week3

April 17, 2024

# 1 Week 3 CNN Cancer Detection Kaggle Mini-Project

Student, University of Colorado Boulder

## 1.1 Step 1: Brief description of the problem and data

For the week 3 mini project, I will be using machine learning algorithm to identify metastatic cancer in small image patches taken from larger digital pathology scans. The problem is a binary image classification problem.

The details are available in Kaggle competition https://www.kaggle.com/c/histopathologic-cancer-detection/overview

I will be using Convolutional Neural Networks (CNN) to process the images and classify them as having metastatic cancer or not having metastatic cancer. A good model could help physicians in detecting metastatic cancer.

[38]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import torch
from torch.utils.data import Dataset

import cv2
import os
import shutil

from sklearn.utils import shuffle
from sklearn.model_selection import train_test_split

import tensorflow as tf

from tensorflow.keras import Input
from tensorflow.keras.preprocessing import image
from tensorflow.keras.preprocessing.image import ImageDataGenerator
from tensorflow.keras.metrics import categorical_crossentropy

from keras.models import Sequential, Model
from keras.layers import Conv2D, MaxPooling2D,GlobalAveragePooling2D
```

```
from keras.layers import Activation, Dropout, BatchNormalization, Flatten,␣
    ↪Dense, AvgPool2D,MaxPool2D
from keras.models import Sequential, Model
from keras.optimizers import Adam
from tensorflow.keras.metrics import AUC

from tensorflow.keras.callbacks import ModelCheckpoint, EarlyStopping,␣
    ↪ReduceLROnPlateau

from tensorflow.keras.applications import ResNet50V2

%maplotlib inline
```

```
UsageError: Line magic function `%maplotlib` not found.
```

### 1.2 Step 2: Exploratory Data Analysis (EDA) — Inspect, Visualize and Clean the Data

**Data Extraction** User has to register on kaggle to get access to the dataset. This data is expected to be stored in data/histopathologic-cancer-detection folder

[4]:
```
train_labels_df = pd.read_csv('data/histopathologic-cancer-detection/
    ↪train_labels.csv')
train_labels_df.head()
```

[4]:

| | id | label |
|---|---|---|
| 0 | f38a6374c348f90b587e046aac6079959adf3835 | 0 |
| 1 | c18f2d887b7ae4f6742ee445113fa1aef383ed77 | 1 |
| 2 | 755db6279dae599ebb4d39a9123cce439965282d | 0 |
| 3 | bc3f0c64fb968ff4a8bd33af6971ecae77c75e08 | 0 |
| 4 | 068aba587a4950175d04c680d38943fd488d6a9d | 0 |

Let us look at the type and shape of data

[5]:
```
train_labels_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 220025 entries, 0 to 220024
Data columns (total 2 columns):
 #   Column  Non-Null Count   Dtype
---  ------  --------------   -----
 0   id      220025 non-null  object
 1   label   220025 non-null  int64
dtypes: int64(1), object(1)
memory usage: 3.4+ MB
```

[6]:
```
train_labels_df.shape
```

[6]: (220025, 2)

Let us check if there are any duplicates and remove if present

[7]:
```
train_labels_df['id'].duplicated().any()
```

[7]:
```
False
```

There are no duplicates.

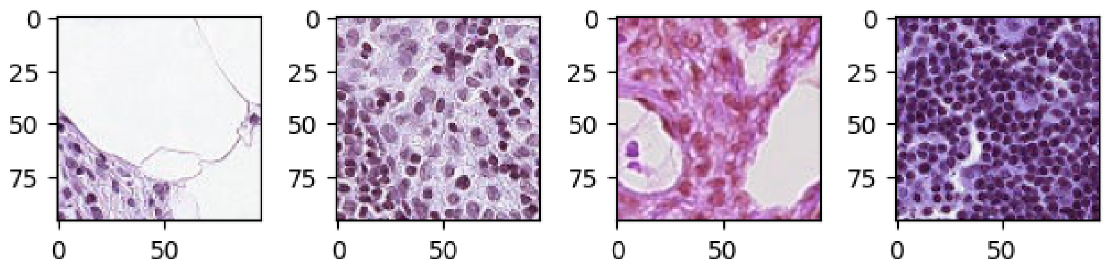
Let us look at the distribution of the labels

[8]:
```
def plot_tumor_existence(df, data_type):
    df['label'].plot.hist()

    x = ["No Tumor", "Has Tumor"]
    y = [df['label'].value_counts()[0.0], df['label'].value_counts()[1.0]]

    plt.bar(x, y)
    plt.title("Training Labels")

    plt.xlabel(f"Tumor existence - {data_type} data")
    plt.ylabel("Count")

    plt.show()

plot_tumor_existence(train_labels_df, 'all training')
```


[9]:
```python
def show_images(df, category, directory):
    f,ax = plt.subplots(nrows=1, ncols=4)
    count = 0
    for _,r in df.iterrows():
        if r['label'] == category:
            image_file = directory+r['id']+'.tif'
            image = cv2.imread(image_file)
            ax[count].imshow(image, resample=True, cmap='gray')
            count += 1
        if count > 3:
            break
    plt.tight_layout()
    plt.show()
```

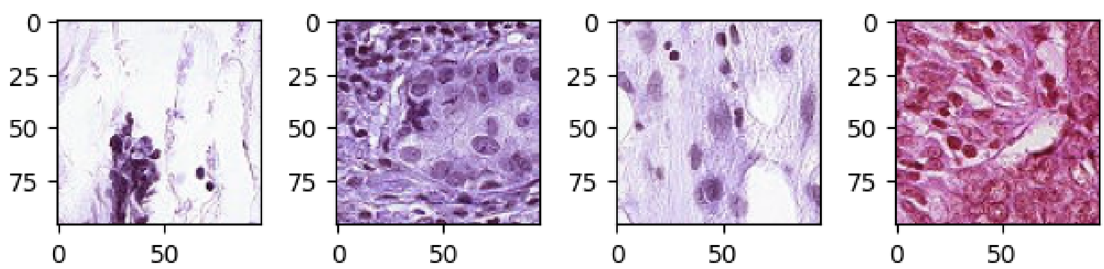
Let us look at a sample of images where the image is labeled as no tumor

[10]:
```python
show_images(train_labels_df, 0, 'data/histopathologic-cancer-detection/train/')
```



Let us look at a sample of images where the image is labeled as has tumor

[11]:
```
show_images(train_labels_df, 1, 'data/histopathologic-cancer-detection/train/')
```



Since the data is imbalanced with more negative cases than positive cases, we will consider only random 80000 entries for the first model

[12]:
```
entry_count = 80000

df_negative = train_labels_df[train_labels_df['label'] == 0]
df_positive = train_labels_df[train_labels_df['label'] == 1]

df_negative = df_negative.sample(entry_count, random_state=123)
df_positive = df_positive.sample(entry_count, random_state=123)

