Label")
    plt.show()

# Evaluate CNN
evaluate_model(cnn_model, val_ds, name="CNN Baseline")
```

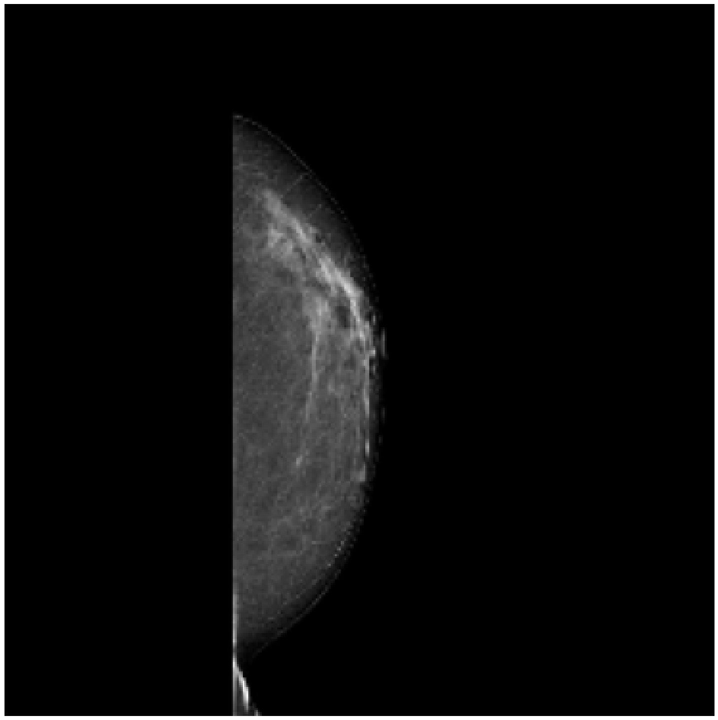
```
1/1             3s 3s/step
1/1             2s 2s/step
1/1             2s 2s/step
1/1             3s 3s/step
1/1             2s 2s/step
1/1             2s 2s/step
1/1             2s 2s/step
1/1             1s 1s/step
1/1             1s 1s/step
1/1             1s 1s/step
1/1             0s 426ms/step

 CNN Baseline - Classification Report
              precision    recall  f1-score   support

   BI-RADS 1       0.98      0.91      0.94       277
           3       0.51      0.78      0.61        40
           4       0.22      0.18      0.20        11
           5       0.50      0.33      0.40         3

    accuracy                           0.87       331
   macro avg       0.55      0.55      0.54       331
weighted avg       0.89      0.87      0.87       331
```



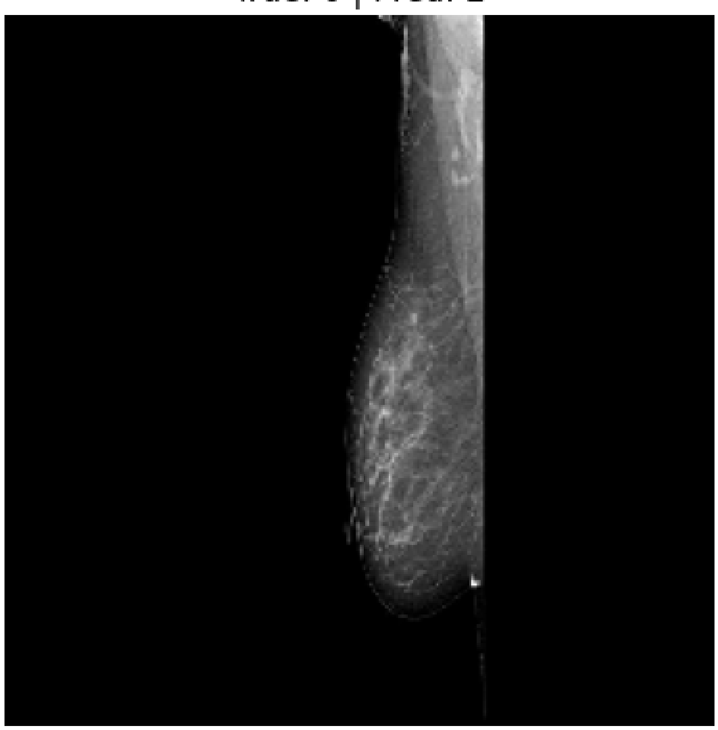
[68]:
```python
# Misclassified samples
misclassified = [(i, t, p) for i, (t, p) in enumerate(zip(y_true, y_pred)) if t␣
↪!= p]
print(f"Total misclassifications: {len(misclassified)}")

# Visualize a few
import matplotlib.pyplot as plt

indices = [i for i, _, _ in misclassified[:5]]
samples = [val_ds.unbatch().skip(i).take(1) for i in indices]

for i, sample in enumerate(samples):
    for img, label in sample:
        plt.imshow(img.numpy())
        plt.title(f"True: {label.numpy()} | Pred: {y_pred[indices[i]]}")
        plt.axis('off')
        plt.show()
```

```
Total misclassifications: 70
```

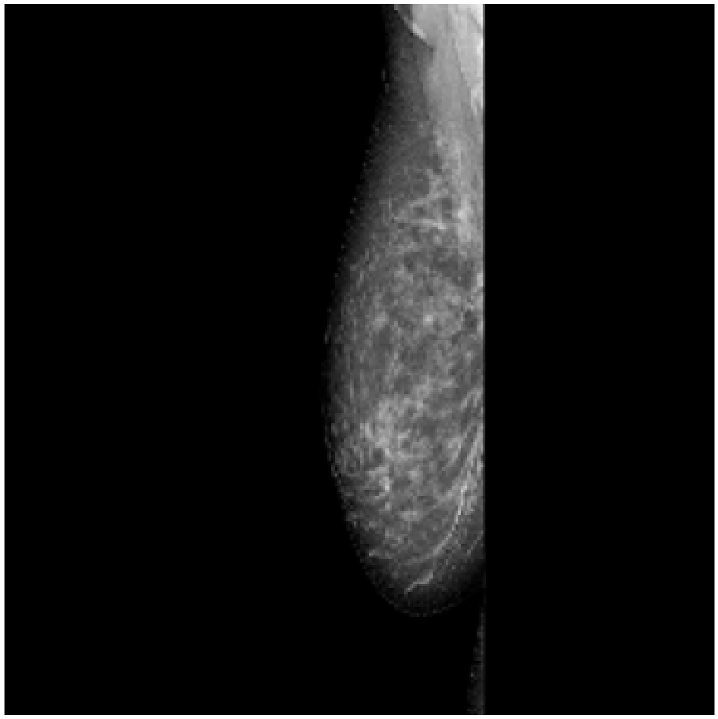
True: 0 | Pred: 1



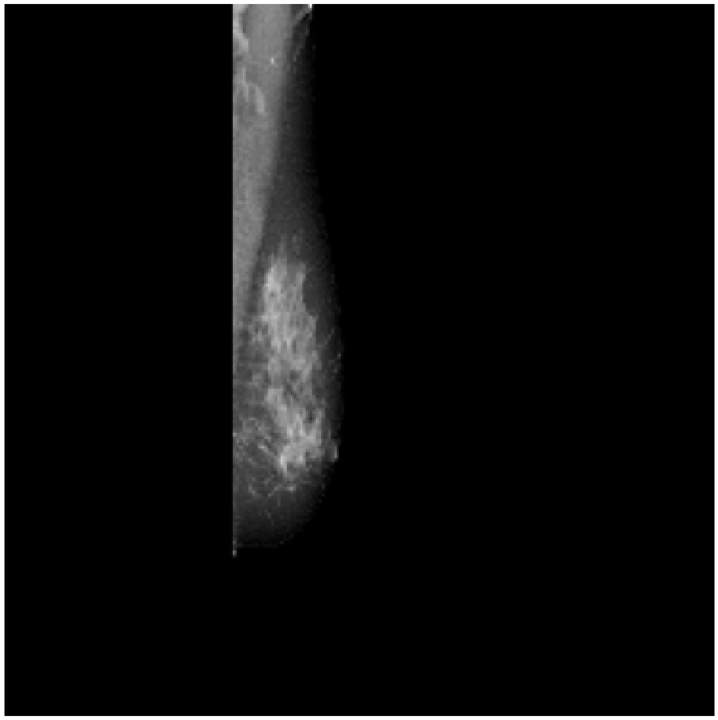
True: 0 | Pred: 2



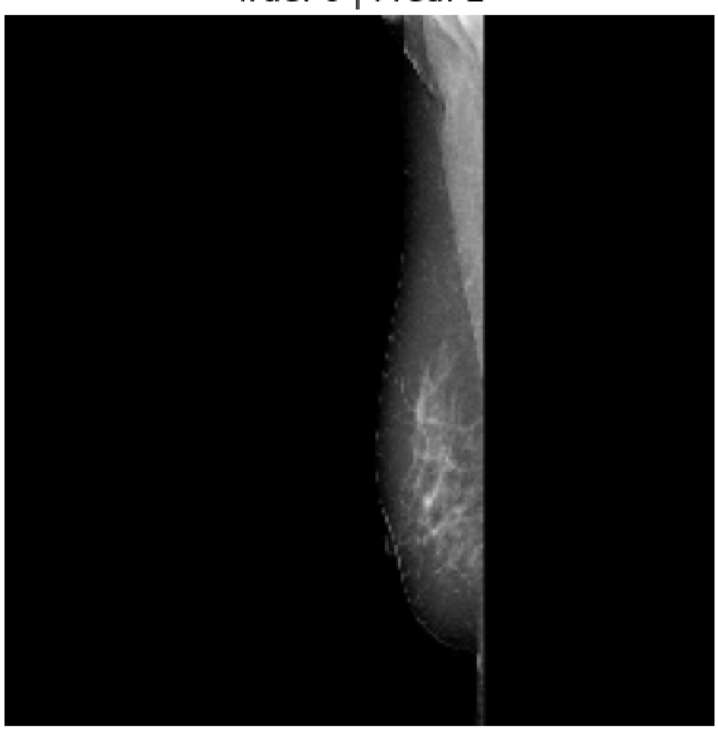
True: 0 | Pred: 2



True: 1 | Pred: 2



True: 0 | Pred: 2



[51]:
```python
# Confirm label mapping and distribution
print("Unique labels:", sorted(df['label'].unique()))
print(df['label'].value_counts())

# Preview some image paths and corresponding labels
df[['label', 'image_full_path']].sample(10)
```

```
Unique labels: [np.int64(0), np.int64(1), np.int64(2), np.int64(3)]
label
0    1847
1     265
2      72
3      22
Name: count, dtype: int64
```

[51]:

	label	image_full_path
5191	0	/content/drive/MyDrive/EEE385L/mammograms/BIRA…
4995	0	/content/drive/MyDrive/EEE385L/mammograms/BIRA…
262	0	/content/drive/MyDrive/EEE385L/mammograms/BIRA…
1952	0	/content/drive/MyDrive/EEE385L/mammograms/BIRA…
3040	0	/content/drive/MyDrive/EEE385L/mammograms/BIRA…
1972	1	/content/drive/MyDrive/EEE385L/mammograms/BIRA…
4082	0	/content/drive/MyDrive/EEE385L/mammograms/BIRA…
4952	0	/content/drive/MyDrive/EEE385L/mammograms/BIRA…
271	0	/content/drive/MyDrive/EEE385L/mammograms/BIRA…
5292	0	/content/drive/MyDrive/EEE385L/mammograms/BIRA…

[52]:
```python
# Check output confidence from the model
for images, labels in val_ds.take(1):
    preds = model.predict(images)
    print("Sample predictions (softmax probs):\n", preds[:5])
    print("Predicted class:", np.argmax(preds[:5], axis=1))
    print("True class:     ", labels[:5].numpy())
```

```
1/1              1s 1s/step
Sample predictions (softmax probs):
 [[0.2506866  0.24972722 0.23617229 0.26341388]
 [0.25066352 0.25195003 0.24364315 0.2537433 ]
 [0.251902   0.24804318 0.23726971 0.26278505]
 [0.25884008 0.2503911  0.23727995 0.25348884]
 [0.23343952 0.24463029 0.24691784 0.27501234]]
Predicted class: [3 3 3 0 3]
True class:      [0 0 0 0 0]
```

6 Advanced Model: MobileNetV2

[59]:
```
from tensorflow.keras import layers, models, applications
```

```
Downloading data from https://storage.googleapis.com/tensorflow/keras-applicatio
ns/mobilenet_v2/mobilenet_v2_weights_tf_dim_ordering_tf_kernels_1.0_224_no_top.h
5
9406464/9406464          0s
0us/step
```

[61]:
```
base_mobile = tf.keras.applications.MobileNetV2(include_top=False,␣
↪weights='imagenet', input_shape=(224,224,3))
base_mobile.trainable = False

mobile_model = models.Sequential([
    base_mobile,
    layers.GlobalAveragePooling2D(),
    layers.Dense(128, activation='relu'),
    layers.Dropout(0.3),
    layers.Dense(4, activation='softmax')
])

mobile_model.compile(optimizer='adam', loss='sparse_categorical_crossentropy',␣
↪metrics=['accuracy'])

