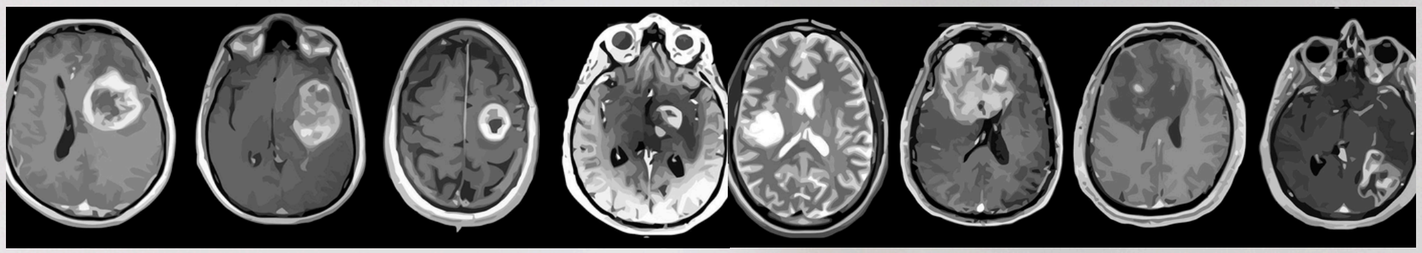
MACS 33002
Prof. Wang

Analysis of ML Models in Medical Imaging Classification



tinyurl.com/helentianp5

presented by
Helen Tian

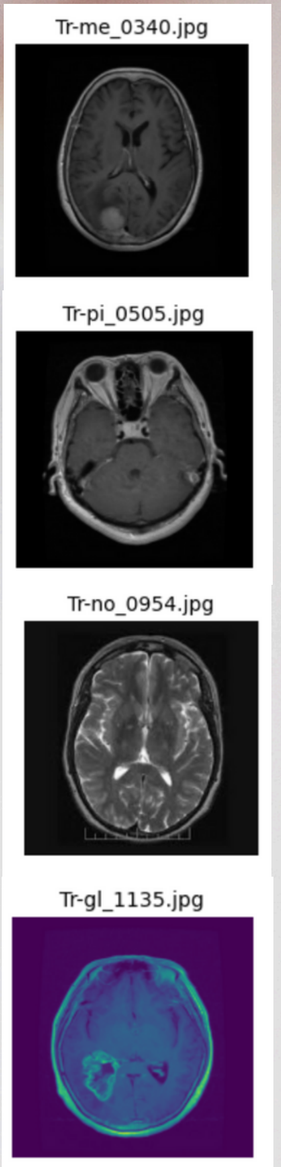
my motivation

combining interests: comp sci and medicine

hands-on learning opportunity for lab research

my research goal and question

how can we accurately classify MRI images of brain tumors into categories of glioma, meningioma, no tumor, and pituitary?

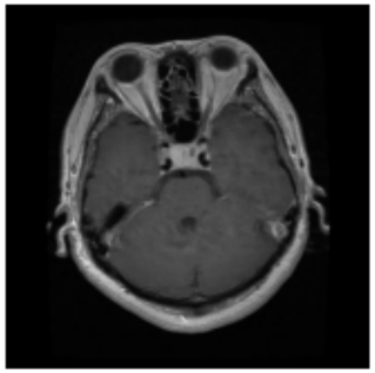


data collection and processing

taken from Kaggle (combination of 3 datasets)
classified into 4 classes: glioma, meningioma, no tumor, and pituitary