df_negative.info()
df_positive.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 80000 entries, 144972 to 179459
Data columns (total 2 columns):
 #   Column  Non-Null Count  Dtype
---  ------  --------------  -----
 0   id      80000 non-null  object
 1   label   80000 non-null  int64
dtypes: int64(1), object(1)
```

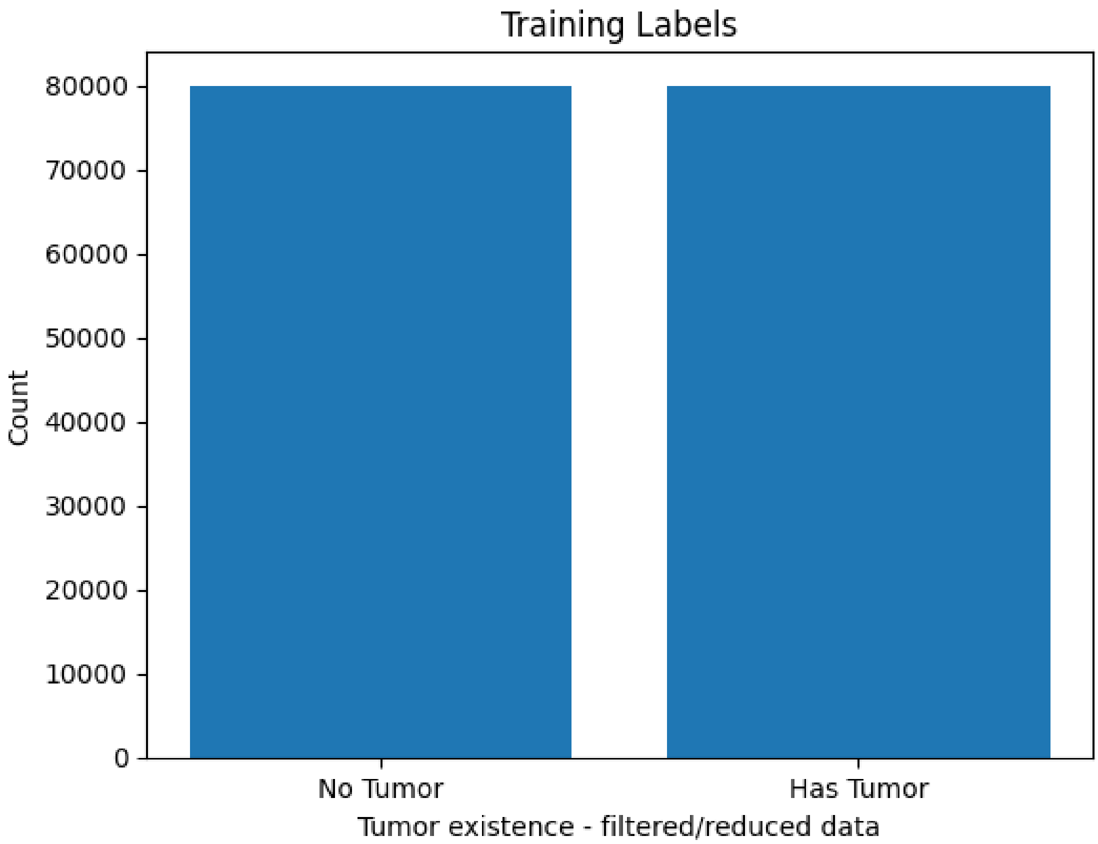
```
memory usage: 1.8+ MB
<class 'pandas.core.frame.DataFrame'>
Index: 80000 entries, 144436 to 61695
Data columns (total 2 columns):
 #   Column  Non-Null Count  Dtype
---  ------  --------------  -----
 0   id      80000 non-null  object
 1   label   80000 non-null  int64
dtypes: int64(1), object(1)
memory usage: 1.8+ MB
```

Now that we have 80000 entries of positive and negative cases, lets combine them and shuffle them into a new dataframe

[13]:
```
df_new_data = shuffle(pd.concat([df_negative, df_positive], axis=0).
↪reset_index(drop=True))
df_new_data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 160000 entries, 4029 to 142497
Data columns (total 2 columns):
 #   Column  Non-Null Count   Dtype
---  ------  --------------   -----
 0   id      160000 non-null  object
 1   label   160000 non-null  int64
dtypes: int64(1), object(1)
memory usage: 3.7+ MB
```

[14]:
```
plot_tumor_existence(df_new_data, 'filtered/reduced')
```




Lets use 80:20 for training and validation with a balanced distribution

[15]:
```
df_train, df_val = train_test_split(df_new_data, test_size=0.2,␣
↪random_state=123, stratify=df_new_data['label'])

plot_tumor_existence(df_train, "training")
plot_tumor_existence(df_val, "validation")
```


Training Labels
60000
50000
40000
30000
20000
10000
0
Count
No Tumor
Has Tumor
Tumor existence - training data


[16]:
```
df_train.head()
```

[16]:

| | id | label |
|---|---|---|
| 6610 | 9e95058fb893e190f7c37981ca39a8acc54324af | 0 |
| 23078 | 04d82e035d7d9995385f2f1f49fbc31d90e69dd7 | 0 |
| 108602 | 1322f75822f0abb9cc04bda0ba1e961106b3ab40 | 1 |
| 8458 | a96c9f5ce8fe48a69bf961a397ac79baa2bce059 | 0 |
| 20479 | 7cf8c1b699629db0b3873cd76a31fd7b2ff69361 | 0 |

We verified that the data is shuffled and there is equal distribution of positive and negative cases.

Let us copy the images into 4 folders - training/1, training/0, validation/1, and validation/0 where 0=negative and 1=positive. Also we change the data frames to contain the path to the images

[17]:
```
training_folder = 'training'
validation_folder = 'validation'
positive_folder = '1'
negative_folder = '0'
train_data_path = 'data/histopathologic-cancer-detection/train'
for t in [training_folder, validation_folder]:
    if not os.path.exists(os.path.join(train_data_path, t)):
```

```python
        os.makedirs(os.path.join(train_data_path, t))
    for p in [positive_folder, negative_folder]:
        if not os.path.exists(os.path.join(train_data_path, t, p)):
            os.makedirs(os.path.join(train_data_path, t, p))

copied = 0
paths = list()
for _, row in df_train.iterrows():
    id = row['id']
    label = row['label']
    src = os.path.join('data/histopathologic-cancer-detection/train', id+ '.tif')
    if label == 0.0:
        dst = os.path.join(train_data_path, training_folder, negative_folder, id+ '.tif')
    else:
        dst = os.path.join(train_data_path, training_folder, positive_folder, id+ '.tif')
    shutil.copyfile(src, dst)
    copied += 1
    paths.append(dst)
df_train['path'] = paths
print(f'copied {copied} files into training folder')

copied = 0
paths = list()
for _, row in df_val.iterrows():
    id = row['id']
    label = row['label']
    src = os.path.join('data/histopathologic-cancer-detection/train', id+ '.tif')
    if label == 0.0:
        dst = os.path.join(train_data_path, validation_folder, negative_folder, id+ '.tif')
    else:
        dst = os.path.join(train_data_path, validation_folder, positive_folder, id+ '.tif')
    shutil.copyfile(src, dst)
    copied += 1
    paths.append(dst)
df_val['path'] = paths
print(f'copied {copied} files into validation folder')
```

```
copied 128000 files into training folder
copied 32000 files into validation folder
```

[18]:
```
training_image_dg = ImageDataGenerator(rescale=1./255., rotation_range=40,␣
↪width_shift_range=0.2, height_shift_range=0.2,
                                   shear_range=0.2, zoom_range=0.2,␣
↪horizontal_flip=True, vertical_flip=True)

train_flow = training_image_dg.flow_from_dataframe(dataframe = df_train,
                                                    x_col = 'path', y_col ='label',
                                                    target_size = (224,224),␣
↪batch_size = 32, class_mode='raw',
                                                    shuffle = True)
val_flow = training_image_dg.flow_from_dataframe(dataframe=df_val,
                                                  target_size=(224,224), x_col =␣
↪'path', y_col ='label', class_mode='raw',
                                                  batch_size= 16, shuffle=True)
```

```
Found 128000 validated image filenames.
Found 32000 validated image filenames.
```

Now let us do the same steps for test data

[19]:
```
test_images_path = 'data/histopathologic-cancer-detection/test'
ids = list()
paths = list()
for _,_, file_names in os.walk(test_images_path):
    for file_name in file_names:
        ids.append(file_name.replace('.tif', ''))
        paths.append(os.path.join(test_images_path, file_name))

df_test = pd.DataFrame({'id':ids, 'path':paths})
df_test.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 57458 entries, 0 to 57457
Data columns (total 2 columns):
 #   Column  Non-Null Count  Dtype
---  ------  --------------  -----
 0   id      57458 non-null  object
 1   path    57458 non-null  object
dtypes: object(2)
memory usage: 897.9+ KB
```

[20]:
```
df_test.describe()
```

[20]:
```
                                              id  \
count                                      57458
unique                                     57458
top     fd0a060ef9c30c9a83f6b4bfb568db74b099154d
freq                                           1
```

