MobileNet_project

September 29, 2025

1 Melanoma Detection using Transfer Learning with MobileNetV2

1.1 Introduction

Transfer learning has become a powerful approach in computer vision, especially for medical imaging tasks where annotated datasets are often limited. Instead of training models from scratch, pretrained convolutional neural networks (CNNs) can be fine-tuned to leverage knowledge gained from large-scale datasets like ImageNet. This strategy enables faster convergence, reduces computational costs, and often yields higher accuracy in specialized domains such as disease classification.

In this project, transfer learning is applied using the MobileNetV2 architecture to the task of melanoma detection, where early and reliable diagnosis is crucial for improving patient outcomes.

1.2 Data

The dataset used in this project is sourced from Kaggle's Melanoma Cancer Dataset. It contains **13,900 high-quality dermoscopic images**, uniformly resized to **224×224 pixels**, representing both benign and malignant skin lesions.

The dataset was curated to support research in dermatology and computer-aided diagnostics, with the goal of enabling the development of machine learning models that can distinguish between healthy and cancerous tissue. Its diversity of lesion appearances provides a realistic challenge for classification tasks, making it a suitable benchmark for evaluating the effectiveness of transfer learning approaches in medical image analysis.

1.2.1 Data loader

Load data from https://www.kaggle.com/datasets/bhaveshmittal/melanoma-cancer-dataset/data

for binary task, where

- 0 → 'Benign'
- 1 → 'Malignant'

Melanoma is class 1 (Malignant)

Folder structure (I put everything in 'data' folder):

data/

  train/

Benign/

Malignant/

test/

Benign/

Malignant/

[60]:
```python
# libraries
import tensorflow as tf
import os
import random
os.environ['TF_CPP_MIN_LOG_LEVEL'] = '2'
os.environ['CUDA_VISIBLE_DEVICES'] = ''
```

[62]:
```python
def load_dataset_simple_streamed(base_dir, img_size=(224, 224), batch_size=16):
    class_names = ['Benign', 'Malignant']
    label_map = {name: idx for idx, name in enumerate(class_names)}

    all_image_paths = []
    all_labels = []

    # Combine all images from train/ and test/ folders
    for subset in ['train', 'test']:
        for class_name in class_names:
            folder = os.path.join(base_dir, subset, class_name)
            label = label_map[class_name]

            for fname in os.listdir(folder):
                if fname.endswith('.jpg'):
                    all_image_paths.append(os.path.join(folder, fname))
                    all_labels.append(label)

    # Shuffle together
    combined = list(zip(all_image_paths, all_labels))
    random.seed(42)
    random.shuffle(combined)
    all_image_paths, all_labels = zip(*combined)

    # Create tf.data.Dataset from paths and labels
    path_ds = tf.data.Dataset.from_tensor_slices(list(all_image_paths))
    label_ds = tf.data.Dataset.from_tensor_slices(list(all_labels))

    def load_and_preprocess(path, label):
        image = tf.io.read_file(path)
        image = tf.image.decode_jpeg(image, channels=3)
```

```
        image = tf.image.resize(image, img_size)
        image = tf.cast(image, tf.float32) / 255.0  # normalization
        return image, label

    full_ds = tf.data.Dataset.zip((path_ds, label_ds))
    full_ds = full_ds.map(load_and_preprocess, num_parallel_calls=tf.data.
↪AUTOTUNE)

    # Split into 70/15/15
    total = len(all_image_paths)
    train_size = int(0.7 * total)
    val_size = int(0.15 * total)

    train_ds = full_ds.take(train_size).batch(batch_size).prefetch(tf.data.
↪AUTOTUNE)
    val_ds = full_ds.skip(train_size).take(val_size).batch(batch_size).
↪prefetch(tf.data.AUTOTUNE)
    test_ds = full_ds.skip(train_size + val_size).batch(batch_size).prefetch(tf.
↪data.AUTOTUNE)

    return train_ds, val_ds, test_ds, class_names
```

[27]:
```
train_ds, val_ds, test_ds, class_names = load_dataset_simple_streamed("data")
```

[29]:
```
for images, labels in train_ds.take(1):
    print("Train batch shape:", images.shape, labels.shape)

for images, labels in val_ds.take(1):
    print("Val batch shape:", images.shape, labels.shape)

for images, labels in test_ds.take(1):
    print("Test batch shape:", images.shape, labels.shape)
```

```
Train batch shape: (16, 224, 224, 3) (16,)
Val batch shape: (16, 224, 224, 3) (16,)
Test batch shape: (16, 224, 224, 3) (16,)
```

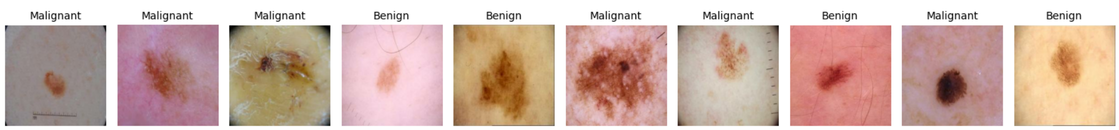
[31]:
```
def count_samples(ds):
    return sum(1 for _ in ds.unbatch())

print("Dataset sizes:")
print("Train size:", count_samples(train_ds))
print("Val size:  ", count_samples(val_ds))
print("Test size: ", count_samples(test_ds))
```

```
Dataset sizes:
Train size: 9715
Val size:   2081
```

```
Test size:  2083
```

[34]:
```python
import matplotlib.pyplot as plt

def plot_images_from_ds(ds, class_names=None, n=10):
    plt.figure(figsize=(15, 3))
    for i, (image, label) in enumerate(ds.unbatch().take(n)):
        plt.subplot(1, n, i + 1)
        plt.imshow(image.numpy())
        label_val = label.numpy()
        plt.title(class_names[label_val] if class_names else str(label_val),␣
 ↪fontsize=10)
        plt.axis('off')
    plt.tight_layout()
    plt.show()
```