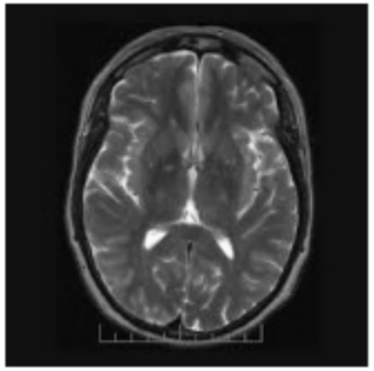
pituitary

Tr-pi_0505.jpg



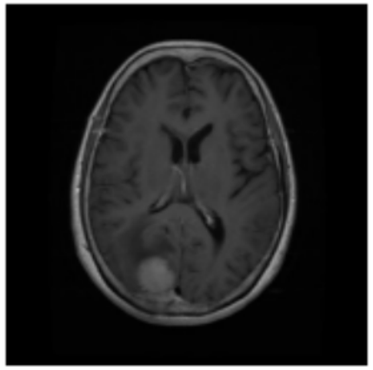
notumor

Tr-no_0954.jpg



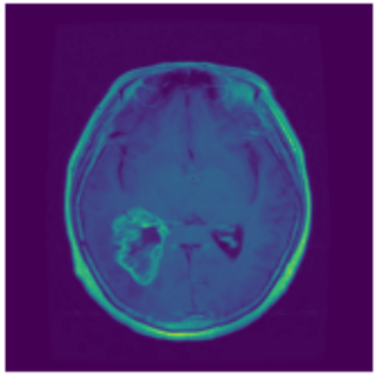
meningioma

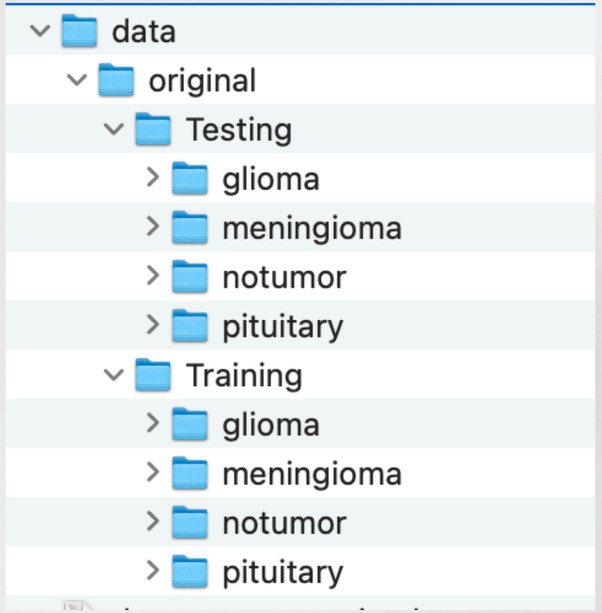
Tr-me_0340.jpg



glioma

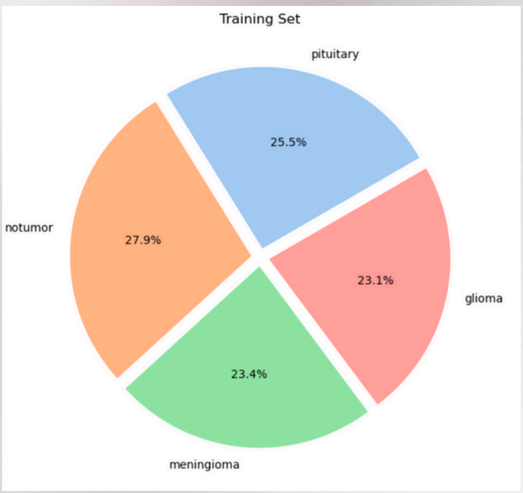
Tr-gl_1135.jpg

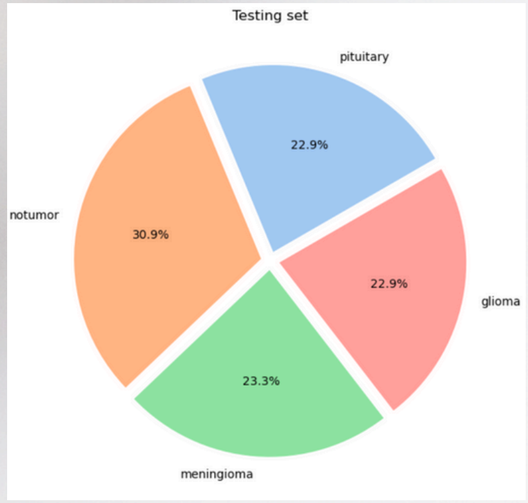




81.3% training data
18.7% testing data

7023 images total
split across folders





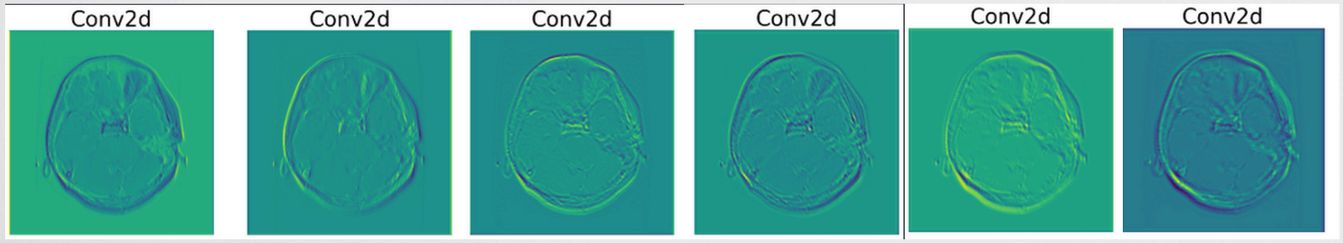
data cleaning and transformation

```python
def validify(img_files, img_dir):
    # Identify unreadable/missing images
    valid_images = []
    for file in img_files:
        try:
            img_path = os.path.join(img_dir, file)
            img = Image.open(img_path)
            valid_images.append(file)
        except Exception as e:
            print(f"Error with image {file}: {e}")

    return valid_images
```

```python
def find_outliers(img_files, img_dir):
    valid_images = validify(img_files, img_dir)

    # Analyze the distribution of image sizes to detect outliers
    img_sizes = []
    for file in valid_images:
        img_path = os.path.join(img_dir, file)
        img = Image.open(img_path)
        img_sizes.append(img.size)

    img_size_distribution = np.array(img_sizes)
    img_size_mean = np.mean(img_size_distribution, axis=0)
    img_size_std = np.std(img_size_distribution, axis=0)

    outlier_indices = np.where(
        (img_size_distribution > img_size_mean + 3 * img_size_std) |
        (img_size_distribution < img_size_mean - 3 * img_size_std)
    )

    outlier_imgs = [valid_images[i] for i in outlier_indices[0]]
    return outlier_imgs
```

```python
def transformation_def(img_files, img_dir):
    # Define standard image transformations
    # Respective order: standardize dimensions, convert to tensor, normalize pixel values
    img_transform = transforms.Compose([
        # transforms.Grayscale(num_output_channels=3),
        transforms.Resize((224, 224)),
        transforms.ToTensor(),
