CNN_Cancer_Detection_Kaggle_MiniProject

November 29, 2024

1 DTSA 5511 Week 3 CNN Cancer Detection Kaggle Mini-Project

2 Objective

The objective of this project is to create an algorithm to identify metastatic cancer in small image patches taken from larger digital pathology scans

3 Data

In this dataset, we are provided with a large number of small pathology images to classify. Files are named with an image id. The train_labels.csv file provides the ground truth for the images in the train folder. We are predicting the labels for the images in the test folder. A positive label indicates that the center 32x32px region of a patch contains at least one pixel of tumor tissue. Tumor tissue in the outer region of the patch does not influence the label. This outer region is provided to enable fully-convolutional models that do not use zero-padding, to ensure consistent behavior when applied to a whole-slide image.

The original PCam dataset contains duplicate images due to its probabilistic sampling, however, the version presented on Kaggle does not contain duplicates. We have otherwise maintained the same data and splits as the PCam benchmark.

[1]:
```
import pandas as pd
from collections import Counter
from matplotlib import pyplot as plt
import os
import seaborn
import numpy as np
import glob
from sklearn.metrics import confusion_matrix, ConfusionMatrixDisplay,␣
↪classification_report
from sklearn.model_selection import train_test_split
import zipfile
from PIL import Image
import pickle
import sys
import tensorflow as tf
```

```python
import keras
from keras import layers
from keras.preprocessing.image import load_img, img_to_array
from tensorflow.keras.layers import Conv2D, MaxPooling2D
from tensorflow.keras.layers import Dense, Dropout, Flatten, Activation
from tensorflow.keras.preprocessing.image import ImageDataGenerator
from tensorflow.keras.models import Sequential
from tensorflow.keras.callbacks import EarlyStopping, ReduceLROnPlateau,␣
↪ModelCheckpoint
from tensorflow.keras.optimizers import Adam
```

[2]:
```python
train_labels_df = pd.read_csv("train_labels.csv")
train_labels_df
```

[2]:
```
                                              id  label
0       f38a6374c348f90b587e046aac6079959adf3835      0
1       c18f2d887b7ae4f6742ee445113fa1aef383ed77      1
2       755db6279dae599ebb4d39a9123cce439965282d      0
3       bc3f0c64fb968ff4a8bd33af6971ecae77c75e08      0
4       068aba587a4950175d04c680d38943fd488d6a9d      0
…                                            …    …
220020  53e9aa9d46e720bf3c6a7528d1fca3ba6e2e49f6      0
220021  d4b854fe38b07fe2831ad73892b3cec877689576      1
220022  3d046cead1a2a5cbe00b2b4847cfb7ba7cf5fe75      0
220023  f129691c13433f66e1e0671ff1fe80944816f5a2      0
220024  a81f84895ddcd522302ddf34be02eb1b3e5af1cb      1

[220025 rows x 2 columns]
```

[3]:
```python
## Function that loads data from the filesystem in the form of file location

def load_tif_images_to_dataframe(directory):
    image_data = []
    for filename in os.listdir(directory):
        if filename.endswith(".tif"):
            filepath = os.path.join(directory, filename)
        try:
            img = Image.open(filepath)
            image_data.append({'filepath': filepath})
            img.close()
        except Exception as e:
            pass
            print(f"Error loading image {filename}: {e}")
    return pd.DataFrame(image_data)
```

[4]:
```python
train_df = load_tif_images_to_dataframe("train")
train_df
```

[4]:
```
                                                filepath
0       train/f0c2a0b8ef3024f407fa97d852d49be0215cafe0…
1       train/99ef485f205645918613cd04281098daa7c17819…
2       train/e2612e173abd0e8bb54a3c3db3f264b63d80bffb…
3       train/6d1bb57c0606f05dbd75f90a8d9e21a57e1267e0…
4       train/9c043ab2adadfeb758c71d21432fccd3e43565c0…
…                                                    …
220020  train/7a5f23a002018cd828cc5e8df89de79850d01050…
220021  train/7cd369c04a37c9da20bbfe1bcba2cfad754fc100…
220022  train/b21c0dc5ba97639f3b5c62ffe00364cfb0c11b40…
220023  train/d16dbdaf3b5cea4b5f6629e2a487f0e01075ba58…
220024  train/229bb0b26c46fa262092d6ad81e0b3719b372843…

[220025 rows x 1 columns]
```

[5]:
```
train_df['id'] = train_df['filepath'].apply(lambda x: os.path.basename(x).
 ↪split('.')[0])
train_df = train_df[train_df['id'] != '_labels']
train_df
```