```
                                                     path
count                                               57458
unique                                              57458
top     data/histopathologic-cancer-detection/test/fd0…
freq                                                    1
```

[22]:
```
df_test.head()
```

[22]:
```
                                         id  \
0  fd0a060ef9c30c9a83f6b4bfb568db74b099154d
1  1f9ee06f06d329eb7902a2e03ab3835dd0484581
2  19709bec800f372d0b1d085da6933dd3ef108846
3  7a34fc34523063f13f0617f7518a0330f6187bd3
4  93be720ca2b95fe2126cf2e1ed752bd759e9b0ed

                                                path
0  data/histopathologic-cancer-detection/test/fd0…
1  data/histopathologic-cancer-detection/test/1f9…
2  data/histopathologic-cancer-detection/test/197…
3  data/histopathologic-cancer-detection/test/7a3…
4  data/histopathologic-cancer-detection/test/93b…
```

[24]:
```
test_flow = training_image_dg.flow_from_dataframe(dataframe=df_test,
                                              x_col='path', y_col=None,
                                              target_size=(224,224),␣
 ↪batch_size=32, class_mode=None,
                                              shuffle=True)
```

```
Found 57458 validated image filenames.
```

### 1.3 Step 3: Model Architecture

I will use ResNet50V2 model that is pre-trained on ImageNet to see how it performs on our data

[50]:
```
# Load weights pre-trained on ImageNet.
base_model = ResNet50V2(
    weights="imagenet",
    input_shape=(224, 224, 3),
    include_top=False,
)

# Freeze the base_model
base_model.trainable = False

# Create new model on top
inputs = Input(shape=(224, 224, 3))
```

```
x = base_model(inputs, training=False)
x = GlobalAveragePooling2D()(x)
x = Dropout(0.2)(x)
outputs = Dense(1, activation="sigmoid")(x)
model = Model(inputs, outputs)

model.summary()
```

**Model: "functional_3"**

| Layer (type) | Output Shape | Param # |
|---|---|---|
| input_layer_3 (InputLayer) | (None, 224, 224, 3) | 0 |
| resnet50v2 (Functional) | (None, 7, 7, 2048) | 23,564,800 |
| global_average_pooling2d_1 (GlobalAveragePooling2D) | (None, 2048) | 0 |
| dropout_1 (Dropout) | (None, 2048) | 0 |
| dense_1 (Dense) | (None, 1) | 2,049 |

**Total params:** 23,566,849 (89.90 MB)

**Trainable params:** 2,049 (8.00 KB)

**Non-trainable params:** 23,564,800 (89.89 MB)

[55]:
```
callbacks = [
    ModelCheckpoint("cnn_classifier_model.keras", save_best_only=True, verbose␣
↪= 0),
    ReduceLROnPlateau(monitor='val_accuracy', factor=0.5, patience=2,␣
↪verbose=1, mode='max', min_lr=0.00001),
    EarlyStopping(monitor='val_accuracy', min_delta=0.0002, patience=5,␣
↪mode='max', verbose=1, restore_best_weights=True)
]

model.compile(loss='binary_crossentropy', optimizer=Adam(learning_rate= 0.
↪0001), metrics=['accuracy'])

history = model.fit(train_flow, validation_data = val_flow, epochs = 100,
```

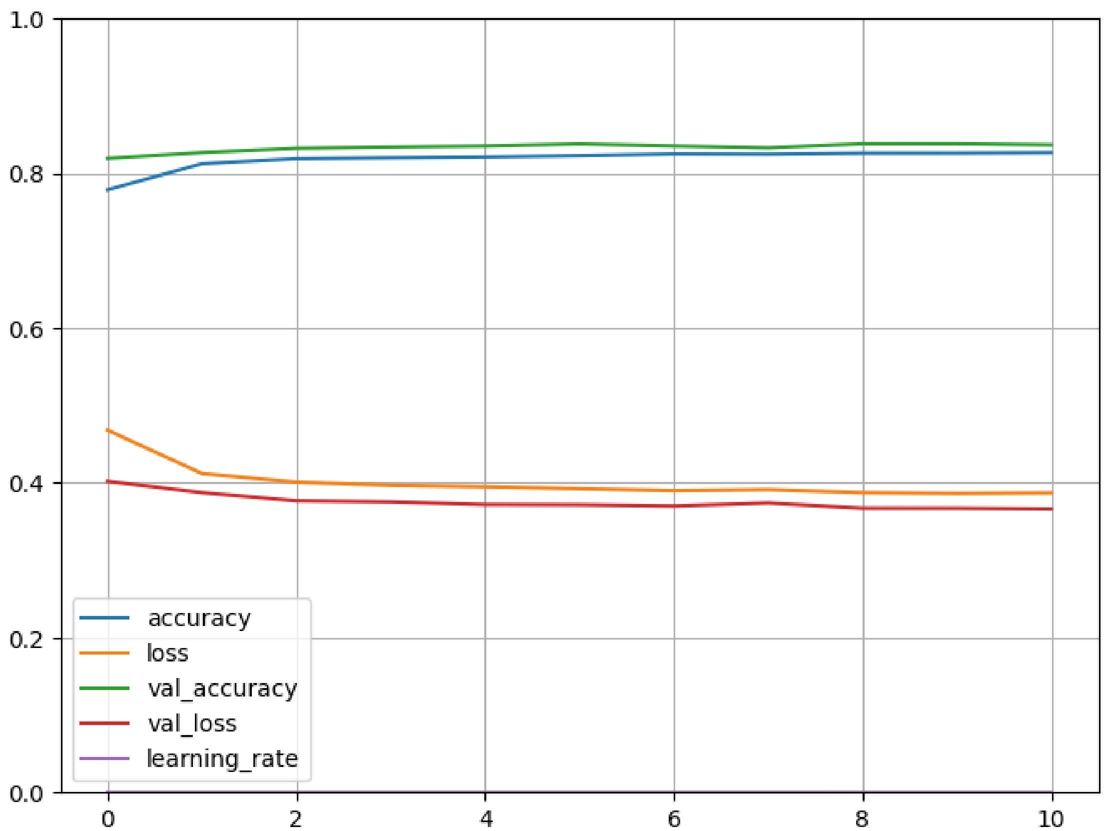
```
                    callbacks = [callbacks], verbose = 1)
```

```
Epoch 1/100

/Users/kkuruvad/Desktop/masters/UniversityOfColoradoBoulder/DTSA 5511
Introduction to Deep Learning/week3/venv/lib/python3.9/site-
packages/keras/src/trainers/data_adapters/py_dataset_adapter.py:120:
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()

4000/4000           2904s
725ms/step - accuracy: 0.7341 - loss: 0.5271 - val_accuracy: 0.8194 - val_loss:
0.4022 - learning_rate: 1.0000e-04
Epoch 2/100
4000/4000           2900s
725ms/step - accuracy: 0.8099 - loss: 0.4144 - val_accuracy: 0.8268 - val_loss:
0.3874 - learning_rate: 1.0000e-04
Epoch 3/100
4000/4000           2904s
726ms/step - accuracy: 0.8167 - loss: 0.4034 - val_accuracy: 0.8324 - val_loss:
0.3769 - learning_rate: 1.0000e-04
Epoch 4/100
4000/4000           2912s
728ms/step - accuracy: 0.8188 - loss: 0.4000 - val_accuracy: 0.8341 - val_loss:
0.3755 - learning_rate: 1.0000e-04
Epoch 5/100
4000/4000           2950s
737ms/step - accuracy: 0.8211 - loss: 0.3948 - val_accuracy: 0.8355 - val_loss:
0.3721 - learning_rate: 1.0000e-04
Epoch 6/100
4000/4000           2968s
742ms/step - accuracy: 0.8215 - loss: 0.3947 - val_accuracy: 0.8382 - val_loss:
0.3717 - learning_rate: 1.0000e-04
Epoch 7/100
4000/4000           2898s
724ms/step - accuracy: 0.8250 - loss: 0.3903 - val_accuracy: 0.8355 - val_loss:
0.3702 - learning_rate: 1.0000e-04
Epoch 8/100
4000/4000           0s 570ms/step -
accuracy: 0.8226 - loss: 0.3942
Epoch 8: ReduceLROnPlateau reducing learning rate to 4.999999873689376e-05.
4000/4000           2919s
730ms/step - accuracy: 0.8226 - loss: 0.3942 - val_accuracy: 0.8331 - val_loss:
0.3740 - learning_rate: 1.0000e-04
Epoch 9/100
4000/4000           2966s
```

