HW5 Kaggle Competition

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To start, let's get one thing straight--my goal was not to get the most accurate model here. My goal was to explore how these tools work and intentionally make a less complicated, less computationally intensive model and solution to this problem.

I like to do development locally and don't like to wait for models to train overnight. Focusing on efficiency for this assignment has allowed me to more rapidly iterate on my model and experiment with different strategies.

What is the problem? Histopathologic Cancer Detection.

This Kaggle competition comes with about 6GB of training images from digital pathology scans. Each image is only 96x96 pixels, so that is a lot of entries. The data is divided into training and testing data already. My task is to make a model that classifies images as either cancer or not cancer.

Load and Preprocess Data

The data provided is included as 96x96 pixel images, but reading the competition description, only the center 32x32 pixels are considered. In other words, is there cancer present in the center of the image? Cropping the images to focus on the center only was a convenient step to reduce the computation time--both on loading and training the model.

Another benefit of this cropping, I hypothesize, is that this allows my model to learn only on the part of the image that will be evaluated on as opposed to identifying patterns in the outside portions of the image which may not be relevant to "identifying cancer in the center of the image".

I normalized the RGB values, but that's not really to save space. I also included a `fraction` variable to randomly select a portion of the training data only. The selection happens with the IDs, so only the necessary images are loaded into memory. Using `0.1` as the `fraction`, I was able to load all the images in one minute.

In [ ]:
```
# Check if TensorFlow is installed and if GPU is available

import tensorflow as tf
print("TensorFlow version:", tf.__version__)
print("GPU available:", tf.config.list_physical_devices('GPU'))
```

```
TensorFlow version: 2.16.1
GPU available: []
```

In [ ]:
```
# Load Data

import os
import pandas as pd
import numpy as np
import tensorflow as tf
from tensorflow.keras.preprocessing.image import load_img, img_to_array
from sklearn.model_selection import train_test_split

# Load the labels
train_labels = pd.read_csv('data/train_labels.csv')
sample_submission = pd.read_csv('data/sample_submission.csv')

# The images sizes are 96x96 despite the competition focus on the center 32x
IMAGE_SIZE = (96, 96)
CROP_SIZE = (32, 32)

# Crop an image and return only the center 32x32 pixels
def crop_center(image, crop_size=CROP_SIZE):
    center_x, center_y = image.shape[1] // 2, image.shape[0] // 2
    half_crop_size_x, half_crop_size_y = crop_size[1] // 2, crop_size[0] //
    return image[center_y - half_crop_size_y:center_y + half_crop_size_y,
                 center_x - half_crop_size_x:center_x + half_crop_size_x, :]

# Load, crop, and normalize the images
def load_image(image_path, crop=False):
    image = load_img(image_path, target_size=IMAGE_SIZE)
    image = img_to_array(image)
    if crop:
        image = crop_center(image)
    image = image / 255.0
    return image

def load_images(image_ids, image_dir, crop=False):
    image_paths = [os.path.join(image_dir, f'{image_id}.tif') for image_id i
    images = [load_image(image_path, crop) for image_path in image_paths]
    return np.array(images)

# Load the images and labels
image_ids = train_labels['id'].values
labels = train_labels['label'].values

# Split the data into training and validation sets
train_ids, val_ids, train_labels, val_labels = train_test_split(image_ids, l

# Define a fraction of the dataset to use for testing
fraction = 1  # Use 0.1 for quick testing

# Sample the training and validation IDs
train_sample_ids = np.random.choice(train_ids, size=int(len(train_ids) * fra
val_sample_ids = np.random.choice(val_ids, size=int(len(val_ids) * fraction)

# Load the training and validation images with cropping
```

```
train_images = load_images(train_sample_ids, 'data/train', crop=True)
val_images = load_images(val_sample_ids, 'data/train', crop=True)

# Convert labels to numpy arrays
train_labels = np.array([labels[image_ids.tolist().index(id)] for id in trai
val_labels = np.array([labels[image_ids.tolist().index(id)] for id in val_sa

# Check data shapes and types
print(f"train_images shape: {train_images.shape}, dtype: {train_images.dtype
print(f"train_labels shape: {train_labels.shape}, dtype: {train_labels.dtype
print(f"val_images shape: {val_images.shape}, dtype: {val_images.dtype}")
print(f"val_labels shape: {val_labels.shape}, dtype: {val_labels.dtype}")

# Check for NaNs in the data
print(f"NaNs in train_images: {np.isnan(train_images).sum()}")
print(f"NaNs in train_labels: {np.isnan(train_labels).sum()}")
print(f"NaNs in val_images: {np.isnan(val_images).sum()}")
print(f"NaNs in val_labels: {np.isnan(val_labels).sum()}")
```

```
train_images shape: (176020, 32, 32, 3), dtype: float32
train_labels shape: (176020,), dtype: int64
val_images shape: (44005, 32, 32, 3), dtype: float32
val_labels shape: (44005,), dtype: int64
NaNs in train_images: 0
NaNs in train_labels: 0
NaNs in val_images: 0
NaNs in val_labels: 0
```