[5]:
```
                                                filepath  \
0       train/f0c2a0b8ef3024f407fa97d852d49be0215cafe0…
1       train/99ef485f205645918613cd04281098daa7c17819…
2       train/e2612e173abd0e8bb54a3c3db3f264b63d80bffb…
3       train/6d1bb57c0606f05dbd75f90a8d9e21a57e1267e0…
4       train/9c043ab2adadfeb758c71d21432fccd3e43565c0…
…                                                    …
220020  train/7a5f23a002018cd828cc5e8df89de79850d01050…
220021  train/7cd369c04a37c9da20bbfe1bcba2cfad754fc100…
220022  train/b21c0dc5ba97639f3b5c62ffe00364cfb0c11b40…
220023  train/d16dbdaf3b5cea4b5f6629e2a487f0e01075ba58…
220024  train/229bb0b26c46fa262092d6ad81e0b3719b372843…

                                              id
0       f0c2a0b8ef3024f407fa97d852d49be0215cafe0
1       99ef485f205645918613cd04281098daa7c17819
2       e2612e173abd0e8bb54a3c3db3f264b63d80bffb
3       6d1bb57c0606f05dbd75f90a8d9e21a57e1267e0
4       9c043ab2adadfeb758c71d21432fccd3e43565c0
…                                              …
220020  7a5f23a002018cd828cc5e8df89de79850d01050
220021  7cd369c04a37c9da20bbfe1bcba2cfad754fc100
220022  b21c0dc5ba97639f3b5c62ffe00364cfb0c11b40
220023  d16dbdaf3b5cea4b5f6629e2a487f0e01075ba58
220024  229bb0b26c46fa262092d6ad81e0b3719b372843

[220025 rows x 2 columns]
```

[6]:
```python
train_data_df = pd.merge(train_df, train_labels_df, on='id').drop(columns =
    ['id'])
train_df = None # Resetting for system memory
train_labels_df = None # Resetting for system memory
print(Counter(train_data_df.label))
print(train_data_df.info())
train_data_df
```

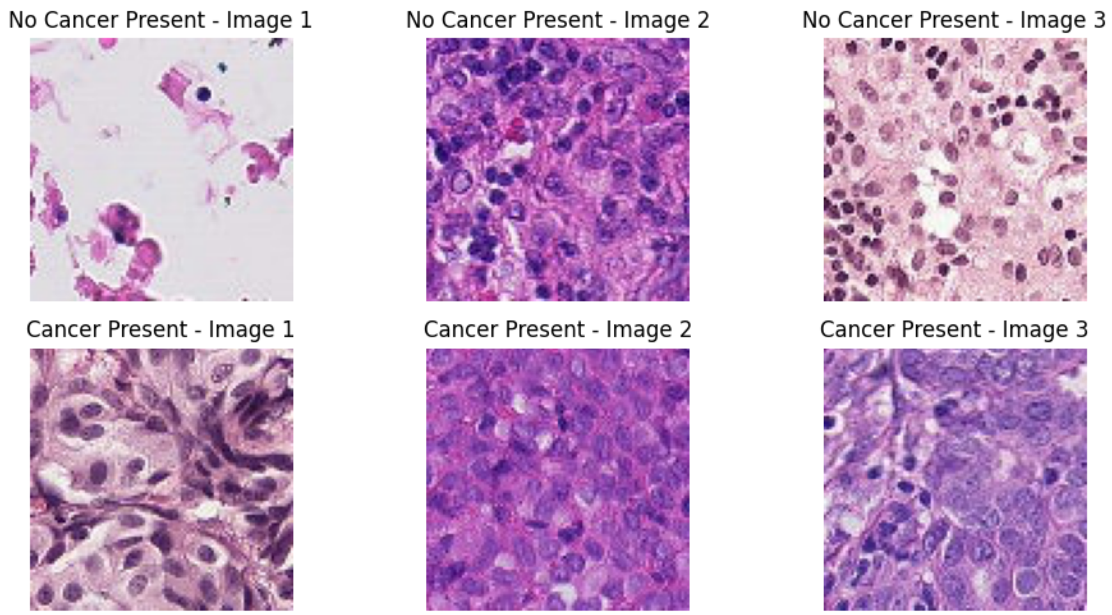
```
Counter({0: 130908, 1: 89117})
<class 'pandas.core.frame.DataFrame'>
Int64Index: 220025 entries, 0 to 220024
Data columns (total 2 columns):
 #   Column    Non-Null Count   Dtype
---  ------    --------------   -----
 0   filepath  220025 non-null  object
 1   label     220025 non-null  int64
dtypes: int64(1), object(1)
memory usage: 5.0+ MB
None
```

[6]:
```
                                                  filepath  label
0       train/f0c2a0b8ef3024f407fa97d852d49be0215cafe0…      0
1       train/99ef485f205645918613cd04281098daa7c17819…      1
2       train/e2612e173abd0e8bb54a3c3db3f264b63d80bffb…      1
3       train/6d1bb57c0606f05dbd75f90a8d9e21a57e1267e0…      0
4       train/9c043ab2adadfeb758c71d21432fccd3e43565c0…      1
…                                                    …    …
220020  train/7a5f23a002018cd828cc5e8df89de79850d01050…      1
220021  train/7cd369c04a37c9da20bbfe1bcba2cfad754fc100…      1
220022  train/b21c0dc5ba97639f3b5c62ffe00364cfb0c11b40…      0
220023  train/d16dbdaf3b5cea4b5f6629e2a487f0e01075ba58…      0
220024  train/229bb0b26c46fa262092d6ad81e0b3719b372843…      0

[220025 rows x 2 columns]
```

