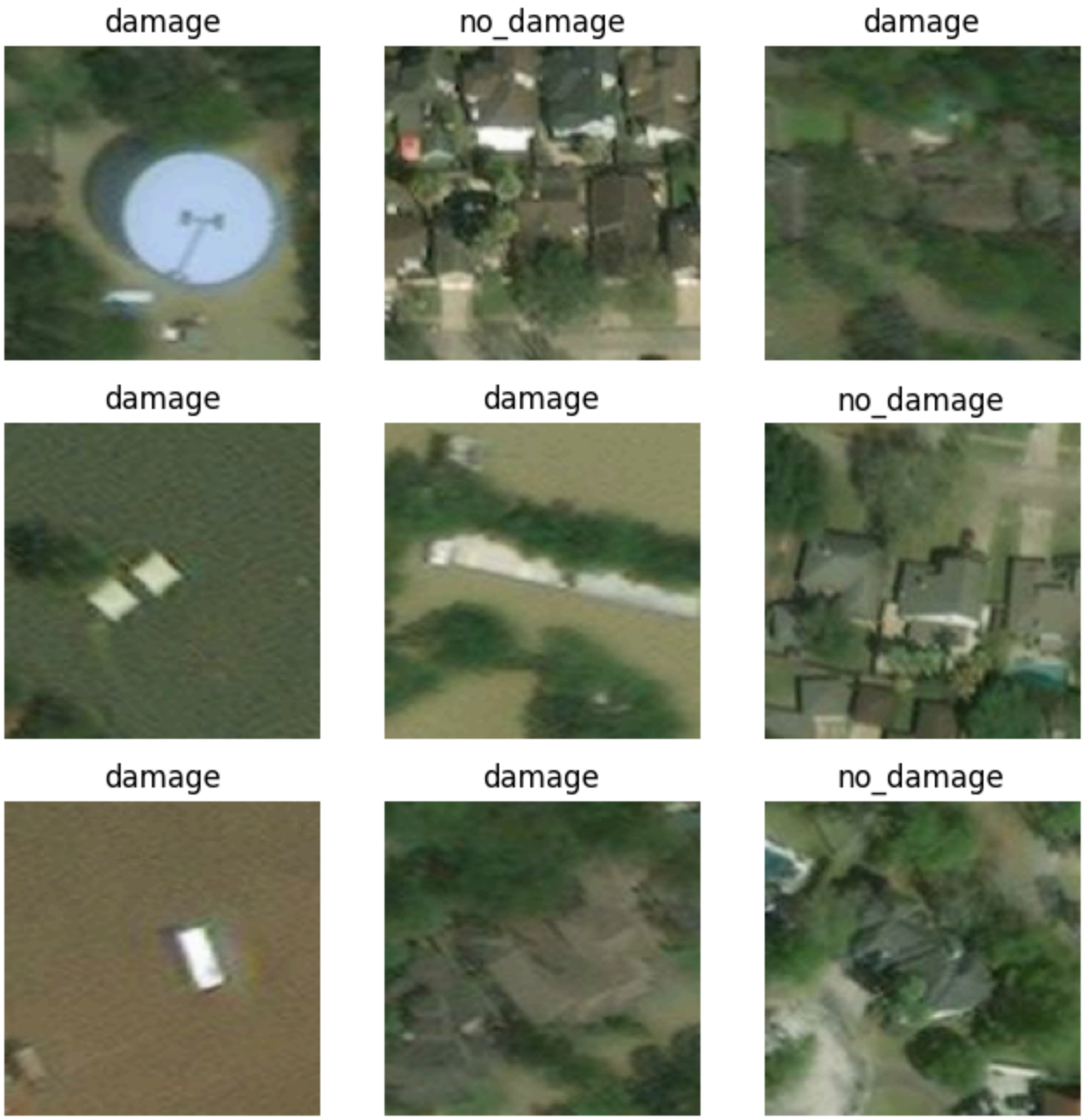
In [92]:
```
import numpy as np
import matplotlib.pyplot as plt
import tensorflow as tf
from tensorflow.keras.preprocessing import image_dataset_from_directory
from tensorflow.data import AUTOTUNE
from tensorflow.keras import layers
from tensorflow.keras.applications.vgg16 import preprocess_input
from tensorflow.keras.applications import VGG16, VGG19
from tensorflow.keras.callbacks import EarlyStopping, ReduceLROnPlateau
from sklearn.metrics import f1_score
from sklearn.utils.class_weight import compute_class_weight
```

In [69]:
```
data_dir = 'datasets-unit03_Project2'
train_ds = image_dataset_from_directory(
  data_dir,
  validation_split=0.2,
  subset='training',
  seed=42,
  image_size=(128, 128),
  batch_size=32
)
val_ds = image_dataset_from_directory(
  data_dir,
  validation_split=0.2,
  subset='validation',
  seed=42,
  image_size=(128, 128),
  batch_size=32
)
val_batches = tf.data.experimental.cardinality(val_ds)
test_ds = val_ds.take(val_batches // 2)
val_ds = val_ds.skip(val_batches // 2)

print(f'Class names: {train_ds.class_names}')

for images, labels in train_ds.take(1):
  print('Image batch shape:', images.shape)
  print('Label batch shape:', labels.shape)

damage_count = 0
```

```
no_damage_count = 0

for _, labels in train_ds:
  damage_count += np.sum(labels.numpy() == 0)
  no_damage_count += np.sum(labels.numpy() == 1)

total = damage_count + no_damage_count
print(f"damage: {damage_count} images ({damage_count / total * 100:.2f}%)")
print(f"no_damage: {no_damage_count} images ({no_damage_count / total * 100:.2f}%)")

class_weights_arr = compute_class_weight(
  class_weight='balanced',
  classes=np.array([0, 1]),
  y=[0] * damage_count + [1] * no_damage_count
)
class_weights = dict(enumerate(class_weights_arr))

plt.figure(figsize=(8, 8))
for images, labels in train_ds.take(1):
  for i in range(9):
    ax = plt.subplot(3, 3, i + 1)
    plt.imshow(images[i].numpy().astype('uint8'))
    plt.title(train_ds.class_names[labels[i]])
    plt.axis('off')
plt.show()
```

```
Found 21322 files belonging to 2 classes.
Using 17058 files for training.
Found 21322 files belonging to 2 classes.
Using 4264 files for validation.
Class names: ['damage', 'no_damage']
Image batch shape: (32, 128, 128, 3)
Label batch shape: (32,)
damage: 11353 images (66.56%)
no_damage: 5705 images (33.44%)
```



In [71]:
```
def preprocess_grayscale_ann(ds):
    ds = ds.map(lambda x, y: (tf.image.rgb_to_grayscale(x) / 255.0, y))
```

```
    return ds

def preprocess_color_ann(ds):
    ds = ds.map(lambda x, y: (x / 255.0, y))
    return ds

light_aug = tf.keras.Sequential([
    layers.RandomRotation(0.05),
    layers.RandomBrightness(0.05)
])

moderate_aug = tf.keras.Sequential([
    layers.RandomRotation(0.05),
    layers.RandomTranslation(0.05, 0.05),
    layers.RandomBrightness(0.05)
])

heavy_aug = tf.keras.Sequential([
    layers.RandomFlip('horizontal'),
    layers.RandomRotation(0.1),
    layers.RandomZoom(0.1),
    layers.RandomBrightness(0.1)
])

def preprocess_lenet_no_aug(ds):
    ds = ds.map(lambda x, y: (tf.image.rgb_to_grayscale(x) / 255.0, y))
    ds = ds.map(lambda x, y: (tf.image.resize(x, [28, 28]), y))
    return ds

def preprocess_lenet_light_aug(ds):
    ds = preprocess_lenet_no_aug(ds)
    ds = ds.map(lambda x, y: (light_aug(x, training=True), y))
    return ds

def preprocess_lenet_moderate_aug(ds):
    ds = preprocess_lenet_no_aug(ds)
    ds = ds.map(lambda x, y: (moderate_aug(x, training=True), y))
    return ds

def preprocess_modified_lenet_no_aug(ds):
    ds = ds.map(lambda x, y: (x/255.0, y))
    ds = ds.map(lambda x, y: (tf.image.resize(x, [150, 150]), y))
```

```
    return ds

def preprocess_modified_lenet_light_aug(ds):
    ds = preprocess_modified_lenet_no_aug(ds)
    ds = ds.map(lambda x, y: (light_aug(x, training=True), y))
    return ds

def preprocess_modified_lenet_moderate_aug(ds):
    ds = preprocess_modified_lenet_no_aug(ds)
    ds = ds.map(lambda x, y: (moderate_aug(x, training=True), y))
    return ds

def preprocess_modified_lenet_heavy_aug(ds):
    ds = preprocess_modified_lenet_no_aug(ds)
    ds = ds.map(lambda x, y: (heavy_aug(x, training=True), y))
    return ds

def preprocess_vgg_no_aug(ds):
    ds = ds.map(lambda x, y: (tf.image.resize(x, [224, 224]), y))
    ds = ds.map(lambda x, y: (preprocess_input(x), y))
    return ds

def preprocess_vgg_light_aug(ds):
    ds = ds.map(lambda x, y: (tf.image.resize(x, [224, 224]), y))
    ds = ds.map(lambda x, y: (light_aug(x, training=True), y))
    ds = ds.map(lambda x, y: (preprocess_input(x), y))
    return ds

def preprocess_vgg_moderate_aug(ds):
    ds = ds.map(lambda x, y: (tf.image.resize(x, [224, 224]), y))
    ds = ds.map(lambda x, y: (moderate_aug(x, training=True), y))
    ds = ds.map(lambda x, y: (preprocess_input(x), y))
    return ds

def preprocess_vgg_heavy_aug(ds):
    ds = ds.map(lambda x, y: (tf.image.resize(x, [224, 224]), y))
    ds = ds.map(lambda x, y: (heavy_aug(x, training=True), y))
    ds = ds.map(lambda x, y: (preprocess_input(x), y))
    return ds
```

In [72]:

```
def cache(ds, shuffle=False):
  return ds.cache().shuffle(1000).prefetch(buffer_size=AUTOTUNE) if shuffle else ds.cache().prefetch(buffe
```

```
train_grayscale_ann_ds = cache(preprocess_grayscale_ann(train_ds), shuffle=True)
val_grayscale_ann_ds = cache(preprocess_grayscale_ann(val_ds))
test_grayscale_ann_ds = cache(preprocess_grayscale_ann(test_ds))

train_color_ann_ds = cache(preprocess_color_ann(train_ds), shuffle=True)
val_color_ann_ds = cache(preprocess_color_ann(val_ds))
test_color_ann_ds = cache(preprocess_color_ann(test_ds))

train_lenet_no_aug_ds = cache(preprocess_lenet_no_aug(train_ds), shuffle=True)
train_lenet_light_aug_ds = cache(preprocess_lenet_light_aug(train_ds), shuffle=True)
train_lenet_moderate_aug_ds = cache(preprocess_lenet_moderate_aug(train_ds), shuffle=True)
val_lenet_ds = cache(preprocess_lenet_no_aug(val_ds))
test_lenet_ds = cache(preprocess_lenet_no_aug(test_ds))

train_mod_lenet_no_aug_ds = cache(preprocess_modified_lenet_no_aug(train_ds), shuffle=True)
train_mod_lenet_light_aug_ds = cache(preprocess_modified_lenet_light_aug(train_ds), shuffle=True)
train_mod_lenet_moderate_aug_ds = cache(preprocess_modified_lenet_moderate_aug(train_ds), shuffle=True)
train_mod_lenet_heavy_aug_ds = cache(preprocess_modified_lenet_heavy_aug(train_ds), shuffle=True)
val_mod_lenet_ds = cache(preprocess_modified_lenet_no_aug(val_ds))
test_mod_lenet_ds = cache(preprocess_modified_lenet_no_aug(test_ds))

train_vgg_no_aug_ds = cache(preprocess_vgg_no_aug(train_ds), shuffle=True)
train_vgg_light_aug_ds = cache(preprocess_vgg_light_aug(train_ds), shuffle=True)
train_vgg_moderate_aug_ds = cache(preprocess_vgg_moderate_aug(train_ds), shuffle=True)
train_vgg_heavy_aug_ds = cache(preprocess_vgg_heavy_aug(train_ds), shuffle=True)
val_vgg_ds = cache(preprocess_vgg_no_aug(val_ds))
test_vgg_ds = cache(preprocess_vgg_no_aug(test_ds))
```