# Train
mobile_history = mobile_model.fit(
    train_ds,
    validation_data=val_ds,
    epochs=30,
    class_weight=class_weights,
    callbacks=[EarlyStopping(patience=5, restore_best_weights=True)]
)
```

```
Epoch 1/30
52/52          177s 3s/step -
accuracy: 0.4445 - loss: 1.6284 - val_accuracy: 0.7583 - val_loss: 0.5127
Epoch 2/30
52/52          148s 2s/step -
accuracy: 0.7611 - loss: 0.7774 - val_accuracy: 0.8218 - val_loss: 0.4425
Epoch 3/30
52/52          215s 2s/step -
accuracy: 0.7722 - loss: 0.5404 - val_accuracy: 0.8218 - val_loss: 0.5217
Epoch 4/30
52/52          201s 2s/step -
accuracy: 0.7946 - loss: 0.5295 - val_accuracy: 0.7644 - val_loss: 0.5729
Epoch 5/30
52/52          187s 2s/step -
```

```
accuracy: 0.6346 - loss: 0.6562 - val_accuracy: 0.7825 - val_loss: 0.4888
Epoch 6/30
52/52            218s 2s/step -
accuracy: 0.8107 - loss: 0.4662 - val_accuracy: 0.8066 - val_loss: 0.3956
Epoch 7/30
52/52            203s 3s/step -
accuracy: 0.8266 - loss: 0.4310 - val_accuracy: 0.7885 - val_loss: 0.3764
Epoch 8/30
52/52            143s 2s/step -
accuracy: 0.8244 - loss: 0.4497 - val_accuracy: 0.7976 - val_loss: 0.4335
Epoch 9/30
52/52            223s 3s/step -
accuracy: 0.8181 - loss: 0.4474 - val_accuracy: 0.7734 - val_loss: 0.5583
Epoch 10/30
52/52            199s 2s/step -
accuracy: 0.8106 - loss: 0.4220 - val_accuracy: 0.7946 - val_loss: 0.4776
Epoch 11/30
52/52            204s 2s/step -
accuracy: 0.8378 - loss: 0.4358 - val_accuracy: 0.7855 - val_loss: 0.5494
Epoch 12/30
52/52            202s 3s/step -
accuracy: 0.8215 - loss: 0.3927 - val_accuracy: 0.8157 - val_loss: 0.4015
```

7 Metrics & Classification

[62]:

```
from sklearn.metrics import classification_report, confusion_matrix
import numpy as np

y_true, y_pred = [], []
for images, labels in val_ds:
    preds = model.predict(images)
    y_true.extend(labels.numpy())
    y_pred.extend(np.argmax(preds, axis=1))

print(classification_report(y_true, y_pred, target_names=["BIRADS 1", "3", "4",␣
 ↪"5"]))
```

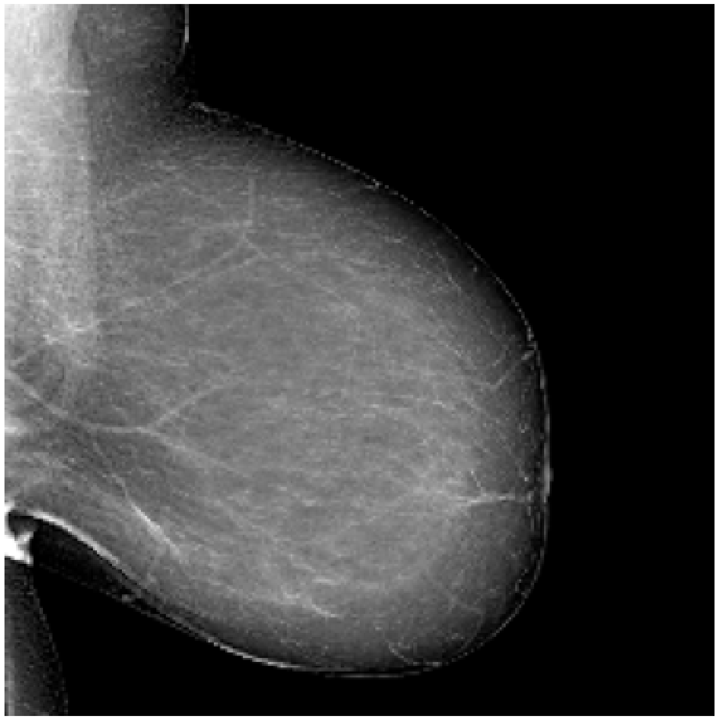
```
1/1            5s 5s/step
1/1            2s 2s/step
1/1            3s 3s/step
1/1            3s 3s/step
1/1            2s 2s/step
1/1            3s 3s/step
1/1            3s 3s/step
1/1            4s 4s/step
1/1            2s 2s/step
1/1            2s 2s/step
```

```
1/1              3s 3s/step
              precision    recall  f1-score   support

    BIRADS 1       1.00      0.03      0.05       277
           3       0.18      0.41      0.25        39
           4       0.02      0.36      0.03        11
           5       0.00      0.00      0.00         4

    accuracy                           0.08       331
   macro avg       0.30      0.20      0.08       331
weighted avg       0.86      0.08      0.07       331

/usr/local/lib/python3.11/dist-packages/sklearn/metrics/_classification.py:1565:
UndefinedMetricWarning: Precision is ill-defined and being set to 0.0 in labels
with no predicted samples. Use `zero_division` parameter to control this
behavior.
  _warn_prf(average, modifier, f"{metric.capitalize()} is", len(result))
/usr/local/lib/python3.11/dist-packages/sklearn/metrics/_classification.py:1565:
UndefinedMetricWarning: Precision is ill-defined and being set to 0.0 in labels
with no predicted samples. Use `zero_division` parameter to control this
behavior.
  _warn_prf(average, modifier, f"{metric.capitalize()} is", len(result))
/usr/local/lib/python3.11/dist-packages/sklearn/metrics/_classification.py:1565:
UndefinedMetricWarning: Precision is ill-defined and being set to 0.0 in labels
with no predicted samples. Use `zero_division` parameter to control this
behavior.
  _warn_prf(average, modifier, f"{metric.capitalize()} is", len(result))
```

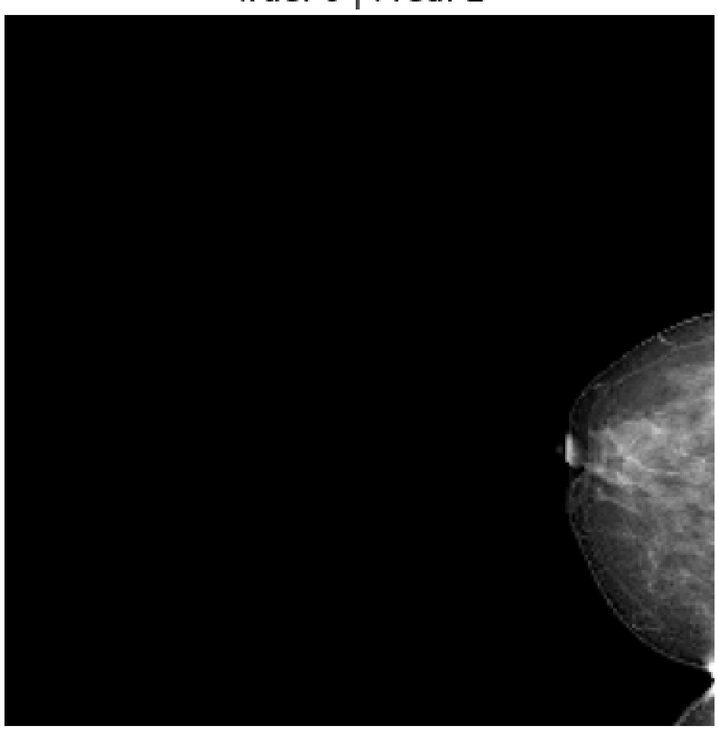
[63]:
```
# Misclassified samples
misclassified = [(i, t, p) for i, (t, p) in enumerate(zip(y_true, y_pred)) if t␣
↪!= p]
print(f"Total misclassifications: {len(misclassified)}")

# Visualize a few
import matplotlib.pyplot as plt

indices = [i for i, _, _ in misclassified[:5]]
samples = [val_ds.unbatch().skip(i).take(1) for i in indices]

for i, sample in enumerate(samples):
    for img, label in sample:
        plt.imshow(img.numpy())
        plt.title(f"True: {label.numpy()} | Pred: {y_pred[indices[i]]}")
        plt.axis('off')
        plt.show()
```

```
Total misclassifications: 304
```

True: 0 | Pred: 2

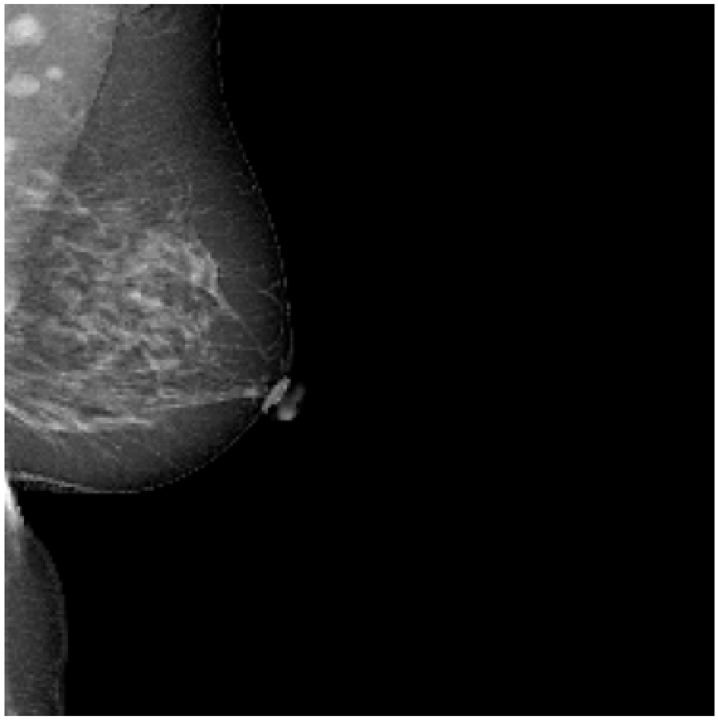


True: 0 | Pred: 2

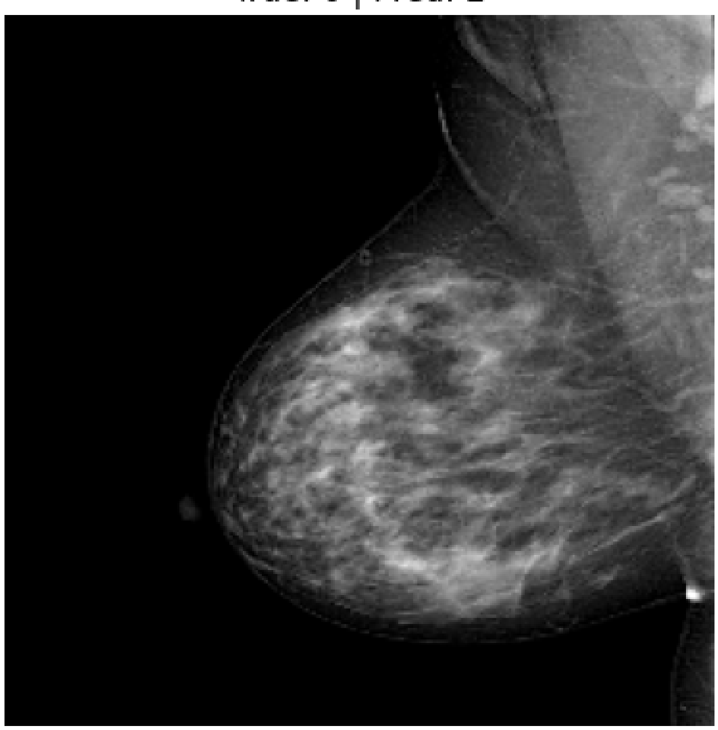


True: 0 | Pred: 2

True: 0 | Pred: 2



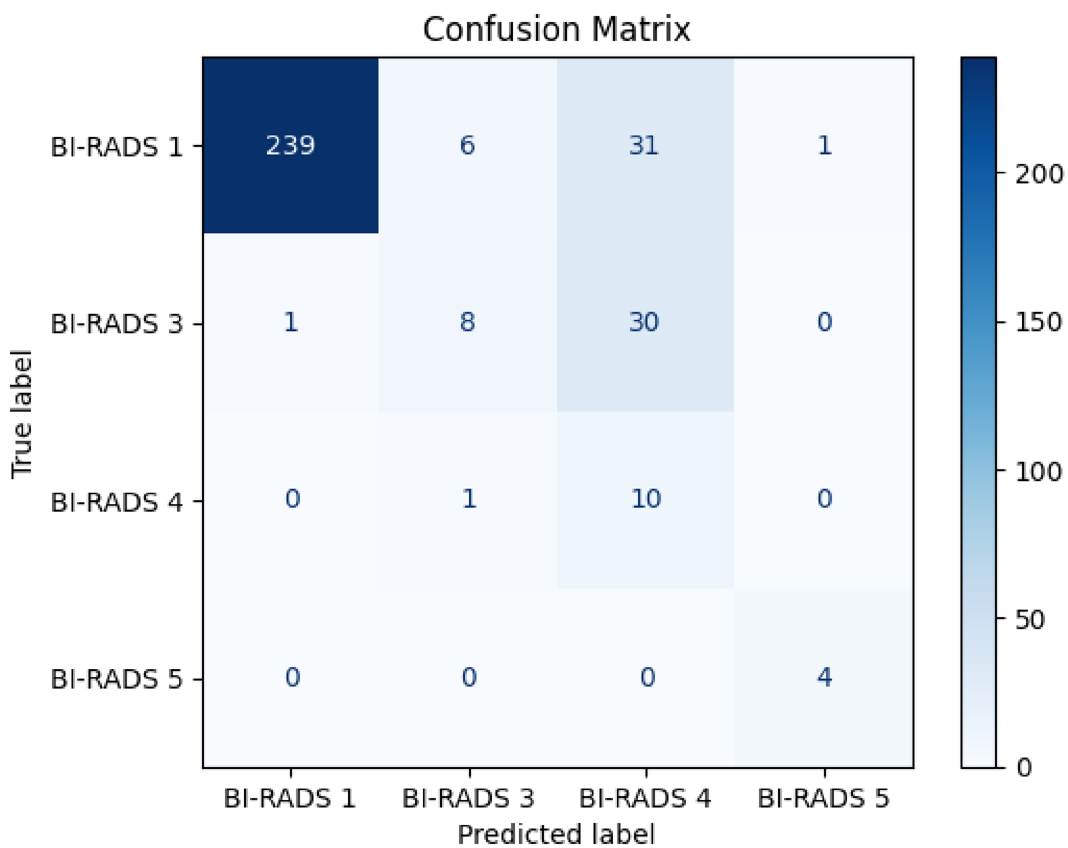
True: 0 | Pred: 2

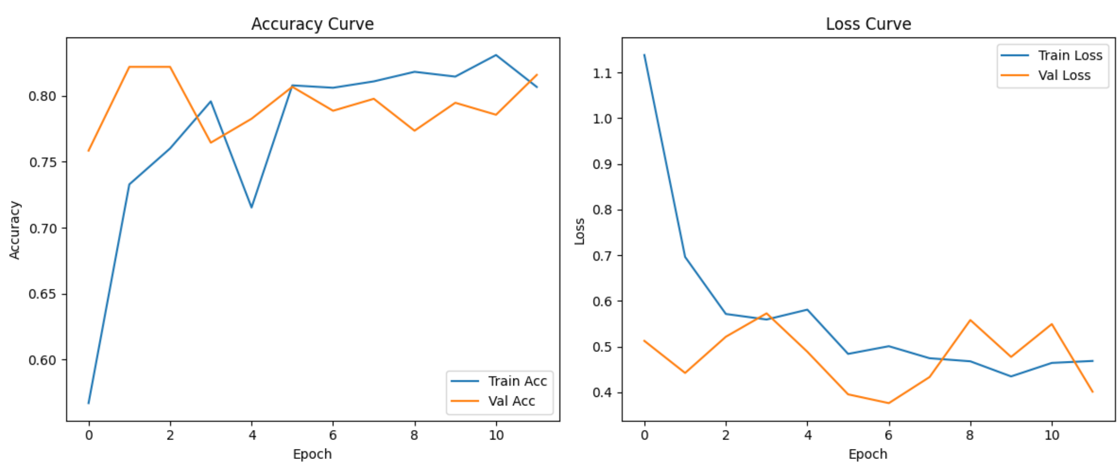


[67]:
```python
import numpy as np
import matplotlib.pyplot as plt
from sklearn.metrics import classification_report, confusion_matrix,␣
↪ConfusionMatrixDisplay