4 Exploratory Data Analysis

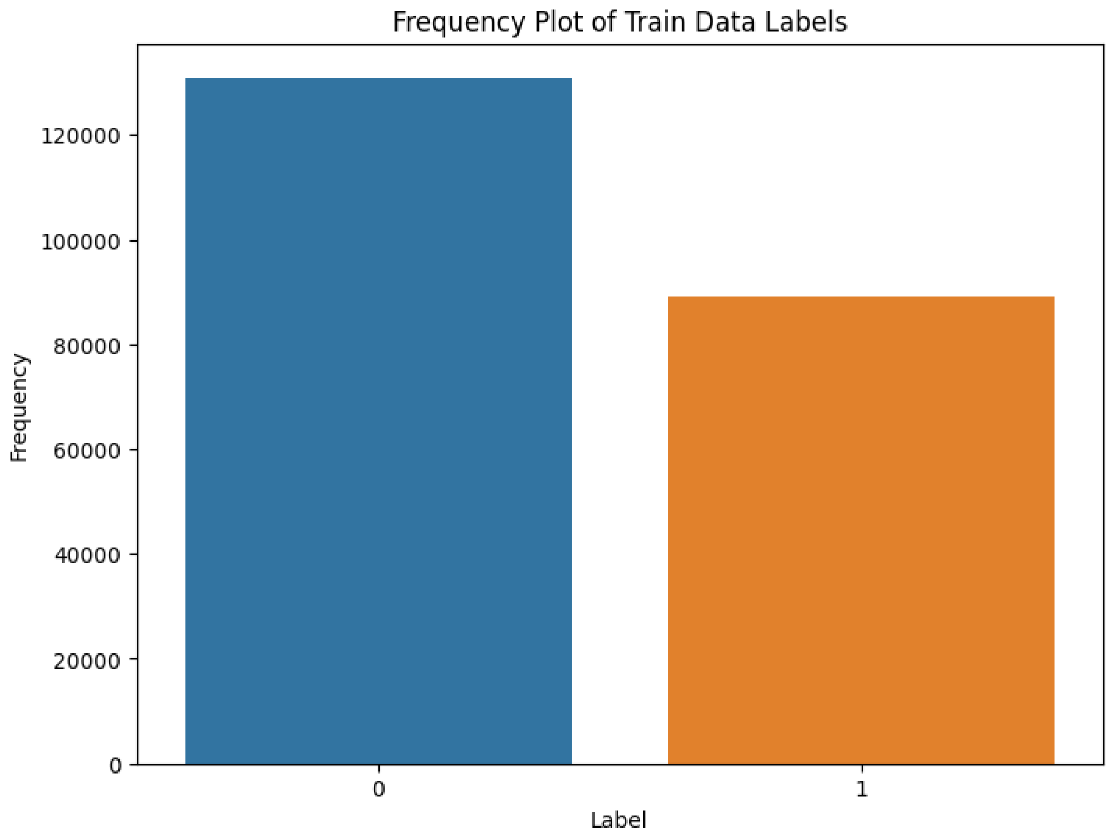
[7]:
```python
## Display images of each class

label_0 = train_data_df[train_data_df['label'] == 0][0:3]
label_1 = train_data_df[train_data_df['label'] == 1][0:3]

plt.figure(figsize=(10, 5))

for i in range(3):
    # Label 0 images
    img_path = label_0.iloc[i]['filepath']
```

```
    img = Image.open(img_path)
    plt.subplot(2, 3, i + 1)
    plt.imshow(img)
    plt.title(f'No Cancer Present - Image {i+1}')
    plt.axis('off')

for i in range(3):
    # Label 1 images
    img_path = label_1.iloc[i]['filepath']
    img = Image.open(img_path)
    plt.subplot(2, 3, i + 4)
    plt.imshow(img)
    plt.title(f'Cancer Present - Image {i+1}')
    plt.axis('off')

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



[8]:
```
## Display a frequency plot of the train data label distribution

label_counts = train_data_df['label'].value_counts()
plt.figure(figsize=(8, 6))
seaborn.countplot(x='label', data=train_data_df)
plt.title('Frequency Plot of Train Data Labels')
plt.xlabel('Label')
plt.ylabel('Frequency')
```

```
plt.show()
```



From the plot above we see that there are ~130,000+ non cancer images and ~90,000 cancerous images.

5 Setup and Train Model

[9]:
```
## Setup the train and validation data for model development

train_df, validation_df = train_test_split(train_data_df, test_size = 0.3,␣
 ↪random_state = 0)
train_data_df = None # Reseting for memory
```

[10]:
```
validation_df
```

[10]:

	filepath	label
155115	train/e3424e29c515bc20ae7fdd84b742aadd0f14838b...	0
145742	train/0c8492c5ab94a2a011452d34c6019ba691b40b69...	0
105400	train/cc1191e93b9c344bd12cb240e1122622081d3079...	0
61543	train/5bf7dbaddc83ab08f162d451a63470acb2baff5b...	0

```
32978   train/74e8d06b196e97b94aab93207681b34f4a3cba6f…     0
…                                                     …    …
180112  train/2c8dd8ef25e1ef661115742b8b4977f52741003f…     1
192655  train/c30795e221aa96b940cc5d795ceaebeead95d5cf…     1
124067  train/0c29b70885ed002397d2bae068e2fbb55c3b8b89…     0
122609  train/cf8076828ab540a9f46f8e2a94fbad0689abd593…     1
88673   train/67c77b94c136ddc81388a0924fd0469e4c91f8d4…     0