In [73]:

```
def create_grayscale_ann():
  model = tf.keras.Sequential([
    tf.keras.layers.Input(shape=(128, 128, 1)),
    tf.keras.layers.Flatten(),
    tf.keras.layers.Dense(512, activation='relu'),
    tf.keras.layers.Dense(128, activation='relu'),
    tf.keras.layers.Dense(1, activation='sigmoid')
  ])
  model.compile(optimizer='adam', loss='binary_crossentropy', metrics=['accuracy'])
  return model

def create_color_ann():
  model = tf.keras.Sequential([
```

```
    tf.keras.layers.Input(shape=(128, 128, 3)),
    tf.keras.layers.Flatten(),
    tf.keras.layers.Dense(1024, activation='relu'),
    tf.keras.layers.Dense(512, activation='relu'),
    tf.keras.layers.Dense(1, activation='sigmoid')
  ])
  model.compile(optimizer='adam', loss='binary_crossentropy', metrics=['accuracy'])
  return model

def create_lenet():
  model = tf.keras.Sequential([
    tf.keras.layers.Input(shape=(28, 28, 1)),
    tf.keras.layers.Conv2D(6, (5, 5), activation='tanh', padding='same'),
    tf.keras.layers.AveragePooling2D((2, 2)),
    tf.keras.layers.Conv2D(16, (5, 5), activation='tanh'),
    tf.keras.layers.AveragePooling2D((2, 2)),
    tf.keras.layers.Flatten(),
    tf.keras.layers.Dense(120, activation='tanh'),
    tf.keras.layers.Dense(84, activation='tanh'),
    tf.keras.layers.Dense(1, activation='sigmoid')
  ])
  model.compile(optimizer='adam', loss='binary_crossentropy', metrics=['accuracy'])
  return model

def create_modified_lenet():
  model = tf.keras.Sequential([
    tf.keras.layers.Input(shape=(150, 150, 3)),
    tf.keras.layers.Conv2D(32, (3, 3), activation='relu'),
    tf.keras.layers.MaxPooling2D((2, 2)),
    tf.keras.layers.Conv2D(64, (3, 3), activation='relu'),
    tf.keras.layers.MaxPooling2D((2, 2)),
    tf.keras.layers.Conv2D(128, (3, 3), activation='relu'),
    tf.keras.layers.MaxPooling2D((2, 2)),
    tf.keras.layers.Conv2D(128, (3, 3), activation='relu'),
    tf.keras.layers.MaxPooling2D((2, 2)),
    tf.keras.layers.Flatten(),
    tf.keras.layers.Dropout(0.5),
    tf.keras.layers.Dense(512, activation='relu'),
    tf.keras.layers.Dense(1, activation='sigmoid')
  ])
  model.compile(optimizer='adam', loss='binary_crossentropy', metrics=['accuracy'])
  return model
```

```
def create_vgg16():
  base_model = VGG16(weights='imagenet', include_top=False, input_shape=(224, 224, 3))
  base_model.trainable = False
  model = tf.keras.Sequential([
      base_model,
    tf.keras.layers.Flatten(),
    tf.keras.layers.Dense(512, activation='relu'),
    tf.keras.layers.Dropout(0.5),
    tf.keras.layers.Dense(1, activation='sigmoid')
  ])
  model.compile(optimizer='adam', loss='binary_crossentropy', metrics=['accuracy'])
  return model

def create_vgg19():
  base_model = VGG19(weights='imagenet', include_top=False, input_shape=(224, 224, 3))
  base_model.trainable = False
  model = tf.keras.Sequential([
      base_model,
    tf.keras.layers.Flatten(),
    tf.keras.layers.Dense(512, activation='relu'),
    tf.keras.layers.Dropout(0.5),
    tf.keras.layers.Dense(1, activation='sigmoid')
  ])
  model.compile(optimizer='adam', loss='binary_crossentropy', metrics=['accuracy'])
  return model
```

In [74]:

```
def train_model(model, train_ds, val_ds, test_ds):
    callbacks = [
        EarlyStopping(
            monitor='val_loss',
            patience=5,
            restore_best_weights=True
        )
    ]
    model.fit(
        train_ds,
        validation_data=val_ds,
        epochs=50,
        callbacks=callbacks,
        class_weight=class_weights
    )
```

```
    y_pred = model.predict(test_ds)
    y_pred_labels = (y_pred > 0.5).astype(int).flatten()
    print(f'Unique predictions: {np.unique(y_pred_labels, return_counts=True)}')
    y_true = np.concatenate([y for _, y in test_ds], axis=0).flatten()
    f1 = f1_score(y_true, y_pred_labels)
    print(f'F1 score: {f1}')
    return model
```

In [75]:

```
train_model(create_grayscale_ann(), train_grayscale_ann_ds, val_grayscale_ann_ds, test_grayscale_ann_ds)
train_model(create_color_ann(), train_color_ann_ds, val_color_ann_ds, test_color_ann_ds)
```

```
Epoch 1/50
534/534 ━━━━━━━━━━━━━━━━━━━━ 10s 17ms/step - accuracy: 0.5517 - loss: 1.2005 - val_accuracy: 0.5774 - val_l
oss: 0.6621
Epoch 2/50
534/534 ━━━━━━━━━━━━━━━━━━━━ 8s 15ms/step - accuracy: 0.6175 - loss: 0.6515 - val_accuracy: 0.7184 - val_lo
ss: 0.6318
Epoch 3/50
534/534 ━━━━━━━━━━━━━━━━━━━━ 9s 17ms/step - accuracy: 0.6544 - loss: 0.6367 - val_accuracy: 0.7127 - val_lo
ss: 0.5894
Epoch 4/50
534/534 ━━━━━━━━━━━━━━━━━━━━ 9s 16ms/step - accuracy: 0.6687 - loss: 0.6590 - val_accuracy: 0.6670 - val_lo
ss: 0.6382
Epoch 5/50
534/534 ━━━━━━━━━━━━━━━━━━━━ 9s 17ms/step - accuracy: 0.6211 - loss: 0.6711 - val_accuracy: 0.5316 - val_lo
ss: 0.6701
Epoch 6/50
534/534 ━━━━━━━━━━━━━━━━━━━━ 9s 17ms/step - accuracy: 0.6049 - loss: 0.6716 - val_accuracy: 0.5401 - val_lo
ss: 0.6709
Epoch 7/50
534/534 ━━━━━━━━━━━━━━━━━━━━ 9s 17ms/step - accuracy: 0.6333 - loss: 0.6526 - val_accuracy: 0.6561 - val_lo
ss: 0.6392
Epoch 8/50
534/534 ━━━━━━━━━━━━━━━━━━━━ 9s 17ms/step - accuracy: 0.6538 - loss: 0.6464 - val_accuracy: 0.6575 - val_lo
ss: 0.6444
67/67 ━━━━━━━━━━━━━━━━━━━━ 0s 6ms/step
Unique predictions: (array([0, 1]), array([1893,  251]))
F1 score: 0.35907723169508526
Epoch 1/50
534/534 ━━━━━━━━━━━━━━━━━━━━ 42s 77ms/step - accuracy: 0.5408 - loss: 3.3136 - val_accuracy: 0.3382 - val_l
oss: 1.9206
Epoch 2/50
534/534 ━━━━━━━━━━━━━━━━━━━━ 41s 77ms/step - accuracy: 0.6203 - loss: 0.6643 - val_accuracy: 0.7514 - val_l
oss: 0.5564
Epoch 3/50
534/534 ━━━━━━━━━━━━━━━━━━━━ 41s 77ms/step - accuracy: 0.6900 - loss: 0.5959 - val_accuracy: 0.6005 - val_l
oss: 0.6839
Epoch 4/50
534/534 ━━━━━━━━━━━━━━━━━━━━ 42s 78ms/step - accuracy: 0.7187 - loss: 0.5612 - val_accuracy: 0.5500 - val_l
oss: 0.7623
Epoch 5/50
534/534 ━━━━━━━━━━━━━━━━━━━━ 41s 77ms/step - accuracy: 0.7292 - loss: 0.5524 - val_accuracy: 0.5976 - val_l
oss: 0.6896
```

```
Epoch 6/50
534/534 ━━━━━━━━━━━━━━━━━━━━ 42s 78ms/step - accuracy: 0.7295 - loss: 0.5499 - val_accuracy: 0.6142 - val_l
oss: 0.6754
Epoch 7/50
534/534 ━━━━━━━━━━━━━━━━━━━━ 41s 77ms/step - accuracy: 0.7270 - loss: 0.5527 - val_accuracy: 0.7467 - val_l
oss: 0.5418
Epoch 8/50
534/534 ━━━━━━━━━━━━━━━━━━━━ 41s 77ms/step - accuracy: 0.7489 - loss: 0.5310 - val_accuracy: 0.7472 - val_l
oss: 0.5242
Epoch 9/50
534/534 ━━━━━━━━━━━━━━━━━━━━ 41s 77ms/step - accuracy: 0.7501 - loss: 0.5374 - val_accuracy: 0.7736 - val_l
oss: 0.5100
Epoch 10/50
534/534 ━━━━━━━━━━━━━━━━━━━━ 41s 77ms/step - accuracy: 0.7587 - loss: 0.5207 - val_accuracy: 0.7783 - val_l
oss: 0.5050
Epoch 11/50
534/534 ━━━━━━━━━━━━━━━━━━━━ 41s 76ms/step - accuracy: 0.7622 - loss: 0.5194 - val_accuracy: 0.6774 - val_l
oss: 0.6046
Epoch 12/50
534/534 ━━━━━━━━━━━━━━━━━━━━ 41s 76ms/step - accuracy: 0.7551 - loss: 0.5237 - val_accuracy: 0.7731 - val_l
oss: 0.5187
Epoch 13/50
534/534 ━━━━━━━━━━━━━━━━━━━━ 41s 76ms/step - accuracy: 0.7700 - loss: 0.5018 - val_accuracy: 0.6321 - val_l
oss: 0.6882
Epoch 14/50
534/534 ━━━━━━━━━━━━━━━━━━━━ 41s 77ms/step - accuracy: 0.7629 - loss: 0.5127 - val_accuracy: 0.7882 - val_l
oss: 0.5080
Epoch 15/50
534/534 ━━━━━━━━━━━━━━━━━━━━ 41s 77ms/step - accuracy: 0.7706 - loss: 0.5073 - val_accuracy: 0.6264 - val_l
oss: 0.6823
67/67 ━━━━━━━━━━━━━━━━━━━━ 1s 14ms/step
Unique predictions: (array([0, 1]), array([1557,  587]))
F1 score: 0.6616654163540885
```

Out[75]: `<Sequential name=sequential_41, built=True>`

The above models had F1 scores of .36 and .66, respectively, which suggests that color carries important detail for these models.