In [ ]:

```
# Load Plot Function

import matplotlib.pyplot as plt

def plot_training_history(history):
    """
    Plots the training and validation accuracy and loss from the history obj

    Parameters:
    history (History): The history object returned by the fit method of a Ke
    """
    plt.figure(figsize=(12, 4))

    # Plot training & validation accuracy values
    plt.subplot(1, 2, 1)
    plt.plot(history.history['accuracy'])
    plt.plot(history.history['val_accuracy'])
    plt.title('Model Accuracy')
    plt.ylabel('Accuracy')
    plt.xlabel('Epoch')
    plt.legend(['Train', 'Validation'], loc='upper left')
    plt.xticks(range(len(history.history['accuracy'])))  # Set x-ticks to be

    # Plot training & validation loss values
    plt.subplot(1, 2, 2)
    plt.plot(history.history['loss'])
    plt.plot(history.history['val_loss'])
    plt.title('Model Loss')
```

```
    plt.ylabel('Loss')
    plt.xlabel('Epoch')
    plt.legend(['Train', 'Validation'], loc='upper left')
    plt.xticks(range(len(history.history['loss'])))  # Set x-ticks to be int

    plt.show()
```

Build and Train Model

In building the model, I tried not to use too many layers because each layer is additional computation. The main layers in my model attempt to make use of the RGB information first, then pool by half the amount of data, flatten, drop some of the data to prevent over-fitting, then look for more complex, dense patterns.

I included early stopping so if after a specified number of epics there is no improvement in the monitored metric, it stops training. I try to also select the best model based on the validation accuracy and loss.

The longer I went on playing with this project, the more I wanted to improve the models accuracy. You'll see I added more to the model, trying to capture information by performing convolutions of different sizes since the sample images tend to have blobs of different sizes. I also increased the patience, lowered the min_delta, and increased the maximum number of epoch to let the model over train itself. The early stopping class and best model selection should select the best one. Sometimes the accuracy goes down for a few epochs before increasing again, so it's worth seeing what happens.

After the training section, there are two graphs which show the model accuracy and loss for training and validation.

These are the configurations I used for submission. In the code blocks below, I used the same cropped image size and training data for all models just to show 1 for 1 comparison.

Model #	Image Size	Training Data Proportion	Kaggle Accuracy**
1	32x32	0.1	0.7652
2	32x32	0.1	0.7853
3*	96x96	0.1	0.8472
3	96x96	1	0.8266
3	32x32	1	0.