[66008 rows x 2 columns]
```

[11]:
```
## Setup data for ImageDataGenerator and flow_from_dataframe

train_df['label'] = train_df['label'].astype(str)
validation_df['label'] = validation_df['label'].astype(str)
```

[12]:
```
## Obtain image dimensions

image = Image.open(train_df.iloc[0]['filepath'])
width, height = image.size
batch_size = 64
img_size = (width, height)
channels = 3
img_shape = (img_size[0], img_size[1], channels)
print("Image shape:", img_shape)
```

```
Image shape: (96, 96, 3)
```

[13]:
```
## Transform the train and validation data for use by keras

train_datagen = ImageDataGenerator(rescale = 1./255)
validation_datagen = ImageDataGenerator(rescale = 1./255)

train_generator = train_datagen.flow_from_dataframe(
    dataframe = train_df,
    x_col = 'filepath',
    y_col = 'label',
    target_size = img_size,
    batch_size = batch_size,
    class_mode = 'binary')
train_df = None # Reset for memory

validation_generator = validation_datagen.flow_from_dataframe(
    dataframe = validation_df,
    x_col = 'filepath',
    y_col = 'label',
    target_size = img_size,
    batch_size = batch_size,
    class_mode= 'binary')
```

```
validation_df = None # Reset for memory
```

```
Found 154017 validated image filenames belonging to 2 classes.
Found 66008 validated image filenames belonging to 2 classes.
```

[14]:
```
## Setup test data, only file paths needed for now as the images will be loaded␣
↪later for prediction

def load_filepaths(directory):
    file_paths = []
    for filename in os.listdir(directory):
        filepath = os.path.join(directory, filename)
        file_paths.append(filepath)
    test_data_prepared = pd.DataFrame({'file_paths': file_paths})
    file_paths = None
    return test_data_prepared

test_data_prepared = load_filepaths("test")
test_data_prepared
```

[14]:
```
                                              file_paths
0      test/fd0a060ef9c30c9a83f6b4bfb568db74b099154d.tif
1      test/1f9ee06f06d329eb7902a2e03ab3835dd0484581.tif
2      test/19709bec800f372d0b1d085da6933dd3ef108846.tif
3      test/7a34fc34523063f13f0617f7518a0330f6187bd3.tif
4      test/93be720ca2b95fe2126cf2e1ed752bd759e9b0ed.tif
…                                                    …
57453  test/2581931c6ef068f105a872f2c5500275fc678242.tif
57454  test/11b250a664d09ab59fd2afbdb2f8d786763b185d.tif
57455  test/18a6030935ec1ef1ce486ec51bc95abb4008fbf1.tif
57456  test/f541404e501e23a0188c852eb37eac94053cfdc0.tif
57457  test/3cb6f5e2db8ad046c946b581fa12d20df5ce2927.tif

[57458 rows x 1 columns]
```

6 Max Pooling Model

We are going to use a max pooling model. Max pooling is a feature extraction technique used in convolutional neural networks (CNNs) to reduce the spatial dimensions of an input image. It works by dividing an image into non-overlapping regions and selecting the maximum value from each region. The result is a downsampled image that contains the most important information while discarding less important details

[15]:
```
## Create a CNN using max pooling layers

model_max_pooling = keras.Sequential([
    layers.Conv2D(32, (3, 3), activation='relu', input_shape=img_shape),
```

```python
    layers.MaxPooling2D((2, 2)),
    layers.Conv2D(64, (3, 3), activation='relu'),
    layers.MaxPooling2D((2, 2)),
    layers.Flatten(),
    layers.Dense(64, activation='relu'),
    layers.Dense(1, activation='sigmoid')
])

model_max_pooling.compile(optimizer='adam',
              loss='binary_crossentropy',
              metrics=['accuracy'])

history_max_pooling = model_max_pooling.fit(
    train_generator,
    epochs=8,
    validation_data=validation_generator
)

loss_max_pooling, accuracy_max_pooling = model_max_pooling.
 ↪evaluate(validation_generator)
print(f"Validation Loss: {loss_max_pooling}")
print(f"Validation Accuracy: {accuracy_max_pooling}")

model_max_pooling.save('models/model_max_pooling.keras')
```

```
Epoch 1/8
```

```
/Library/Frameworks/Python.framework/Versions/3.11/lib/python3.11/site-
packages/keras/src/layers/convolutional/base_conv.py:107: UserWarning: Do not
pass an `input_shape`/`input_dim` argument to a layer. When using Sequential
models, prefer using an `Input(shape)` object as the first layer in the model
instead.
  super().__init__(activity_regularizer=activity_regularizer, **kwargs)
/Library/Frameworks/Python.framework/Versions/3.11/lib/python3.11/site-
packages/keras/src/trainers/data_adapters/py_dataset_adapter.py:121:
UserWarning: Your `PyDataset` class should call `super().__init__(**kwargs)` in
its constructor. `**kwargs` can include `workers`, `use_multiprocessing`,
`max_queue_size`. Do not pass these arguments to `fit()`, as they will be
ignored.
  self._warn_if_super_not_called()
```