In [76]:
```
train_model(create_lenet(), train_lenet_no_aug_ds, val_lenet_ds, test_lenet_ds)
```

```
Epoch 1/50
534/534 ━━━━━━━━━━━━━━━━━━━━ 4s 4ms/step - accuracy: 0.6310 - loss: 0.6436 - val_accuracy: 0.6948 - val_los
s: 0.5960
Epoch 2/50
534/534 ━━━━━━━━━━━━━━━━━━━━ 2s 4ms/step - accuracy: 0.6784 - loss: 0.6120 - val_accuracy: 0.6245 - val_los
s: 0.6506
Epoch 3/50
534/534 ━━━━━━━━━━━━━━━━━━━━ 2s 4ms/step - accuracy: 0.6756 - loss: 0.5927 - val_accuracy: 0.6892 - val_los
s: 0.5554
Epoch 4/50
534/534 ━━━━━━━━━━━━━━━━━━━━ 2s 4ms/step - accuracy: 0.6873 - loss: 0.5718 - val_accuracy: 0.6637 - val_los
s: 0.5964
Epoch 5/50
534/534 ━━━━━━━━━━━━━━━━━━━━ 2s 4ms/step - accuracy: 0.7086 - loss: 0.5525 - val_accuracy: 0.6613 - val_los
s: 0.5920
Epoch 6/50
534/534 ━━━━━━━━━━━━━━━━━━━━ 2s 4ms/step - accuracy: 0.7173 - loss: 0.5379 - val_accuracy: 0.7184 - val_los
s: 0.5443
Epoch 7/50
534/534 ━━━━━━━━━━━━━━━━━━━━ 2s 4ms/step - accuracy: 0.7359 - loss: 0.5285 - val_accuracy: 0.7368 - val_los
s: 0.5331
Epoch 8/50
534/534 ━━━━━━━━━━━━━━━━━━━━ 2s 4ms/step - accuracy: 0.7289 - loss: 0.5257 - val_accuracy: 0.7325 - val_los
s: 0.5368
Epoch 9/50
534/534 ━━━━━━━━━━━━━━━━━━━━ 2s 4ms/step - accuracy: 0.7511 - loss: 0.5038 - val_accuracy: 0.7283 - val_los
s: 0.5389
Epoch 10/50
534/534 ━━━━━━━━━━━━━━━━━━━━ 2s 4ms/step - accuracy: 0.7543 - loss: 0.4920 - val_accuracy: 0.7434 - val_los
s: 0.5306
Epoch 11/50
534/534 ━━━━━━━━━━━━━━━━━━━━ 2s 4ms/step - accuracy: 0.7754 - loss: 0.4764 - val_accuracy: 0.7769 - val_los
s: 0.4834
Epoch 12/50
534/534 ━━━━━━━━━━━━━━━━━━━━ 2s 4ms/step - accuracy: 0.7751 - loss: 0.4640 - val_accuracy: 0.7575 - val_los
s: 0.5013
Epoch 13/50
534/534 ━━━━━━━━━━━━━━━━━━━━ 2s 4ms/step - accuracy: 0.7835 - loss: 0.4574 - val_accuracy: 0.7193 - val_los
s: 0.5594
Epoch 14/50
534/534 ━━━━━━━━━━━━━━━━━━━━ 2s 4ms/step - accuracy: 0.8023 - loss: 0.4262 - val_accuracy: 0.7618 - val_los
s: 0.5017
```

```
Epoch 15/50
534/534 ━━━━━━━━━━━━━━━━━━━━ 2s 4ms/step - accuracy: 0.8070 - loss: 0.4156 - val_accuracy: 0.7594 - val_los
s: 0.4958
Epoch 16/50
534/534 ━━━━━━━━━━━━━━━━━━━━ 2s 4ms/step - accuracy: 0.8243 - loss: 0.3910 - val_accuracy: 0.7811 - val_los
s: 0.4794
Epoch 17/50
534/534 ━━━━━━━━━━━━━━━━━━━━ 2s 4ms/step - accuracy: 0.8441 - loss: 0.3537 - val_accuracy: 0.7774 - val_los
s: 0.4788
Epoch 18/50
534/534 ━━━━━━━━━━━━━━━━━━━━ 2s 4ms/step - accuracy: 0.8557 - loss: 0.3379 - val_accuracy: 0.7788 - val_los
s: 0.4937
Epoch 19/50
534/534 ━━━━━━━━━━━━━━━━━━━━ 2s 4ms/step - accuracy: 0.8721 - loss: 0.3128 - val_accuracy: 0.7684 - val_los
s: 0.5103
Epoch 20/50
534/534 ━━━━━━━━━━━━━━━━━━━━ 2s 4ms/step - accuracy: 0.8877 - loss: 0.2789 - val_accuracy: 0.7708 - val_los
s: 0.5206
Epoch 21/50
534/534 ━━━━━━━━━━━━━━━━━━━━ 2s 4ms/step - accuracy: 0.8985 - loss: 0.2519 - val_accuracy: 0.7660 - val_los
s: 0.5498
Epoch 22/50
534/534 ━━━━━━━━━━━━━━━━━━━━ 2s 4ms/step - accuracy: 0.9103 - loss: 0.2251 - val_accuracy: 0.7802 - val_los
s: 0.5339
67/67 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step
Unique predictions: (array([0, 1]), array([1418,  726]))
F1 score: 0.6847826086956522
```

Out[76]: <Sequential name=sequential_42, built=True>

In [77]:
```
train_model(create_lenet(), train_lenet_light_aug_ds, val_lenet_ds, test_lenet_ds)
```

```
Epoch 1/50
534/534 ━━━━━━━━━━━━━━━━━━━━ 3s 4ms/step - accuracy: 0.4678 - loss: 0.7021 - val_accuracy: 0.3335 - val_los
s: 0.7320
Epoch 2/50
534/534 ━━━━━━━━━━━━━━━━━━━━ 2s 4ms/step - accuracy: 0.4885 - loss: 0.6949 - val_accuracy: 0.6651 - val_los
s: 0.6875
Epoch 3/50
534/534 ━━━━━━━━━━━━━━━━━━━━ 2s 4ms/step - accuracy: 0.4948 - loss: 0.6940 - val_accuracy: 0.6646 - val_los
s: 0.6288
Epoch 4/50
534/534 ━━━━━━━━━━━━━━━━━━━━ 2s 4ms/step - accuracy: 0.4958 - loss: 0.6935 - val_accuracy: 0.3363 - val_los
s: 0.7549
Epoch 5/50
534/534 ━━━━━━━━━━━━━━━━━━━━ 2s 4ms/step - accuracy: 0.4989 - loss: 0.6948 - val_accuracy: 0.6693 - val_los
s: 0.6452
Epoch 6/50
534/534 ━━━━━━━━━━━━━━━━━━━━ 2s 4ms/step - accuracy: 0.5132 - loss: 0.6931 - val_accuracy: 0.6698 - val_los
s: 0.6254
Epoch 7/50
534/534 ━━━━━━━━━━━━━━━━━━━━ 2s 4ms/step - accuracy: 0.5248 - loss: 0.6919 - val_accuracy: 0.5703 - val_los
s: 0.6701
Epoch 8/50
534/534 ━━━━━━━━━━━━━━━━━━━━ 2s 4ms/step - accuracy: 0.5410 - loss: 0.6886 - val_accuracy: 0.6825 - val_los
s: 0.6202
Epoch 9/50
534/534 ━━━━━━━━━━━━━━━━━━━━ 2s 4ms/step - accuracy: 0.5074 - loss: 0.6913 - val_accuracy: 0.5920 - val_los
s: 0.6820
Epoch 10/50
534/534 ━━━━━━━━━━━━━━━━━━━━ 2s 4ms/step - accuracy: 0.5251 - loss: 0.6806 - val_accuracy: 0.6344 - val_los
s: 0.6455
Epoch 11/50
534/534 ━━━━━━━━━━━━━━━━━━━━ 2s 4ms/step - accuracy: 0.5425 - loss: 0.6775 - val_accuracy: 0.6429 - val_los
s: 0.6662
Epoch 12/50
534/534 ━━━━━━━━━━━━━━━━━━━━ 2s 4ms/step - accuracy: 0.5392 - loss: 0.6738 - val_accuracy: 0.6708 - val_los
s: 0.6114
Epoch 13/50
534/534 ━━━━━━━━━━━━━━━━━━━━ 2s 4ms/step - accuracy: 0.5509 - loss: 0.6753 - val_accuracy: 0.6542 - val_los
s: 0.6561
Epoch 14/50
534/534 ━━━━━━━━━━━━━━━━━━━━ 2s 4ms/step - accuracy: 0.5854 - loss: 0.6686 - val_accuracy: 0.6642 - val_los
s: 0.6592
```

```
Epoch 15/50
534/534 ━━━━━━━━━━━━━━━━━━━━ 2s 4ms/step - accuracy: 0.5546 - loss: 0.6716 - val_accuracy: 0.6783 - val_los
s: 0.6017
Epoch 16/50
534/534 ━━━━━━━━━━━━━━━━━━━━ 2s 4ms/step - accuracy: 0.5707 - loss: 0.6677 - val_accuracy: 0.6708 - val_los
s: 0.6264
Epoch 17/50
534/534 ━━━━━━━━━━━━━━━━━━━━ 2s 4ms/step - accuracy: 0.5684 - loss: 0.6704 - val_accuracy: 0.6679 - val_los
s: 0.6288
Epoch 18/50
534/534 ━━━━━━━━━━━━━━━━━━━━ 2s 4ms/step - accuracy: 0.5530 - loss: 0.6728 - val_accuracy: 0.6590 - val_los
s: 0.6045
Epoch 19/50
534/534 ━━━━━━━━━━━━━━━━━━━━ 2s 4ms/step - accuracy: 0.5785 - loss: 0.6724 - val_accuracy: 0.6708 - val_los
s: 0.6175
Epoch 20/50
534/534 ━━━━━━━━━━━━━━━━━━━━ 2s 4ms/step - accuracy: 0.5634 - loss: 0.6733 - val_accuracy: 0.6561 - val_los
s: 0.6526
67/67 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
Unique predictions: (array([0, 1]), array([1376,  768]))
F1 score: 0.5653896961690885
```

Out[77]: <Sequential name=sequential_43, built=True>

In [78]:
```
train_model(create_lenet(), train_lenet_moderate_aug_ds, val_lenet_ds, test_lenet_ds)
```

```
Epoch 1/50
534/534 ━━━━━━━━━━━━━━━━━━━━ 4s 5ms/step - accuracy: 0.4678 - loss: 0.7075 - val_accuracy: 0.3307 - val_los
s: 0.7655
Epoch 2/50
534/534 ━━━━━━━━━━━━━━━━━━━━ 2s 4ms/step - accuracy: 0.5207 - loss: 0.6951 - val_accuracy: 0.6693 - val_los
s: 0.6712
Epoch 3/50
534/534 ━━━━━━━━━━━━━━━━━━━━ 2s 4ms/step - accuracy: 0.5258 - loss: 0.6947 - val_accuracy: 0.3566 - val_los
s: 0.7021
Epoch 4/50
534/534 ━━━━━━━━━━━━━━━━━━━━ 2s 4ms/step - accuracy: 0.5304 - loss: 0.6943 - val_accuracy: 0.6693 - val_los
s: 0.6713
Epoch 5/50
534/534 ━━━━━━━━━━━━━━━━━━━━ 2s 4ms/step - accuracy: 0.5200 - loss: 0.6972 - val_accuracy: 0.6712 - val_los
s: 0.6666
Epoch 6/50
534/534 ━━━━━━━━━━━━━━━━━━━━ 2s 4ms/step - accuracy: 0.5273 - loss: 0.6935 - val_accuracy: 0.6684 - val_los
s: 0.6775
Epoch 7/50
534/534 ━━━━━━━━━━━━━━━━━━━━ 2s 4ms/step - accuracy: 0.4925 - loss: 0.6946 - val_accuracy: 0.3307 - val_los
s: 0.7264
Epoch 8/50
534/534 ━━━━━━━━━━━━━━━━━━━━ 2s 4ms/step - accuracy: 0.5207 - loss: 0.6946 - val_accuracy: 0.3307 - val_los
s: 0.7429
Epoch 9/50
534/534 ━━━━━━━━━━━━━━━━━━━━ 2s 4ms/step - accuracy: 0.4949 - loss: 0.6948 - val_accuracy: 0.3307 - val_los
s: 0.7219
Epoch 10/50
534/534 ━━━━━━━━━━━━━━━━━━━━ 2s 4ms/step - accuracy: 0.5039 - loss: 0.6954 - val_accuracy: 0.3307 - val_los
s: 0.7249
67/67 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step
Unique predictions: (array([0, 1]), array([2133,   11]))
F1 score: 0.018494055482166448
```