        transforms.Normalize(mean=[0.5], std=[0.5]),
    ])

    img_pil = [Image.open(os.path.join(img_dir, file)) for file in img_files]
    return img_pil, img_transform
```

```python
def extract_conv_layers(pretrained_model):
    conv_weights = []
    conv_layers = []
    # Traverse through the model to extract convolutional layers and weights
    for module in pretrained_model.features.children():
        if isinstance(module, nn.Conv2d):
            conv_weights.append(module.weight)
            conv_layers.append(module)
    return conv_weights, conv_layers
```



model exploration

VGG19

```
VGG19Model (VGG19Model)
├─VGG (backbone_model)
│    └─Sequential (features)
│    │    └─Conv2d (0)
│    │    └─ReLU (1)
│    │    └─Conv2d (2)
│    │    └─ReLU (3)
│    │    └─MaxPool2d (4)
│    │    └─Conv2d (5)
│    │    └─ReLU (6)
│    │    └─Conv2d (7)
│    │    └─ReLU (8)
│    │    └─MaxPool2d (9)
│    │    └─Conv2d (10)
│    │    └─ReLU (11)
│    │    └─Conv2d (12)
│    │    └─ReLU (13)
│    │    └─Conv2d (14)
│    │    └─ReLU (15)
│    │    └─Conv2d (16)
│    │    └─ReLU (17)
│    │    └─MaxPool2d (18)
│    │    └─Conv2d (19)
│    │    └─ReLU (20)
│    │    └─Conv2d (21)
│    │    └─ReLU (22)
│    │    └─Conv2d (23)
│    │    └─ReLU (24)
│    │    └─Conv2d (25)
│    │    └─ReLU (26)
│    │    └─MaxPool2d (27)
│    │    └─Conv2d (28)
│    │    └─ReLU (29)
│    │    └─Conv2d (30)
│    │    └─ReLU (31)
│    │    └─Conv2d (32)
│    │    └─ReLU (33)
│    │    └─Conv2d (34)
│    │    └─ReLU (35)
│    │    └─MaxPool2d (36)
│    └─AdaptiveAvgPool2d (avgpool)
│    └─Sequential (classifier)
│    │    └─Linear (0)
│    │    └─ReLU (1)
│    │    └─Dropout (2)
│    │    └─Linear (3)
│    │    └─ReLU (4)
│    │    └─Dropout (5)
│    │    └─Linear (6)
==========
==
Total params: 139,586,628
Trainable params: 119,562,244
Non-trainable params: 20,024,384
Total mult-adds (G): 628.57
==========
==
Input size (MB): 19.27
Forward/backward pass size (MB): 3804.23
Params size (MB): 558.35
Estimated Total Size (MB): 4381.85
==========
```