```
2407/2407                193s 80ms/step
- accuracy: 0.6757 - loss: 0.5611 - val_accuracy: 0.8148 - val_loss: 0.4163
Epoch 2/8
2407/2407                196s 81ms/step
- accuracy: 0.8256 - loss: 0.3935 - val_accuracy: 0.8373 - val_loss: 0.3726
Epoch 3/8
2407/2407                192s 80ms/step
- accuracy: 0.8488 - loss: 0.3493 - val_accuracy: 0.8524 - val_loss: 0.3442
```

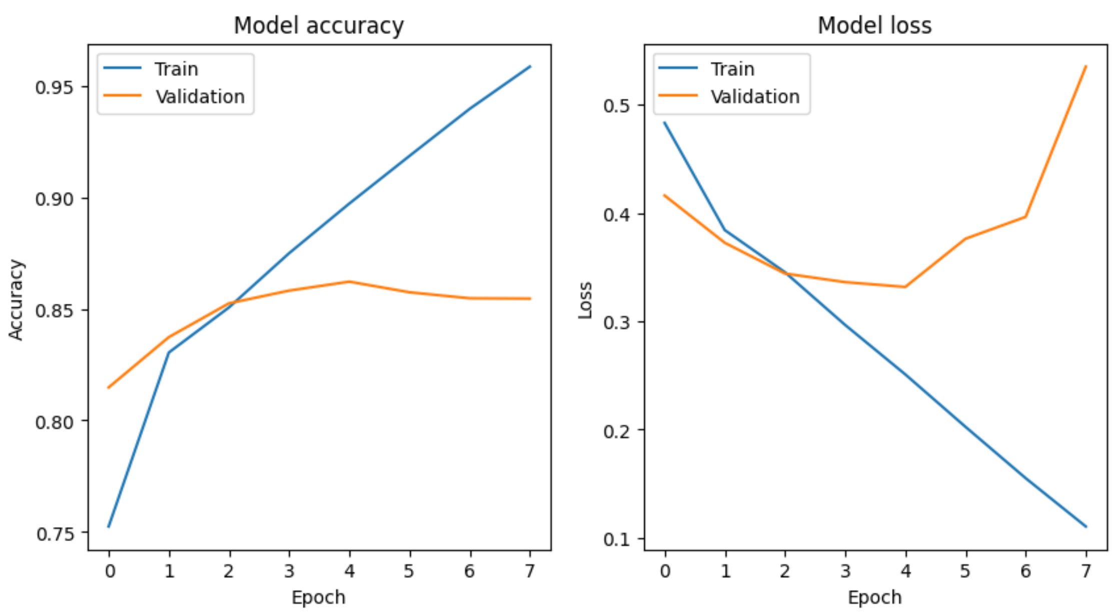
```
Epoch 4/8
2407/2407          193s 80ms/step
- accuracy: 0.8745 - loss: 0.2980 - val_accuracy: 0.8581 - val_loss: 0.3362
Epoch 5/8
2407/2407          192s 80ms/step
- accuracy: 0.8972 - loss: 0.2498 - val_accuracy: 0.8622 - val_loss: 0.3318
Epoch 6/8
2407/2407          192s 80ms/step
- accuracy: 0.9205 - loss: 0.1988 - val_accuracy: 0.8574 - val_loss: 0.3763
Epoch 7/8
2407/2407          193s 80ms/step
- accuracy: 0.9424 - loss: 0.1503 - val_accuracy: 0.8547 - val_loss: 0.3965
Epoch 8/8
2407/2407          192s 80ms/step
- accuracy: 0.9614 - loss: 0.1047 - val_accuracy: 0.8546 - val_loss: 0.5354
1032/1032          22s 21ms/step -
accuracy: 0.8544 - loss: 0.5278
Validation Loss: 0.535365879535675
Validation Accuracy: 0.8545630574226379
```

[25]:

```
model_max_pooling = keras.models.load_model('models/model_max_pooling.keras')
predictions = []
with open(os.devnull, 'w') as devnull:
    old_stdout = sys.stdout
    sys.stdout = devnull
    try:
        # Iterate over test image filepaths
        for filepath in test_data_prepared.file_paths:
            # Load and preprocess the image
            img = Image.open(filepath)
            img = img.resize(img.size) # Assuming img_size is defined from␣
↪previous code
            img_array = np.array(img) / 255.0 # Normalize pixel values
            img.close()
            img_array = np.expand_dims(img_array, axis=0) # Add batch dimension
            prediction = model_max_pooling.predict(img_array)
            predictions.append(prediction[0][0])
        results = pd.DataFrame({'id': test_data_prepared.file_paths, 'label':␣
↪predictions})
        results['label'] = results['label'].round()
        results['id'] = results['id'].apply(lambda x: os.path.basename(x).
↪split('.')[0])
    finally:
        sys.stdout = old_stdout
model_max_pooling = None
results.to_csv('results/model_max_pooling_results.csv', index=False)
```

7 Max Pooling - Visualize Results

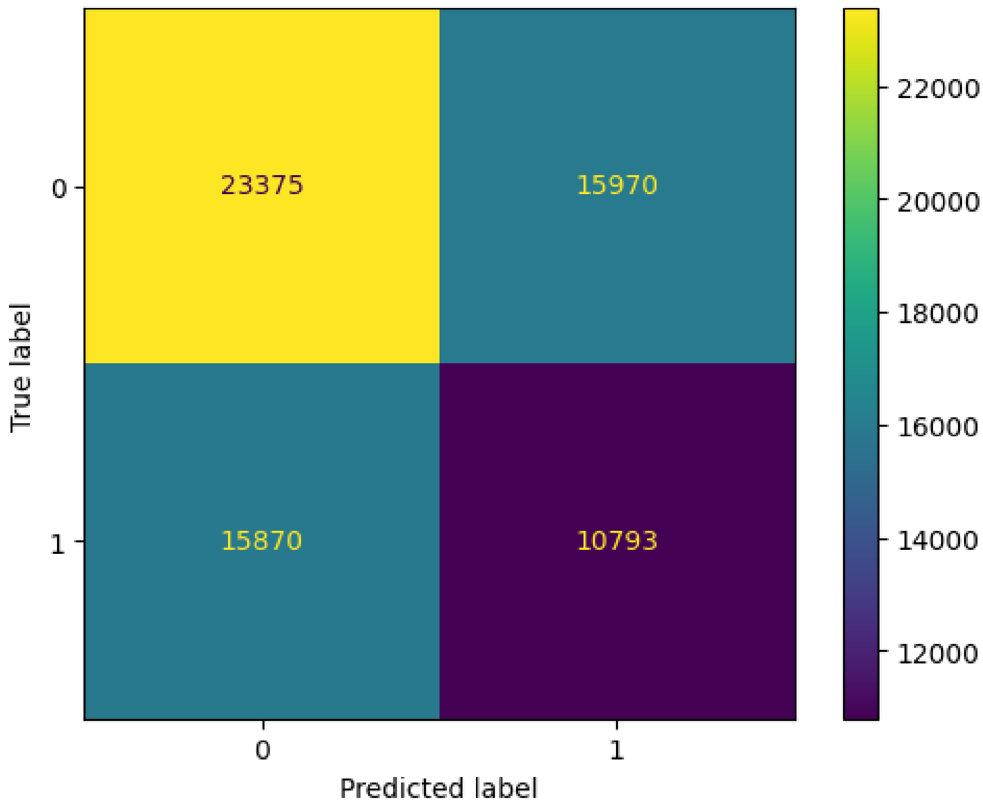
[17]:
```python
plt.figure(figsize=(10, 5))

# Plot training & validation accuracy values
plt.subplot(1, 2, 1)
plt.plot(history_max_pooling.history['accuracy'])
plt.plot(history_max_pooling.history['val_accuracy'])
plt.title('Model accuracy')
plt.ylabel('Accuracy')
plt.xlabel('Epoch')
plt.legend(['Train', 'Validation'], loc='upper left')

# Plot training & validation loss values
plt.subplot(1, 2, 2)
plt.plot(history_max_pooling.history['loss'])
plt.plot(history_max_pooling.history['val_loss'])
plt.title('Model loss')
plt.ylabel('Loss')
plt.xlabel('Epoch')
plt.legend(['Train', 'Validation'], loc='upper left')

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



8 Max Pooling - Classification Report and Confusion Matrix

[18]:
```
## Generate a classification report and confusion matrix for the validation␣
↪predictions

validation_predictions = model_max_pooling.predict(validation_generator)
validation_pred_labels = (validation_predictions > 0.5).astype(int)

# Get true labels
validation_true_labels = validation_generator.classes

# Generate classification report
class_report = classification_report(validation_true_labels,␣
↪validation_pred_labels)
print(class_report)

# Generate confusion matrix
cm = confusion_matrix(validation_true_labels, validation_pred_labels)
disp = ConfusionMatrixDisplay(confusion_matrix=cm, display_labels=['0','1'])
disp.plot()
plt.show()
```

```
1032/1032            25s 25ms/step
              precision    recall  f1-score   support

           0       0.60      0.59      0.59     39345
           1       0.40      0.40      0.40     26663

    accuracy                           0.52     66008
   macro avg       0.50      0.50      0.50     66008
weighted avg       0.52      0.52      0.52     66008
```



9 Average Pooling Model

Average pooling is a technique used in convolutional neural networks (CNNs) to reduce the size of feature maps while keeping important information. It works by calculating the average value of a region in the feature map, and then using that value to create a downsampled feature map