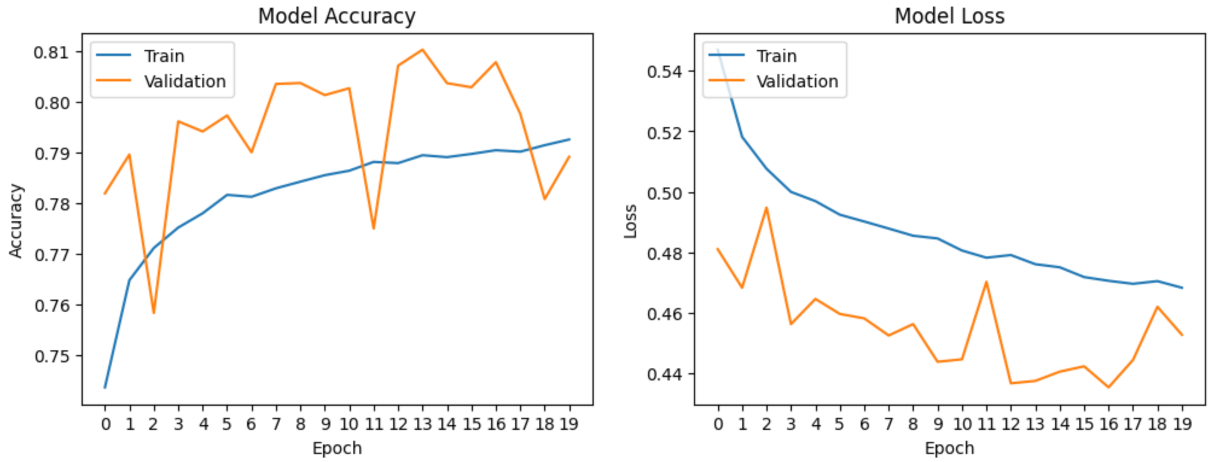
*Model 3 was trained with uncropped images (96x96), where models 1 and 2 were trained on center cropped images (32x32).

**I also don't remember if I trained my model on the full data set for submissions 1 and 2. I don't think I did.

In [ ]:
```
# Model 1

import tensorflow as tf
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Conv2D, MaxPooling2D, Flatten, Dense, Dr

# Define a simple model
model1 = Sequential([
    Input(shape=(32, 32, 3)),
    Conv2D(16, (3, 3), activation='relu'),
    MaxPooling2D((2, 2)),
    Flatten(),
    Dense(32, activation='relu'),
    Dropout(0.5),
    Dense(1, activation='sigmoid')
])

# Compile the model
model1.compile(optimizer='adam', loss='binary_crossentropy', metrics=['accur

# Train the model with verbose output
history1 = model1.fit(train_images, train_labels, epochs=20, validation_data

plot_training_history(history1)
```

```
Epoch 1/20
5501/5501 ━━━━━━━━━━━━━━━━━━━━ 15s 3ms/step - accuracy: 0.7206 - loss: 0.569
4 - val_accuracy: 0.7818 - val_loss: 0.4811
Epoch 2/20
5501/5501 ━━━━━━━━━━━━━━━━━━━━ 15s 3ms/step - accuracy: 0.7605 - loss: 0.523
1 - val_accuracy: 0.7895 - val_loss: 0.4683
Epoch 3/20
5501/5501 ━━━━━━━━━━━━━━━━━━━━ 15s 3ms/step - accuracy: 0.7710 - loss: 0.507
2 - val_accuracy: 0.7582 - val_loss: 0.4948
Epoch 4/20
5501/5501 ━━━━━━━━━━━━━━━━━━━━ 15s 3ms/step - accuracy: 0.7765 - loss: 0.500
2 - val_accuracy: 0.7961 - val_loss: 0.4563
Epoch 5/20
5501/5501 ━━━━━━━━━━━━━━━━━━━━ 15s 3ms/step - accuracy: 0.7788 - loss: 0.495
6 - val_accuracy: 0.7941 - val_loss: 0.4646
Epoch 6/20
5501/5501 ━━━━━━━━━━━━━━━━━━━━ 15s 3ms/step - accuracy: 0.7831 - loss: 0.491
6 - val_accuracy: 0.7972 - val_loss: 0.4597
Epoch 7/20
5501/5501 ━━━━━━━━━━━━━━━━━━━━ 15s 3ms/step - accuracy: 0.7799 - loss: 0.490
8 - val_accuracy: 0.7900 - val_loss: 0.4582
Epoch 8/20
5501/5501 ━━━━━━━━━━━━━━━━━━━━ 15s 3ms/step - accuracy: 0.7826 - loss: 0.486
9 - val_accuracy: 0.8035 - val_loss: 0.4525
Epoch 9/20
5501/5501 ━━━━━━━━━━━━━━━━━━━━ 15s 3ms/step - accuracy: 0.7843 - loss: 0.485
3 - val_accuracy: 0.8036 - val_loss: 0.4563
Epoch 10/20
5501/5501 ━━━━━━━━━━━━━━━━━━━━ 15s 3ms/step - accuracy: 0.7866 - loss: 0.483
4 - val_accuracy: 0.8012 - val_loss: 0.4439
Epoch 11/20
5501/5501 ━━━━━━━━━━━━━━━━━━━━ 15s 3ms/step - accuracy: 0.7853 - loss: 0.481
1 - val_accuracy: 0.8026 - val_loss: 0.4447
Epoch 12/20
5501/5501 ━━━━━━━━━━━━━━━━━━━━ 16s 3ms/step - accuracy: 0.7882 - loss: 0.478
1 - val_accuracy: 0.7749 - val_loss: 0.4703
Epoch 13/20
5501/5501 ━━━━━━━━━━━━━━━━━━━━ 16s 3ms/step - accuracy: 0.7882 - loss: 0.477
9 - val_accuracy: 0.8071 - val_loss: 0.4367
Epoch 14/20
5501/5501 ━━━━━━━━━━━━━━━━━━━━ 15s 3ms/step - accuracy: 0.7903 - loss: 0.474
1 - val_accuracy: 0.8102 - val_loss: 0.4375
Epoch 15/20
5501/5501 ━━━━━━━━━━━━━━━━━━━━ 15s 3ms/step - accuracy: 0.7911 - loss: 0.472
8 - val_accuracy: 0.8036 - val_loss: 0.4406
Epoch 16/20
5501/5501 ━━━━━━━━━━━━━━━━━━━━ 15s 3ms/step - accuracy: 0.7907 - loss: 0.471
8 - val_accuracy: 0.8028 - val_loss: 0.4423
Epoch 17/20
5501/5501 ━━━━━━━━━━━━━━━━━━━━ 15s 3ms/step - accuracy: 0.7911 - loss: 0.469
7 - val_accuracy: 0.8077 - val_loss: 0.4354
Epoch 18/20
5501/5501 ━━━━━━━━━━━━━━━━━━━━ 15s 3ms/step - accuracy: 0.7910 - loss: 0.469
2 - val_accuracy: 0.7976 - val_loss: 0.4445
Epoch 19/20
5501/5501 ━━━━━━━━━━━━━━━━━━━━ 15s 3ms/step - accuracy: 0.7915 - loss: 0.469
```