ResNet50

```
==========
Layer (type (var_name))
==========
ResNet50Model (ResNet50Model)
├─ResNet (backbone_model)
│    └─Conv2d (conv1)
│    └─BatchNorm2d (bn1)
│    └─ReLU (relu)
│    └─MaxPool2d (maxpool)
│    └─Sequential (layer1)
│    │    └─Bottleneck (0)
│    │    └─Bottleneck (1)
│    │    └─Bottleneck (2)
│    └─Sequential (layer2)
│    │    └─Bottleneck (0)
│    │    └─Bottleneck (1)
│    │    └─Bottleneck (2)
│    │    └─Bottleneck (3)
│    └─Sequential (layer3)
│    │    └─Bottleneck (0)
│    │    └─Bottleneck (1)
│    │    └─Bottleneck (2)
│    │    └─Bottleneck (3)
│    │    └─Bottleneck (4)
│    │    └─Bottleneck (5)
│    └─Sequential (layer4)
│    │    └─Bottleneck (0)
│    │    └─Bottleneck (1)
│    │    └─Bottleneck (2)
│    └─AdaptiveAvgPool2d (avgpool)
│    └─Sequential (fc)
│    │    └─Linear (0)
│    │    └─ReLU (1)
│    │    └─Dropout (2)
│    │    └─Linear (3)
==========
Total params: 25,610,308
Trainable params: 2,102,276
Non-trainable params: 23,508,032
Total mult-adds (G): 130.86
==========
Input size (MB): 19.27
Forward/backward pass size (MB): 5690.62
Params size (MB): 102.44
Estimated Total Size (MB): 5812.33
==========
```

EfficientNet

```
==========
Layer (type (var_name))
==========
EfficientNetV2Model (EfficientNetV2Model)
├─EfficientNet (backbone_model)
│    └─Sequential (features)
│    │    └─Conv2dNormActivation (0)
│    │    └─Sequential (1)
alse
│    │    └─Sequential (2)
False
│    │    └─Sequential (3)
lse
│    │    └─Sequential (4)
alse
│    │    └─Sequential (5)
False
│    │    └─Sequential (6)
alse
│    │    └─Sequential (7)
se
│    │    └─Conv2dNormActivation (8)
│    └─AdaptiveAvgPool2d (avgpool)
│    └─Sequential (classifier)
│    │    └─Flatten (0)
│    │    └─Dropout (1)
│    │    └─Linear (2)
│    │    └─GELU (3)
│    │    └─Dropout (4)
│    │    └─Linear (5)
==========
Total params: 117,563,232
Trainable params: 328,960
Non-trainable params: 117,234,272
Total mult-adds (G): 391.39
==========
Input size (MB): 19.27
Forward/backward pass size (MB): 17633.22
Params size (MB): 470.25
Estimated Total Size (MB): 18122.74
==========
```

EfficientNet scales uniformly at width, depth, and resolution. It's also the simplest (least computationally expensive model).

- 328, 960 trainable parameters

Conv2dNormActivation

- Conv2d
- Batch normalization
- Activation (Swish activation function: Y = X * sigmoid(X))