```
741ms/step - accuracy: 0.8262 - loss: 0.3874 - val_accuracy: 0.8384 - val_loss:
0.3673 - learning_rate: 5.0000e-05
Epoch 10/100
4000/4000              2929s
732ms/step - accuracy: 0.8258 - loss: 0.3858 - val_accuracy: 0.8384 - val_loss:
0.3672 - learning_rate: 5.0000e-05
Epoch 11/100
4000/4000              0s 574ms/step -
accuracy: 0.8261 - loss: 0.3867
Epoch 11: ReduceLROnPlateau reducing learning rate to 2.499999936844688e-05.
4000/4000              2959s
739ms/step - accuracy: 0.8261 - loss: 0.3867 - val_accuracy: 0.8370 - val_loss:
0.3664 - learning_rate: 5.0000e-05
Epoch 11: early stopping
Restoring model weights from the end of the best epoch: 6.
```

[58]:

```python
pd.DataFrame(history.history).plot(figsize=(8, 6))
plt.grid(True)
plt.gca().set_ylim(0, 1)
plt.show()
```



```
[50]: loaded_model = tf.keras.models.load_model("cnn_classifier_model.keras")

results = loaded_model.predict(test_flow)
result_labels = np.round(results).astype(int)

output = pd.DataFrame({'id':df_test['id']})
output['label'] = result_labels
print(f'shape: {output.shape}')
output.head()
output.to_csv('ResNet50V2.csv', index=False)
```

```
1796/1796          1002s
557ms/step
shape: (57458, 2)
```

Though the validation results were good enough with ~80+% accuracy, the results were bad on the test data. It seems like the imagenet weights are not finetuned for this data. I could add more layers and retry to get a better test result

| Submission and Description | Private Score | Public Score | Selected |
|---|---|---|---|
| ResNet50V2.csv<br>Complete (after deadline) · 33s ago | 0.5018 | 0.5023 | ☐ |

Let me build a model from scratch and see how that performs on the test data Changes would be to also limit targets to 96x96 and split of 70:30 for training and validation. I will start with epoch 3 and if it is promising, retry with a bigger epoch

```
[43]: base_dp = 'data/histopathologic-cancer-detection'
train_label_path = os.path.join(base_dp, 'train_labels.csv')

train_labels = pd.read_csv(train_label_path)
train_labels['path'] = base_dp + '/train/'+train_labels['id']+'.tif'
train_labels['label'] = train_labels['label'].astype(str)
data_generator = ImageDataGenerator(rescale=1./255, validation_split=0.3)

train_generator = data_generator.flow_from_dataframe(
    dataframe=train_labels,
    x_col='path',
    y_col='label',
    target_size=(96, 96),
    color_mode='rgb',
    batch_size=32,
    class_mode='binary',
    subset='training'
)

validation_generator = data_generator.flow_from_dataframe(
    dataframe=train_labels,
```

```
    x_col='path',
    y_col='label',
    target_size=(96, 96),
    color_mode='rgb',
    batch_size=32,
    class_mode='binary',
    subset='validation'
)

ids = [file[:-4] for file in os.listdir(os.path.join(base_dp, 'test'))]
files = [os.path.join(base_dp, 'test',file) for file in os.listdir(os.path.
 ↪join(base_dp, 'test'))]

test_dataframe = pd.DataFrame({'id':ids, 'file':files})

test_generator = datagenerator.flow_from_dataframe(
    dataframe=test_dataframe,
    x_col='file',
    y_col=None,
    target_size=(96, 96),
    color_mode='rgb',
    batch_size=32,
    shuffle=False,
    class_mode=None
)
```

```
Found 154018 validated image filenames belonging to 2 classes.
Found 66007 validated image filenames belonging to 2 classes.
Found 57458 validated image filenames.
```

I will start with a few sets of Conv2D+BatchNormalization+MaxPooling2D layers

[44]:
```
second_model = Sequential()
second_model.add(Conv2D(96, (3, 3), activation='relu', input_shape=(96, 96, 3)))
second_model.add(BatchNormalization())
second_model.add(MaxPooling2D((2, 2)))

second_model.add(Conv2D(64, (3, 3), activation='relu', input_shape=(96, 96, 3)))
second_model.add(BatchNormalization())
second_model.add(MaxPooling2D((2, 2)))

second_model.add(Conv2D(32, (3, 3), activation='relu'))
second_model.add(BatchNormalization())
second_model.add(MaxPooling2D((2, 2)))

second_model.add(Conv2D(16, (3, 3), activation='relu'))
second_model.add(Flatten())
second_model.add(Dense(256, activation='relu'))
```

```
second_model.add(Dense(1, activation='sigmoid'))

second_model.compile(optimizer='adam',
              loss='binary_crossentropy',
              metrics=['accuracy', AUC(name='auc')])

history_second_model = second_model.fit(train_generator,␣
 ↪validation_data=validation_generator, epochs=3)

test_pred = second_model.predict(test_generator)
output = pd.DataFrame({'id':df_test['id']})
output['label'] = test_pred
print(f'shape: {output.shape}')
output.to_csv('second_model.csv', index=False)
```

```
/Users/kkuruvad/Desktop/masters/UniversityOfColoradoBoulder/DTSA 5511
Introduction to Deep Learning/week3/venv/lib/python3.9/site-
packages/keras/src/layers/convolutional/base_conv.py:99: 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__(
```

```
Epoch 1/3
```

```
/Users/kkuruvad/Desktop/masters/UniversityOfColoradoBoulder/DTSA 5511
Introduction to Deep Learning/week3/venv/lib/python3.9/site-
packages/keras/src/trainers/data_adapters/py_dataset_adapter.py:120:
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()
```