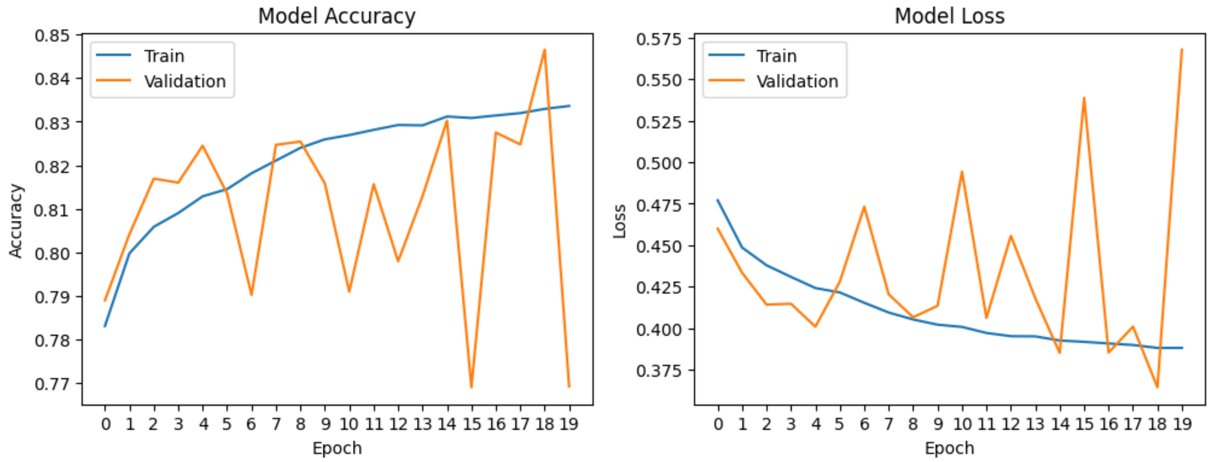
```
5 - val_accuracy: 0.7807 - val_loss: 0.4620
Epoch 20/20
5501/5501 ━━━━━━━━━━━━━━━━━━━━ 15s 3ms/step - accuracy: 0.7919 - loss: 0.469
6 - val_accuracy: 0.7891 - val_loss: 0.4528
```