[20]:
```
## Create a CNN model using average pooling layers

model_average_pooling = keras.Sequential([
    layers.Conv2D(32, (3, 3), activation='relu', input_shape=img_shape),
    layers.AveragePooling2D((2, 2)),
    layers.Conv2D(64, (3, 3), activation='relu'),
    layers.AveragePooling2D((2, 2)),
    layers.Flatten(),
    layers.Dense(64, activation='relu'),
    layers.Dense(1, activation='sigmoid')
])

model_average_pooling.compile(optimizer='adam',
              loss='binary_crossentropy',
```

```
              metrics=['accuracy'])

history_avg_pooling = model_average_pooling.fit(
    train_generator,
    epochs=8,
    validation_data=validation_generator
)

loss_avg_pooling, accuracy_avg_pooling = model_average_pooling.
  ↪evaluate(validation_generator)
print(f"Validation Loss: {loss_avg_pooling}")
print(f"Validation Accuracy: {accuracy_avg_pooling}")

model_average_pooling.save('models/model_average_pooling.keras')
```

```
Epoch 1/8
2407/2407              193s 80ms/step
- accuracy: 0.7417 - loss: 0.5291 - val_accuracy: 0.8147 - val_loss: 0.4175
Epoch 2/8
2407/2407              189s 79ms/step
- accuracy: 0.8161 - loss: 0.4128 - val_accuracy: 0.8365 - val_loss: 0.3736
Epoch 3/8
2407/2407              189s 79ms/step
- accuracy: 0.8377 - loss: 0.3707 - val_accuracy: 0.8379 - val_loss: 0.3657
Epoch 4/8
2407/2407              190s 79ms/step
- accuracy: 0.8522 - loss: 0.3409 - val_accuracy: 0.8381 - val_loss: 0.3673
Epoch 5/8
2407/2407              191s 79ms/step
- accuracy: 0.8668 - loss: 0.3117 - val_accuracy: 0.8507 - val_loss: 0.3432
Epoch 6/8
2407/2407              191s 79ms/step
- accuracy: 0.8795 - loss: 0.2851 - val_accuracy: 0.8518 - val_loss: 0.3444
Epoch 7/8
2407/2407              191s 79ms/step
- accuracy: 0.8968 - loss: 0.2496 - val_accuracy: 0.8457 - val_loss: 0.3574
Epoch 8/8
2407/2407              191s 79ms/step
- accuracy: 0.9106 - loss: 0.2211 - val_accuracy: 0.8459 - val_loss: 0.3996
1032/1032              24s 23ms/step -
accuracy: 0.8480 - loss: 0.3910
Validation Loss: 0.3996047377586365
Validation Accuracy: 0.8459126353263855
```

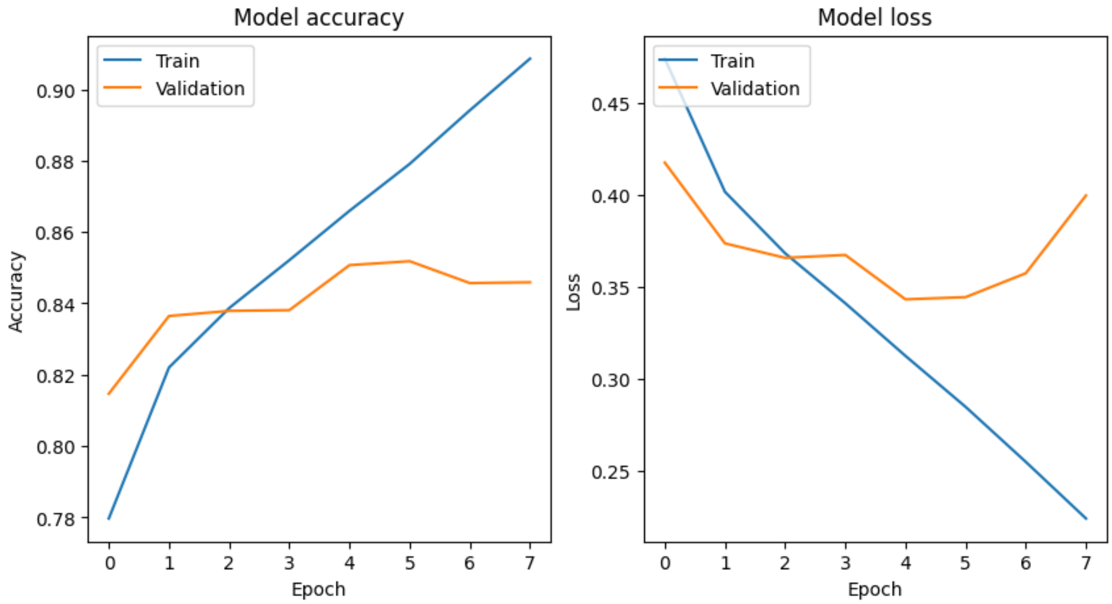
[24]:
```
model_average_pooling = keras.models.load_model('models/model_average_pooling.
  ↪keras')
predictions = []
```

```
with open(os.devnull, 'w') as devnull:
    old_stdout = sys.stdout
    sys.stdout = devnull
    try:
        # Iterate over test image filepaths
        for filepath in test_data_prepared.file_paths:
            # Load and preprocess the image
            img = Image.open(filepath)
            img = img.resize(img.size) # Assuming img_size is defined from␣
↪previous code
            img_array = np.array(img) / 255.0 # Normalize pixel values
            img.close()
            img_array = np.expand_dims(img_array, axis=0) # Add batch dimension
            prediction = model_average_pooling.predict(img_array)
            predictions.append(prediction[0][0])
        results = pd.DataFrame({'id': test_data_prepared.file_paths, 'label':␣
↪predictions})
        results['label'] = results['label'].round()
        results['id'] = results['id'].apply(lambda x: os.path.basename(x).
↪split('.')[0])
    finally:
        sys.stdout = old_stdout
model_average_pooling = None
results.to_csv('results/model_average_pooling_results.csv', index=False)
```