Out[78]: <Sequential name=sequential_44, built=True>

In [80]:
```
train_model(create_modified_lenet(), train_mod_lenet_no_aug_ds, val_mod_lenet_ds, test_mod_lenet_ds)
```

```
Epoch 1/50
534/534 ━━━━━━━━━━━━━━━━━━━━ 87s 162ms/step - accuracy: 0.6676 - loss: 0.5704 - val_accuracy: 0.8226 - val_
loss: 0.3289
Epoch 2/50
534/534 ━━━━━━━━━━━━━━━━━━━━ 85s 160ms/step - accuracy: 0.9081 - loss: 0.2209 - val_accuracy: 0.9330 - val_
loss: 0.1646
Epoch 3/50
534/534 ━━━━━━━━━━━━━━━━━━━━ 85s 159ms/step - accuracy: 0.9379 - loss: 0.1662 - val_accuracy: 0.9387 - val_
loss: 0.1492
Epoch 4/50
534/534 ━━━━━━━━━━━━━━━━━━━━ 85s 160ms/step - accuracy: 0.9465 - loss: 0.1407 - val_accuracy: 0.9415 - val_
loss: 0.1472
Epoch 5/50
534/534 ━━━━━━━━━━━━━━━━━━━━ 85s 159ms/step - accuracy: 0.9589 - loss: 0.1063 - val_accuracy: 0.9358 - val_
loss: 0.1696
Epoch 6/50
534/534 ━━━━━━━━━━━━━━━━━━━━ 85s 159ms/step - accuracy: 0.9619 - loss: 0.0988 - val_accuracy: 0.9453 - val_
loss: 0.1302
Epoch 7/50
534/534 ━━━━━━━━━━━━━━━━━━━━ 85s 160ms/step - accuracy: 0.9567 - loss: 0.1151 - val_accuracy: 0.9382 - val_
loss: 0.1522
Epoch 8/50
534/534 ━━━━━━━━━━━━━━━━━━━━ 85s 159ms/step - accuracy: 0.9664 - loss: 0.0852 - val_accuracy: 0.9637 - val_
loss: 0.0873
Epoch 9/50
534/534 ━━━━━━━━━━━━━━━━━━━━ 85s 159ms/step - accuracy: 0.9709 - loss: 0.0784 - val_accuracy: 0.9722 - val_
loss: 0.0859
Epoch 10/50
534/534 ━━━━━━━━━━━━━━━━━━━━ 86s 161ms/step - accuracy: 0.9775 - loss: 0.0606 - val_accuracy: 0.9693 - val_
loss: 0.0895
Epoch 11/50
534/534 ━━━━━━━━━━━━━━━━━━━━ 85s 159ms/step - accuracy: 0.9788 - loss: 0.0569 - val_accuracy: 0.9755 - val_
loss: 0.0762
Epoch 12/50
534/534 ━━━━━━━━━━━━━━━━━━━━ 85s 160ms/step - accuracy: 0.9802 - loss: 0.0537 - val_accuracy: 0.9731 - val_
loss: 0.0734
Epoch 13/50
534/534 ━━━━━━━━━━━━━━━━━━━━ 84s 158ms/step - accuracy: 0.9822 - loss: 0.0503 - val_accuracy: 0.9684 - val_
loss: 0.0832
Epoch 14/50
534/534 ━━━━━━━━━━━━━━━━━━━━ 85s 158ms/step - accuracy: 0.9846 - loss: 0.0434 - val_accuracy: 0.9627 - val_
loss: 0.1059
```

```
Epoch 15/50
534/534 ━━━━━━━━━━━━━━━━━━━━ 86s 161ms/step - accuracy: 0.9827 - loss: 0.0502 - val_accuracy: 0.9693 - val_
loss: 0.0859
Epoch 16/50
534/534 ━━━━━━━━━━━━━━━━━━━━ 86s 161ms/step - accuracy: 0.9883 - loss: 0.0338 - val_accuracy: 0.9778 - val_
loss: 0.0873
Epoch 17/50
534/534 ━━━━━━━━━━━━━━━━━━━━ 86s 160ms/step - accuracy: 0.9837 - loss: 0.0510 - val_accuracy: 0.9731 - val_
loss: 0.0822
67/67 ━━━━━━━━━━━━━━━━━━━━ 3s 45ms/step
Unique predictions: (array([0, 1]), array([1380,  764]))
F1 score: 0.9686457638425617
```

Out[80]: <Sequential name=sequential_46, built=True>

In [81]:
```
train_model(create_modified_lenet(), train_mod_lenet_light_aug_ds, val_mod_lenet_ds, test_mod_lenet_ds)
```

```
Epoch 1/50
534/534 ━━━━━━━━━━━━━━━━━━━━ 97s 159ms/step - accuracy: 0.4897 - loss: 0.7277 - val_accuracy: 0.6708 - val_
loss: 0.6917
Epoch 2/50
534/534 ━━━━━━━━━━━━━━━━━━━━ 85s 159ms/step - accuracy: 0.4371 - loss: 0.6933 - val_accuracy: 0.6708 - val_
loss: 0.6925
Epoch 3/50
534/534 ━━━━━━━━━━━━━━━━━━━━ 85s 158ms/step - accuracy: 0.5906 - loss: 0.6936 - val_accuracy: 0.3292 - val_
loss: 0.6935
Epoch 4/50
534/534 ━━━━━━━━━━━━━━━━━━━━ 84s 157ms/step - accuracy: 0.3665 - loss: 0.6937 - val_accuracy: 0.3292 - val_
loss: 0.6933
Epoch 5/50
534/534 ━━━━━━━━━━━━━━━━━━━━ 84s 158ms/step - accuracy: 0.5000 - loss: 0.6935 - val_accuracy: 0.6708 - val_
loss: 0.6926
Epoch 6/50
534/534 ━━━━━━━━━━━━━━━━━━━━ 84s 157ms/step - accuracy: 0.4111 - loss: 0.6953 - val_accuracy: 0.6708 - val_
loss: 0.6918
67/67 ━━━━━━━━━━━━━━━━━━━━ 3s 44ms/step
Unique predictions: (array([0]), array([2144]))
F1 score: 0.0
```

Out[81]: <Sequential name=sequential_47, built=True>

In [82]:
```
train_model(create_modified_lenet(), train_mod_lenet_moderate_aug_ds, val_mod_lenet_ds, test_mod_lenet_ds)
```

```
Epoch 1/50
534/534 ━━━━━━━━━━━━━━━━━━━━ 106s 158ms/step - accuracy: 0.4722 - loss: 0.7151 - val_accuracy: 0.3292 - val
_loss: 0.6945
Epoch 2/50
534/534 ━━━━━━━━━━━━━━━━━━━━ 83s 155ms/step - accuracy: 0.5870 - loss: 0.6914 - val_accuracy: 0.3292 - val_
loss: 0.6933
Epoch 3/50
534/534 ━━━━━━━━━━━━━━━━━━━━ 84s 156ms/step - accuracy: 0.5052 - loss: 0.6923 - val_accuracy: 0.3292 - val_
loss: 0.6934
Epoch 4/50
534/534 ━━━━━━━━━━━━━━━━━━━━ 83s 156ms/step - accuracy: 0.4861 - loss: 0.6931 - val_accuracy: 0.6708 - val_
loss: 0.6919
Epoch 5/50
534/534 ━━━━━━━━━━━━━━━━━━━━ 83s 156ms/step - accuracy: 0.5768 - loss: 0.6906 - val_accuracy: 0.3292 - val_
loss: 0.6935
Epoch 6/50
534/534 ━━━━━━━━━━━━━━━━━━━━ 84s 156ms/step - accuracy: 0.3510 - loss: 0.6950 - val_accuracy: 0.6708 - val_
loss: 0.6917
Epoch 7/50
534/534 ━━━━━━━━━━━━━━━━━━━━ 83s 156ms/step - accuracy: 0.6509 - loss: 0.6927 - val_accuracy: 0.6708 - val_
loss: 0.6931
Epoch 8/50
534/534 ━━━━━━━━━━━━━━━━━━━━ 83s 156ms/step - accuracy: 0.5419 - loss: 0.6946 - val_accuracy: 0.6708 - val_
loss: 0.6917
Epoch 9/50
534/534 ━━━━━━━━━━━━━━━━━━━━ 83s 156ms/step - accuracy: 0.6396 - loss: 0.6931 - val_accuracy: 0.3292 - val_
loss: 0.6952
Epoch 10/50
534/534 ━━━━━━━━━━━━━━━━━━━━ 83s 156ms/step - accuracy: 0.4348 - loss: 0.6948 - val_accuracy: 0.6708 - val_
loss: 0.6928
Epoch 11/50
534/534 ━━━━━━━━━━━━━━━━━━━━ 84s 157ms/step - accuracy: 0.4702 - loss: 0.6959 - val_accuracy: 0.6708 - val_
loss: 0.6924
Epoch 12/50
534/534 ━━━━━━━━━━━━━━━━━━━━ 85s 158ms/step - accuracy: 0.6557 - loss: 0.6921 - val_accuracy: 0.3292 - val_
loss: 0.6935
Epoch 13/50
534/534 ━━━━━━━━━━━━━━━━━━━━ 86s 160ms/step - accuracy: 0.4349 - loss: 0.6937 - val_accuracy: 0.6708 - val_
loss: 0.6924
67/67 ━━━━━━━━━━━━━━━━━━━━ 3s 44ms/step
Unique predictions: (array([0]), array([2144]))
F1 score: 0.0
```

Out[82]: <Sequential name=sequential_48, built=True>

In [ ]:
```
# train_model(create_modified_lenet(), train_mod_lenet_heavy_aug_ds, val_mod_lenet_ds, test_mod_lenet_ds)
# I'm not going to bother running this cell because I got such poor results with the last couple of cells
```

In [83]:
```
train_model(create_vgg16(), train_vgg_no_aug_ds, val_vgg_ds, test_vgg_ds)
```

```
Downloading data from https://storage.googleapis.com/tensorflow/keras-applications/vgg16/vgg16_weights_tf_d
im_ordering_tf_kernels_notop.h5
58889256/58889256 ━━━━━━━━━━━━━━━━━━━━ 1s 0us/step
Epoch 1/50
534/534 ━━━━━━━━━━━━━━━━━━━━ 1120s 2s/step - accuracy: 0.8835 - loss: 1.7913 - val_accuracy: 0.9519 - val_l
oss: 0.1098
Epoch 2/50
534/534 ━━━━━━━━━━━━━━━━━━━━ 1113s 2s/step - accuracy: 0.9624 - loss: 0.1019 - val_accuracy: 0.9415 - val_l
oss: 0.1308
Epoch 3/50
534/534 ━━━━━━━━━━━━━━━━━━━━ 1115s 2s/step - accuracy: 0.9733 - loss: 0.0785 - val_accuracy: 0.9434 - val_l
oss: 0.1498
Epoch 4/50
534/534 ━━━━━━━━━━━━━━━━━━━━ 1124s 2s/step - accuracy: 0.9759 - loss: 0.0731 - val_accuracy: 0.9637 - val_l
oss: 0.1127
Epoch 5/50
534/534 ━━━━━━━━━━━━━━━━━━━━ 1117s 2s/step - accuracy: 0.9809 - loss: 0.0555 - val_accuracy: 0.9604 - val_l
oss: 0.1248
Epoch 6/50
534/534 ━━━━━━━━━━━━━━━━━━━━ 1122s 2s/step - accuracy: 0.9836 - loss: 0.0508 - val_accuracy: 0.9547 - val_l
oss: 0.1204
67/67 ━━━━━━━━━━━━━━━━━━━━ 124s 2s/step
Unique predictions: (array([0, 1]), array([1390,  754]))
F1 score: 0.9340439706862091
```