[47]:
```python
plot_images_from_ds(train_ds, class_names)
```



[49]:
```python
# Check image size and dataset size
from PIL import Image
import os

for phase in ['train', 'test']:
    for label in ['Benign', 'Malignant']:
        path = f"./data/{phase}/{label}"
        sample_image = os.listdir(path)[0]
        with Image.open(os.path.join(path, sample_image)) as img:
            print(f"{phase}/{label} - Sample image size: {img.size}, Total␣
 ↪images: {len(os.listdir(path))}")
```

```
train/Benign - Sample image size: (224, 224), Total images: 6289
train/Malignant - Sample image size: (224, 224), Total images: 5590
test/Benign - Sample image size: (224, 224), Total images: 1000
test/Malignant - Sample image size: (224, 224), Total images: 1000
```

[53]:
```python
import numpy as np

def check_class_distribution_ds(train_ds, val_ds, test_ds, class_names):
    def get_counts(ds):
        labels = []
        for _, y in ds.unbatch():
```

```
            labels.append(int(y.numpy()))
        unique, counts = np.unique(labels, return_counts=True)
        return dict(zip(unique, counts)), len(labels)

    for name, ds in zip(['Train', 'Validation', 'Test'], [train_ds, val_ds,␣
↪test_ds]):
        counts, total = get_counts(ds)
        print(f"\n{name} set:")
        for i, cls in enumerate(class_names):
            count = counts.get(i, 0)
            print(f"  {cls}: {count} ({100 * count / total:.2f}%)")
```

[56]:
```
check_class_distribution_ds(train_ds, val_ds, test_ds, class_names)
```

```
Train set:
  Benign: 5087 (52.36%)
  Malignant: 4628 (47.64%)

Validation set:
  Benign: 1104 (53.05%)
  Malignant: 977 (46.95%)

Test set:
  Benign: 1098 (52.71%)
  Malignant: 985 (47.29%)
```

1.3 Model Architecture - MobileNetV2

MobileNetV2 is a lightweight and efficient convolutional neural network architecture proposed by Sandler et al. (2018), optimized for mobile and embedded vision applications. It introduces two key innovations: inverted residual blocks and linear bottlenecks, which significantly reduce computational cost and model size while preserving accuracy. Instead of traditional residual connections, MobileNetV2 expands the number of channels, applies depthwise separable convolutions, and then projects back to a lower-dimensional space—hence the term "inverted." This architecture maintains high representational power with fewer parameters, making it ideal for scenarios where computational efficiency is critical, such as mobile and edge devices.

In this project, I implemented and evaluated three configurations of the MobileNetV2 convolutional neural network, all based on a common architecture that utilized the pretrained MobileNetV2 backbone as a feature extractor. The base model was initialized with ImageNet weights and configured without the top classification layer (include_top=False). A custom classification head was appended to adapt the model for binary classification. All models were compiled using the Adam optimizer with a learning rate of 0.001, the binary cross-entropy loss function (suitable for binary classification tasks), and accuracy as the primary evaluation metric.

Architecture details:
- **Input Preprocessing:** Images resized to 224×224×3 and normalized to [0,1].
- **Backbone:** Pretrained MobileNetV2 (`weights='imagenet'`, `include_top=False`).

- **Custom Classification Head:**
- `GlobalAveragePooling2D`
- `Dense(128, activation='relu')`
- `Dropout(0.3)`
- `Dense(1, activation='sigmoid')`

Training setup:
- Optimizer: Adam (learning rate = 0.001)
- Loss function: Binary Cross-Entropy
- Metric: Accuracy

1.4 Experiments

Three experimental configurations were tested to evaluate the effect of transfer learning and fine-tuning:
1. **Fully frozen base model**
2. **Partially fine-tuned base model (last 30 layers unfrozen)**
3. **Fine-tuned base with data augmentation**

1.4.1 1. Fully frozen base model with custom classification head

[74]:
```
from tensorflow.keras.applications import MobileNetV2
from tensorflow.keras import layers, models

# Load pretrained MobileNetV2 base
base_model = MobileNetV2(input_shape=(224, 224, 3), include_top=False,␣
 ↪weights='imagenet')
base_model.trainable = False  # Freeze all layers

# Add custom classification head
model = models.Sequential([
    base_model,
    layers.GlobalAveragePooling2D(),
    layers.Dense(128, activation='relu'),
    layers.Dropout(0.3),
    layers.Dense(1, activation='sigmoid')  # Binary classification
])
```

[76]:
```
model.summary()
```

```
Model: "sequential_1"


 Layer (type)                        Output Shape                 Param #

 mobilenetv2_1.00_224                (None, 7, 7, 1280)         2,257,984
 (Functional)
```

```
 global_average_pooling2d_1       (None, 1280)                     0
 (GlobalAveragePooling2D)

 dense_2 (Dense)                  (None, 128)                163,968

 dropout_1 (Dropout)              (None, 128)                      0

 dense_3 (Dense)                  (None, 1)                      129
```

Total params: 2,422,081 (9.24 MB)

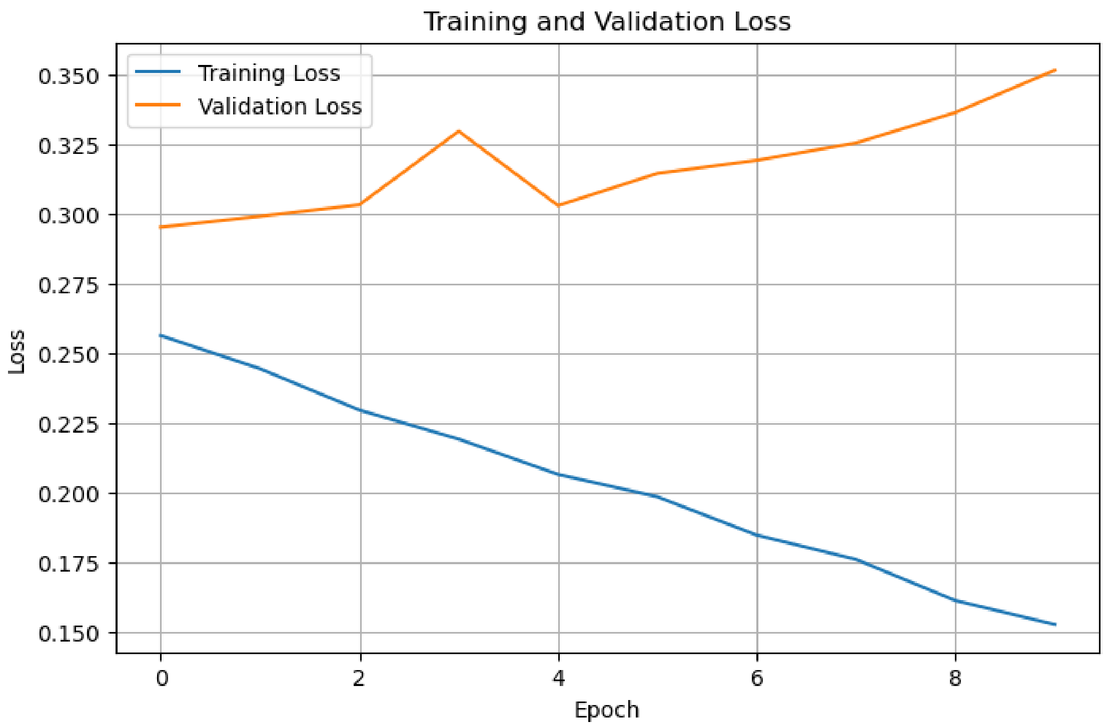
Trainable params: 164,097 (641.00 KB)