```
4814/4814              1060s
220ms/step - accuracy: 0.8225 - auc: 0.8888 - loss: 0.4070 - val_accuracy:
0.8159 - val_auc: 0.9201 - val_loss: 0.4491
Epoch 2/3
4814/4814              1031s
214ms/step - accuracy: 0.8816 - auc: 0.9454 - loss: 0.2897 - val_accuracy:
0.8508 - val_auc: 0.9083 - val_loss: 0.4674
Epoch 3/3
4814/4814              1020s
212ms/step - accuracy: 0.9052 - auc: 0.9623 - loss: 0.2393 - val_accuracy:
0.8526 - val_auc: 0.9441 - val_loss: 0.3390
1796/1796              68s 38ms/step
shape: (57458, 2)
```

This model has better accuracy than the previous model. It scored better as well on the test results

| Submission and Description | Private Score | Public Score | Selected |
|---|---|---|---|
| **second_model.csv**<br>Complete (after deadline) · now | **0.8349** | **0.9315** | ☐ |

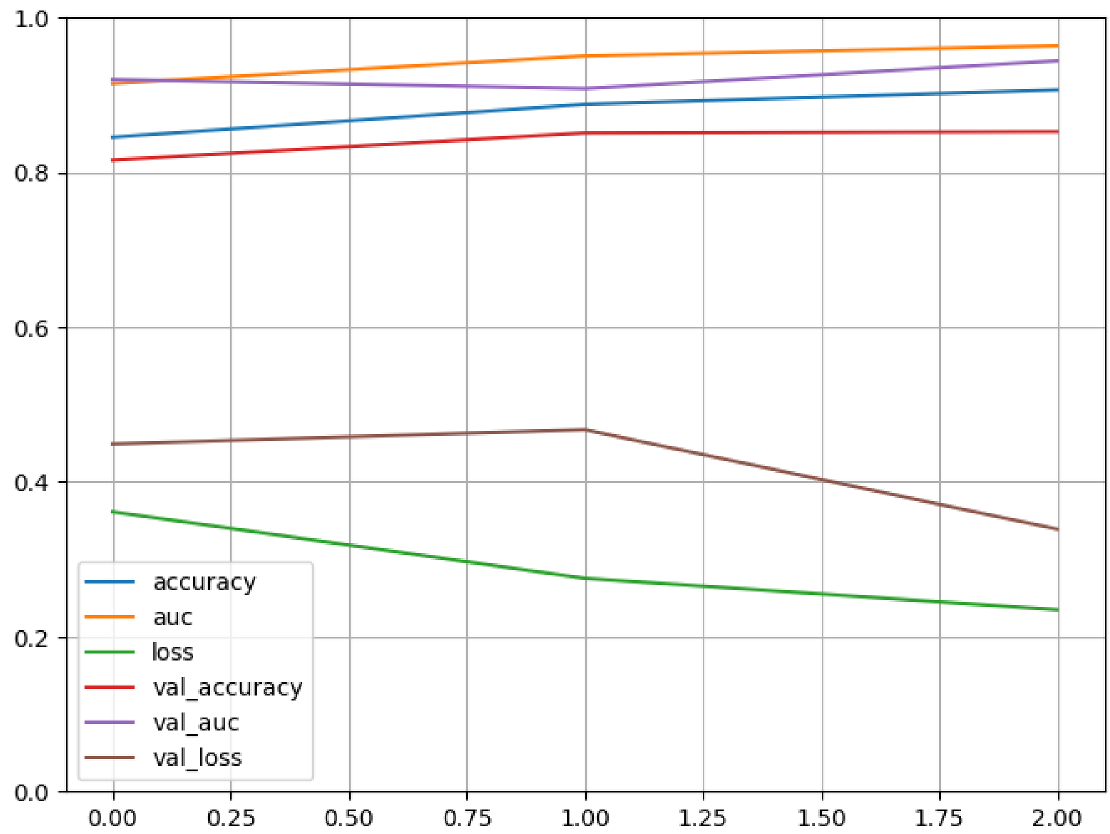
```
[51]: second_model.summary()
```

```
Model: "sequential_2"


 Layer (type)                      Output Shape              Param #

 conv2d_10 (Conv2D)                (None, 94, 94, 96)          2,688

 batch_normalization_8             (None, 94, 94, 96)            384
 (BatchNormalization)

 max_pooling2d_8 (MaxPooling2D)    (None, 47, 47, 96)              0

 conv2d_11 (Conv2D)                (None, 45, 45, 64)         55,360

 batch_normalization_9             (None, 45, 45, 64)            256
 (BatchNormalization)

 max_pooling2d_9 (MaxPooling2D)    (None, 22, 22, 64)              0

 conv2d_12 (Conv2D)                (None, 20, 20, 32)         18,464

 batch_normalization_10            (None, 20, 20, 32)            128
 (BatchNormalization)

 max_pooling2d_10 (MaxPooling2D)   (None, 10, 10, 32)              0

 conv2d_13 (Conv2D)                (None, 8, 8, 16)            4,624

 flatten_2 (Flatten)               (None, 1024)                    0

 dense_4 (Dense)                   (None, 256)               262,400

 dense_5 (Dense)                   (None, 1)                     257


 Total params: 1,032,917 (3.94 MB)

 Trainable params: 344,177 (1.31 MB)
```

**Non-trainable params:** 384 (1.50 KB)

**Optimizer params:** 688,356 (2.63 MB)

[48]:
```
pd.DataFrame(history_second_model.history).plot(figsize=(8, 6))
plt.grid(True)
plt.gca().set_ylim(0, 1)
plt.show()
```




This model seems to be performing well. I will let it run until the val_accuracy peaks and see how better it can get

[45]:
```
third_model = Sequential()
third_model.add(Conv2D(96, (3, 3), activation='relu', input_shape=(96, 96, 3)))
third_model.add(BatchNormalization())
third_model.add(MaxPooling2D((2, 2)))

third_model.add(Conv2D(64, (3, 3), activation='relu', input_shape=(96, 96, 3)))
third_model.add(BatchNormalization())
```

```python
third_model.add(MaxPooling2D((2, 2)))

third_model.add(Conv2D(32, (3, 3), activation='relu'))
third_model.add(BatchNormalization())
third_model.add(MaxPooling2D((2, 2)))

third_model.add(Conv2D(16, (3, 3), activation='relu'))
third_model.add(Flatten())
third_model.add(Dense(256, activation='relu'))
third_model.add(Dense(1, activation='sigmoid'))

third_model.compile(optimizer='adam',
              loss='binary_crossentropy',
              metrics=['accuracy', AUC(name='auc')])

callbacks = [
    ModelCheckpoint("second_model.keras", save_best_only=True, verbose = 0),
    ReduceLROnPlateau(monitor='val_accuracy', factor=0.5, patience=2,␣
  ↪verbose=1, mode='max', min_lr=0.00001),
    EarlyStopping(monitor='val_accuracy', min_delta=0.0005, patience=3,␣
  ↪mode='max', verbose=1, restore_best_weights=True)
]

history_third_model = third_model.fit(train_generator,␣
  ↪validation_data=validation_generator, epochs=50,
                    callbacks = [callbacks], verbose = 1)

test_pred = third_model.predict(test_generator)
output = pd.DataFrame({'id':df_test['id']})
output['label'] = test_pred
print(f'shape: {output.shape}')
output.to_csv('third_model.csv', index=False)
```

```
/Users/kkuruvad/Desktop/masters/UniversityOfColoradoBoulder/DTSA 5511
Introduction to Deep Learning/week3/venv/lib/python3.9/site-
packages/keras/src/layers/convolutional/base_conv.py:99: 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__(
```

```
Epoch 1/50
4814/4814            1072s
222ms/step - accuracy: 0.8262 - auc: 0.8905 - loss: 0.4068 - val_accuracy:
0.8052 - val_auc: 0.8942 - val_loss: 0.4608 - learning_rate: 0.0010
Epoch 2/50
4814/4814            1081s
224ms/step - accuracy: 0.8839 - auc: 0.9469 - loss: 0.2853 - val_accuracy:
```