# Evaluate on validation set
val_loss, val_acc = mobile_model.evaluate(val_ds)
print(f"\n Validation Accuracy: {val_acc:.4f} | Loss: {val_loss:.4f}")

# Predictions
y_true = []
y_pred = []

for images, labels in val_ds:
    preds = mobile_model.predict(images)
    y_true.extend(labels.numpy())
    y_pred.extend(np.argmax(preds, axis=1))

# Classification report
target_names = ['BI-RADS 1', 'BI-RADS 3', 'BI-RADS 4', 'BI-RADS 5']
print("\n Classification Report:")
print(classification_report(y_true, y_pred, target_names=target_names))

# Confusion matrix
cm = confusion_matrix(y_true, y_pred)
disp = ConfusionMatrixDisplay(confusion_matrix=cm, display_labels=target_names)
disp.plot(cmap='Blues')
plt.title("Confusion Matrix")
plt.show()

# Accuracy/Loss curves
plt.figure(figsize=(12, 5))

plt.subplot(1, 2, 1)
plt.plot(mobile_history.history['accuracy'], label="Train Acc")
plt.plot(mobile_history.history['val_accuracy'], label="Val Acc")
plt.title("Accuracy Curve")
plt.xlabel("Epoch")
plt.ylabel("Accuracy")
plt.legend()

plt.subplot(1, 2, 2)
plt.plot(mobile_history.history['loss'], label="Train Loss")
plt.plot(mobile_history.history['val_loss'], label="Val Loss")
plt.title("Loss Curve")
```

```python
plt.xlabel("Epoch")
plt.ylabel("Loss")
plt.legend()

plt.tight_layout()
plt.show()
```

```
11/11             28s 2s/step -
accuracy: 0.7795 - loss: 0.3835

 Validation Accuracy: 0.7885 | Loss: 0.3764
1/1              7s 7s/step
1/1              3s 3s/step
1/1              3s 3s/step
1/1              4s 4s/step
1/1              2s 2s/step
1/1              2s 2s/step
1/1              2s 2s/step
1/1              1s 1s/step
1/1              2s 2s/step
1/1              1s 1s/step
1/1              2s 2s/step

 Classification Report:
              precision    recall  f1-score   support

   BI-RADS 1       1.00      0.86      0.92       277
   BI-RADS 3       0.53      0.21      0.30        39
   BI-RADS 4       0.14      0.91      0.24        11
   BI-RADS 5       0.80      1.00      0.89         4

    accuracy                           0.79       331
   macro avg       0.62      0.74      0.59       331
weighted avg       0.91      0.79      0.83       331
```


Confusion Matrix
True label
Predicted label
BI-RADS 1
BI-RADS 3
BI-RADS 4
BI-RADS 5
239
6
31
1
1
8
30
0
0
1
10
0
0
0
0
4
200
150
100
50
0


Accuracy Curve
Accuracy
Epoch
Train Acc
Val Acc
Loss Curve
Loss
Epoch
Train Loss
Val Loss

8 ResNet50 + Training + Evaluation

[69]:
```
# Imports
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import tensorflow as tf
from tensorflow.keras import layers, models, optimizers, callbacks
from tensorflow.keras.applications import ResNet50
from sklearn.metrics import classification_report, confusion_matrix

#  Constants
IMG_SIZE = 224
NUM_CLASSES = 4

#  Model Definition (with pretrained ResNet50)
base_model = ResNet50(weights='imagenet', include_top=False,␣
 ↪input_shape=(IMG_SIZE, IMG_SIZE, 3))
base_model.trainable = False  # Fine-tune later if needed

model = models.Sequential([
    base_model,
    layers.GlobalAveragePooling2D(),
    layers.BatchNormalization(),
    layers.Dropout(0.5),
    layers.Dense(256, activation='relu'),
    layers.Dense(NUM_CLASSES, activation='softmax')
])

model.compile(
    optimizer=optimizers.Adam(),
    loss='sparse_categorical_crossentropy',
    metrics=['accuracy']
)

model.summary()
```

```
Downloading data from https://storage.googleapis.com/tensorflow/keras-
applications/resnet/resnet50_weights_tf_dim_ordering_tf_kernels_notop.h5
94765736/94765736          1s
0us/step
```

Model: "sequential_7"

```
 Layer (type)                    Output Shape               Param #
```

resnet50 (Functional)	(None, 7, 7, 2048)	23,587,712
global_average_pooling2d_3 (GlobalAveragePooling2D)	(None, 2048)	0
batch_normalization_13 (BatchNormalization)	(None, 2048)	8,192
dropout_7 (Dropout)	(None, 2048)	0
dense_15 (Dense)	(None, 256)	524,544
dense_16 (Dense)	(None, 4)	1,028

Total params: 24,121,476 (92.02 MB)

Trainable params: 529,668 (2.02 MB)

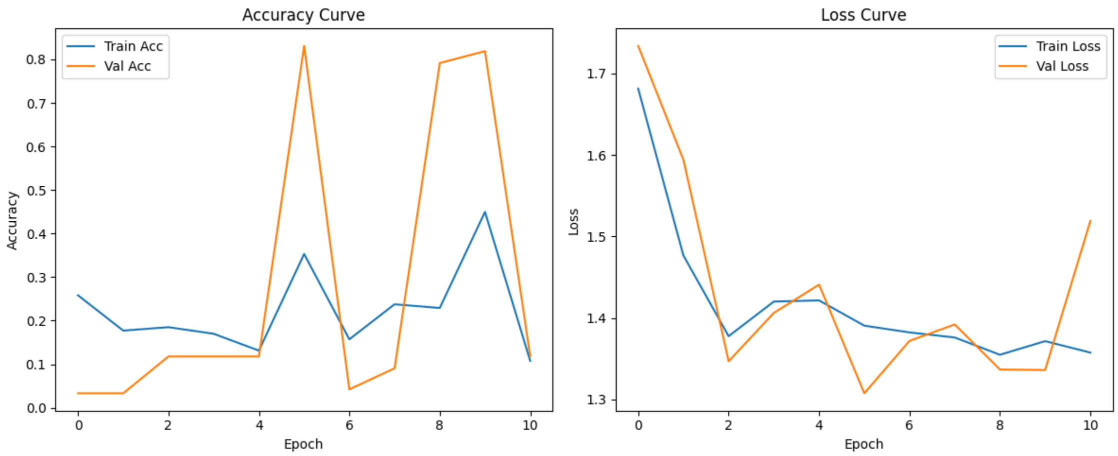
Non-trainable params: 23,591,808 (90.00 MB)

[70]:
```
#  ResNet50 Feature Extractor
base_resnet = tf.keras.applications.ResNet50(include_top=False,␣
↪weights='imagenet', input_shape=(224,224,3))
base_resnet.trainable = False

resnet_model = models.Sequential([
    base_resnet,
    layers.GlobalAveragePooling2D(),
    layers.Dense(128, activation='relu'),
    layers.Dropout(0.3),
    layers.Dense(4, activation='softmax')
])

resnet_model.compile(optimizer='adam', loss='sparse_categorical_crossentropy',␣
↪metrics=['accuracy'])

#  Train
resnet_history = resnet_model.fit(
    train_ds,
    validation_data=val_ds,
    epochs=30,
    class_weight=class_weights,
    callbacks=[EarlyStopping(patience=5, restore_best_weights=True)]
)
```

```
Epoch 1/30
52/52              477s 8s/step -
accuracy: 0.3610 - loss: 1.6028 - val_accuracy: 0.0332 - val_loss: 1.7337
Epoch 2/30
52/52              478s 8s/step -
accuracy: 0.1763 - loss: 1.3765 - val_accuracy: 0.0332 - val_loss: 1.5940
Epoch 3/30
52/52              494s 8s/step -
accuracy: 0.1449 - loss: 1.3717 - val_accuracy: 0.1178 - val_loss: 1.3469
Epoch 4/30
52/52              433s 8s/step -
accuracy: 0.2307 - loss: 1.4765 - val_accuracy: 0.1178 - val_loss: 1.4063
Epoch 5/30
52/52              444s 8s/step -
accuracy: 0.1511 - loss: 1.4678 - val_accuracy: 0.1178 - val_loss: 1.4409
Epoch 6/30
52/52              443s 8s/step -
accuracy: 0.2755 - loss: 1.3097 - val_accuracy: 0.8308 - val_loss: 1.3077
Epoch 7/30
52/52              437s 8s/step -
accuracy: 0.2596 - loss: 1.3513 - val_accuracy: 0.0423 - val_loss: 1.3720
Epoch 8/30
52/52              442s 8s/step -
accuracy: 0.2884 - loss: 1.3834 - val_accuracy: 0.0906 - val_loss: 1.3921
Epoch 9/30
52/52              441s 8s/step -
accuracy: 0.2234 - loss: 1.2739 - val_accuracy: 0.7915 - val_loss: 1.3368
Epoch 10/30
52/52              443s 8s/step -
accuracy: 0.4453 - loss: 1.1524 - val_accuracy: 0.8187 - val_loss: 1.3362
Epoch 11/30
52/52              442s 8s/step -
accuracy: 0.1922 - loss: 1.3534 - val_accuracy: 0.1178 - val_loss: 1.5191
```

[72]:
```
def plot_history(history):
    acc =resnet_history.history['accuracy']
    val_acc = resnet_history.history['val_accuracy']
    loss = resnet_history.history['loss']
    val_loss =resnet_history.history['val_loss']

    plt.figure(figsize=(12, 5))

    plt.subplot(1, 2, 1)
    plt.plot(acc, label='Train Acc')
    plt.plot(val_acc, label='Val Acc')
    plt.title('Accuracy Curve')
    plt.xlabel('Epoch')
```