10 Average Pooling - Visualize Results

[21]:
```
plt.figure(figsize=(10, 5))

# Plot training & validation accuracy values
plt.subplot(1, 2, 1)
plt.plot(history_avg_pooling.history['accuracy'])
plt.plot(history_avg_pooling.history['val_accuracy'])
plt.title('Model accuracy')
plt.ylabel('Accuracy')
plt.xlabel('Epoch')
plt.legend(['Train', 'Validation'], loc='upper left')

# Plot training & validation loss values
plt.subplot(1, 2, 2)
plt.plot(history_avg_pooling.history['loss'])
plt.plot(history_avg_pooling.history['val_loss'])
plt.title('Model loss')
plt.ylabel('Loss')
plt.xlabel('Epoch')
plt.legend(['Train', 'Validation'], loc='upper left')
```

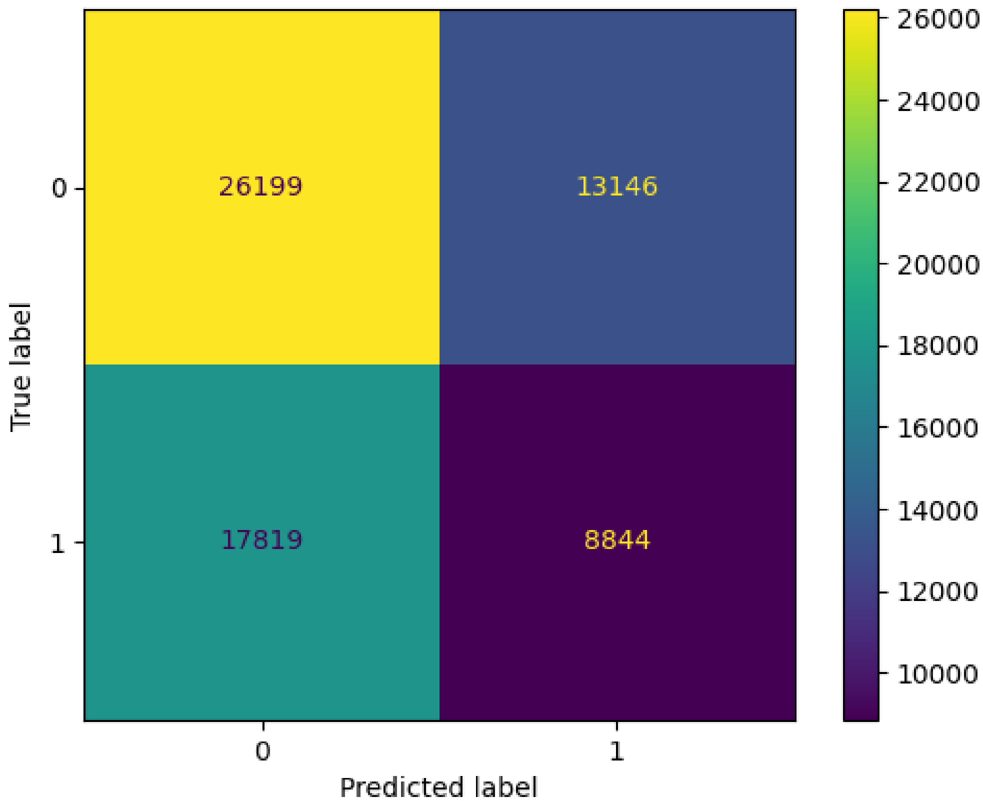
```
# plt.tight_layout()
plt.show()
```



11 Average Pooling - Classification Report and Confusion Matrix

[22]:
```
## Generate a classification report and confusion matrix for the validation␣
↪predictions

validation_predictions = model_average_pooling.predict(validation_generator)
validation_pred_labels = (validation_predictions > 0.5).astype(int)

# Get true labels
validation_true_labels = validation_generator.classes

# Generate classification report
class_report = classification_report(validation_true_labels,␣
↪validation_pred_labels)
print(class_report)

# Generate confusion matrix
cm = confusion_matrix(validation_true_labels, validation_pred_labels)
disp = ConfusionMatrixDisplay(confusion_matrix=cm, display_labels=['0','1'])
disp.plot()
plt.show()
```

```
1032/1032          23s 23ms/step
              precision    recall  f1-score   support

           0       0.60      0.67      0.63     39345
           1       0.40      0.33      0.36     26663

    accuracy                           0.53     66008
   macro avg       0.50      0.50      0.50     66008
weighted avg       0.52      0.53      0.52     66008
```



12 Conclusion

The main takeaway regarding model selection indicates that using specialized max and average pooling layers results in the best scores, with the best model I created resulting in a Kaggle score of 82.

While the max pooling model resulted in a slightly higher accuracy, the average pooling model had less validation loss.

These models exhibit significantly longer training times compared to a baseline model. Training duration is influenced by several hyperparameters, including the number of epochs and network architecture (number of layers and neurons per layer). Increasing network complexity (e.g., adding layers or increasing neuron counts) expands the model's parameter space, raising the risk of overfitting and necessitating adjustments to the epoch count.

Future improvements warrant exploration of several avenues. Increasing the number of layers and experimenting with diverse layer types could enhance performance. Furthermore, feature engineering techniques, such as data augmentation, could augment the training dataset, potentially mitigating class imbalance and improving generalization to the Kaggle test set. Finally, optimization of hyperparameters, including the loss function and optimizer, should be investigated using the established model architectures.

[ ]:

```

```