```
0.8395 - val_auc: 0.9053 - val_loss: 0.4062 - learning_rate: 0.0010
Epoch 3/50
4814/4814                1025s
213ms/step - accuracy: 0.9038 - auc: 0.9608 - loss: 0.2432 - val_accuracy:
0.8196 - val_auc: 0.9346 - val_loss: 0.4295 - learning_rate: 0.0010
Epoch 4/50
4814/4814                1029s
214ms/step - accuracy: 0.9151 - auc: 0.9682 - loss: 0.2184 - val_accuracy:
0.9189 - val_auc: 0.9703 - val_loss: 0.2144 - learning_rate: 0.0010
Epoch 5/50
4814/4814                1037s
215ms/step - accuracy: 0.9215 - auc: 0.9729 - loss: 0.2015 - val_accuracy:
0.8955 - val_auc: 0.9638 - val_loss: 0.2604 - learning_rate: 0.0010
Epoch 6/50
4814/4814                0s 197ms/step -
accuracy: 0.9289 - auc: 0.9769 - loss: 0.1848
Epoch 6: ReduceLROnPlateau reducing learning rate to 0.0005000000237487257.
4814/4814                1026s
213ms/step - accuracy: 0.9289 - auc: 0.9769 - loss: 0.1848 - val_accuracy:
0.8559 - val_auc: 0.9206 - val_loss: 0.3896 - learning_rate: 0.0010
Epoch 7/50
4814/4814                1036s
215ms/step - accuracy: 0.9412 - auc: 0.9840 - loss: 0.1534 - val_accuracy:
0.9183 - val_auc: 0.9724 - val_loss: 0.2170 - learning_rate: 5.0000e-04
Epoch 7: early stopping
Restoring model weights from the end of the best epoch: 4.
1796/1796                65s 36ms/step
shape: (57458, 2)
```

This model scored well both on validation as well as test

| Submission and Description | Private Score | Public Score | Selected |
|---|---|---|---|
| third_model.csv<br>Complete (after deadline) · now | 0.9170 | 0.9512 | ☐ |

[52]:
```
third_model.summary()
```

**Model: "sequential_3"**

| Layer (type) | Output Shape | Param # |
|---|---|---|
| conv2d_14 (Conv2D) | (None, 94, 94, 96) | 2,688 |
| batch_normalization_11 (BatchNormalization) | (None, 94, 94, 96) | 384 |
| max_pooling2d_11 (MaxPooling2D) | (None, 47, 47, 96) | 0 |

| | | |
|---|---|---|
| conv2d_15 (Conv2D) | (None, 45, 45, 64) | 55,360 |
| batch_normalization_12 (BatchNormalization) | (None, 45, 45, 64) | 256 |
| max_pooling2d_12 (MaxPooling2D) | (None, 22, 22, 64) | 0 |
| conv2d_16 (Conv2D) | (None, 20, 20, 32) | 18,464 |
| batch_normalization_13 (BatchNormalization) | (None, 20, 20, 32) | 128 |
| max_pooling2d_13 (MaxPooling2D) | (None, 10, 10, 32) | 0 |
| conv2d_17 (Conv2D) | (None, 8, 8, 16) | 4,624 |
| flatten_3 (Flatten) | (None, 1024) | 0 |
| dense_6 (Dense) | (None, 256) | 262,400 |
| dense_7 (Dense) | (None, 1) | 257 |

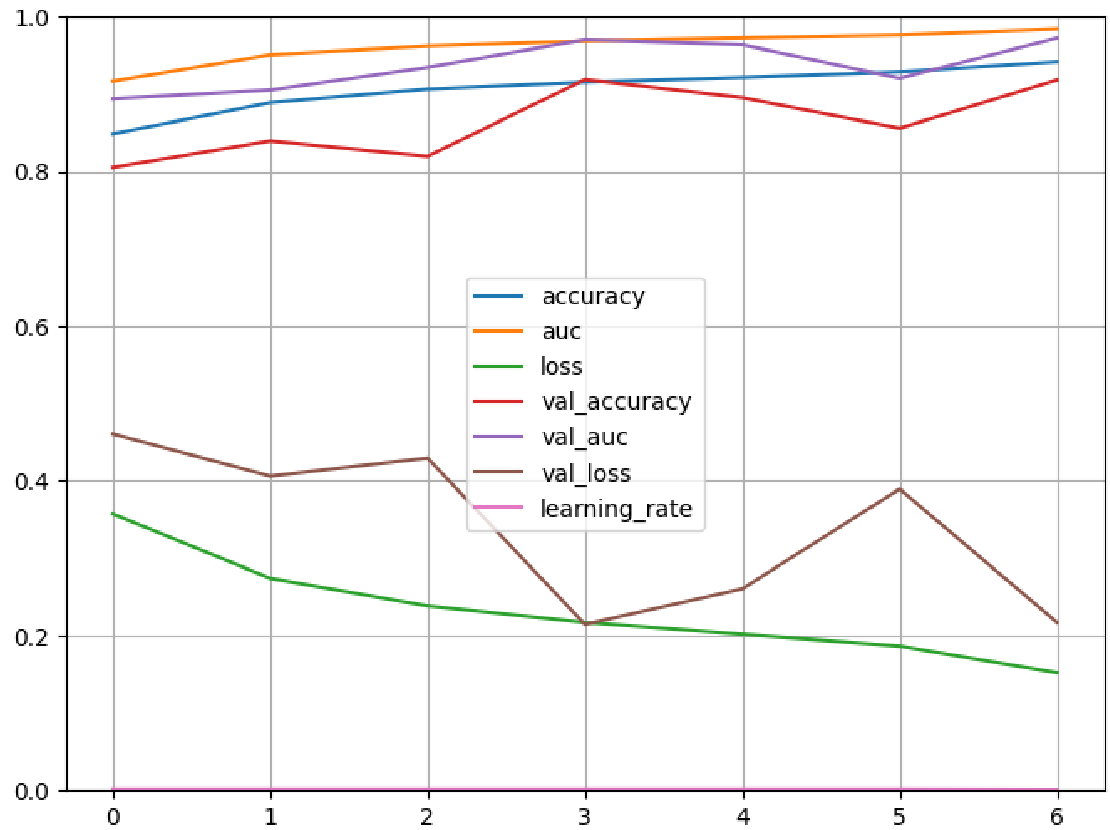
**Total params:** 1,032,917 (3.94 MB)

**Trainable params:** 344,177 (1.31 MB)

**Non-trainable params:** 384 (1.50 KB)

**Optimizer params:** 688,356 (2.63 MB)

[49]:
```
pd.DataFrame(history_third_model.history).plot(figsize=(8, 6))
plt.grid(True)
plt.gca().set_ylim(0, 1)
plt.show()
```




Let us try a final model by adding one more set of layers

[47]:
```
final_model = Sequential()

final_model.add(Conv2D(96, (3, 3), activation='relu', input_shape=(96, 96, 3)))
final_model.add(BatchNormalization())
final_model.add(MaxPooling2D((2, 2)))

final_model.add(Conv2D(64, (3, 3), activation='relu', input_shape=(96, 96, 3)))
final_model.add(BatchNormalization())
final_model.add(MaxPooling2D((2, 2)))

final_model.add(Conv2D(32, (3, 3), activation='relu', input_shape=(96, 96, 3)))
final_model.add(BatchNormalization())
final_model.add(MaxPooling2D((2, 2)))

final_model.add(Conv2D(32, (3, 3), activation='relu'))
final_model.add(BatchNormalization())
final_model.add(MaxPooling2D((2, 2)))
```

```
final_model.add(Conv2D(16, (3, 3), activation='relu'))
final_model.add(Flatten())
final_model.add(Dense(256, activation='relu'))
final_model.add(Dense(1, activation='sigmoid'))


final_model.compile(optimizer='adam',
              loss='binary_crossentropy',
              metrics=['accuracy', AUC(name='auc')])

callbacks = [
    ModelCheckpoint("second_model.keras", save_best_only=True, verbose = 0),
    ReduceLROnPlateau(monitor='val_accuracy', factor=0.5, patience=2,␣
 ↪verbose=1, mode='max', min_lr=0.00001),
    EarlyStopping(monitor='val_accuracy', min_delta=0.0005, patience=3,␣
 ↪mode='max', verbose=1, restore_best_weights=True)
]

history_final_model = final_model.fit(train_generator,␣
 ↪validation_data=validation_generator, epochs=50,
                    callbacks = [callbacks], verbose=1)

test_pred = final_model.predict(test_generator)
output = pd.DataFrame({'id':df_test['id']})
output['label'] = test_pred
print(f'shape: {output.shape}')
output.to_csv('final_model.csv', index=False)
```

```
/Users/kkuruvad/Desktop/masters/UniversityOfColoradoBoulder/DTSA 5511
Introduction to Deep Learning/week3/venv/lib/python3.9/site-
packages/keras/src/layers/convolutional/base_conv.py:99: 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__(
```