```
    plt.ylabel('Accuracy')
    plt.legend()

    plt.subplot(1, 2, 2)
    plt.plot(loss, label='Train Loss')
    plt.plot(val_loss, label='Val Loss')
    plt.title('Loss Curve')
    plt.xlabel('Epoch')
    plt.ylabel('Loss')
    plt.legend()

    plt.tight_layout()
    plt.show()

plot_history(resnet_history)
```



[74]:

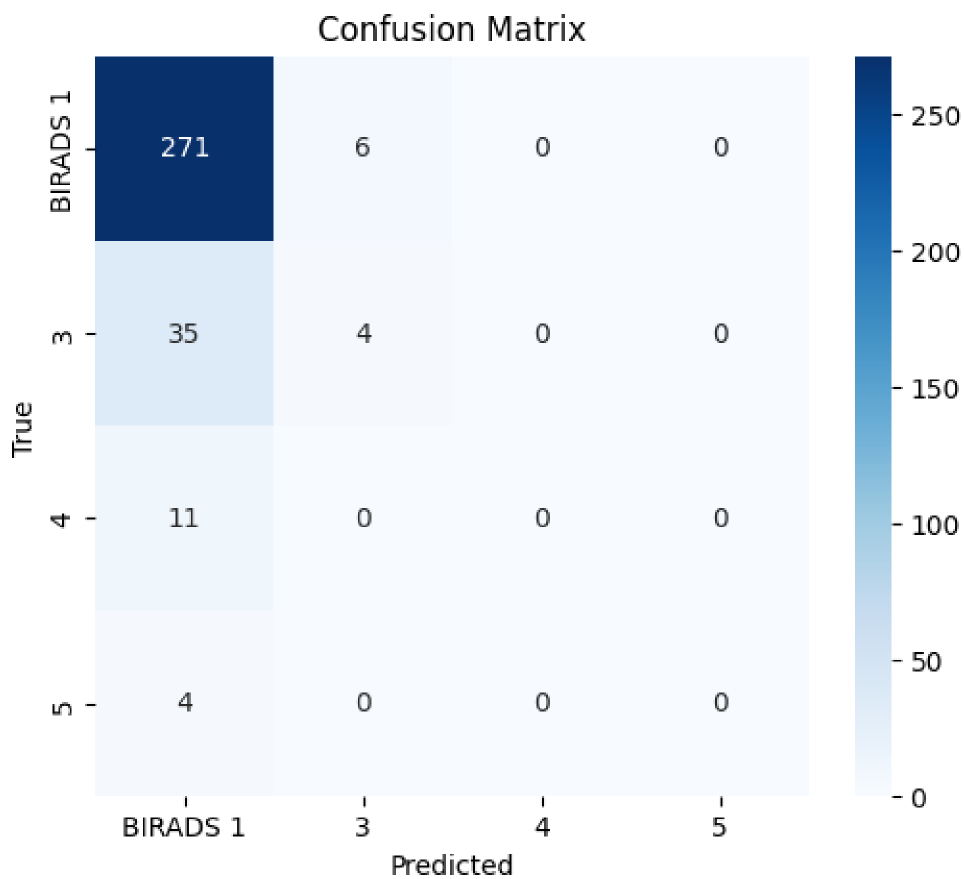
```
# Get true & predicted labels
y_true, y_pred = [], []
for images, labels in val_ds:
    preds = resnet_model.predict(images)
    y_true.extend(labels.numpy())
    y_pred.extend(np.argmax(preds, axis=1))

# Classification report
print(classification_report(y_true, y_pred, target_names=["BIRADS 1", "3", "4",␣
 ↪"5"]))

# Confusion matrix
conf_matrix = confusion_matrix(y_true, y_pred)

plt.figure(figsize=(6, 5))
```

```python
sns.heatmap(conf_matrix, annot=True, fmt='d', cmap='Blues',
            xticklabels=["BIRADS 1", "3", "4", "5"],
            yticklabels=["BIRADS 1", "3", "4", "5"])
plt.xlabel('Predicted')
plt.ylabel('True')
plt.title('Confusion Matrix')
plt.show()
```

```
1/1               18s 18s/step
1/1               6s 6s/step
1/1               7s 7s/step
1/1               8s 8s/step
1/1               6s 6s/step
1/1               8s 8s/step
1/1               7s 7s/step
1/1               7s 7s/step
1/1               5s 5s/step
1/1               8s 8s/step
1/1               4s 4s/step
```

```
/usr/local/lib/python3.11/dist-packages/sklearn/metrics/_classification.py:1565:
UndefinedMetricWarning: Precision is ill-defined and being set to 0.0 in labels
with no predicted samples. Use `zero_division` parameter to control this
behavior.
  _warn_prf(average, modifier, f"{metric.capitalize()} is", len(result))
/usr/local/lib/python3.11/dist-packages/sklearn/metrics/_classification.py:1565:
UndefinedMetricWarning: Precision is ill-defined and being set to 0.0 in labels
with no predicted samples. Use `zero_division` parameter to control this
behavior.
  _warn_prf(average, modifier, f"{metric.capitalize()} is", len(result))
/usr/local/lib/python3.11/dist-packages/sklearn/metrics/_classification.py:1565:
UndefinedMetricWarning: Precision is ill-defined and being set to 0.0 in labels
with no predicted samples. Use `zero_division` parameter to control this
behavior.
  _warn_prf(average, modifier, f"{metric.capitalize()} is", len(result))
```

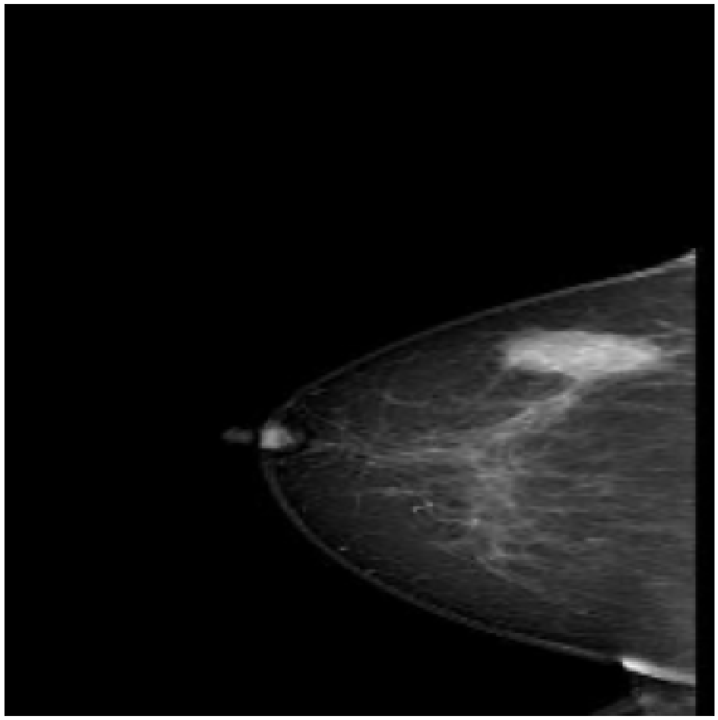
```
              precision    recall  f1-score   support

    BIRADS 1       0.84      0.98      0.91       277
           3       0.40      0.10      0.16        39
           4       0.00      0.00      0.00        11
           5       0.00      0.00      0.00         4

    accuracy                           0.83       331
   macro avg       0.31      0.27      0.27       331
weighted avg       0.75      0.83      0.78       331
```



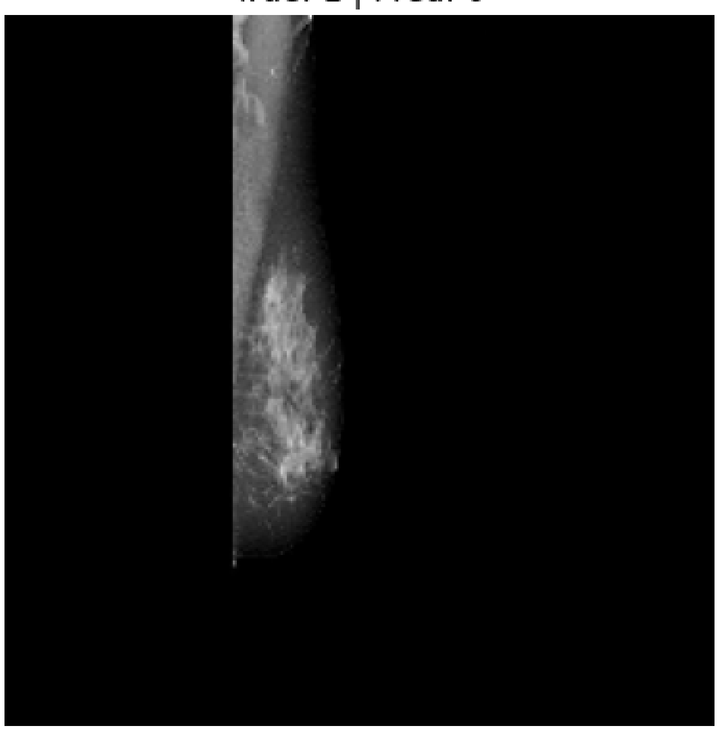
[75]:
```
# Misclassified samples
misclassified = [(i, t, p) for i, (t, p) in enumerate(zip(y_true, y_pred)) if t != p]
print(f"Total misclassifications: {len(misclassified)}")

# Visualize a few
import matplotlib.pyplot as plt

indices = [i for i, _, _ in misclassified[:5]]
samples = [val_ds.unbatch().skip(i).take(1) for i in indices]

for i, sample in enumerate(samples):
    for img, label in sample:
        plt.imshow(img.numpy())
        plt.title(f"True: {label.numpy()} | Pred: {y_pred[indices[i]]}")
        plt.axis('off')
        plt.show()
```