Out[83]: <Sequential name=sequential_49, built=True>

In [84]:
```
train_model(create_vgg19(), train_vgg_no_aug_ds, val_vgg_ds, test_vgg_ds)
```

```
Downloading data from https://storage.googleapis.com/tensorflow/keras-applications/vgg19/vgg19_weights_tf_d
im_ordering_tf_kernels_notop.h5
80134624/80134624 ━━━━━━━━━━━━━━━━━━━━ 1s 0us/step
Epoch 1/50
534/534 ━━━━━━━━━━━━━━━━━━━━ 1391s 3s/step - accuracy: 0.8669 - loss: 1.9017 - val_accuracy: 0.8934 - val_l
oss: 0.2247
Epoch 2/50
534/534 ━━━━━━━━━━━━━━━━━━━━ 1398s 3s/step - accuracy: 0.9565 - loss: 0.1150 - val_accuracy: 0.9538 - val_l
oss: 0.1042
Epoch 3/50
534/534 ━━━━━━━━━━━━━━━━━━━━ 1396s 3s/step - accuracy: 0.9661 - loss: 0.0827 - val_accuracy: 0.9519 - val_l
oss: 0.1081
Epoch 4/50
534/534 ━━━━━━━━━━━━━━━━━━━━ 1391s 3s/step - accuracy: 0.9666 - loss: 0.0806 - val_accuracy: 0.9623 - val_l
oss: 0.1058
Epoch 5/50
534/534 ━━━━━━━━━━━━━━━━━━━━ 1391s 3s/step - accuracy: 0.9723 - loss: 0.0686 - val_accuracy: 0.9505 - val_l
oss: 0.1177
Epoch 6/50
534/534 ━━━━━━━━━━━━━━━━━━━━ 1393s 3s/step - accuracy: 0.9740 - loss: 0.0568 - val_accuracy: 0.9585 - val_l
oss: 0.1315
Epoch 7/50
534/534 ━━━━━━━━━━━━━━━━━━━━ 1393s 3s/step - accuracy: 0.9789 - loss: 0.0508 - val_accuracy: 0.9580 - val_l
oss: 0.1373
67/67 ━━━━━━━━━━━━━━━━━━━━ 154s 2s/step
Unique predictions: (array([0, 1]), array([1391,  753]))
F1 score: 0.9386666666666666
```

Out[84]: <Sequential name=sequential_50, built=True>

In [88]:
```python
def create_modified_lenet2():
  model = tf.keras.Sequential([
    tf.keras.layers.Input(shape=(150, 150, 3)),
    tf.keras.layers.Conv2D(32, (3, 3), activation='relu'),
    tf.keras.layers.MaxPooling2D((2, 2)),
    tf.keras.layers.Conv2D(64, (3, 3), activation='relu'),
    tf.keras.layers.MaxPooling2D((2, 2)),
    tf.keras.layers.Conv2D(128, (3, 3), activation='relu'),
    tf.keras.layers.MaxPooling2D((2, 2)),
    tf.keras.layers.Conv2D(128, (3, 3), activation='relu'),
    tf.keras.layers.MaxPooling2D((2, 2)),
    tf.keras.layers.GlobalAveragePooling2D(),
```

```
    tf.keras.layers.Dropout(0.5),
    tf.keras.layers.Dense(512, activation='relu'),
    tf.keras.layers.Dense(1, activation='sigmoid')
  ])
  model.compile(optimizer='adam', loss='binary_crossentropy', metrics=['accuracy'])
  return model

def create_modified_lenet3():
  model = tf.keras.Sequential([
    tf.keras.layers.Input(shape=(150, 150, 3)),
    tf.keras.layers.Conv2D(32, (3, 3), activation='relu'),
    tf.keras.layers.BatchNormalization(),
    tf.keras.layers.MaxPooling2D((2, 2)),
    tf.keras.layers.Conv2D(64, (3, 3), activation='relu'),
    tf.keras.layers.BatchNormalization(),
    tf.keras.layers.MaxPooling2D((2, 2)),
    tf.keras.layers.Conv2D(128, (3, 3), activation='relu'),
    tf.keras.layers.BatchNormalization(),
    tf.keras.layers.MaxPooling2D((2, 2)),
    tf.keras.layers.Conv2D(128, (3, 3), activation='relu'),
    tf.keras.layers.BatchNormalization(),
    tf.keras.layers.MaxPooling2D((2, 2)),
    tf.keras.layers.Flatten(),
    tf.keras.layers.Dropout(0.5),
    tf.keras.layers.Dense(512, activation='relu'),
    tf.keras.layers.Dense(1, activation='sigmoid')
  ])
  model.compile(optimizer='adam', loss='binary_crossentropy', metrics=['accuracy'])
  return model

def create_modified_lenet4():
  model = tf.keras.Sequential([
    tf.keras.layers.Input(shape=(150, 150, 3)),
    tf.keras.layers.Conv2D(32, (3, 3), activation='relu'),
    tf.keras.layers.BatchNormalization(),
    tf.keras.layers.MaxPooling2D((2, 2)),
    tf.keras.layers.Conv2D(64, (3, 3), activation='relu'),
    tf.keras.layers.BatchNormalization(),
    tf.keras.layers.MaxPooling2D((2, 2)),
    tf.keras.layers.Conv2D(128, (3, 3), activation='relu'),
    tf.keras.layers.BatchNormalization(),
    tf.keras.layers.MaxPooling2D((2, 2)),
```

```
    tf.keras.layers.Conv2D(128, (3, 3), activation='relu'),
    tf.keras.layers.BatchNormalization(),
    tf.keras.layers.MaxPooling2D((2, 2)),
    tf.keras.layers.GlobalAveragePooling2D(),
    tf.keras.layers.Dropout(0.5),
    tf.keras.layers.Dense(512, activation='relu'),
    tf.keras.layers.Dense(1, activation='sigmoid')
  ])
  model.compile(optimizer='adam', loss='binary_crossentropy', metrics=['accuracy'])
  return model
```

In [89]:
```
train_model(create_modified_lenet2(), train_mod_lenet_no_aug_ds, val_mod_lenet_ds, test_mod_lenet_ds)
```

```
Epoch 1/50
534/534 ━━━━━━━━━━━━━━━━━━━━ 85s 157ms/step - accuracy: 0.6888 - loss: 0.5241 - val_accuracy: 0.9099 - val_
loss: 0.2217
Epoch 2/50
534/534 ━━━━━━━━━━━━━━━━━━━━ 83s 156ms/step - accuracy: 0.9181 - loss: 0.2069 - val_accuracy: 0.9410 - val_
loss: 0.1493
Epoch 3/50
534/534 ━━━━━━━━━━━━━━━━━━━━ 340s 637ms/step - accuracy: 0.9337 - loss: 0.1796 - val_accuracy: 0.9358 - val
_loss: 0.1619
Epoch 4/50
534/534 ━━━━━━━━━━━━━━━━━━━━ 86s 161ms/step - accuracy: 0.9472 - loss: 0.1397 - val_accuracy: 0.9519 - val_
loss: 0.1197
Epoch 5/50
534/534 ━━━━━━━━━━━━━━━━━━━━ 85s 159ms/step - accuracy: 0.9535 - loss: 0.1249 - val_accuracy: 0.9491 - val_
loss: 0.1290
Epoch 6/50
534/534 ━━━━━━━━━━━━━━━━━━━━ 84s 157ms/step - accuracy: 0.9567 - loss: 0.1106 - val_accuracy: 0.9608 - val_
loss: 0.0967
Epoch 7/50
534/534 ━━━━━━━━━━━━━━━━━━━━ 82s 154ms/step - accuracy: 0.9653 - loss: 0.0885 - val_accuracy: 0.8500 - val_
loss: 0.3126
Epoch 8/50
534/534 ━━━━━━━━━━━━━━━━━━━━ 82s 154ms/step - accuracy: 0.9386 - loss: 0.1445 - val_accuracy: 0.9656 - val_
loss: 0.0932
Epoch 9/50
534/534 ━━━━━━━━━━━━━━━━━━━━ 81s 152ms/step - accuracy: 0.9662 - loss: 0.0936 - val_accuracy: 0.9575 - val_
loss: 0.1120
Epoch 10/50
534/534 ━━━━━━━━━━━━━━━━━━━━ 83s 155ms/step - accuracy: 0.9715 - loss: 0.0831 - val_accuracy: 0.9632 - val_
loss: 0.1019
Epoch 11/50
534/534 ━━━━━━━━━━━━━━━━━━━━ 83s 156ms/step - accuracy: 0.9697 - loss: 0.0851 - val_accuracy: 0.9736 - val_
loss: 0.0724
Epoch 12/50
534/534 ━━━━━━━━━━━━━━━━━━━━ 82s 154ms/step - accuracy: 0.9754 - loss: 0.0669 - val_accuracy: 0.9755 - val_
loss: 0.0663
Epoch 13/50
534/534 ━━━━━━━━━━━━━━━━━━━━ 82s 154ms/step - accuracy: 0.9688 - loss: 0.0875 - val_accuracy: 0.9722 - val_
loss: 0.0715
Epoch 14/50
534/534 ━━━━━━━━━━━━━━━━━━━━ 84s 157ms/step - accuracy: 0.9776 - loss: 0.0625 - val_accuracy: 0.9708 - val_
loss: 0.0761
```

```
Epoch 15/50
534/534 ━━━━━━━━━━━━━━━━━━━━ 82s 154ms/step - accuracy: 0.9793 - loss: 0.0609 - val_accuracy: 0.9717 - val_
loss: 0.0814
Epoch 16/50
534/534 ━━━━━━━━━━━━━━━━━━━━ 83s 155ms/step - accuracy: 0.9795 - loss: 0.0556 - val_accuracy: 0.9821 - val_
loss: 0.0590
Epoch 17/50
534/534 ━━━━━━━━━━━━━━━━━━━━ 82s 153ms/step - accuracy: 0.9790 - loss: 0.0569 - val_accuracy: 0.9797 - val_
loss: 0.0630
Epoch 18/50
534/534 ━━━━━━━━━━━━━━━━━━━━ 83s 156ms/step - accuracy: 0.9822 - loss: 0.0522 - val_accuracy: 0.9825 - val_
loss: 0.0537
Epoch 19/50
534/534 ━━━━━━━━━━━━━━━━━━━━ 82s 154ms/step - accuracy: 0.9858 - loss: 0.0412 - val_accuracy: 0.9755 - val_
loss: 0.0716
Epoch 20/50
534/534 ━━━━━━━━━━━━━━━━━━━━ 81s 152ms/step - accuracy: 0.9850 - loss: 0.0464 - val_accuracy: 0.9764 - val_
loss: 0.0668
Epoch 21/50
534/534 ━━━━━━━━━━━━━━━━━━━━ 82s 153ms/step - accuracy: 0.9841 - loss: 0.0491 - val_accuracy: 0.9783 - val_
loss: 0.0596
Epoch 22/50
534/534 ━━━━━━━━━━━━━━━━━━━━ 81s 152ms/step - accuracy: 0.9839 - loss: 0.0469 - val_accuracy: 0.9788 - val_
loss: 0.0544
Epoch 23/50
534/534 ━━━━━━━━━━━━━━━━━━━━ 82s 153ms/step - accuracy: 0.9892 - loss: 0.0319 - val_accuracy: 0.9778 - val_
loss: 0.0650
67/67 ━━━━━━━━━━━━━━━━━━━━ 3s 43ms/step
Unique predictions: (array([0, 1]), array([1411,  733]))
F1 score: 0.9754768392370572
```