Non-trainable params: 2,257,984 (8.61 MB)

[96]:
```
model.compile(
    optimizer='adam',
    loss='binary_crossentropy',
    metrics=['accuracy']
)
```

[108]:
```
import matplotlib.pyplot as plt

# Train the model
start_train = time.time()
history = model.fit(
    train_ds,
    validation_data=val_ds,
    epochs=10
)
end_train = time.time()
train_duration = end_train - start_train
print(f"\n Training time: {train_duration:.2f} seconds")

# Plot training & validation loss
plt.figure(figsize=(8, 5))
plt.plot(history.history['loss'], label='Training Loss')
plt.plot(history.history['val_loss'], label='Validation Loss')
plt.xlabel('Epoch')
plt.ylabel('Loss')
plt.title('Training and Validation Loss')
plt.legend()
plt.grid(True)
plt.show()
```

```
Epoch 1/10
608/608            67s 110ms/step -
accuracy: 0.8985 - loss: 0.2495 - val_accuracy: 0.8779 - val_loss: 0.2953
Epoch 2/10
608/608            69s 114ms/step -
accuracy: 0.9089 - loss: 0.2335 - val_accuracy: 0.8698 - val_loss: 0.2992
Epoch 3/10
608/608            65s 107ms/step -
accuracy: 0.9112 - loss: 0.2248 - val_accuracy: 0.8693 - val_loss: 0.3033
Epoch 4/10
608/608            65s 108ms/step -
accuracy: 0.9154 - loss: 0.2133 - val_accuracy: 0.8698 - val_loss: 0.3298
Epoch 5/10
608/608            67s 111ms/step -
accuracy: 0.9193 - loss: 0.2015 - val_accuracy: 0.8784 - val_loss: 0.3031
Epoch 6/10
608/608            67s 111ms/step -
accuracy: 0.9240 - loss: 0.1961 - val_accuracy: 0.8765 - val_loss: 0.3146
Epoch 7/10
608/608            67s 110ms/step -
accuracy: 0.9296 - loss: 0.1792 - val_accuracy: 0.8784 - val_loss: 0.3193
Epoch 8/10
608/608            66s 108ms/step -
accuracy: 0.9310 - loss: 0.1720 - val_accuracy: 0.8779 - val_loss: 0.3256
Epoch 9/10
608/608            66s 108ms/step -
accuracy: 0.9396 - loss: 0.1600 - val_accuracy: 0.8746 - val_loss: 0.3364
Epoch 10/10
608/608            66s 109ms/step -
accuracy: 0.9442 - loss: 0.1520 - val_accuracy: 0.8722 - val_loss: 0.3516

 Training time: 666.30 seconds
```



Evaluation

[121]:
```
import numpy as np
import matplotlib.pyplot as plt
import time
from sklearn.metrics import (
    confusion_matrix, ConfusionMatrixDisplay, classification_report,
    accuracy_score, f1_score, precision_score, recall_score
)

def evaluate_classification_model(model, train_ds, test_ds, class_names=None):
    def extract_labels(ds):
        y_true = []
        for _, label in ds.unbatch():
            y_true.append(int(label.numpy()))
        return np.array(y_true)

    def get_predictions(ds, label=""):
        start_predict = time.time()
        y_pred_probs = model.predict(ds, verbose=0).flatten()
        end_predict = time.time()

        predict_duration = end_predict - start_predict
```