```
Total misclassifications: 56
```

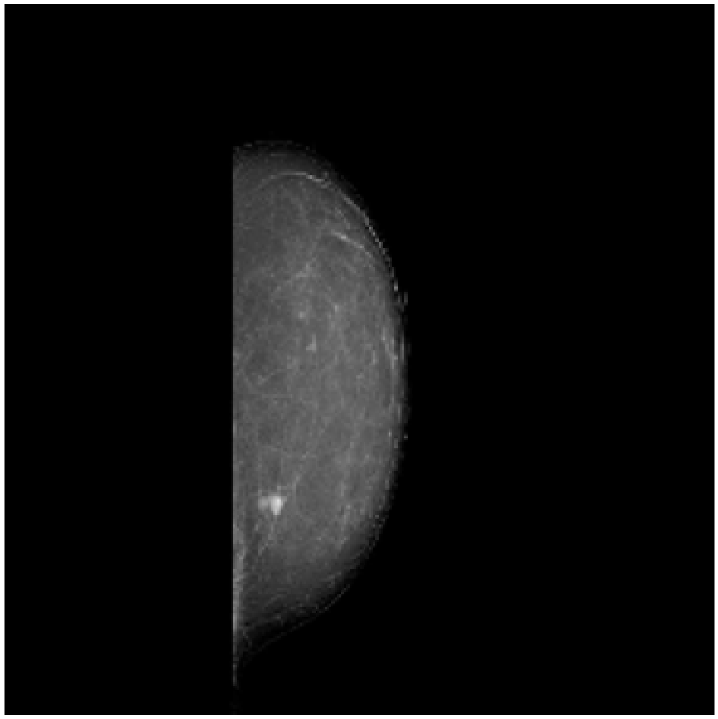
True: 3 | Pred: 0



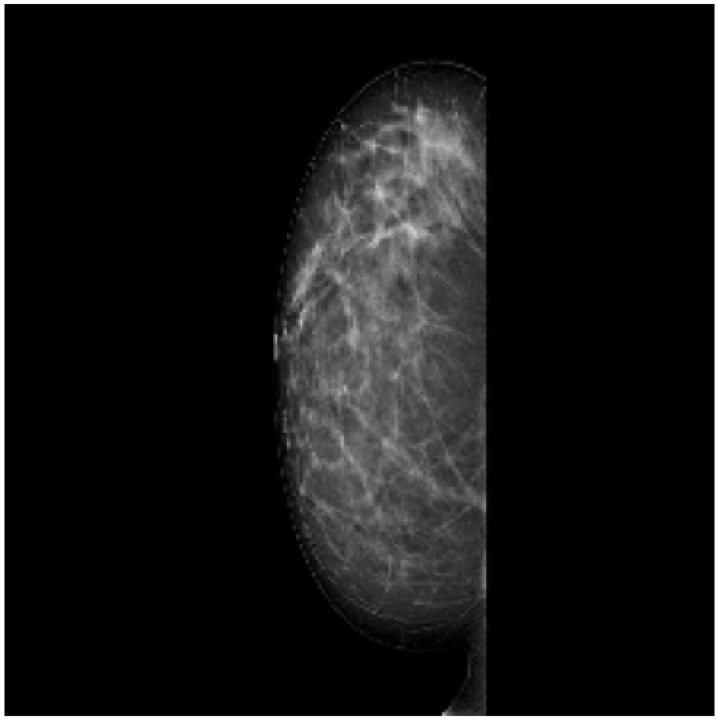
True: 1 | Pred: 0



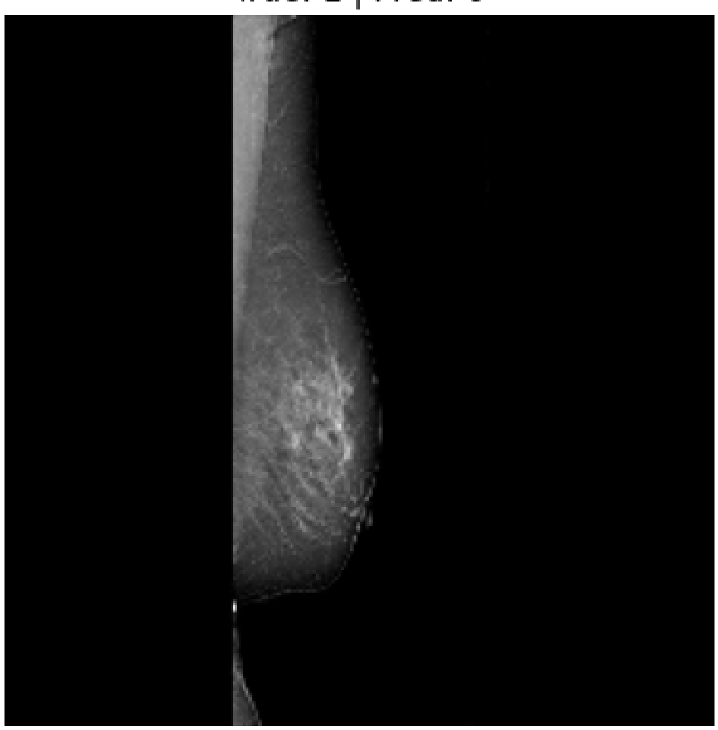
True: 2 | Pred: 0



True: 1 | Pred: 0



True: 1 | Pred: 0



9 EfficientNetB0 Model + Training Block

[76]:
```
from tensorflow.keras.applications import EfficientNetB0
from tensorflow.keras.models import Model
from tensorflow.keras.layers import Input, Dense, GlobalAveragePooling2D,␣
↪Dropout
from tensorflow.keras.optimizers import Adam
from tensorflow.keras.callbacks import EarlyStopping

base_effnet = tf.keras.applications.EfficientNetB0(include_top=False,␣
↪weights='imagenet', input_shape=(224,224,3))
base_effnet.trainable = False

effnet_model = models.Sequential([
    base_effnet,
    layers.GlobalAveragePooling2D(),
    layers.Dense(128, activation='relu'),
    layers.Dropout(0.3),
    layers.Dense(4, activation='softmax')
])

effnet_model.compile(optimizer='adam', loss='sparse_categorical_crossentropy',␣
↪metrics=['accuracy'])

#  Train
effnet_history = effnet_model.fit(
    train_ds,
    validation_data=val_ds,
    epochs=30,
    class_weight=class_weights,
    callbacks=[EarlyStopping(patience=5, restore_best_weights=True)]
)
```

```
Downloading data from https://storage.googleapis.com/keras-
applications/efficientnetb0_notop.h5
16705208/16705208            0s
0us/step
Epoch 1/30
52/52              295s 5s/step -
accuracy: 0.4386 - loss: 1.3472 - val_accuracy: 0.0121 - val_loss: 1.4917
Epoch 2/30
52/52              252s 3s/step -
accuracy: 0.1403 - loss: 1.2978 - val_accuracy: 0.0121 - val_loss: 1.4020
Epoch 3/30
```

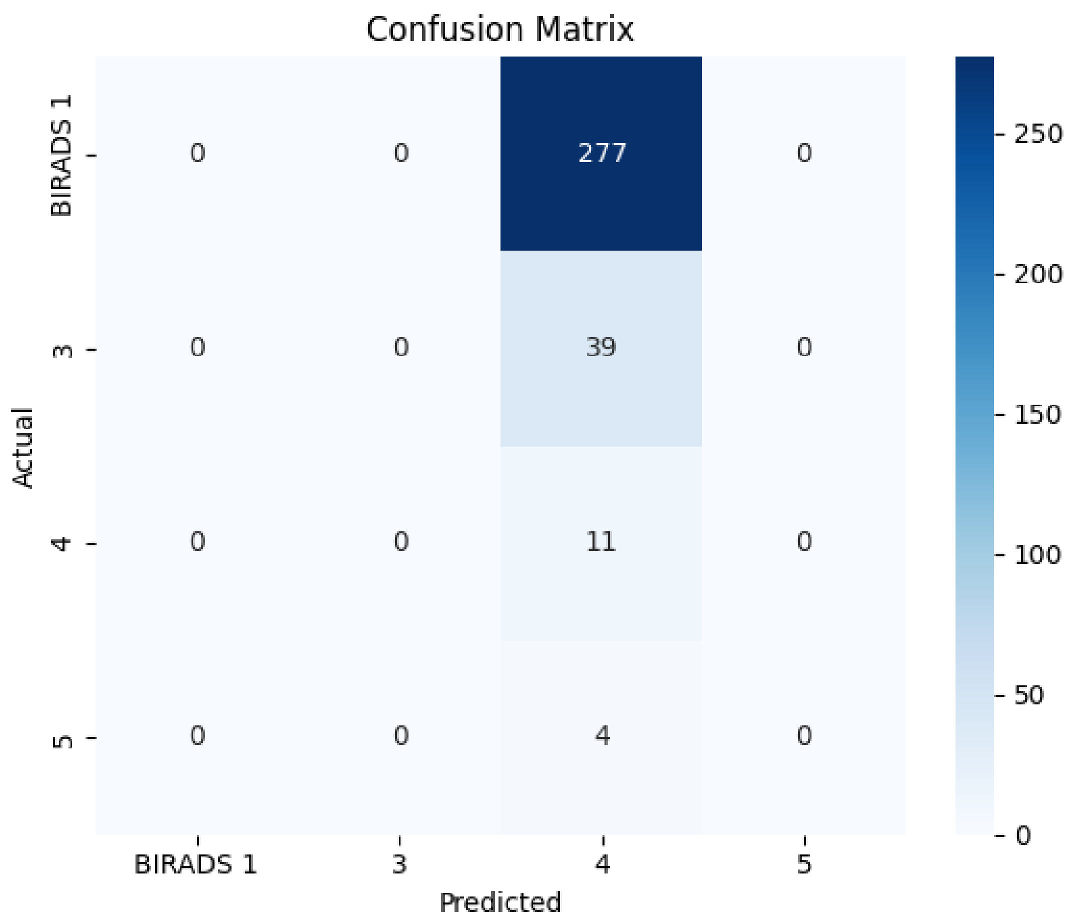
```
52/52              213s 3s/step -
accuracy: 0.0942 - loss: 1.3769 - val_accuracy: 0.0332 - val_loss: 1.3822
Epoch 4/30
52/52              245s 3s/step -
accuracy: 0.1418 - loss: 1.4810 - val_accuracy: 0.0332 - val_loss: 1.2780
Epoch 5/30
52/52              209s 3s/step -
accuracy: 0.2025 - loss: 1.4057 - val_accuracy: 0.1178 - val_loss: 1.3887
Epoch 6/30
52/52              267s 3s/step -
accuracy: 0.2913 - loss: 1.2519 - val_accuracy: 0.0121 - val_loss: 1.4029
Epoch 7/30
52/52              263s 3s/step -
accuracy: 0.0075 - loss: 1.2323 - val_accuracy: 0.0121 - val_loss: 1.4012
Epoch 8/30
52/52              260s 3s/step -
accuracy: 0.0134 - loss: 1.3745 - val_accuracy: 0.0121 - val_loss: 1.4011
Epoch 9/30
52/52              263s 3s/step -
accuracy: 0.0091 - loss: 1.3183 - val_accuracy: 0.0121 - val_loss: 1.4010
```

[77]:

```
import numpy as np
from sklearn.metrics import classification_report, confusion_matrix
import seaborn as sns
import matplotlib.pyplot as plt

# Get true & predicted labels
y_true, y_pred = [], []

for images, labels in val_ds:
    preds = effnet_model.predict(images, verbose=0)
    y_true.extend(labels.numpy())
    y_pred.extend(np.argmax(preds, axis=1))

# Classification report
class_names = ["BIRADS 1", "3", "4", "5"]
print("Classification Report")
print(classification_report(y_true, y_pred, target_names=class_names))

# Confusion matrix
conf_matrix = confusion_matrix(y_true, y_pred)

# Plot confusion matrix
plt.figure(figsize=(6, 5))
sns.heatmap(conf_matrix, annot=True, fmt='d', cmap='Blues',
            xticklabels=class_names,
            yticklabels=class_names)
```

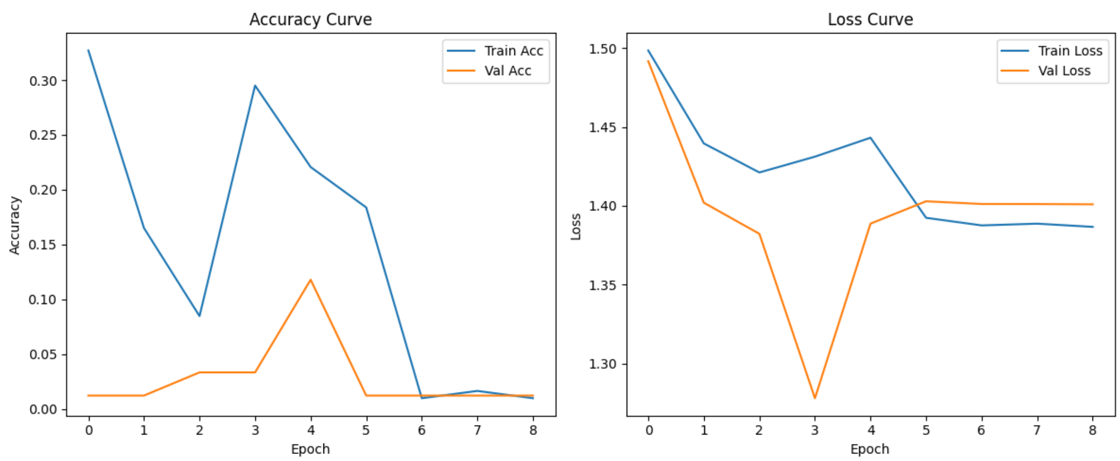
```python
plt.xlabel('Predicted')
plt.ylabel('Actual')
plt.title('Confusion Matrix')
plt.tight_layout()
plt.show()
```

```
Classification Report
              precision    recall  f1-score   support

    BIRADS 1       0.00      0.00      0.00       277
           3       0.00      0.00      0.00        39
           4       0.03      1.00      0.06        11
           5       0.00      0.00      0.00         4

    accuracy                           0.03       331
   macro avg       0.01      0.25      0.02       331
weighted avg       0.00      0.03      0.00       331