Out[89]: <Sequential name=sequential_51, built=True>

In [90]:
```
train_model(create_modified_lenet3(), train_mod_lenet_no_aug_ds, val_mod_lenet_ds, test_mod_lenet_ds)
```

```
Epoch 1/50
534/534 ━━━━━━━━━━━━━━━━━━━━ 124s 228ms/step - accuracy: 0.8664 - loss: 0.5618 - val_accuracy: 0.6835 - val
_loss: 1.0811
Epoch 2/50
534/534 ━━━━━━━━━━━━━━━━━━━━ 121s 227ms/step - accuracy: 0.9461 - loss: 0.1377 - val_accuracy: 0.6972 - val
_loss: 1.0489
Epoch 3/50
534/534 ━━━━━━━━━━━━━━━━━━━━ 121s 227ms/step - accuracy: 0.9634 - loss: 0.0912 - val_accuracy: 0.9561 - val
_loss: 0.1302
Epoch 4/50
534/534 ━━━━━━━━━━━━━━━━━━━━ 121s 226ms/step - accuracy: 0.9705 - loss: 0.0705 - val_accuracy: 0.9557 - val
_loss: 0.1203
Epoch 5/50
534/534 ━━━━━━━━━━━━━━━━━━━━ 121s 227ms/step - accuracy: 0.9815 - loss: 0.0528 - val_accuracy: 0.8939 - val
_loss: 0.3369
Epoch 6/50
534/534 ━━━━━━━━━━━━━━━━━━━━ 126s 236ms/step - accuracy: 0.9782 - loss: 0.0578 - val_accuracy: 0.9712 - val
_loss: 0.0779
Epoch 7/50
534/534 ━━━━━━━━━━━━━━━━━━━━ 129s 241ms/step - accuracy: 0.9867 - loss: 0.0362 - val_accuracy: 0.9156 - val
_loss: 0.4938
Epoch 8/50
534/534 ━━━━━━━━━━━━━━━━━━━━ 124s 232ms/step - accuracy: 0.9847 - loss: 0.0370 - val_accuracy: 0.9042 - val
_loss: 0.6571
Epoch 9/50
534/534 ━━━━━━━━━━━━━━━━━━━━ 125s 235ms/step - accuracy: 0.9868 - loss: 0.0358 - val_accuracy: 0.8458 - val
_loss: 0.6304
Epoch 10/50
534/534 ━━━━━━━━━━━━━━━━━━━━ 125s 234ms/step - accuracy: 0.9925 - loss: 0.0215 - val_accuracy: 0.9679 - val
_loss: 0.0944
Epoch 11/50
534/534 ━━━━━━━━━━━━━━━━━━━━ 127s 238ms/step - accuracy: 0.9910 - loss: 0.0279 - val_accuracy: 0.9722 - val
_loss: 0.1161
67/67 ━━━━━━━━━━━━━━━━━━━━ 3s 49ms/step
Unique predictions: (array([0, 1]), array([1418,  726]))
F1 score: 0.9623545516769336
```

Out[90]: <Sequential name=sequential_52, built=True>

In [91]:
```
train_model(create_modified_lenet4(), train_mod_lenet_no_aug_ds, val_mod_lenet_ds, test_mod_lenet_ds)
```

```
Epoch 1/50
534/534 ━━━━━━━━━━━━━━━━━━━━ 126s 233ms/step - accuracy: 0.8948 - loss: 0.2491 - val_accuracy: 0.3726 - val
_loss: 4.2180
Epoch 2/50
534/534 ━━━━━━━━━━━━━━━━━━━━ 122s 229ms/step - accuracy: 0.9440 - loss: 0.1484 - val_accuracy: 0.8887 - val
_loss: 0.3109
Epoch 3/50
534/534 ━━━━━━━━━━━━━━━━━━━━ 121s 226ms/step - accuracy: 0.9543 - loss: 0.1143 - val_accuracy: 0.7590 - val
_loss: 0.4927
Epoch 4/50
534/534 ━━━━━━━━━━━━━━━━━━━━ 120s 225ms/step - accuracy: 0.9638 - loss: 0.0951 - val_accuracy: 0.7906 - val
_loss: 0.9322
Epoch 5/50
534/534 ━━━━━━━━━━━━━━━━━━━━ 118s 222ms/step - accuracy: 0.9684 - loss: 0.0799 - val_accuracy: 0.9175 - val
_loss: 0.2001
Epoch 6/50
534/534 ━━━━━━━━━━━━━━━━━━━━ 119s 223ms/step - accuracy: 0.9777 - loss: 0.0595 - val_accuracy: 0.9349 - val
_loss: 0.1785
Epoch 7/50
534/534 ━━━━━━━━━━━━━━━━━━━━ 120s 224ms/step - accuracy: 0.9816 - loss: 0.0530 - val_accuracy: 0.9373 - val
_loss: 0.1400
Epoch 8/50
534/534 ━━━━━━━━━━━━━━━━━━━━ 121s 226ms/step - accuracy: 0.9802 - loss: 0.0551 - val_accuracy: 0.7118 - val
_loss: 0.8779
Epoch 9/50
534/534 ━━━━━━━━━━━━━━━━━━━━ 120s 224ms/step - accuracy: 0.9843 - loss: 0.0439 - val_accuracy: 0.9792 - val
_loss: 0.0536
Epoch 10/50
534/534 ━━━━━━━━━━━━━━━━━━━━ 122s 229ms/step - accuracy: 0.9851 - loss: 0.0407 - val_accuracy: 0.7745 - val
_loss: 0.6086
Epoch 11/50
534/534 ━━━━━━━━━━━━━━━━━━━━ 124s 232ms/step - accuracy: 0.9890 - loss: 0.0311 - val_accuracy: 0.7208 - val
_loss: 1.4688
Epoch 12/50
534/534 ━━━━━━━━━━━━━━━━━━━━ 125s 234ms/step - accuracy: 0.9841 - loss: 0.0399 - val_accuracy: 0.9717 - val
_loss: 0.0779
Epoch 13/50
534/534 ━━━━━━━━━━━━━━━━━━━━ 122s 229ms/step - accuracy: 0.9893 - loss: 0.0292 - val_accuracy: 0.9448 - val
_loss: 0.2124
Epoch 14/50
534/534 ━━━━━━━━━━━━━━━━━━━━ 128s 240ms/step - accuracy: 0.9912 - loss: 0.0248 - val_accuracy: 0.9675 - val
_loss: 0.1055
```

```
67/67 ━━━━━━━━━━━━━━━━━━━━ 4s 53ms/step
Unique predictions: (array([0, 1]), array([1416,  728]))
F1 score: 0.9760765550239234
```

Out[91]: <Sequential name=sequential_53, built=True>

In [93]:
```python
def create_modified_lenet5():
  model = tf.keras.Sequential([
    tf.keras.layers.Input(shape=(150, 150, 3)),
    tf.keras.layers.Conv2D(32, (3, 3), activation='relu', padding='same'),
    tf.keras.layers.BatchNormalization(),
    tf.keras.layers.MaxPooling2D((2, 2)),
    tf.keras.layers.Conv2D(64, (3, 3), activation='relu', padding='same'),
    tf.keras.layers.BatchNormalization(),
    tf.keras.layers.MaxPooling2D((2, 2)),
    tf.keras.layers.Conv2D(128, (3, 3), activation='relu', padding='same'),
    tf.keras.layers.BatchNormalization(),
    tf.keras.layers.MaxPooling2D((2, 2)),
    tf.keras.layers.Conv2D(128, (3, 3), activation='relu', padding='same'),
    tf.keras.layers.BatchNormalization(),
    tf.keras.layers.MaxPooling2D((2, 2)),
    tf.keras.layers.GlobalAveragePooling2D(),
    tf.keras.layers.Dropout(0.5),
    tf.keras.layers.Dense(512, activation='relu'),
    tf.keras.layers.Dense(1, activation='sigmoid')
  ])
  model.compile(optimizer='adam', loss='binary_crossentropy', metrics=['accuracy'])
  return model

def create_modified_lenet6():
  model = tf.keras.Sequential([
    tf.keras.layers.Input(shape=(150, 150, 3)),
    tf.keras.layers.Conv2D(32, (3, 3), activation='relu', padding='same', kernel_regularizer=tf.keras.regu
    tf.keras.layers.BatchNormalization(),
    tf.keras.layers.MaxPooling2D((2, 2)),
    tf.keras.layers.Conv2D(64, (3, 3), activation='relu', padding='same', kernel_regularizer=tf.keras.regu
    tf.keras.layers.BatchNormalization(),
    tf.keras.layers.MaxPooling2D((2, 2)),
    tf.keras.layers.Conv2D(128, (3, 3), activation='relu', padding='same', kernel_regularizer=tf.keras.regu
    tf.keras.layers.BatchNormalization(),
    tf.keras.layers.MaxPooling2D((2, 2)),
    tf.keras.layers.Conv2D(128, (3, 3), activation='relu', padding='same', kernel_regularizer=tf.keras.regu
```

```
    tf.keras.layers.BatchNormalization(),
    tf.keras.layers.MaxPooling2D((2, 2)),
    tf.keras.layers.GlobalAveragePooling2D(),
    tf.keras.layers.Dropout(0.5),
    tf.keras.layers.Dense(512, activation='relu', kernel_regularizer=tf.keras.regularizers.l2(1e-4)),
    tf.keras.layers.Dense(1, activation='sigmoid', kernel_regularizer=tf.keras.regularizers.l2(1e-4))
  ])
  model.compile(optimizer='adam', loss='binary_crossentropy', metrics=['accuracy'])
  return model

def create_modified_lenet7():
  model = tf.keras.Sequential([
    tf.keras.layers.Input(shape=(150, 150, 3)),
    tf.keras.layers.Conv2D(32, (3, 3), activation='relu', padding='same', kernel_regularizer=tf.keras.regu
    tf.keras.layers.BatchNormalization(),
    tf.keras.layers.MaxPooling2D((2, 2)),
    tf.keras.layers.Conv2D(64, (3, 3), activation='relu', padding='same', kernel_regularizer=tf.keras.regu
    tf.keras.layers.BatchNormalization(),
    tf.keras.layers.MaxPooling2D((2, 2)),
    tf.keras.layers.Conv2D(128, (3, 3), activation='relu', padding='same', kernel_regularizer=tf.keras.regu
    tf.keras.layers.BatchNormalization(),
    tf.keras.layers.MaxPooling2D((2, 2)),
    tf.keras.layers.Conv2D(128, (3, 3), activation='relu', padding='same', kernel_regularizer=tf.keras.regu
    tf.keras.layers.BatchNormalization(),
    tf.keras.layers.MaxPooling2D((2, 2)),
    tf.keras.layers.GlobalAveragePooling2D(),
    tf.keras.layers.Dropout(0.5),
    tf.keras.layers.Dense(512, activation='relu', kernel_regularizer=tf.keras.regularizers.l2(1e-5)),
    tf.keras.layers.Dense(1, activation='sigmoid', kernel_regularizer=tf.keras.regularizers.l2(1e-5))
  ])
  model.compile(optimizer='adam', loss='binary_crossentropy', metrics=['accuracy'])
  return model
```

In [96]:

```
def train_model2(model, train_ds, val_ds, test_ds, lr=1e-3):
    callbacks = [
        EarlyStopping(
            monitor='val_loss',
            patience=5,
            restore_best_weights=True
        ),
        ReduceLROnPlateau(
            monitor='val_loss',
```

```
            factor=0.2,
            patience=3,
            min_lr=1e-6,
            verbose=1
        ),
    ]
    optimizer = tf.keras.optimizers.Adam(learning_rate=lr)
    model.compile(
        optimizer=optimizer,
        loss=tf.keras.losses.BinaryCrossentropy(label_smoothing=0.05),
        metrics=['accuracy']
    )
    model.fit(
        train_ds,
        validation_data=val_ds,
        epochs=50,
        callbacks=callbacks,
        class_weight=class_weights
    )
    y_pred = model.predict(test_ds)
    y_pred_labels = (y_pred > 0.5).astype(int).flatten()
    print(f'Unique predictions: {np.unique(y_pred_labels, return_counts=True)}')
    y_true = np.concatenate([y for _, y in test_ds], axis=0).flatten()
    f1 = f1_score(y_true, y_pred_labels)
    print(f'F1 score: {f1}')
    return model
```