In [ ]:
```python
# Model 2

from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Conv2D, Dense, Dropout, Input, BatchNorm

# Define a simple model
model2 = Sequential([
    Input(shape=(32, 32, 3)),

    Conv2D(4, (3, 3), activation='relu', padding='same'),
    BatchNormalization(),

    Conv2D(8, (3, 3), activation='relu', padding='same'),
    BatchNormalization(),

    Conv2D(16, (3, 3), activation='relu', padding='same'),
    BatchNormalization(),

    GlobalAveragePooling2D(),

    Dense(32, activation='relu'),
    Dropout(0.33),

    Dense(1, activation='sigmoid')
])

# Compile the model
model2.compile(optimizer='adam', loss='binary_crossentropy', metrics=['accur

# Train the model with verbose output
history2 = model2.fit(train_images, train_labels, epochs=20, validation_data

plot_training_history(history2)
```

```
Epoch 1/20
5501/5501 ━━━━━━━━━━━━━━━━━━━━ 55s 10ms/step - accuracy: 0.7657 - loss: 0.50
09 - val_accuracy: 0.7889 - val_loss: 0.4600
Epoch 2/20
5501/5501 ━━━━━━━━━━━━━━━━━━━━ 58s 10ms/step - accuracy: 0.7992 - loss: 0.44
97 - val_accuracy: 0.8041 - val_loss: 0.4334
Epoch 3/20
5501/5501 ━━━━━━━━━━━━━━━━━━━━ 66s 12ms/step - accuracy: 0.8045 - loss: 0.44
14 - val_accuracy: 0.8169 - val_loss: 0.4143
Epoch 4/20
5501/5501 ━━━━━━━━━━━━━━━━━━━━ 67s 12ms/step - accuracy: 0.8056 - loss: 0.43
68 - val_accuracy: 0.8160 - val_loss: 0.4148
Epoch 5/20
5501/5501 ━━━━━━━━━━━━━━━━━━━━ 67s 12ms/step - accuracy: 0.8123 - loss: 0.42
53 - val_accuracy: 0.8245 - val_loss: 0.4010
Epoch 6/20
5501/5501 ━━━━━━━━━━━━━━━━━━━━ 68s 12ms/step - accuracy: 0.8136 - loss: 0.42
42 - val_accuracy: 0.8135 - val_loss: 0.4281
Epoch 7/20
5501/5501 ━━━━━━━━━━━━━━━━━━━━ 72s 13ms/step - accuracy: 0.8176 - loss: 0.41
77 - val_accuracy: 0.7902 - val_loss: 0.4732
Epoch 8/20
5501/5501 ━━━━━━━━━━━━━━━━━━━━ 84s 15ms/step - accuracy: 0.8213 - loss: 0.40
91 - val_accuracy: 0.8247 - val_loss: 0.4205
Epoch 9/20
5501/5501 ━━━━━━━━━━━━━━━━━━━━ 82s 15ms/step - accuracy: 0.8239 - loss: 0.40
58 - val_accuracy: 0.8254 - val_loss: 0.4067
Epoch 10/20
5501/5501 ━━━━━━━━━━━━━━━━━━━━ 186s 34ms/step - accuracy: 0.8250 - loss: 0.4
024 - val_accuracy: 0.8158 - val_loss: 0.4136
Epoch 11/20
5501/5501 ━━━━━━━━━━━━━━━━━━━━ 88s 16ms/step - accuracy: 0.8279 - loss: 0.39
99 - val_accuracy: 0.7909 - val_loss: 0.4942
Epoch 12/20
5501/5501 ━━━━━━━━━━━━━━━━━━━━ 90s 16ms/step - accuracy: 0.8260 - loss: 0.40
02 - val_accuracy: 0.8156 - val_loss: 0.4063
Epoch 13/20
5501/5501 ━━━━━━━━━━━━━━━━━━━━ 87s 16ms/step - accuracy: 0.8286 - loss: 0.39
60 - val_accuracy: 0.7979 - val_loss: 0.4556
Epoch 14/20
5501/5501 ━━━━━━━━━━━━━━━━━━━━ 84s 15ms/step - accuracy: 0.8293 - loss: 0.39
42 - val_accuracy: 0.8129 - val_loss: 0.4181
Epoch 15/20
5501/5501 ━━━━━━━━━━━━━━━━━━━━ 87s 16ms/step - accuracy: 0.8318 - loss: 0.39
24 - val_accuracy: 0.8302 - val_loss: 0.3852
Epoch 16/20
5501/5501 ━━━━━━━━━━━━━━━━━━━━ 79s 14ms/step - accuracy: 0.8299 - loss: 0.39
34 - val_accuracy: 0.7689 - val_loss: 0.5387
Epoch 17/20
5501/5501 ━━━━━━━━━━━━━━━━━━━━ 84s 15ms/step - accuracy: 0.8311 - loss: 0.39
05 - val_accuracy: 0.8275 - val_loss: 0.3854
Epoch 18/20
5501/5501 ━━━━━━━━━━━━━━━━━━━━ 85s 15ms/step - accuracy: 0.8334 - loss: 0.38
87 - val_accuracy: 0.8248 - val_loss: 0.4011
Epoch 19/20
5501/5501 ━━━━━━━━━━━━━━━━━━━━ 88s 16ms/step - accuracy: 0.8337 - loss: 0.38
```

```
58 - val_accuracy: 0.8466 - val_loss: 0.3645
Epoch 20/20
5501/5501 ━━━━━━━━━━━━━━━━━━━━ 91s 17ms/step - accuracy: 0.8343 - loss: 0.38
62 - val_accuracy: 0.7691 - val_loss: 0.5677
```