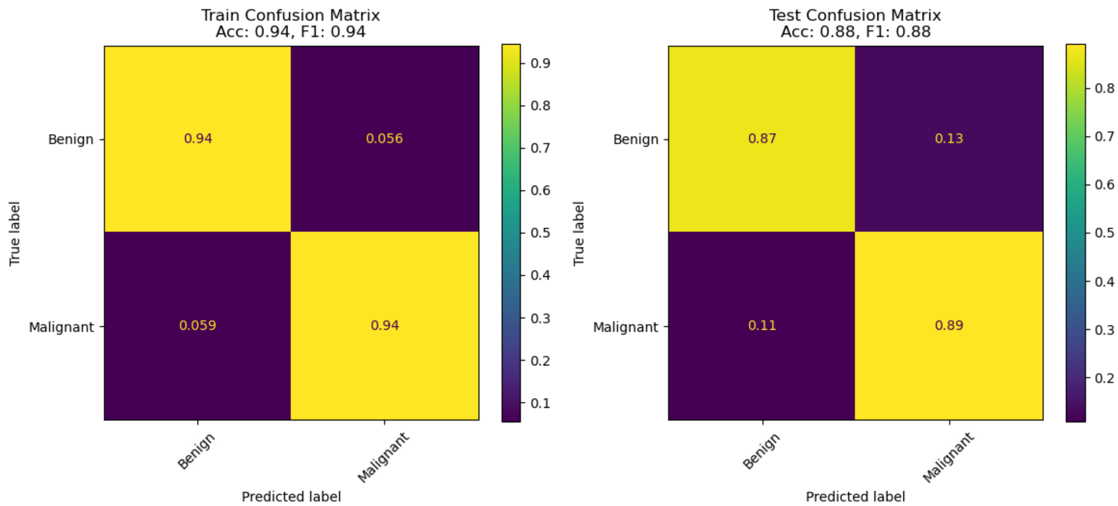
```
        print(f"\nPrediction time on {label} set: {predict_duration:.2f}␣
↪seconds")
        y_pred = (y_pred_probs > 0.5).astype(np.int64)
        return y_pred

    def evaluate(y_true, y_pred, label=""):
        acc = accuracy_score(y_true, y_pred)
        f1 = f1_score(y_true, y_pred)
        prec = precision_score(y_true, y_pred)
        rec = recall_score(y_true, y_pred)

        print(f"\n{label} SET METRICS")
        print(f"  Accuracy:       {acc:.4f}")
        print(f"  F1 Score:       {f1:.4f}")
        print(f"  Precision:      {prec:.4f}")
        print(f"  Recall:         {rec:.4f}")
        print(f"\nClassification Report ({label}):")
        print(classification_report(
            y_true, y_pred,
            target_names=class_names if class_names else None,
            zero_division=0
        ))

        return acc, f1, y_true, y_pred

    # Ground truth
    y_true_train = extract_labels(train_ds)
    y_true_test = extract_labels(test_ds)

    # Predictions
    y_pred_train = get_predictions(train_ds, "TRAIN" )
    y_pred_test = get_predictions(test_ds,  "TEST")

    # Evaluate
    train_acc, train_f1, y_train, y_train_pred = evaluate(y_true_train,␣
↪y_pred_train, "TRAIN")
    test_acc, test_f1, y_test, y_test_pred = evaluate(y_true_test, y_pred_test,␣
↪"TEST")

    # Plot confusion matrices
    fig, (ax1, ax2) = plt.subplots(1, 2, figsize=(12, 5))

    ConfusionMatrixDisplay.from_predictions(
        y_train, y_train_pred,
        normalize='true', ax=ax1, display_labels=class_names
    )
```

```
    ax1.set_title(f'Train Confusion Matrix\nAcc: {train_acc:.2f}, F1: {train_f1:
↪.2f}')
    ax1.tick_params(axis='x', rotation=45)

    ConfusionMatrixDisplay.from_predictions(
        y_test, y_test_pred,
        normalize='true', ax=ax2, display_labels=class_names
    )
    ax2.set_title(f'Test Confusion Matrix\nAcc: {test_acc:.2f}, F1: {test_f1:.
↪2f}')
    ax2.tick_params(axis='x', rotation=45)

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

[123]:
```
evaluate_classification_model(model, train_ds, test_ds, class_names=['Benign',␣
↪'Malignant'])
```

```
Prediction time on TRAIN set: 52.40 seconds

Prediction time on TEST set: 12.16 seconds

TRAIN SET METRICS
  Accuracy:       0.9425
  F1 Score:       0.9397
  Precision:      0.9386
  Recall:         0.9408

Classification Report (TRAIN):
              precision    recall  f1-score   support

      Benign       0.95      0.94      0.94      5087
   Malignant       0.94      0.94      0.94      4628

    accuracy                           0.94      9715
   macro avg       0.94      0.94      0.94      9715
weighted avg       0.94      0.94      0.94      9715


TEST SET METRICS
  Accuracy:       0.8805
  F1 Score:       0.8757
  Precision:      0.8615
  Recall:         0.8904

Classification Report (TEST):
              precision    recall  f1-score   support
```

```
      Benign       0.90      0.87      0.88      1098
   Malignant       0.86      0.89      0.88       985

    accuracy                           0.88      2083
   macro avg       0.88      0.88      0.88      2083
weighted avg       0.88      0.88      0.88      2083
```



[129]:
```
model.save_weights("fine_tuned_final.weights.h5")
```

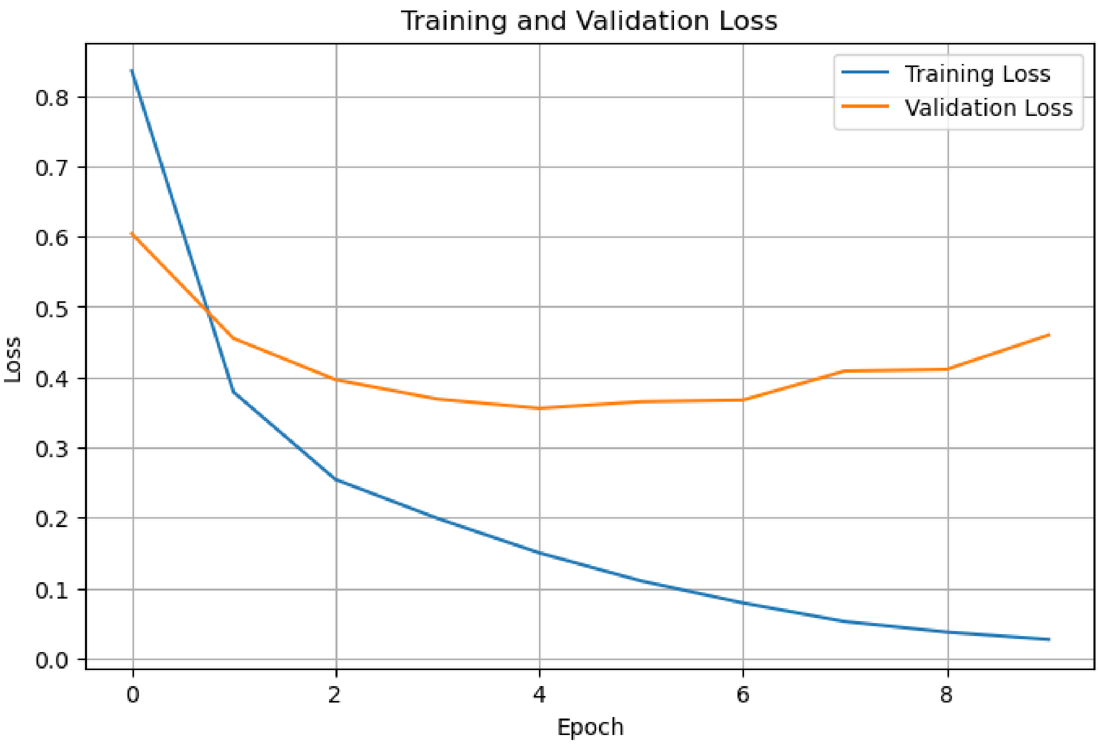
1.4.2 2. Partially fine-tuned base model (last 30 layers unfrozen)

[131]:
```
# Unfreeze from a specific layer
base_model.trainable = True
for layer in base_model.layers[:-30]:  # Freeze all except last 30
    layer.trainable = False