```
Epoch 1/50
4814/4814            1035s
215ms/step - accuracy: 0.8238 - auc: 0.8947 - loss: 0.3955 - val_accuracy:
0.8241 - val_auc: 0.9172 - val_loss: 0.4268 - learning_rate: 0.0010
Epoch 2/50
4814/4814            1035s
215ms/step - accuracy: 0.8850 - auc: 0.9477 - loss: 0.2827 - val_accuracy:
0.7701 - val_auc: 0.8126 - val_loss: 0.6114 - learning_rate: 0.0010
Epoch 3/50
4814/4814            1047s
217ms/step - accuracy: 0.9061 - auc: 0.9629 - loss: 0.2373 - val_accuracy:
0.8586 - val_auc: 0.9592 - val_loss: 0.3558 - learning_rate: 0.0010
```

```
Epoch 4/50
4814/4814               1052s
219ms/step - accuracy: 0.9168 - auc: 0.9707 - loss: 0.2101 - val_accuracy:
0.7815 - val_auc: 0.8427 - val_loss: 0.7437 - learning_rate: 0.0010
Epoch 5/50
4814/4814               0s 1s/step -
accuracy: 0.9216 - auc: 0.9734 - loss: 0.1999
Epoch 5: ReduceLROnPlateau reducing learning rate to 0.0005000000237487257.
4814/4814               14847s 3s/step
- accuracy: 0.9216 - auc: 0.9734 - loss: 0.1999 - val_accuracy: 0.8517 -
val_auc: 0.9404 - val_loss: 0.3547 - learning_rate: 0.0010
Epoch 6/50
4814/4814               15766s 3s/step
- accuracy: 0.9346 - auc: 0.9806 - loss: 0.1696 - val_accuracy: 0.9091 -
val_auc: 0.9668 - val_loss: 0.2328 - learning_rate: 5.0000e-04
Epoch 7/50
4814/4814               1073s
223ms/step - accuracy: 0.9408 - auc: 0.9834 - loss: 0.1554 - val_accuracy:
0.9032 - val_auc: 0.9661 - val_loss: 0.2465 - learning_rate: 5.0000e-04
Epoch 8/50
4814/4814               0s 232ms/step -
accuracy: 0.9449 - auc: 0.9855 - loss: 0.1453
Epoch 8: ReduceLROnPlateau reducing learning rate to 0.0002500000118743628.
4814/4814               1196s
248ms/step - accuracy: 0.9449 - auc: 0.9855 - loss: 0.1453 - val_accuracy:
0.8865 - val_auc: 0.9607 - val_loss: 0.3183 - learning_rate: 5.0000e-04
Epoch 9/50
4814/4814               1078s
224ms/step - accuracy: 0.9509 - auc: 0.9882 - loss: 0.1311 - val_accuracy:
0.9402 - val_auc: 0.9820 - val_loss: 0.1624 - learning_rate: 2.5000e-04
Epoch 10/50
4814/4814               1076s
224ms/step - accuracy: 0.9528 - auc: 0.9889 - loss: 0.1265 - val_accuracy:
0.9342 - val_auc: 0.9791 - val_loss: 0.1786 - learning_rate: 2.5000e-04
Epoch 11/50
4814/4814               0s 206ms/step -
accuracy: 0.9554 - auc: 0.9903 - loss: 0.1184
Epoch 11: ReduceLROnPlateau reducing learning rate to 0.0001250000059371814.
4814/4814               1068s
222ms/step - accuracy: 0.9554 - auc: 0.9903 - loss: 0.1184 - val_accuracy:
0.9238 - val_auc: 0.9719 - val_loss: 0.2079 - learning_rate: 2.5000e-04
Epoch 12/50
4814/4814               1039s
216ms/step - accuracy: 0.9599 - auc: 0.9918 - loss: 0.1079 - val_accuracy:
0.9332 - val_auc: 0.9803 - val_loss: 0.1803 - learning_rate: 1.2500e-04
Epoch 12: early stopping
Restoring model weights from the end of the best epoch: 9.
1796/1796               69s 38ms/step
```

```
shape: (57458, 2)
```

This model is trained well, worked fine with validation and gives a much better test score than the first model. But it took longer to train and its results are a little less than the previous model.

| Submission and Description | Private Score | Public Score | Selected |
|---|---|---|---|
| **final_model.csv**<br>Complete (after deadline) · now | **0.9125** | **0.9433** | ☐ |

[53]:
```python
final_model.summary()
```

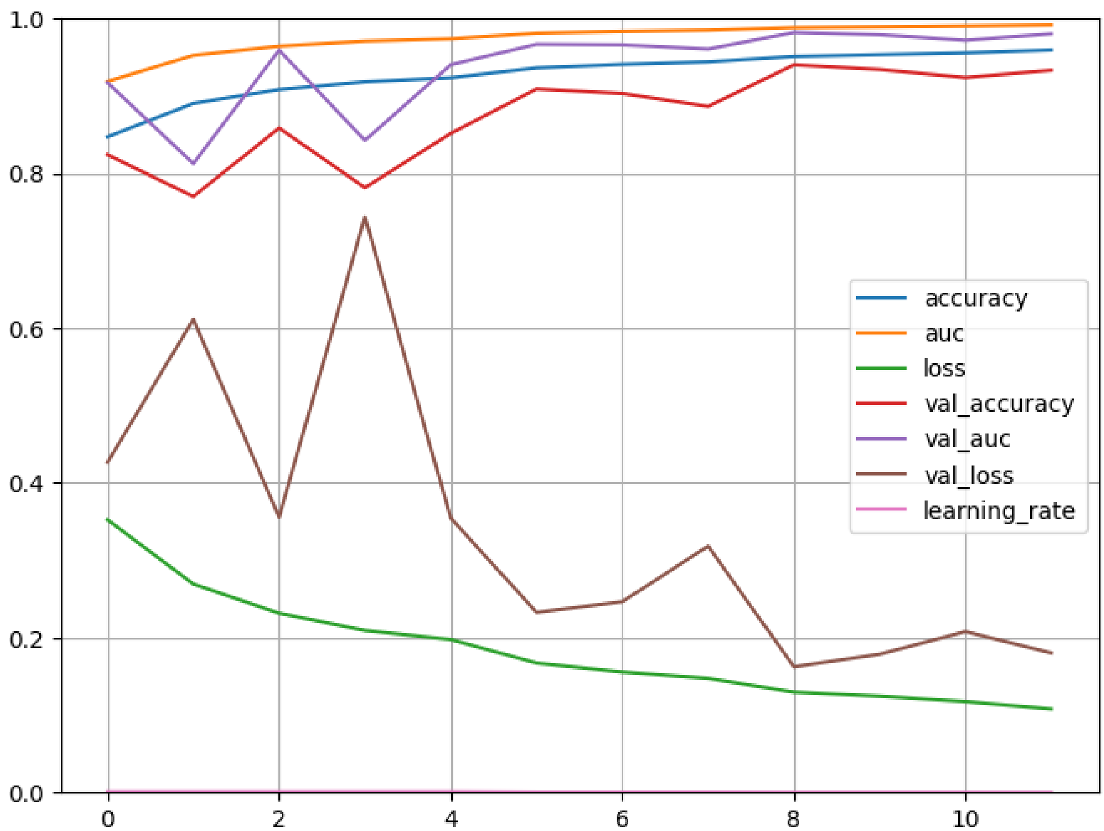
```
Model: "sequential_4"


 Layer (type)                     Output Shape              Param #

 conv2d_18 (Conv2D)               (None, 94, 94, 96)          2,688

 batch_normalization_14           (None, 94, 94, 96)            384
 (BatchNormalization)

 max_pooling2d_14 (MaxPooling2D)  (None, 47, 47, 96)              0

 conv2d_19 (Conv2D)               (None, 45, 45, 64)         55,360

 batch_normalization_15           (None, 45, 45, 64)            256
 (BatchNormalization)

 max_pooling2d_15 (MaxPooling2D)  (None, 22, 22, 64)              0

 conv2d_20 (Conv2D)               (None, 20, 20, 32)         18,464

 batch_normalization_16           (None, 20, 20, 32)            128
 (BatchNormalization)

 max_pooling2d_16 (MaxPooling2D)  (None, 10, 10, 32)              0

 conv2d_21 (Conv2D)               (None, 8, 8, 32)            9,248

 batch_normalization_17           (None, 8, 8, 32)              128
 (BatchNormalization)

 max_pooling2d_17 (MaxPooling2D)  (None, 4, 4, 32)                0

 conv2d_22 (Conv2D)               (None, 2, 2, 16)            4,624

 flatten_4 (Flatten)              (None, 64)                      0
```

```
 dense_8 (Dense)                      (None, 256)                      16,640

 dense_9 (Dense)                      (None, 1)                           257
```

```
Total params: 323,637 (1.23 MB)