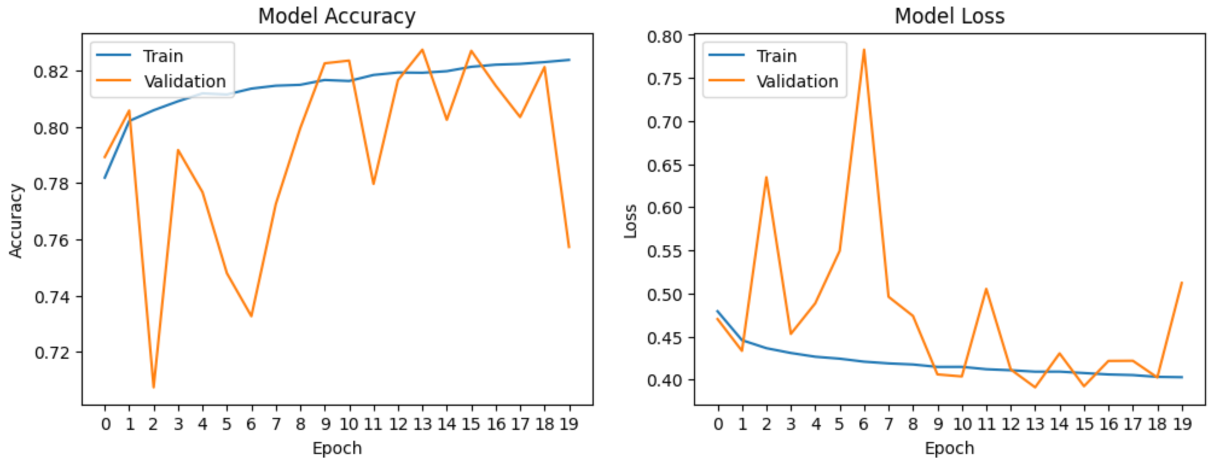


In [ ]:

```python
# Model 3

from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Conv2D, Dense, Dropout, Input, BatchNorm

# Define a simple model
model3 = Sequential([
    Input(shape=(32, 32, 3)),

    Conv2D(4, (3, 3), activation='relu', padding='same'),
    BatchNormalization(),

    Conv2D(8, (3, 3), activation='relu', padding='same', strides=(2, 2)),
    BatchNormalization(),
    MaxPooling2D(pool_size=(2, 2)),

    Conv2D(16, (3, 3), activation='relu', padding='same', strides=(2, 2)),
    BatchNormalization(),
    MaxPooling2D(pool_size=(2, 2)),

    Conv2D(32, (3, 3), activation='relu', padding='same', strides=(2, 2)),
    BatchNormalization(),
    GlobalAveragePooling2D(),

    Dense(32, activation='relu'),
    Dropout(0.33),

    Dense(1, activation='sigmoid')
])

# Compile the model
model3.compile(optimizer='adam', loss='binary_crossentropy', metrics=['accur

# Train the model with verbose output
history3 = model3.fit(train_images, train_labels, epochs=20, validation_data

plot_training_history(history3)
```

```
Epoch 1/20
5501/5501 ━━━━━━━━━━━━━━━━━━━━ 49s 9ms/step - accuracy: 0.7580 - loss: 0.517
4 - val_accuracy: 0.7892 - val_loss: 0.4703
Epoch 2/20
5501/5501 ━━━━━━━━━━━━━━━━━━━━ 45s 8ms/step - accuracy: 0.7999 - loss: 0.449
3 - val_accuracy: 0.8057 - val_loss: 0.4334
Epoch 3/20
5501/5501 ━━━━━━━━━━━━━━━━━━━━ 45s 8ms/step - accuracy: 0.8056 - loss: 0.436
7 - val_accuracy: 0.7073 - val_loss: 0.6348
Epoch 4/20
5501/5501 ━━━━━━━━━━━━━━━━━━━━ 42s 8ms/step - accuracy: 0.8085 - loss: 0.432
3 - val_accuracy: 0.7917 - val_loss: 0.4530
Epoch 5/20
5501/5501 ━━━━━━━━━━━━━━━━━━━━ 46s 8ms/step - accuracy: 0.8123 - loss: 0.426
6 - val_accuracy: 0.7767 - val_loss: 0.4886
Epoch 6/20
5501/5501 ━━━━━━━━━━━━━━━━━━━━ 42s 8ms/step - accuracy: 0.8110 - loss: 0.425
4 - val_accuracy: 0.7479 - val_loss: 0.5494