/usr/local/lib/python3.11/dist-packages/sklearn/metrics/_classification.py:1565:
UndefinedMetricWarning: Precision is ill-defined and being set to 0.0 in labels
with no predicted samples. Use `zero_division` parameter to control this
behavior.
  _warn_prf(average, modifier, f"{metric.capitalize()} is", len(result))
/usr/local/lib/python3.11/dist-packages/sklearn/metrics/_classification.py:1565:
UndefinedMetricWarning: Precision is ill-defined and being set to 0.0 in labels
with no predicted samples. Use `zero_division` parameter to control this
behavior.
  _warn_prf(average, modifier, f"{metric.capitalize()} is", len(result))
/usr/local/lib/python3.11/dist-packages/sklearn/metrics/_classification.py:1565:
UndefinedMetricWarning: Precision is ill-defined and being set to 0.0 in labels
with no predicted samples. Use `zero_division` parameter to control this
behavior.
  _warn_prf(average, modifier, f"{metric.capitalize()} is", len(result))
```



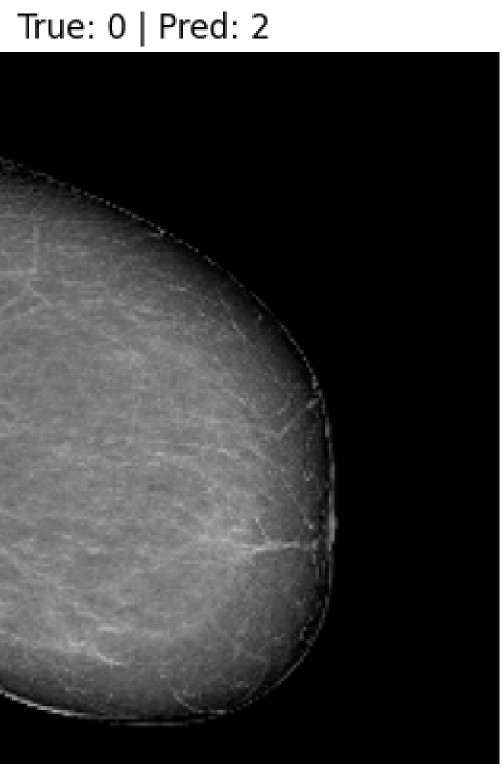
[78]:
```
def plot_history(history):
    acc = effnet_history.history['accuracy']
    val_acc = effnet_history.history['val_accuracy']
    loss = effnet_history.history['loss']
    val_loss =effnet_history.history['val_loss']

    plt.figure(figsize=(12, 5))

    plt.subplot(1, 2, 1)
    plt.plot(acc, label='Train Acc')
    plt.plot(val_acc, label='Val Acc')
    plt.title('Accuracy Curve')
    plt.xlabel('Epoch')
    plt.ylabel('Accuracy')
    plt.legend()

    plt.subplot(1, 2, 2)
    plt.plot(loss, label='Train Loss')
```

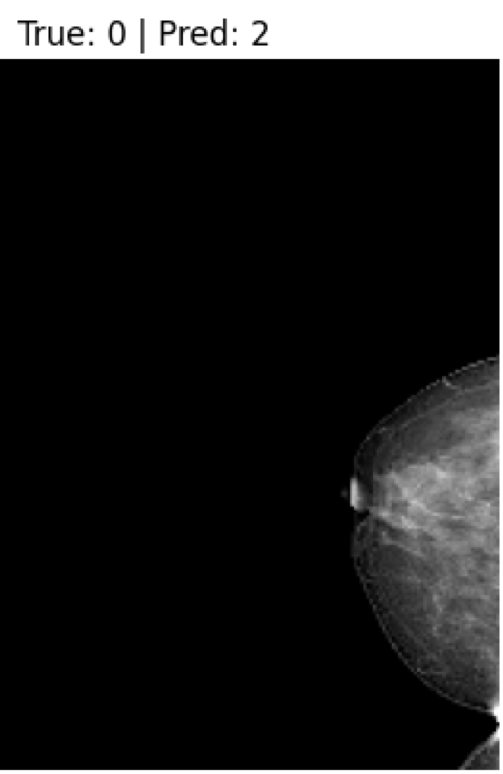
```
    plt.plot(val_loss, label='Val Loss')
    plt.title('Loss Curve')
    plt.xlabel('Epoch')
    plt.ylabel('Loss')
    plt.legend()

    plt.tight_layout()
    plt.show()

plot_history(effnet_history)
```



[79]:
```
# Misclassified samples
misclassified = [(i, t, p) for i, (t, p) in enumerate(zip(y_true, y_pred)) if t␣
 ↪!= p]
print(f"Total misclassifications: {len(misclassified)}")

# Visualize a few
import matplotlib.pyplot as plt

indices = [i for i, _, _ in misclassified[:5]]
samples = [val_ds.unbatch().skip(i).take(1) for i in indices]

for i, sample in enumerate(samples):
    for img, label in sample:
        plt.imshow(img.numpy())
        plt.title(f"True: {label.numpy()} | Pred: {y_pred[indices[i]]}")
        plt.axis('off')
        plt.show()
```

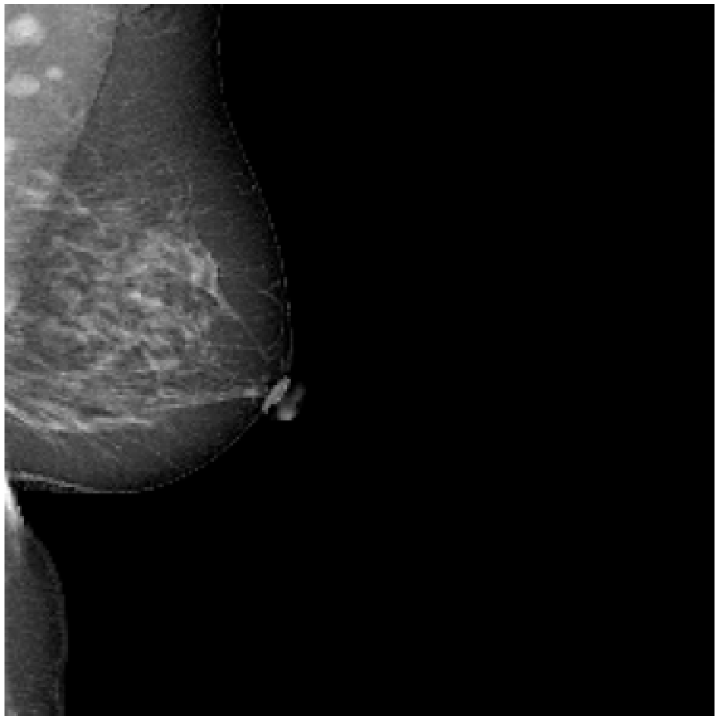
```
Total misclassifications: 320
```


True: 0 | Pred: 2

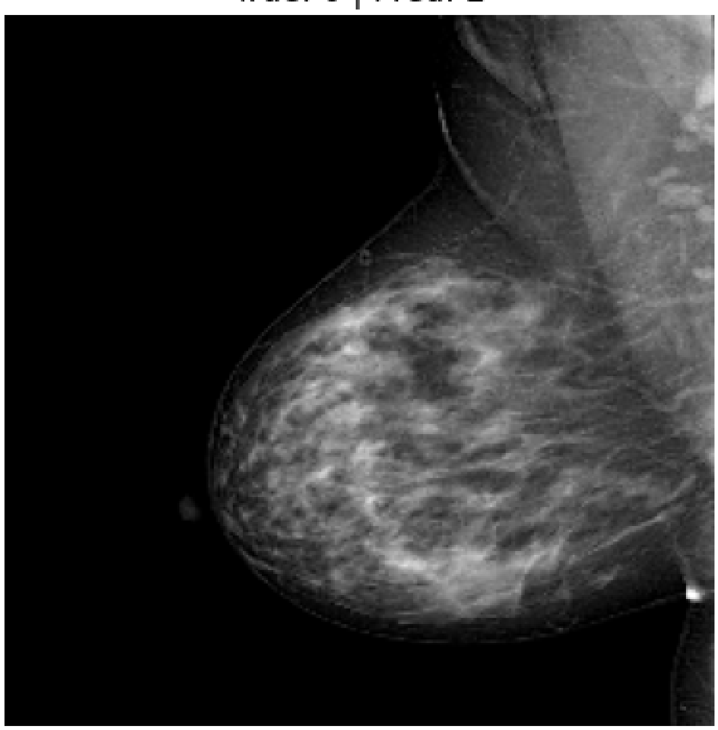

True: 0 | Pred: 2

True: 0 | Pred: 2

True: 0 | Pred: 2



True: 0 | Pred: 2



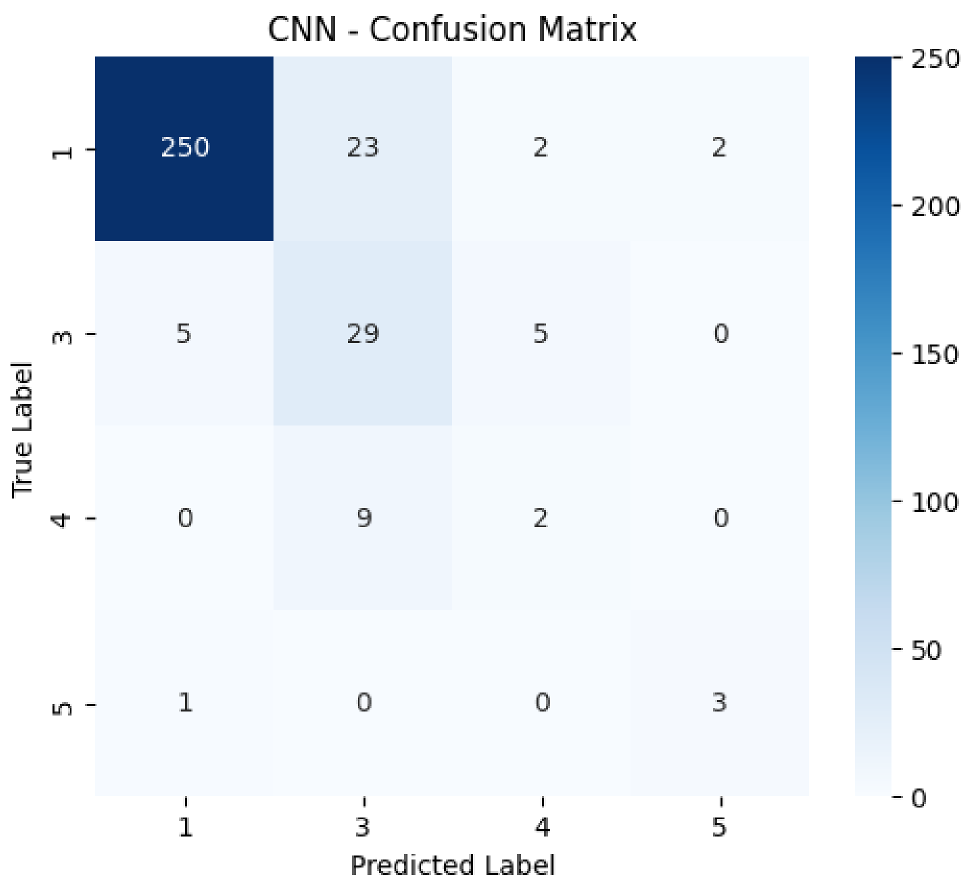
10 Final Comparison

Evaluation + Metrics + Confusion Matrix + Grad-CAM

[81]:
```
from sklearn.metrics import classification_report, confusion_matrix
import seaborn as sns

def evaluate_model(model, val_ds, name="Model"):
    y_true, y_pred = [], []
    for images, labels in val_ds:
        preds = model.predict(images)
        y_true.extend(labels.numpy())
        y_pred.extend(np.argmax(preds, axis=1))

    print(f"\n {name} Classification Report")
    print(classification_report(y_true, y_pred, target_names=["BIRADS 1", "3",␣
↪"4", "5"]))

    cm = confusion_matrix(y_true, y_pred)
    plt.figure(figsize=(6, 5))
    sns.heatmap(cm, annot=True, fmt="d", cmap="Blues", xticklabels=["1", "3",␣
↪"4", "5"], yticklabels=["1", "3", "4", "5"])
    plt.title(f"{name} - Confusion Matrix")
    plt.ylabel('True Label')
    plt.xlabel('Predicted Label')
    plt.show()

# Accuracy/Loss plotting utility
def plot_histories(histories, names):
    plt.figure(figsize=(14, 5))

    # Accuracy
    plt.subplot(1, 2, 1)
    for hist, label in zip(histories, names):
        plt.plot(hist.history['accuracy'], label=f'{label} Train')
        plt.plot(hist.history['val_accuracy'], linestyle='--', label=f'{label}␣
↪Val')
    plt.title('Model Accuracy')
    plt.xlabel('Epoch')
    plt.ylabel('Accuracy')
    plt.legend()