# Recompile
model.compile(
    optimizer=tf.keras.optimizers.Adam(1e-5), #smaller learning rate
    loss='binary_crossentropy',
    metrics=['accuracy']
)

# Fine-tune
start_train = time.time()
history_finetune = model.fit(
    train_ds,
    validation_data=val_ds,
```

```python
    epochs=10
)
end_train = time.time()
train_duration = end_train - start_train
print(f"\n Training time: {train_duration:.2f} seconds")

# Plot training & validation loss
plt.figure(figsize=(8, 5))
plt.plot(history_finetune.history['loss'], label='Training Loss')
plt.plot(history_finetune.history['val_loss'], label='Validation Loss')
plt.xlabel('Epoch')
plt.ylabel('Loss')
plt.title('Training and Validation Loss')
plt.legend()
plt.grid(True)
plt.show()
```

```
Epoch 1/10
608/608            93s 148ms/step -
accuracy: 0.7542 - loss: 1.2247 - val_accuracy: 0.8496 - val_loss: 0.6041
Epoch 2/10
608/608            89s 146ms/step -
accuracy: 0.8563 - loss: 0.3947 - val_accuracy: 0.8611 - val_loss: 0.4549
Epoch 3/10
608/608            90s 148ms/step -
accuracy: 0.9014 - loss: 0.2504 - val_accuracy: 0.8693 - val_loss: 0.3964
Epoch 4/10
608/608            90s 148ms/step -
accuracy: 0.9178 - loss: 0.2014 - val_accuracy: 0.8731 - val_loss: 0.3688
Epoch 5/10
608/608            89s 147ms/step -
accuracy: 0.9369 - loss: 0.1517 - val_accuracy: 0.8751 - val_loss: 0.3557
Epoch 6/10
608/608            89s 147ms/step -
accuracy: 0.9574 - loss: 0.1113 - val_accuracy: 0.8746 - val_loss: 0.3651
Epoch 7/10
608/608            88s 145ms/step -
accuracy: 0.9692 - loss: 0.0830 - val_accuracy: 0.8779 - val_loss: 0.3674
Epoch 8/10
608/608            88s 146ms/step -
accuracy: 0.9838 - loss: 0.0549 - val_accuracy: 0.8803 - val_loss: 0.4086
Epoch 9/10
608/608            90s 148ms/step -
accuracy: 0.9871 - loss: 0.0395 - val_accuracy: 0.8789 - val_loss: 0.4109
Epoch 10/10
608/608            92s 151ms/step -
accuracy: 0.9926 - loss: 0.0282 - val_accuracy: 0.8770 - val_loss: 0.4598
```

```
Training time: 898.50 seconds
```

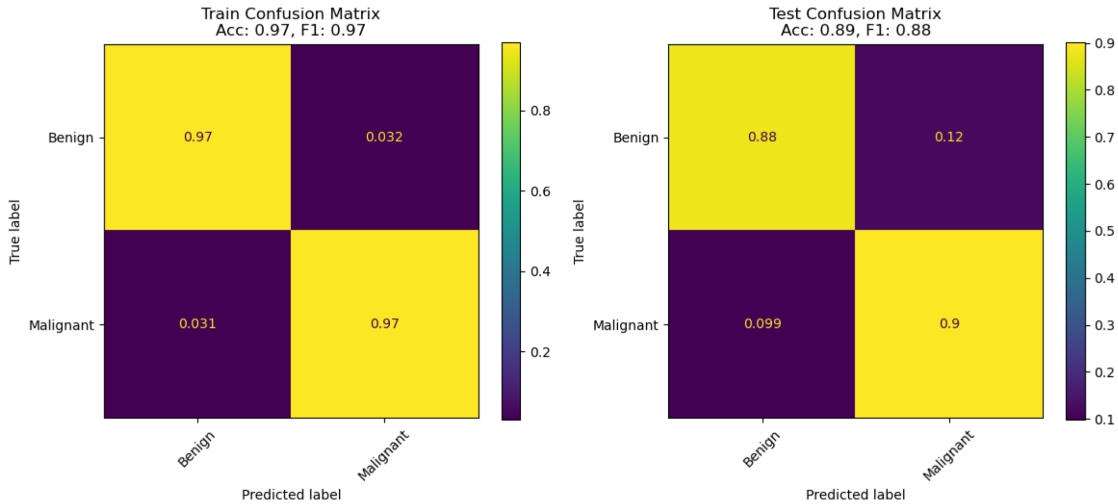


Evaluation

[133]:
```
evaluate_classification_model(model, train_ds, test_ds, class_names=['Benign',
    'Malignant'])
```

```
2025-05-28 16:27:01.920955: I tensorflow/core/framework/local_rendezvous.cc:407]
Local rendezvous is aborting with status: OUT_OF_RANGE: End of sequence


Prediction time on TRAIN set: 53.78 seconds

Prediction time on TEST set: 12.14 seconds

TRAIN SET METRICS
  Accuracy:       0.9686
  F1 Score:       0.9671
  Precision:      0.9653
  Recall:         0.9689

Classification Report (TRAIN):
              precision    recall  f1-score   support


      Benign       0.97      0.97      0.97      5087
```

```
   Malignant       0.97      0.97      0.97      4628

    accuracy                           0.97      9715
   macro avg       0.97      0.97      0.97      9715
weighted avg       0.97      0.97      0.97      9715


TEST SET METRICS
  Accuracy:       0.8891
  F1 Score:       0.8848
  Precision:      0.8696
  Recall:         0.9005

Classification Report (TEST):
              precision    recall  f1-score   support