Trainable params: 107,729 (420.82 KB)

Non-trainable params: 448 (1.75 KB)

Optimizer params: 215,460 (841.64 KB)
```

[54]:

```
pd.DataFrame(history_final_model.history).plot(figsize=(8, 6))
plt.grid(True)
plt.gca().set_ylim(0, 1)
plt.show()
```



## 1.4 Step 4: Results and Analysis

I have tried multiple models and different hyperparameters with some yielding good results overall. A summary of the models and their performance is given below | model | accuracy| epoch | auc | loss | val_accuracy | val_auc | val_loss | kaggle private score | kaggle public score | |:———:|:———:|:———:|:———:|:———:|:———:|:———:|:———:|:———:|:———:| | ResNet50V2 | 0.8215 | 6 | - | 0.3947 | 0.8382 | - | 0.3717 | 0.5018 | 0.5023 | | second_model | 0.9052 |3| 0.9623 | 0.2393 | 0.8526 | 0.9441 | 0.3390 | 0.8349 | 0.9315 | | third_model | 0.9151 | 4| 0.9682 | 0.2184 | 0.9189 | 0.9703 | 0.2144 | 0.9170 | 0.9512 | | final_model | 0.9509 | 9 | 0.9882 | 0.1311 | 0.9402 | 0.9820 | 0.1624 | 0.9125 | 0.9433 |

The third model was the best among the models that I have tried and it provided the best Kaggle score. The final model seems to have a little overfitting since it has better statistics than the third model but has slightly lower score on Kaggle.

## 1.5 Step 5: Conclusion

After using transfer and hand written models, it seems like a general algorithm may or may not provide the best outcomes. The change I did may not have been enough to suit this requirement. Having a better knowledge of data might help in forming better performing models. Training time is a big problem unless we have GPUs at disposal.

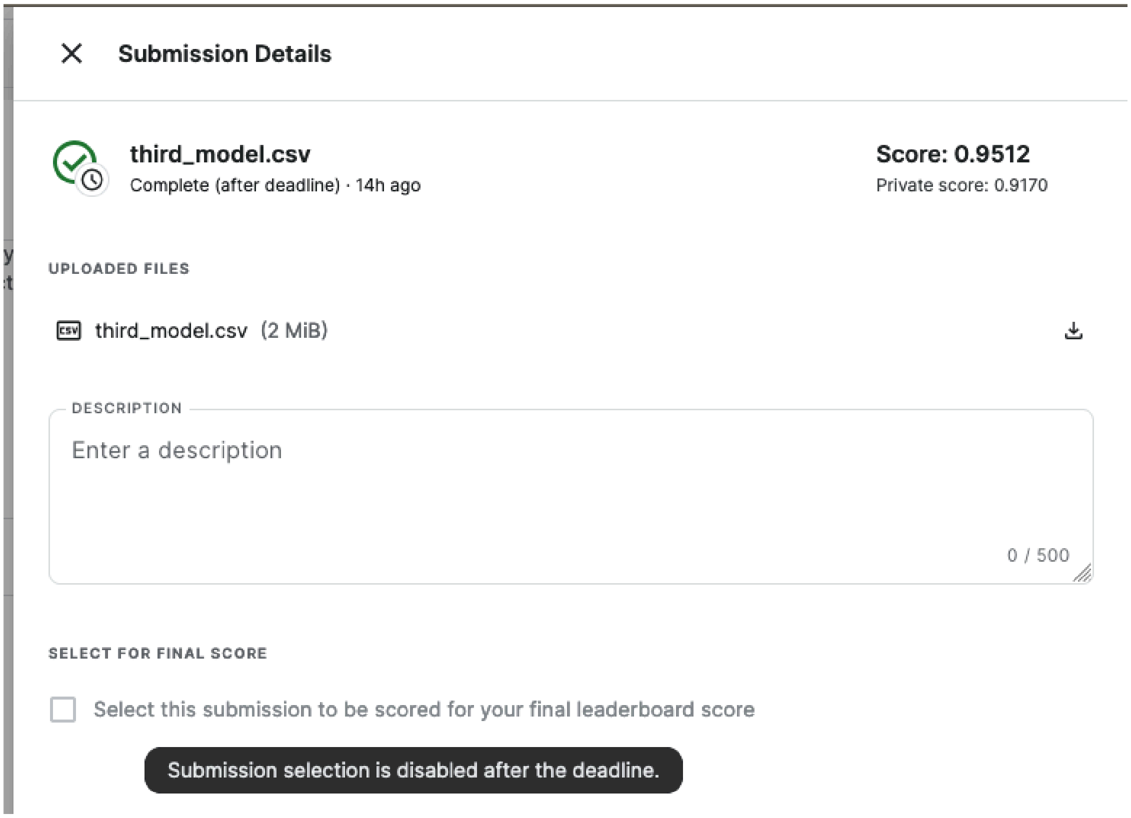
## 1.6 Step 6: Produce Deliverables: High-Quality, Organized Jupyter Notebook Report, GitHub Repository, and screenshot of Kaggle leaderboard

Jupyter notebook: https://github.com/krishnakuruvadi/week3_CNN/blob/main/week3.ipynb

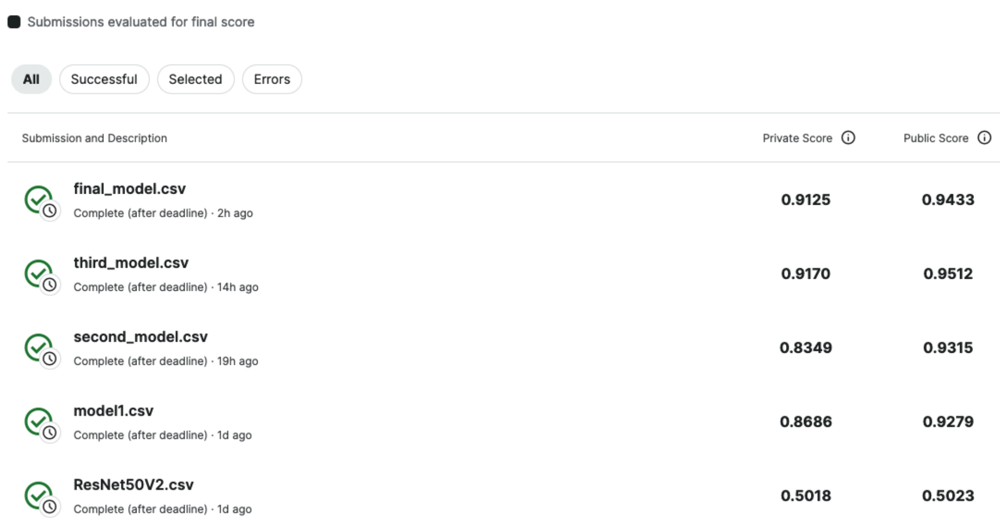
Jupyter report: https://github.com/krishnakuruvadi/week3_CNN/tree/main

Github repository: https://github.com/krishnakuruvadi/week3_CNN/tree/main

Leaderboard: Unfortunately Kaggle is not showing my position in leaderboard so I am not able to provide the same




Scores for all models I have tried:




## References


- ResNet50V2: https://www.tensorflow.org/api_docs/python/tf/keras/applications/ResNet50V2