    # Loss
    plt.subplot(1, 2, 2)
```

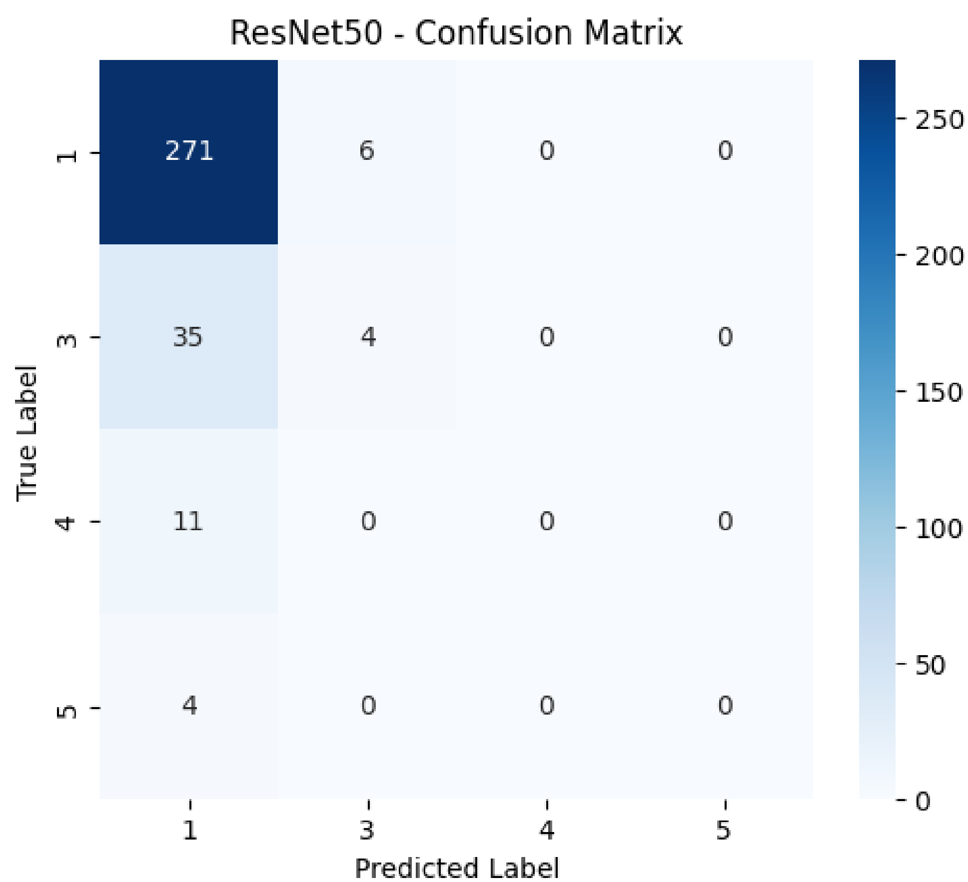
```
    for hist, label in zip(histories, names):
        plt.plot(hist.history['loss'], label=f'{label} Train')
        plt.plot(hist.history['val_loss'], linestyle='--', label=f'{label} Val')
    plt.title('Model Loss')
    plt.xlabel('Epoch')
    plt.ylabel('Loss')
    plt.legend()

    plt.tight_layout()
    plt.show()

#  Evaluate all models
evaluate_model(cnn_model, val_ds, "CNN")
evaluate_model(resnet_model, val_ds, "ResNet50")
evaluate_model(effnet_model, val_ds, "EfficientNetB0")
evaluate_model(mobile_model, val_ds, "MobileNetV2")

#  Plot training curves
plot_histories(
    [cnn_history, resnet_history, effnet_history, mobile_history],
    ["CNN", "ResNet50", "EffNetB0", "MobileNetV2"]
)
```

```
1/1               2s 2s/step
1/1               4s 4s/step
1/1               3s 3s/step
1/1               6s 6s/step
1/1               5s 5s/step
1/1               2s 2s/step
1/1               2s 2s/step
1/1               3s 3s/step
1/1               3s 3s/step
1/1               3s 3s/step
1/1               0s 288ms/step

 CNN Classification Report
              precision    recall  f1-score   support

    BIRADS 1       0.98      0.90      0.94       277
           3       0.48      0.74      0.58        39
           4       0.22      0.18      0.20        11
           5       0.60      0.75      0.67         4

    accuracy                           0.86       331
   macro avg       0.57      0.64      0.60       331
weighted avg       0.89      0.86      0.87       331
```

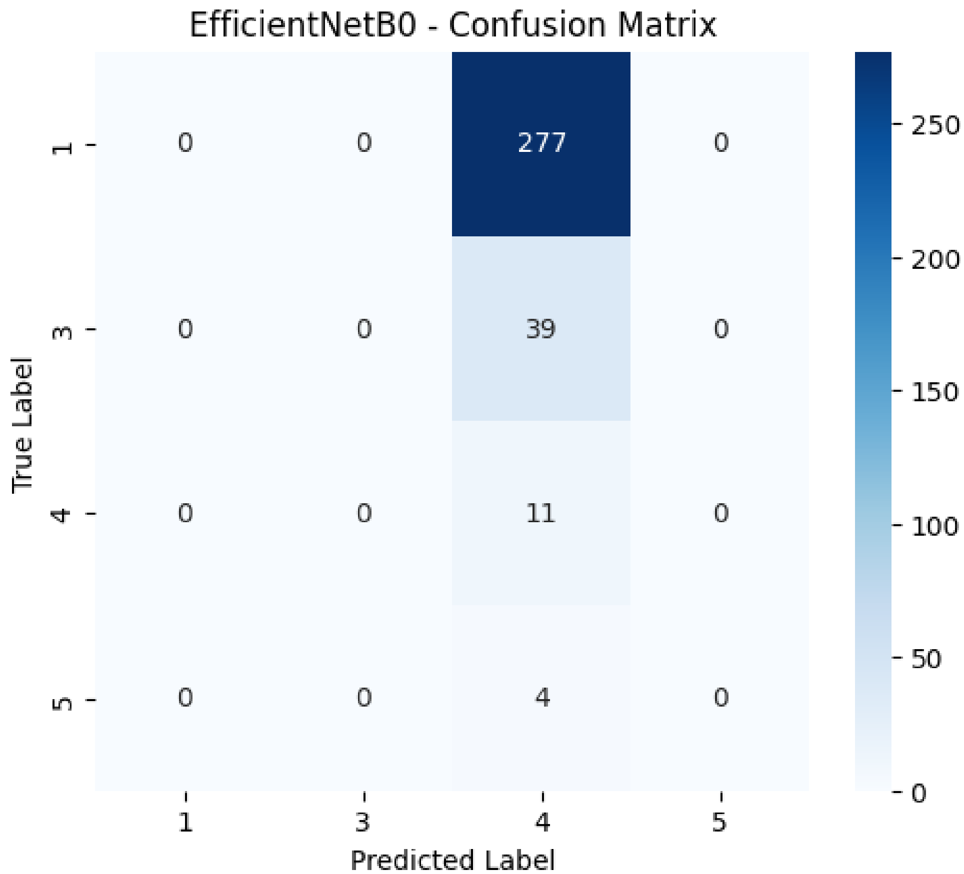



```
1/1              9s 9s/step
1/1              7s 7s/step
1/1              10s 10s/step
1/1              7s 7s/step
1/1              6s 6s/step
1/1              7s 7s/step
1/1              6s 6s/step
1/1              7s 7s/step
1/1              5s 5s/step
1/1              7s 7s/step
1/1              3s 3s/step

 ResNet50 Classification Report
              precision    recall  f1-score   support

    BIRADS 1       0.84      0.98      0.91       277
           3       0.40      0.10      0.16        39
           4       0.00      0.00      0.00        11
           5       0.00      0.00      0.00         4
```

```
    accuracy                           0.83       331
   macro avg       0.31      0.27      0.27       331
weighted avg       0.75      0.83      0.78       331

/usr/local/lib/python3.11/dist-packages/sklearn/metrics/_classification.py:1565:
UndefinedMetricWarning: Precision is ill-defined and being set to 0.0 in labels
with no predicted samples. Use `zero_division` parameter to control this
behavior.
  _warn_prf(average, modifier, f"{metric.capitalize()} is", len(result))
/usr/local/lib/python3.11/dist-packages/sklearn/metrics/_classification.py:1565:
UndefinedMetricWarning: Precision is ill-defined and being set to 0.0 in labels
with no predicted samples. Use `zero_division` parameter to control this
behavior.
  _warn_prf(average, modifier, f"{metric.capitalize()} is", len(result))
/usr/local/lib/python3.11/dist-packages/sklearn/metrics/_classification.py:1565:
UndefinedMetricWarning: Precision is ill-defined and being set to 0.0 in labels
with no predicted samples. Use `zero_division` parameter to control this
behavior.
  _warn_prf(average, modifier, f"{metric.capitalize()} is", len(result))
```

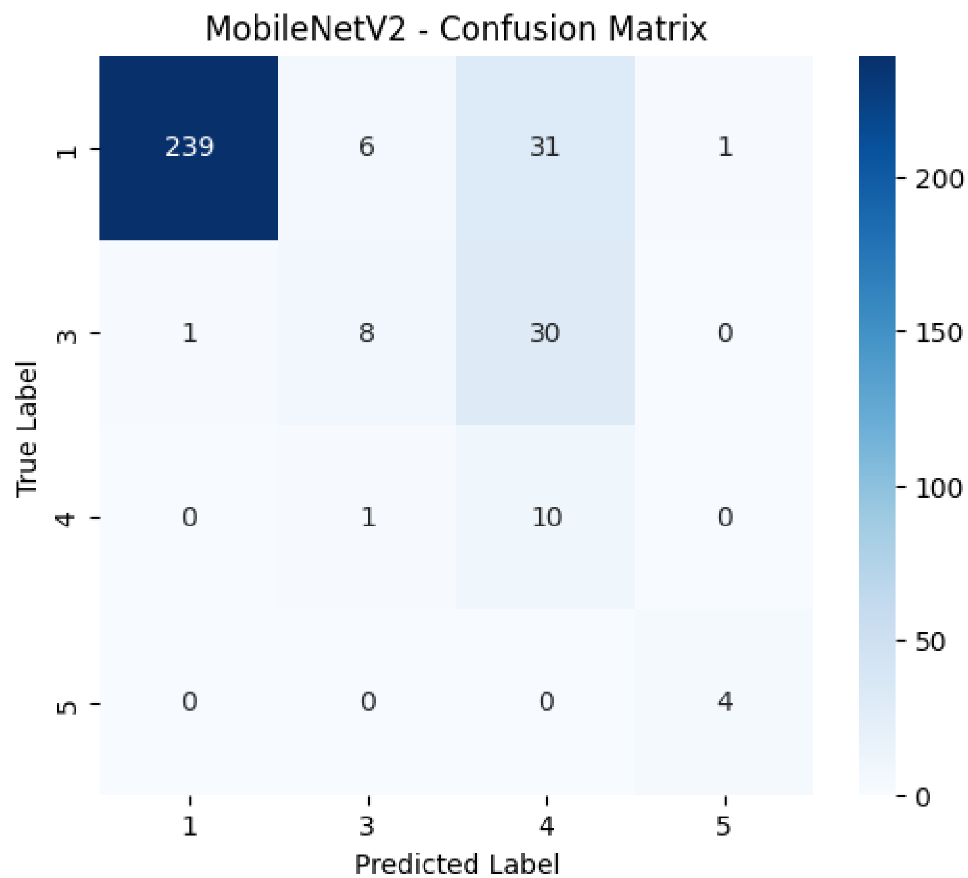


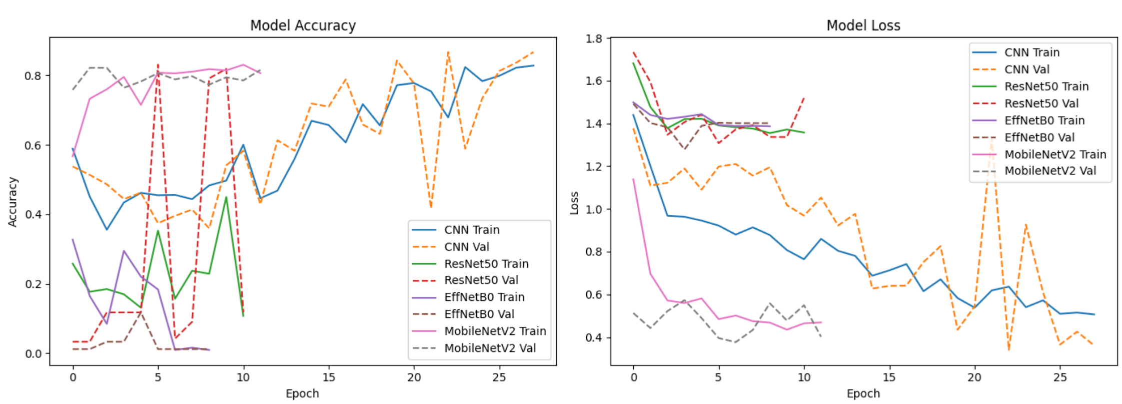
```
1/1            7s 7s/step
1/1            4s 4s/step
1/1            5s 5s/step
1/1            3s 3s/step
1/1            3s 3s/step
1/1            3s 3s/step
1/1            3s 3s/step
1/1            3s 3s/step
1/1            2s 2s/step
1/1            2s 2s/step
1/1            1s 662ms/step

 EfficientNetB0 Classification Report
             precision    recall  f1-score   support

    BIRADS 1       0.00      0.00      0.00       277
           3       0.00      0.00      0.00        39
           4       0.03      1.00      0.06        11
           5       0.00      0.00      0.00         4

    accuracy                           0.03       331
   macro avg       0.01      0.25      0.02       331
weighted avg       0.00      0.03      0.00       331


/usr/local/lib/python3.11/dist-packages/sklearn/metrics/_classification.py:1565:
UndefinedMetricWarning: Precision is ill-defined and being set to 0.0 in labels
with no predicted samples. Use `zero_division` parameter to control this
behavior.
  _warn_prf(average, modifier, f"{metric.capitalize()} is", len(result))
/usr/local/lib/python3.11/dist-packages/sklearn/metrics/_classification.py:1565:
UndefinedMetricWarning: Precision is ill-defined and being set to 0.0 in labels
with no predicted samples. Use `zero_division` parameter to control this
behavior.
  _warn_prf(average, modifier, f"{metric.capitalize()} is", len(result))
/usr/local/lib/python3.11/dist-packages/sklearn/metrics/_classification.py:1565:
UndefinedMetricWarning: Precision is ill-defined and being set to 0.0 in labels
with no predicted samples. Use `zero_division` parameter to control this
behavior.
  _warn_prf(average, modifier, f"{metric.capitalize()} is", len(result))
```