Epoch 7/20
5501/5501 ━━━━━━━━━━━━━━━━━━━━ 40s 7ms/step - accuracy: 0.8144 - loss: 0.418
7 - val_accuracy: 0.7326 - val_loss: 0.7828
Epoch 8/20
5501/5501 ━━━━━━━━━━━━━━━━━━━━ 47s 9ms/step - accuracy: 0.8146 - loss: 0.419
7 - val_accuracy: 0.7725 - val_loss: 0.4961
Epoch 9/20
5501/5501 ━━━━━━━━━━━━━━━━━━━━ 43s 8ms/step - accuracy: 0.8158 - loss: 0.415
7 - val_accuracy: 0.7995 - val_loss: 0.4739
Epoch 10/20
5501/5501 ━━━━━━━━━━━━━━━━━━━━ 45s 8ms/step - accuracy: 0.8169 - loss: 0.413
9 - val_accuracy: 0.8225 - val_loss: 0.4061
Epoch 11/20
5501/5501 ━━━━━━━━━━━━━━━━━━━━ 46s 8ms/step - accuracy: 0.8180 - loss: 0.414
1 - val_accuracy: 0.8235 - val_loss: 0.4037
Epoch 12/20
5501/5501 ━━━━━━━━━━━━━━━━━━━━ 47s 9ms/step - accuracy: 0.8178 - loss: 0.412
9 - val_accuracy: 0.7796 - val_loss: 0.5053
Epoch 13/20
5501/5501 ━━━━━━━━━━━━━━━━━━━━ 46s 8ms/step - accuracy: 0.8183 - loss: 0.411
6 - val_accuracy: 0.8165 - val_loss: 0.4119
Epoch 14/20
5501/5501 ━━━━━━━━━━━━━━━━━━━━ 45s 8ms/step - accuracy: 0.8196 - loss: 0.409
5 - val_accuracy: 0.8274 - val_loss: 0.3911
Epoch 15/20
5501/5501 ━━━━━━━━━━━━━━━━━━━━ 45s 8ms/step - accuracy: 0.8204 - loss: 0.408
4 - val_accuracy: 0.8024 - val_loss: 0.4304
Epoch 16/20
5501/5501 ━━━━━━━━━━━━━━━━━━━━ 43s 8ms/step - accuracy: 0.8236 - loss: 0.402
4 - val_accuracy: 0.8270 - val_loss: 0.3924
Epoch 17/20
5501/5501 ━━━━━━━━━━━━━━━━━━━━ 45s 8ms/step - accuracy: 0.8217 - loss: 0.406
2 - val_accuracy: 0.8146 - val_loss: 0.4217
Epoch 18/20
5501/5501 ━━━━━━━━━━━━━━━━━━━━ 41s 7ms/step - accuracy: 0.8219 - loss: 0.406
5 - val_accuracy: 0.8034 - val_loss: 0.4219
Epoch 19/20
5501/5501 ━━━━━━━━━━━━━━━━━━━━ 47s 8ms/step - accuracy: 0.8243 - loss: 0.402
```

```
1 - val_accuracy: 0.8212 - val_loss: 0.4025
Epoch 20/20
5501/5501 ━━━━━━━━━━━━━━━━━━━━ 42s 8ms/step - accuracy: 0.8236 - loss: 0.402
4 - val_accuracy: 0.7572 - val_loss: 0.5121
```