In [97]:
```
train_model2(create_modified_lenet4(), train_mod_lenet_no_aug_ds, val_mod_lenet_ds, test_mod_lenet_ds)
```

```
Epoch 1/50
534/534 ━━━━━━━━━━━━━━━━━━━━ 134s 248ms/step - accuracy: 0.8888 - loss: 0.3421 - val_accuracy: 0.7453 - val
_loss: 0.5253 - learning_rate: 0.0010
Epoch 2/50
534/534 ━━━━━━━━━━━━━━━━━━━━ 162s 304ms/step - accuracy: 0.9440 - loss: 0.2336 - val_accuracy: 0.9184 - val
_loss: 0.2744 - learning_rate: 0.0010
Epoch 3/50
534/534 ━━━━━━━━━━━━━━━━━━━━ 163s 304ms/step - accuracy: 0.9573 - loss: 0.2057 - val_accuracy: 0.9585 - val
_loss: 0.2097 - learning_rate: 0.0010
Epoch 4/50
534/534 ━━━━━━━━━━━━━━━━━━━━ 166s 310ms/step - accuracy: 0.9680 - loss: 0.1882 - val_accuracy: 0.9208 - val
_loss: 0.2803 - learning_rate: 0.0010
Epoch 5/50
534/534 ━━━━━━━━━━━━━━━━━━━━ 129s 242ms/step - accuracy: 0.9777 - loss: 0.1698 - val_accuracy: 0.8033 - val
_loss: 0.4442 - learning_rate: 0.0010
Epoch 6/50
534/534 ━━━━━━━━━━━━━━━━━━━━ 0s 446ms/step - accuracy: 0.9771 - loss: 0.1674
Epoch 6: ReduceLROnPlateau reducing learning rate to 0.00020000000949949026.
534/534 ━━━━━━━━━━━━━━━━━━━━ 241s 452ms/step - accuracy: 0.9771 - loss: 0.1674 - val_accuracy: 0.8566 - val
_loss: 0.4596 - learning_rate: 0.0010
Epoch 7/50
534/534 ━━━━━━━━━━━━━━━━━━━━ 119s 223ms/step - accuracy: 0.9876 - loss: 0.1496 - val_accuracy: 0.9882 - val
_loss: 0.1491 - learning_rate: 2.0000e-04
Epoch 8/50
534/534 ━━━━━━━━━━━━━━━━━━━━ 127s 238ms/step - accuracy: 0.9929 - loss: 0.1383 - val_accuracy: 0.9792 - val
_loss: 0.1612 - learning_rate: 2.0000e-04
Epoch 9/50
534/534 ━━━━━━━━━━━━━━━━━━━━ 123s 230ms/step - accuracy: 0.9947 - loss: 0.1354 - val_accuracy: 0.9858 - val
_loss: 0.1457 - learning_rate: 2.0000e-04
Epoch 10/50
534/534 ━━━━━━━━━━━━━━━━━━━━ 124s 232ms/step - accuracy: 0.9966 - loss: 0.1315 - val_accuracy: 0.9892 - val
_loss: 0.1504 - learning_rate: 2.0000e-04
Epoch 11/50
534/534 ━━━━━━━━━━━━━━━━━━━━ 123s 230ms/step - accuracy: 0.9964 - loss: 0.1312 - val_accuracy: 0.9873 - val
_loss: 0.1428 - learning_rate: 2.0000e-04
Epoch 12/50
534/534 ━━━━━━━━━━━━━━━━━━━━ 125s 235ms/step - accuracy: 0.9970 - loss: 0.1277 - val_accuracy: 0.9835 - val
_loss: 0.1517 - learning_rate: 2.0000e-04
Epoch 13/50
534/534 ━━━━━━━━━━━━━━━━━━━━ 123s 230ms/step - accuracy: 0.9982 - loss: 0.1260 - val_accuracy: 0.9896 - val
_loss: 0.1401 - learning_rate: 2.0000e-04
Epoch 14/50
```

```
534/534 ━━━━━━━━━━━━━━━━━━━━ 120s 225ms/step - accuracy: 0.9982 - loss: 0.1257 - val_accuracy: 0.9788 - val
_loss: 0.1619 - learning_rate: 2.0000e-04
Epoch 15/50
534/534 ━━━━━━━━━━━━━━━━━━━━ 122s 228ms/step - accuracy: 0.9989 - loss: 0.1235 - val_accuracy: 0.9887 - val
_loss: 0.1442 - learning_rate: 2.0000e-04
Epoch 16/50
534/534 ━━━━━━━━━━━━━━━━━━━━ 0s 220ms/step - accuracy: 0.9982 - loss: 0.1240
Epoch 16: ReduceLROnPlateau reducing learning rate to 4.0000001899898055e-05.
534/534 ━━━━━━━━━━━━━━━━━━━━ 121s 226ms/step - accuracy: 0.9982 - loss: 0.1240 - val_accuracy: 0.9906 - val
_loss: 0.1434 - learning_rate: 2.0000e-04
Epoch 17/50
534/534 ━━━━━━━━━━━━━━━━━━━━ 119s 223ms/step - accuracy: 0.9994 - loss: 0.1212 - val_accuracy: 0.9896 - val
_loss: 0.1415 - learning_rate: 4.0000e-05
Epoch 18/50
534/534 ━━━━━━━━━━━━━━━━━━━━ 121s 227ms/step - accuracy: 0.9996 - loss: 0.1209 - val_accuracy: 0.9910 - val
_loss: 0.1410 - learning_rate: 4.0000e-05
67/67 ━━━━━━━━━━━━━━━━━━━━ 3s 48ms/step
Unique predictions: (array([0, 1]), array([1404,  740]))
F1 score: 0.9871186440677966
```

Out[97]: <Sequential name=sequential_55, built=True>

In [ ]:
```
train_model2(create_modified_lenet5(), train_mod_lenet_no_aug_ds, val_mod_lenet_ds, test_mod_lenet_ds)
```

In [98]:
```
train_model2(create_modified_lenet6(), train_mod_lenet_no_aug_ds, val_mod_lenet_ds, test_mod_lenet_ds)
```

```
Epoch 1/50
534/534 ━━━━━━━━━━━━━━━━━━━━ 139s 257ms/step - accuracy: 0.8889 - loss: 0.3820 - val_accuracy: 0.7208 - val
_loss: 0.6638 - learning_rate: 0.0010
Epoch 2/50
534/534 ━━━━━━━━━━━━━━━━━━━━ 132s 247ms/step - accuracy: 0.9528 - loss: 0.2602 - val_accuracy: 0.9094 - val
_loss: 0.4164 - learning_rate: 0.0010
Epoch 3/50
534/534 ━━━━━━━━━━━━━━━━━━━━ 137s 257ms/step - accuracy: 0.9681 - loss: 0.2265 - val_accuracy: 0.7472 - val
_loss: 0.7143 - learning_rate: 0.0010
Epoch 4/50
534/534 ━━━━━━━━━━━━━━━━━━━━ 135s 253ms/step - accuracy: 0.9733 - loss: 0.2120 - val_accuracy: 0.9175 - val
_loss: 0.3304 - learning_rate: 0.0010
Epoch 5/50
534/534 ━━━━━━━━━━━━━━━━━━━━ 216s 405ms/step - accuracy: 0.9790 - loss: 0.1977 - val_accuracy: 0.9547 - val
_loss: 0.2348 - learning_rate: 0.0010
Epoch 6/50
534/534 ━━━━━━━━━━━━━━━━━━━━ 294s 550ms/step - accuracy: 0.9742 - loss: 0.2096 - val_accuracy: 0.7184 - val
_loss: 0.7852 - learning_rate: 0.0010
Epoch 7/50
534/534 ━━━━━━━━━━━━━━━━━━━━ 156s 292ms/step - accuracy: 0.9817 - loss: 0.1883 - val_accuracy: 0.9712 - val
_loss: 0.2061 - learning_rate: 0.0010
Epoch 8/50
534/534 ━━━━━━━━━━━━━━━━━━━━ 139s 261ms/step - accuracy: 0.9838 - loss: 0.1857 - val_accuracy: 0.9099 - val
_loss: 0.3457 - learning_rate: 0.0010
Epoch 9/50
534/534 ━━━━━━━━━━━━━━━━━━━━ 135s 252ms/step - accuracy: 0.9852 - loss: 0.1833 - val_accuracy: 0.7840 - val
_loss: 0.5989 - learning_rate: 0.0010
Epoch 10/50
534/534 ━━━━━━━━━━━━━━━━━━━━ 0s 238ms/step - accuracy: 0.9890 - loss: 0.1725
Epoch 10: ReduceLROnPlateau reducing learning rate to 0.00020000000949949026.
534/534 ━━━━━━━━━━━━━━━━━━━━ 131s 245ms/step - accuracy: 0.9890 - loss: 0.1725 - val_accuracy: 0.9632 - val
_loss: 0.2237 - learning_rate: 0.0010
Epoch 11/50
534/534 ━━━━━━━━━━━━━━━━━━━━ 356s 668ms/step - accuracy: 0.9929 - loss: 0.1651 - val_accuracy: 0.9830 - val
_loss: 0.1807 - learning_rate: 2.0000e-04
Epoch 12/50
534/534 ━━━━━━━━━━━━━━━━━━━━ 430s 806ms/step - accuracy: 0.9964 - loss: 0.1555 - val_accuracy: 0.9882 - val
_loss: 0.1647 - learning_rate: 2.0000e-04
Epoch 13/50
534/534 ━━━━━━━━━━━━━━━━━━━━ 138s 258ms/step - accuracy: 0.9983 - loss: 0.1486 - val_accuracy: 0.9868 - val
_loss: 0.1651 - learning_rate: 2.0000e-04
Epoch 14/50
```

```
534/534 ━━━━━━━━━━━━━━━━━━━━ 135s 253ms/step - accuracy: 0.9990 - loss: 0.1459 - val_accuracy: 0.9892 - val
_loss: 0.1579 - learning_rate: 2.0000e-04
Epoch 15/50
534/534 ━━━━━━━━━━━━━━━━━━━━ 140s 262ms/step - accuracy: 0.9983 - loss: 0.1443 - val_accuracy: 0.9613 - val
_loss: 0.2163 - learning_rate: 2.0000e-04
Epoch 16/50
534/534 ━━━━━━━━━━━━━━━━━━━━ 132s 247ms/step - accuracy: 0.9980 - loss: 0.1423 - val_accuracy: 0.9906 - val
_loss: 0.1511 - learning_rate: 2.0000e-04
Epoch 17/50
534/534 ━━━━━━━━━━━━━━━━━━━━ 133s 248ms/step - accuracy: 0.9988 - loss: 0.1393 - val_accuracy: 0.9825 - val
_loss: 0.1713 - learning_rate: 2.0000e-04
Epoch 18/50
534/534 ━━━━━━━━━━━━━━━━━━━━ 133s 249ms/step - accuracy: 0.9981 - loss: 0.1387 - val_accuracy: 0.9910 - val
_loss: 0.1531 - learning_rate: 2.0000e-04
Epoch 19/50
534/534 ━━━━━━━━━━━━━━━━━━━━ 0s 243ms/step - accuracy: 0.9990 - loss: 0.1363
Epoch 19: ReduceLROnPlateau reducing learning rate to 4.0000001899898055e-05.
534/534 ━━━━━━━━━━━━━━━━━━━━ 133s 249ms/step - accuracy: 0.9990 - loss: 0.1363 - val_accuracy: 0.9910 - val
_loss: 0.1518 - learning_rate: 2.0000e-04
Epoch 20/50
534/534 ━━━━━━━━━━━━━━━━━━━━ 131s 245ms/step - accuracy: 0.9992 - loss: 0.1361 - val_accuracy: 0.9906 - val
_loss: 0.1522 - learning_rate: 4.0000e-05
Epoch 21/50
534/534 ━━━━━━━━━━━━━━━━━━━━ 131s 246ms/step - accuracy: 0.9998 - loss: 0.1346 - val_accuracy: 0.9901 - val
_loss: 0.1522 - learning_rate: 4.0000e-05
67/67 ━━━━━━━━━━━━━━━━━━━━ 4s 55ms/step
Unique predictions: (array([0, 1]), array([1403,  741]))
F1 score: 0.991869918699187
```