      Benign       0.91      0.88      0.89      1098
   Malignant       0.87      0.90      0.88       985

    accuracy                           0.89      2083
   macro avg       0.89      0.89      0.89      2083
weighted avg       0.89      0.89      0.89      2083
```



[135]:
```
model.save_weights("unfreezed_final.weights.h5")
```

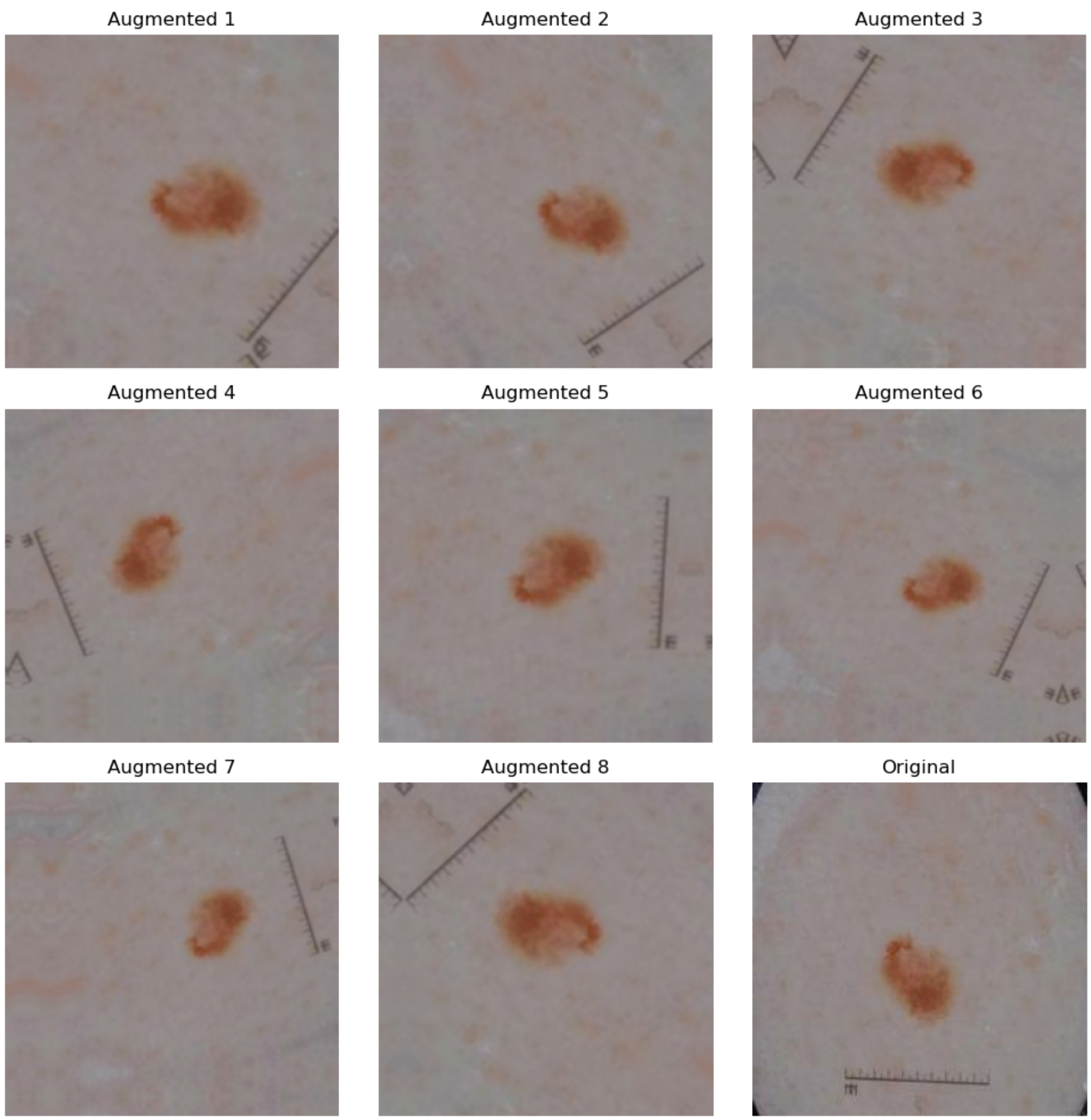
1.4.3 3. Fine-tuned base with data augmentation

[137]:
```
from tensorflow.keras.callbacks import EarlyStopping, ReduceLROnPlateau

early_stop = EarlyStopping(
    monitor='val_loss',
    patience=10,
    restore_best_weights=True
)

reduce_lr = ReduceLROnPlateau(
    monitor='val_loss',
    factor=0.5,
    patience=5,
    min_lr=1e-6
)
```

Augmentation

[167]:
```
import tensorflow as tf
import matplotlib.pyplot as plt
from tensorflow.keras import layers

# Define augmentation
data_augmentation = tf.keras.Sequential([
    layers.RandomFlip("horizontal_and_vertical"), # Randomly flips images␣
 ↪horizontally and vertically
    layers.RandomRotation(0.5), # Rotates images randomly by up to 50% of 360°
    layers.RandomZoom(0.2), #        Zooms in or out randomly by up to 20%
    layers.RandomTranslation(0.1, 0.1), #Shifts image horizontally and␣
 ↪vertically by 10%
])

# Get a sample image from train_ds
for images, labels in train_ds.take(1):
    sample_image = images[0]
    break

# Plot 8 augmented + 1 original
plt.figure(figsize=(10, 10))
for i in range(9):
    ax = plt.subplot(3, 3, i + 1)

    if i < 8:
        # Force training=True so augmentations apply
        augmented_img = data_augmentation(tf.expand_dims(sample_image, 0),␣
 ↪training=True)[0]
        img = tf.clip_by_value(augmented_img, 0.0, 1.0)
```

```
        title = f"Augmented {i + 1}"
    else:
        img = sample_image
        title = "Original"

    plt.imshow(img.numpy())
    plt.title(title)
    plt.axis("off")

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



Adding augmentation layer

[169]:
```
from tensorflow.keras.applications import MobileNetV2
from tensorflow.keras import layers, models

# Load pretrained MobileNetV2 base
base_model = MobileNetV2(input_shape=(224, 224, 3), include_top=False,␣
 ↪weights='imagenet')
base_model.trainable = False  # Freeze all layers

# Add custom classification head
model = models.Sequential([
    data_augmentation,
    base_model,
    layers.GlobalAveragePooling2D(),
    layers.Dense(128, activation='relu'),
    layers.Dropout(0.3),
    layers.Dense(1, activation='sigmoid')  # Binary classification
])
```