Evaluate Model

In [ ]:
```python
# Choose Model for Evaluation/Submission
model = model3
```

In [ ]:
```python
# Evaluate the model on the validation set
val_loss, val_accuracy = model.evaluate(val_images, val_labels)
print(f'Validation Accuracy: {val_accuracy}')
print(f'Validation Loss: {val_loss}')
```

```
1376/1376 ━━━━━━━━━━━━━━━━━━━━ 3s 3ms/step - accuracy: 0.7562 - loss: 0.5109
Validation Accuracy: 0.757232129573822
Validation Loss: 0.5121429562568665
```

Make Predictions

In [ ]:
```python
# Create Submission File

# Load the test images
test_ids = sample_submission['id'].values
test_images = load_images(test_ids, 'data/test', crop=True)

# Make predictions
predictions = model.predict(test_images)
predictions = (predictions > 0.5).astype(int).flatten()

# Prepare the submission file
submission = pd.DataFrame({'id': test_ids, 'label': predictions})
submission.to_csv('submission.csv', index=False)
```

```
1796/1796 ━━━━━━━━━━━━━━━━━━━━ 5s 2ms/step
```

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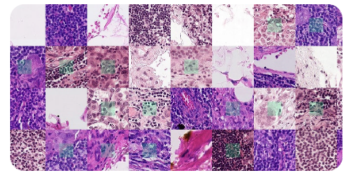
Late Submission

Histopathologic Cancer Detection

Identify metastatic tissue in histopathologic scans of lymph node sections



Overview Data Code Models Discussion Leaderboard Rules Team Submissions

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All Successful Selected Errors Public Score

Submission and Description	Private Score	Public Score	Selected
submission.csv Complete (after deadline) · 20h ago · Third Model (Full Image / 0.1 Trai...	0.7681	0.8472	☐
submission.csv Complete (after deadline) · 20h ago · Model 3, All Data, Full Image	0.7582	0.8266	☐
submission.csv Complete (after deadline) · 21h ago · Second model	0.7400	0.7853	☐
submission.csv Complete (after deadline) · 20h ago · Model Three (All Data, Cropped I...	0.7459	0.7704	☐
submission.csv Complete (after deadline) · 2d ago · First try -- using training on only t...	0.7261	0.7652	☐

Conclusion

I reformatted this notebook to have all three models run in their own cells and generate plots for review. They are all run with the cropped 32x32 images and the full training dataset.

For every Kaggle submissions I left some notes on what I did, and I think what is most interesting is comparing how the different configurations of model three performed. The first model performed the worst, but not unremarkably worse than the second.

The three model three submissions in increasing score: all data, cropped image; all data, full image; 10% data, full image. It appears that in the case of model three, more training data is not better, which means I must be over-fitting. It also appears that using the full 96x96 image is better than using the cropped images as the two models submitted with cropped images were at the end of the list. Initially I thought training on more than the center 32x32 pixels would teach the model to use information it wouldn't have access to, but despite the competition claiming the challenge is to classifying the center of the image only, the test images are 96x96, which explains why using the full image in training leads to higher accuracy. If they really only wanted to classify the center of the image, that is all the data that should be used in evaluation.