Out[98]: <Sequential name=sequential_56, built=True>

In [100…

```
best = train_model2(create_modified_lenet7(), train_mod_lenet_no_aug_ds, val_mod_lenet_ds, test_mod_lenet_
best.save("modified_lenet7.h5")
```

```
Epoch 1/50
534/534 ━━━━━━━━━━━━━━━━━━━━ 132s 243ms/step - accuracy: 0.8986 - loss: 0.3261 - val_accuracy: 0.6708 - val
_loss: 1.5663 - learning_rate: 0.0010
Epoch 2/50
534/534 ━━━━━━━━━━━━━━━━━━━━ 128s 241ms/step - accuracy: 0.9413 - loss: 0.2370 - val_accuracy: 0.6005 - val
_loss: 0.7206 - learning_rate: 0.0010
Epoch 3/50
534/534 ━━━━━━━━━━━━━━━━━━━━ 131s 245ms/step - accuracy: 0.9675 - loss: 0.1998 - val_accuracy: 0.9288 - val
_loss: 0.2685 - learning_rate: 0.0010
Epoch 4/50
534/534 ━━━━━━━━━━━━━━━━━━━━ 130s 243ms/step - accuracy: 0.9756 - loss: 0.1795 - val_accuracy: 0.7193 - val
_loss: 0.5347 - learning_rate: 0.0010
Epoch 5/50
534/534 ━━━━━━━━━━━━━━━━━━━━ 129s 242ms/step - accuracy: 0.9837 - loss: 0.1651 - val_accuracy: 0.7071 - val
_loss: 0.6254 - learning_rate: 0.0010
Epoch 6/50
534/534 ━━━━━━━━━━━━━━━━━━━━ 0s 237ms/step - accuracy: 0.9831 - loss: 0.1639
Epoch 6: ReduceLROnPlateau reducing learning rate to 0.00020000000949949026.
534/534 ━━━━━━━━━━━━━━━━━━━━ 130s 243ms/step - accuracy: 0.9831 - loss: 0.1639 - val_accuracy: 0.7113 - val
_loss: 1.1778 - learning_rate: 0.0010
Epoch 7/50
534/534 ━━━━━━━━━━━━━━━━━━━━ 130s 243ms/step - accuracy: 0.9887 - loss: 0.1540 - val_accuracy: 0.9892 - val
_loss: 0.1462 - learning_rate: 2.0000e-04
Epoch 8/50
534/534 ━━━━━━━━━━━━━━━━━━━━ 129s 242ms/step - accuracy: 0.9942 - loss: 0.1421 - val_accuracy: 0.9882 - val
_loss: 0.1470 - learning_rate: 2.0000e-04
Epoch 9/50
534/534 ━━━━━━━━━━━━━━━━━━━━ 131s 245ms/step - accuracy: 0.9961 - loss: 0.1386 - val_accuracy: 0.9844 - val
_loss: 0.1584 - learning_rate: 2.0000e-04
Epoch 10/50
534/534 ━━━━━━━━━━━━━━━━━━━━ 130s 243ms/step - accuracy: 0.9978 - loss: 0.1359 - val_accuracy: 0.9925 - val
_loss: 0.1425 - learning_rate: 2.0000e-04
Epoch 11/50
534/534 ━━━━━━━━━━━━━━━━━━━━ 130s 243ms/step - accuracy: 0.9980 - loss: 0.1336 - val_accuracy: 0.9863 - val
_loss: 0.1473 - learning_rate: 2.0000e-04
Epoch 12/50
534/534 ━━━━━━━━━━━━━━━━━━━━ 130s 244ms/step - accuracy: 0.9988 - loss: 0.1317 - val_accuracy: 0.9901 - val
_loss: 0.1465 - learning_rate: 2.0000e-04
Epoch 13/50
534/534 ━━━━━━━━━━━━━━━━━━━━ 0s 238ms/step - accuracy: 0.9983 - loss: 0.1333
Epoch 13: ReduceLROnPlateau reducing learning rate to 4.0000001899898055e-05.
534/534 ━━━━━━━━━━━━━━━━━━━━ 131s 244ms/step - accuracy: 0.9983 - loss: 0.1333 - val_accuracy: 0.9783 - val
```

```
_loss: 0.1707 - learning_rate: 2.0000e-04
Epoch 14/50
534/534 ━━━━━━━━━━━━━━━━━━━━ 131s 244ms/step - accuracy: 0.9994 - loss: 0.1291 - val_accuracy: 0.9939 - val
_loss: 0.1388 - learning_rate: 4.0000e-05
Epoch 15/50
534/534 ━━━━━━━━━━━━━━━━━━━━ 130s 244ms/step - accuracy: 0.9997 - loss: 0.1274 - val_accuracy: 0.9920 - val
_loss: 0.1401 - learning_rate: 4.0000e-05
Epoch 16/50
534/534 ━━━━━━━━━━━━━━━━━━━━ 129s 242ms/step - accuracy: 0.9996 - loss: 0.1290 - val_accuracy: 0.9925 - val
_loss: 0.1396 - learning_rate: 4.0000e-05
Epoch 17/50
534/534 ━━━━━━━━━━━━━━━━━━━━ 0s 242ms/step - accuracy: 0.9996 - loss: 0.1280
Epoch 17: ReduceLROnPlateau reducing learning rate to 8.000000525498762e-06.
534/534 ━━━━━━━━━━━━━━━━━━━━ 133s 249ms/step - accuracy: 0.9996 - loss: 0.1280 - val_accuracy: 0.9939 - val
_loss: 0.1392 - learning_rate: 4.0000e-05
Epoch 18/50
534/534 ━━━━━━━━━━━━━━━━━━━━ 130s 244ms/step - accuracy: 0.9999 - loss: 0.1270 - val_accuracy: 0.9925 - val
_loss: 0.1392 - learning_rate: 8.0000e-06
Epoch 19/50
534/534 ━━━━━━━━━━━━━━━━━━━━ 129s 241ms/step - accuracy: 0.9998 - loss: 0.1266 - val_accuracy: 0.9929 - val
_loss: 0.1391 - learning_rate: 8.0000e-06
67/67 ━━━━━━━━━━━━━━━━━━━━ 4s 53ms/step
WARNING:absl:You are saving your model as an HDF5 file via `model.save()` or `keras.saving.save_model(mode
l)`. This file format is considered legacy. We recommend using instead the native Keras format, e.g. `mode
l.save('my_model.keras')` or `keras.saving.save_model(model, 'my_model.keras')`.
Unique predictions: (array([0, 1]), array([1409,  735]))
F1 score: 0.9931972789115646
```

Use of AI

[1] Tool: ChatGPT

> Prompt: I'm going to try using an ANN, a Lenet-5 CNN, a modified Lenet-5 CNN, and a VGG-16 based approach to classify images. Don't write code for those, but knowing that, what preprocessing techniques should I try using on the data? A tencrop maybe? Something else?
>
> Output:

You said you'll train:

ANN

LeNet-5

Modified LeNet-5

VGG-16-based model

So your preprocessing pipeline should balance simplicity (for LeNet/ANN) and rich augmentation (for CNNs/VGG).

🧰 Recommended preprocessing techniques: Technique Purpose Notes Resizing Standardize input dimensions (128,128) is fine for simple CNNs; use (224,224) for VGG-16 Normalization Scale pixel values to [0,1] or [-1,1] Already done via Rescaling layer Data augmentation Increase robustness Use flips, rotations, zoom, brightness changes Standardization (optional) Zero-center and scale by std Only needed if you preprocess manually TenCrop / MultiCrop For evaluation, not training Applies to test-time augmentation (VGG-style models) Grayscale conversion Optional for LeNet-5 (originally grayscale) If your data is RGB, you can test both color and grayscale versions Example augmentation layer (to plug into your model): from tensorflow.keras import layers

data_augmentation = tf.keras.Sequential([layers.RandomFlip("horizontal"), layers.RandomRotation(0.1), layers.RandomZoom(0.1), layers.RandomBrightness(factor=0.1)])

You can add this before your first Conv2D or Flatten layer in your models.

🧠 TL;DR — Preprocessing Summary Step For Models Description Resize to (128,128) ANN, LeNet Light networks Resize to (224,224) VGG-16 Matches pretrained input Normalize [0,1] All Essential Augmentations CNNs Boost robustness Convert to grayscale LeNet (optional) Try both RGB & grayscale TenCrop VGG evaluation Optional advanced test-time augmentation

Would you like me to extend this to include a data augmentation pipeline that automatically applies random transformations during training (ready to feed into your CNNs)?

[2] Tool: ChatGPT

```
Prompt: Ok what can I do to my modified lenet and vgg16 models to improve performance?
Also, I might try averaging or weighted-averaging all 3 models or something
```

```
Output:
```

🔧 1. Modified LeNet — low-hanging improvements Your LeNet is small and efficient, so a few tweaks can usually yield noticeable gains. ✅ Architectural tweaks

Batch Normalization after each Conv layer. → stabilizes and speeds up convergence.

Dropout (0.3–0.5) before the first Dense layer. → reduces overfitting.

GlobalAveragePooling instead of Flatten (if using conv blocks throughout). → smaller parameter count, often better generalization.

✅ Training tweaks

Learning rate sweep: try 1e-3, 5e-4, 1e-4 — small nets are sensitive to this.

Weight decay (L2 regularization): 1e-4 or 1e-5.

Label smoothing: e.g. label_smoothing=0.05 in your loss function. → helps with overconfident predictions, often +0.002–0.005 F1.

Early stopping + ReduceLROnPlateau.

Mild augmentation: only flips and small rotations (±10°). Avoid heavy transforms — you already saw collapse from aggressive aug.

✅ Quick example layer stack x = Conv2D(32, (3,3), activation='relu', padding='same')(inputs) x = BatchNormalization()(x) x = MaxPooling2D()(x)

x = Conv2D(64, (3,3), activation='relu', padding='same')(x) x = BatchNormalization()(x) x = MaxPooling2D()(x)

x = GlobalAveragePooling2D()(x) x = Dropout(0.4)(x) outputs = Dense(num_classes, activation='softmax')(x)

That alone can sometimes push performance by a few points.

🧠 2. VGG16 — make it actually fine-tuned If your current VGG16 was trained from scratch or only partially fine-tuned, that's why it lags. ✅ Start from pretrained ImageNet weights base = tf.keras.applications.VGG16(include_top=False, weights='imagenet', input_shape=(224,224,3))

Then freeze base, train the new head, unfreeze last 1–2 blocks later. ✅ Head design x = base.output x = GlobalAveragePooling2D()(x) x = Dropout(0.5)(x) outputs = Dense(num_classes, activation='softmax')(x)

✅ Training schedule

Stage 1: Freeze all conv blocks. Train classifier head (lr = 1e-3, ~5–10 epochs).

Stage 2: Unfreeze last 2 conv blocks. Fine-tune (lr = 1e-5 or 1e-4, weight_decay=1e-4, 10–30 epochs).

Use ReduceLROnPlateau and early stopping. ✅ Regularization

Use AdamW (if available) or SGD(momentum=0.9, weight_decay=1e-4).

Gradient clipping (clipnorm=1.0) can help avoid collapse.

Label smoothing 0.1 for robustness.

⚗️ 3. Model ensembling (simple & effective) Once you have final checkpoints for all 3 models, you can ensemble them in a few ways: ✅ Unweighted averaging preds_lenet = model_lenet.predict(X_test) preds_vgg16 = model_vgg16.predict(X_test) preds_vgg19 = model_vgg19.predict(X_test)

avg_preds = (preds_lenet + preds_vgg16 + preds_vgg19) / 3 final_labels = np.argmax(avg_preds, axis=1)

✅ Weighted averaging If you know their relative F1 scores: w1, w2, w3 = 0.5, 0.3, 0.2 # e.g., LeNet is strongest weighted_preds = w1*preds_lenet + w2*preds_vgg16 + w3*preds_vgg19 final_labels = np.argmax(weighted_preds, axis=1)

Even simple averaging often gives +0.005–0.015 F1 boost if models make different mistakes.

⚙️ 4. Optional micro-optimizations If you have a few hours:

Stochastic Weight Averaging (SWA): average weights from the last few epochs → smoother minima.

TTA (Test-Time Augmentation): predict with flipped/rotated versions of each test image and average.

Ensemble different seeds for the same architecture (e.g., two LeNets trained with different seeds).

🚀 TL;DR – Where to focus PriorityModelKey improvements⭐ Modified LeNetBN + Dropout + mild aug + label smoothing + small LR sweep⭐ VG16Pretrained weights + two-stage fine-tuning + weight decay + label smoothing💤 VGG19Skip training; use in ensemble only⚡ EnsembleWeighted average predictions (LeNet-heavy)

If you want, I can give you a short Keras code snippet that ensembles your trained models and outputs final F1 — literally plug-and-run. Would you like me to draft that?