[171]:
```
model.summary()
```

Model: "sequential_10"

Layer (type)	Output Shape	Param #
sequential_9 (Sequential)	(1, 224, 224, 3)	0
mobilenetv2_1.00_224 (Functional)	(1, 7, 7, 1280)	2,257,984
global_average_pooling2d_2 (GlobalAveragePooling2D)	(1, 1280)	0
dense_4 (Dense)	(1, 128)	163,968
dropout_2 (Dropout)	(1, 128)	0
dense_5 (Dense)	(1, 1)	129

Total params: 2,422,081 (9.24 MB)

Trainable params: 164,097 (641.00 KB)

Non-trainable params: 2,257,984 (8.61 MB)

[173]:
```python
import matplotlib.pyplot as plt
import time

# Unfreeze from a specific layer
base_model.trainable = True
for layer in base_model.layers[:-30]:  # Freeze all except last 30
    layer.trainable = False

# Recompile
model.compile(
    optimizer=tf.keras.optimizers.Adam(1e-5), #smaller learning rate
    loss='binary_crossentropy',
    metrics=['accuracy']
)

batch_size=64
# Fine-tune
start_train = time.time()
history_finetune = model.fit(
    train_ds,
    validation_data=val_ds,
    epochs=30,
    callbacks=[early_stop]
)

end_train = time.time()
train_duration = end_train - start_train
print(f"\n Training time: {train_duration:.2f} seconds")

# Plot training & validation loss
plt.figure(figsize=(8, 5))
plt.plot(history_finetune.history['loss'], label='Training Loss')
plt.plot(history_finetune.history['val_loss'], label='Validation Loss')
plt.xlabel('Epoch')
plt.ylabel('Loss')
plt.title('Training and Validation Loss')
plt.legend()
plt.grid(True)
plt.show()
```

```
Epoch 1/30
608/608             94s 149ms/step -
accuracy: 0.6815 - loss: 0.5764 - val_accuracy: 0.7876 - val_loss: 0.4327
Epoch 2/30
608/608             90s 147ms/step -
accuracy: 0.8049 - loss: 0.4169 - val_accuracy: 0.8275 - val_loss: 0.3702
```

```
Epoch 3/30
608/608              94s 155ms/step -
accuracy: 0.8233 - loss: 0.3881 - val_accuracy: 0.8496 - val_loss: 0.3401
Epoch 4/30
608/608              94s 155ms/step -
accuracy: 0.8335 - loss: 0.3733 - val_accuracy: 0.8525 - val_loss: 0.3298
Epoch 5/30
608/608              95s 156ms/step -
accuracy: 0.8501 - loss: 0.3554 - val_accuracy: 0.8544 - val_loss: 0.3298
Epoch 6/30
608/608              96s 158ms/step -
accuracy: 0.8541 - loss: 0.3390 - val_accuracy: 0.8467 - val_loss: 0.3319
Epoch 7/30
608/608              97s 160ms/step -
accuracy: 0.8540 - loss: 0.3341 - val_accuracy: 0.8578 - val_loss: 0.3188
Epoch 8/30
608/608              95s 157ms/step -
accuracy: 0.8567 - loss: 0.3292 - val_accuracy: 0.8587 - val_loss: 0.3135
Epoch 9/30
608/608              93s 153ms/step -
accuracy: 0.8617 - loss: 0.3198 - val_accuracy: 0.8630 - val_loss: 0.3062
Epoch 10/30
608/608              92s 152ms/step -
accuracy: 0.8645 - loss: 0.3162 - val_accuracy: 0.8635 - val_loss: 0.3071
Epoch 11/30
608/608              94s 154ms/step -
accuracy: 0.8734 - loss: 0.3069 - val_accuracy: 0.8597 - val_loss: 0.3122
Epoch 12/30
608/608              93s 153ms/step -
accuracy: 0.8672 - loss: 0.3056 - val_accuracy: 0.8606 - val_loss: 0.3112
Epoch 13/30
608/608              95s 156ms/step -
accuracy: 0.8717 - loss: 0.3020 - val_accuracy: 0.8630 - val_loss: 0.3061
Epoch 14/30
608/608              93s 153ms/step -
accuracy: 0.8749 - loss: 0.2951 - val_accuracy: 0.8717 - val_loss: 0.2946
Epoch 15/30
608/608              94s 155ms/step -
accuracy: 0.8765 - loss: 0.2910 - val_accuracy: 0.8640 - val_loss: 0.3057
Epoch 16/30
608/608              95s 155ms/step -
accuracy: 0.8842 - loss: 0.2777 - val_accuracy: 0.8707 - val_loss: 0.2974
Epoch 17/30
608/608              94s 155ms/step -
accuracy: 0.8840 - loss: 0.2815 - val_accuracy: 0.8717 - val_loss: 0.2927
Epoch 18/30
608/608              94s 155ms/step -
accuracy: 0.8865 - loss: 0.2727 - val_accuracy: 0.8640 - val_loss: 0.3038
```