```
1/1              3s 3s/step
1/1              2s 2s/step
1/1              2s 2s/step
1/1              2s 2s/step
1/1              2s 2s/step
1/1              2s 2s/step
1/1              3s 3s/step
1/1              1s 1s/step
1/1              1s 1s/step
1/1              1s 1s/step
1/1              0s 397ms/step

 MobileNetV2 Classification Report
              precision    recall  f1-score   support

    BIRADS 1       1.00      0.86      0.92       277
           3       0.53      0.21      0.30        39
           4       0.14      0.91      0.24        11
           5       0.80      1.00      0.89         4
```

accuracy			0.79	331
macro avg	0.62	0.74	0.59	331
weighted avg	0.91	0.79	0.83	331





[82]:
```python
model_info = {
    "CNN Baseline": (cnn_model, 'conv2d_8'),
    "ResNet50":     (resnet_model, 'resnet50'),
    "EffNetB0":     (effnet_model, 'efficientnetb0'),
    "MobileNetV2":  (mobile_model, 'mobilenetv2_1.00_224'),
}
```

[83]:
```python
for model in [cnn_model, resnet_model, effnet_model, mobile_model]:
    dummy_input = tf.random.normal((1, 224, 224, 3))
    _ = model(dummy_input)  # Ensure all models are built
```

11 Ablation Studies

Ablation Study – Dropout Off

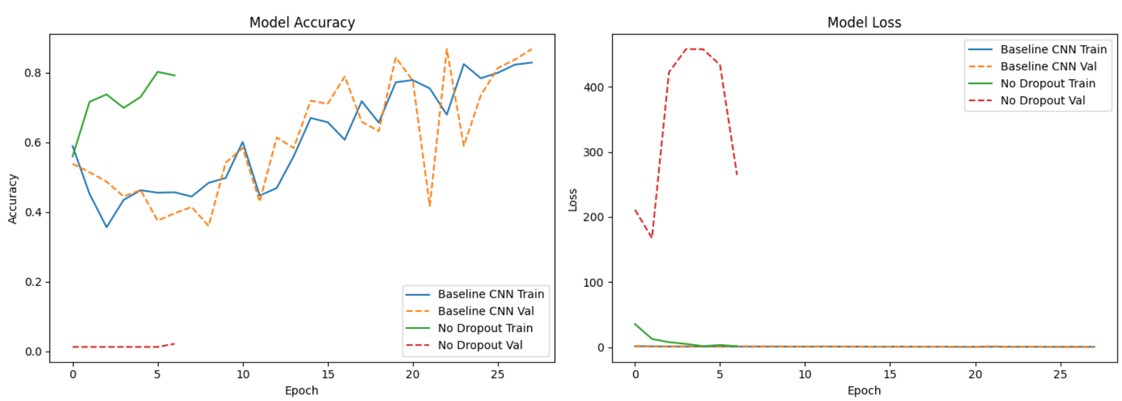
[84]:
```python
def build_cnn_ablation(dropout=False):
    model = models.Sequential([
        layers.Conv2D(32, (3, 3), activation='relu', input_shape=(224, 224, 3)),
        layers.BatchNormalization(),
        layers.MaxPooling2D(2, 2),

        layers.Conv2D(64, (3, 3), activation='relu'),
        layers.BatchNormalization(),
        layers.MaxPooling2D(2, 2),

        layers.Conv2D(128, (3, 3), activation='relu'),
        layers.BatchNormalization(),
        layers.MaxPooling2D(2, 2),

        layers.Flatten(),
        layers.Dense(256, activation='relu'),
        layers.Dropout(0.5) if dropout else layers.Activation('linear'),
        layers.Dense(4, activation='softmax')
    ])
    model.compile(optimizer='adam', loss='sparse_categorical_crossentropy',␣
 ↪metrics=['accuracy'])
    return model

#  Without dropout
cnn_no_dropout = build_cnn_ablation(dropout=False)
history_no_dropout = cnn_no_dropout.fit(train_ds, validation_data=val_ds,␣
 ↪epochs=30, callbacks=[early_stop], class_weight=class_weights)
```

```
/usr/local/lib/python3.11/dist-
packages/keras/src/layers/convolutional/base_conv.py:107: UserWarning: Do not
pass an `input_shape`/`input_dim` argument to a layer. When using Sequential
models, prefer using an `Input(shape)` object as the first layer in the model
```

```
instead.
  super().__init__(activity_regularizer=activity_regularizer, **kwargs)

Epoch 1/30
52/52                 379s 6s/step -
accuracy: 0.5432 - loss: 42.8081 - val_accuracy: 0.0121 - val_loss: 211.3209
Epoch 2/30
52/52                 405s 7s/step -
accuracy: 0.7484 - loss: 10.1158 - val_accuracy: 0.0121 - val_loss: 167.6053
Epoch 3/30
52/52                 446s 7s/step -
accuracy: 0.7061 - loss: 7.8079 - val_accuracy: 0.0121 - val_loss: 422.4654
Epoch 4/30
52/52                 424s 7s/step -
accuracy: 0.7032 - loss: 4.5207 - val_accuracy: 0.0121 - val_loss: 458.0958
Epoch 5/30
52/52                 448s 7s/step -
accuracy: 0.6884 - loss: 1.7956 - val_accuracy: 0.0121 - val_loss: 457.9253
Epoch 6/30
52/52                 443s 7s/step -
accuracy: 0.7897 - loss: 5.5065 - val_accuracy: 0.0121 - val_loss: 433.6779
Epoch 7/30
52/52                 422s 6s/step -
accuracy: 0.7742 - loss: 1.3411 - val_accuracy: 0.0211 - val_loss: 264.6202
```

Compare Ablation Results

[85]:
```
plot_histories([cnn_history, history_no_dropout], ["Baseline CNN", "No␣
↪Dropout"])
```

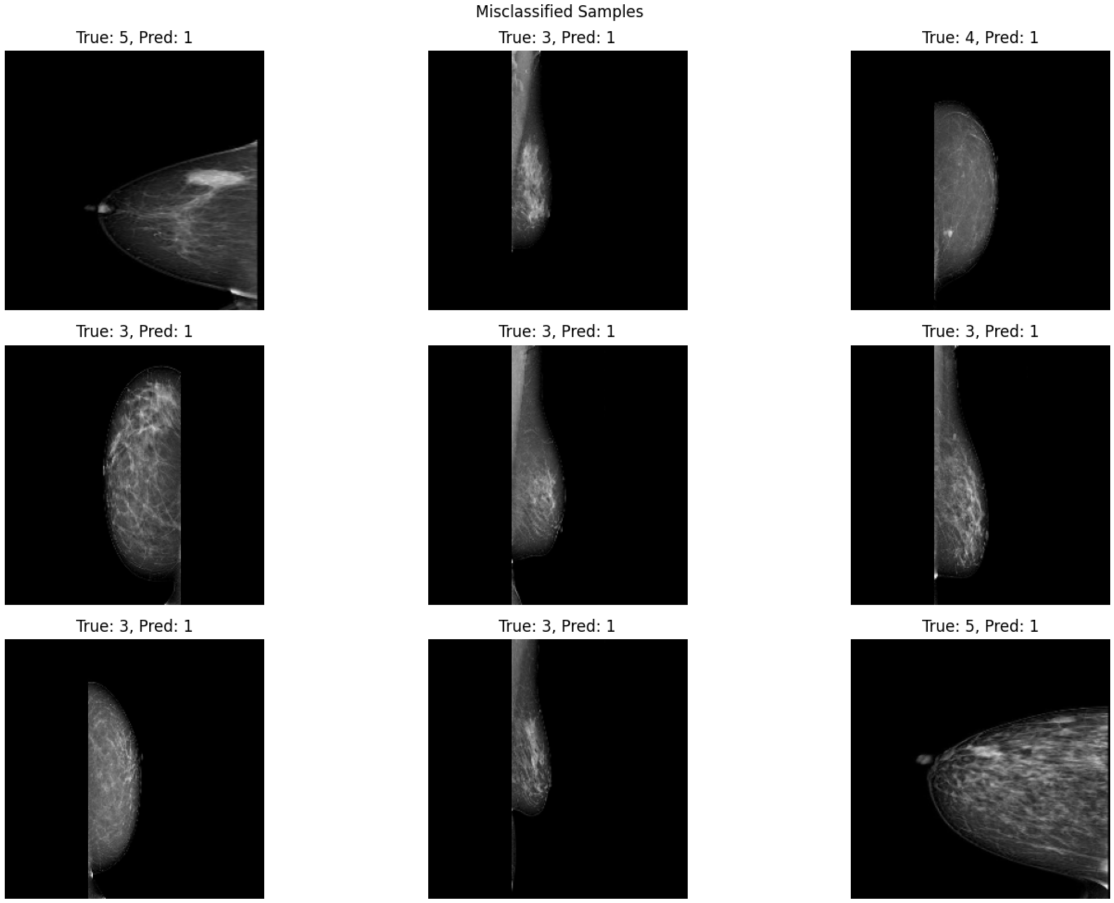


Error Analysis

Show Misclassified Images

[86]:
```python
def show_misclassified_samples(model, val_ds, label_names=["1", "3", "4", "5"]):
    y_true, y_pred = [], []
    imgs = []

    for x_batch, y_batch in val_ds:
        preds = model.predict(x_batch)
        y_pred_batch = np.argmax(preds, axis=1)
        y_true.extend(y_batch.numpy())
        y_pred.extend(y_pred_batch)
        imgs.extend(x_batch.numpy())

    y_true = np.array(y_true)
    y_pred = np.array(y_pred)
    imgs = np.array(imgs)

    mis_idx = np.where(y_true != y_pred)[0][:9]  # take first 9 mistakes

    plt.figure(figsize=(15, 10))
    for i, idx in enumerate(mis_idx):
        plt.subplot(3, 3, i + 1)
        plt.imshow(imgs[idx])
        plt.title(f"True: {label_names[y_true[idx]]}, Pred:␣
↪{label_names[y_pred[idx]]}")
        plt.axis("off")
    plt.suptitle(" Misclassified Samples")
    plt.tight_layout()
    plt.show()

# Apply to best model
show_misclassified_samples(resnet_model, val_ds)
```

```
1/1              10s 10s/step
1/1              6s 6s/step
1/1              7s 7s/step
1/1              6s 6s/step
1/1              8s 8s/step
1/1              6s 6s/step
1/1              6s 6s/step
1/1              6s 6s/step
1/1              7s 7s/step
1/1              5s 5s/step
1/1              2s 2s/step
```



Accuracy & F1 Score

[87]:
```
from sklearn.metrics import accuracy_score, f1_score
import pandas as pd

def evaluate_simple(model, val_ds, name="Model"):
    y_true, y_pred = [], []
    for x, y in val_ds:
        preds = model.predict(x)
        y_pred.extend(np.argmax(preds, axis=1))
        y_true.extend(y.numpy())

    acc = accuracy_score(y_true, y_pred)
    f1 = f1_score(y_true, y_pred, average='macro')  # macro averages across all␣
↪classes
    return {"Model": name, "Accuracy": acc, "F1 Score": f1}

# Evaluate each variant
results = []
```

```
results.append(evaluate_simple(cnn_model, val_ds, "CNN Baseline"))
results.append(evaluate_simple(cnn_no_dropout, val_ds, "CNN No Dropout"))



#  Create DataFrame
df_results = pd.DataFrame(results)
print(df_results)
```

```
1/1               2s 2s/step
1/1               2s 2s/step
1/1               3s 3s/step
1/1               3s 3s/step
1/1               2s 2s/step
1/1               2s 2s/step
1/1               2s 2s/step
1/1               1s 1s/step
1/1               1s 910ms/step
1/1               2s 2s/step
1/1               0s 424ms/step
1/1               4s 4s/step
1/1               4s 4s/step
1/1               4s 4s/step
1/1               2s 2s/step
1/1               2s 2s/step
1/1               2s 2s/step
1/1               3s 3s/step
1/1               1s 1s/step
1/1               1s 1s/step
1/1               1s 1s/step
1/1               1s 545ms/step
            Model  Accuracy  F1 Score
0    CNN Baseline  0.858006  0.596188
1  CNN No Dropout  0.012085  0.005970
```

[92]:
```
# Install the package for Tex and then convert to PDF directly as LaTex
%%capture
!sudo apt-get install texlive-xetex texlive-fonts-recommended␣
 ↪texlive-plain-generic pandoc > /dev/null
# Provide the file path of the notebook file inside the quotations
!jupyter nbconvert --to pdf "/content/drive/MyDrive/Colab Notebooks"
```