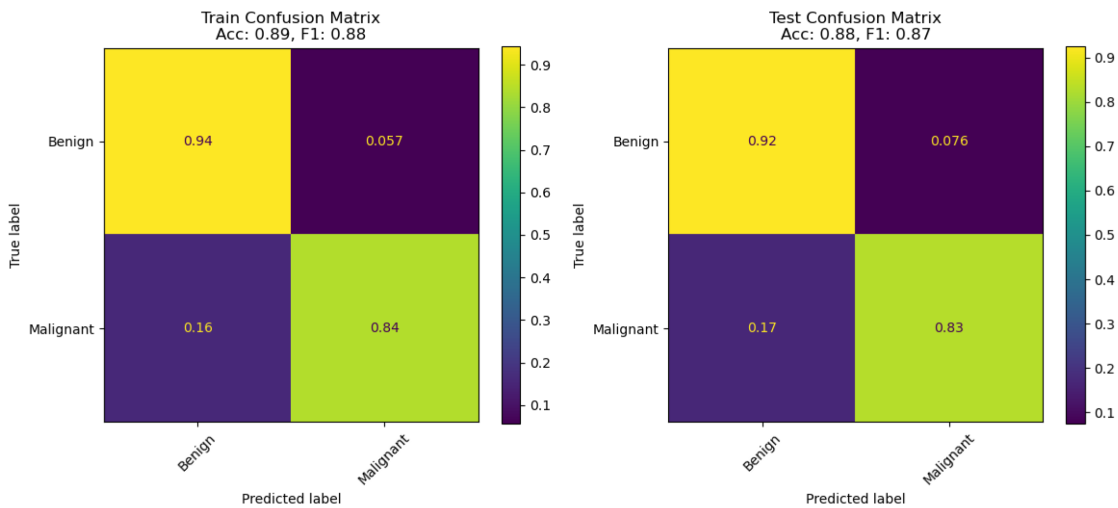
```
Epoch 19/30
608/608             93s 153ms/step -
accuracy: 0.8858 - loss: 0.2731 - val_accuracy: 0.8626 - val_loss: 0.3101
Epoch 20/30
608/608             95s 156ms/step -
accuracy: 0.8871 - loss: 0.2663 - val_accuracy: 0.8779 - val_loss: 0.2887
Epoch 21/30
608/608             92s 151ms/step -
accuracy: 0.8870 - loss: 0.2653 - val_accuracy: 0.8799 - val_loss: 0.2802
Epoch 22/30
608/608             94s 154ms/step -
accuracy: 0.8921 - loss: 0.2590 - val_accuracy: 0.8659 - val_loss: 0.3165
Epoch 23/30
608/608             94s 155ms/step -
accuracy: 0.8935 - loss: 0.2519 - val_accuracy: 0.8784 - val_loss: 0.2953
Epoch 24/30
608/608             94s 155ms/step -
accuracy: 0.8906 - loss: 0.2568 - val_accuracy: 0.8760 - val_loss: 0.2915
Epoch 25/30
608/608             93s 153ms/step -
accuracy: 0.9007 - loss: 0.2462 - val_accuracy: 0.8707 - val_loss: 0.3074
Epoch 26/30
608/608             92s 152ms/step -
accuracy: 0.8924 - loss: 0.2516 - val_accuracy: 0.8794 - val_loss: 0.2860
Epoch 27/30
608/608             92s 151ms/step -
accuracy: 0.9007 - loss: 0.2465 - val_accuracy: 0.8775 - val_loss: 0.2917
Epoch 28/30
608/608             91s 150ms/step -
accuracy: 0.8998 - loss: 0.2363 - val_accuracy: 0.8760 - val_loss: 0.3003
Epoch 29/30
608/608             93s 153ms/step -
accuracy: 0.9075 - loss: 0.2290 - val_accuracy: 0.8827 - val_loss: 0.2803
Epoch 30/30
608/608             94s 155ms/step -
accuracy: 0.9030 - loss: 0.2386 - val_accuracy: 0.8799 - val_loss: 0.2907

 Training time: 2809.18 seconds
```

Evaluation

[182]:
```
evaluate_classification_model(model, train_ds, test_ds, class_names=['Benign',␣
↪'Malignant'])
```

```
Prediction time on TRAIN set: 50.10 seconds

Prediction time on TEST set: 11.14 seconds

TRAIN SET METRICS
  Accuracy:        0.8938
  F1 Score:        0.8828
  Precision:       0.9301
  Recall:          0.8401

Classification Report (TRAIN):
              precision    recall  f1-score   support

      Benign       0.87      0.94      0.90      5087
   Malignant       0.93      0.84      0.88      4628

    accuracy                           0.89      9715
   macro avg       0.90      0.89      0.89      9715
```

```
weighted avg       0.90      0.89      0.89      9715


TEST SET METRICS
  Accuracy:       0.8805
  F1 Score:       0.8680
  Precision:      0.9080
  Recall:         0.8315

Classification Report (TEST):
              precision    recall  f1-score   support

      Benign       0.86      0.92      0.89      1098
   Malignant       0.91      0.83      0.87       985

    accuracy                           0.88      2083
   macro avg       0.88      0.88      0.88      2083
weighted avg       0.88      0.88      0.88      2083
```



[184]:
```python
model.save_weights("unfreezed_augmented_final.weights.h5")
```

1.5 Conclusion

We evaluated three different transfer learning strategies with MobileNetV2 for melanoma classification. The results are summarized below:

Configuration	Epochs	Accuracy	F1-score	Recall (Malignant)
Frozen MobileNetV2 base + custom head	10	**88.05%**	0.8757	0.89

Configuration	Epochs	Accuracy	F1-score	Recall (Malignant)
Partially fine-tuned MobileNetV2 (last 30 layers unfrozen)	10	**88.91%**	0.8848	**0.90**
Fine-tuned MobileNetV2 with data augmentation	30	**88.05%**	0.8680	0.83

1.5.1 Analysis

- The **frozen base model with only a custom classification head** produced a strong baseline, transferring general ImageNet features but showing limited adaptation to the unique visual characteristics of melanoma lesions.

- The **partially fine-tuned model (last 30 layers unfrozen)** provided the best results. Allowing deeper layers to adapt to lesion-specific features improved generalization and delivered the highest recall, which is especially critical for medical applications where false negatives must be minimized.

- The **fine-tuned model with additional data augmentation**, even when trained for longer, demonstrated steady learning but did not surpass the selectively fine-tuned configuration. The increased complexity and regularization from augmentation likely slowed convergence and reduced sensitivity to malignant cases.

1.5.2 Final Conclusion

Among the three strategies, the **partially fine-tuned MobileNetV2** demonstrated the most effective trade-off between accuracy, F1-score, and recall. This highlights the importance of selective fine-tuning in transfer learning, as it allows the model to adapt deeper layers to domain-specific features without over-regularization. For melanoma detection tasks, where minimizing false negatives is critical, this configuration provides the most reliable results.

1.6 Contributions

This project contributes by:
- Applying and comparing three distinct MobileNetV2 configurations on a curated melanoma dataset.
- Emphasizing **recall** as a critical metric for clinical tasks.
- Analyzing the impact of **layer unfreezing, data augmentation, and training duration**.
- Providing practical insights for deploying lightweight CNNs in sensitive domains like dermatology.