Sequential

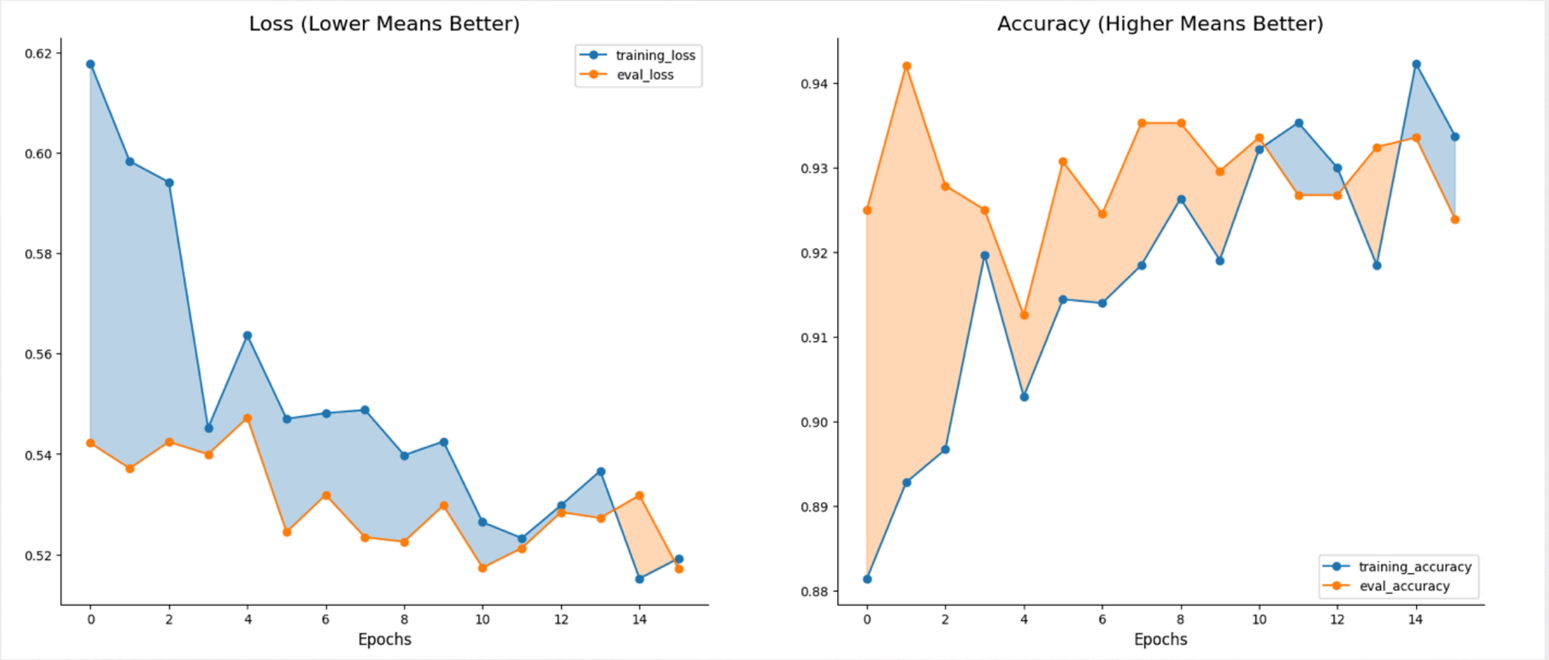
- To stack layers to form a feed-forward network

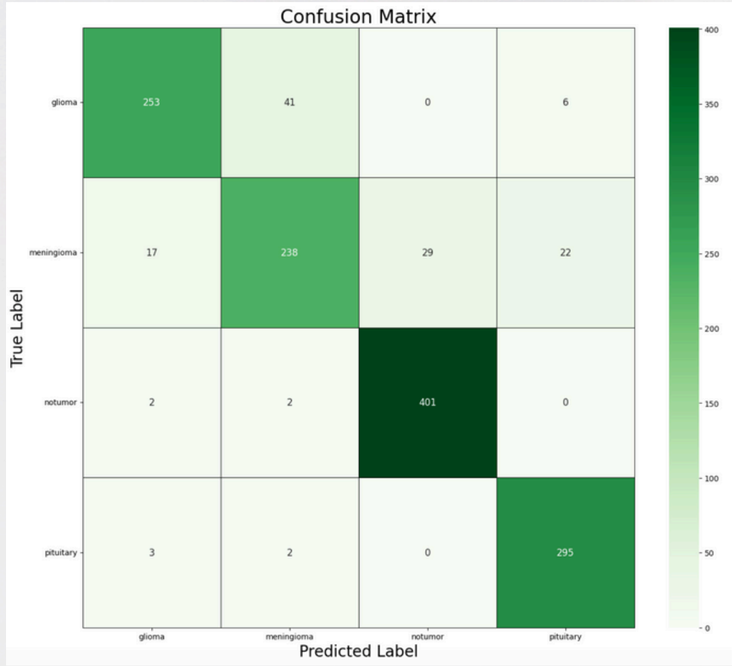
supervised learning

trained on 10%, 20%, and 30% of our data to see which one produced the best accuracy and stable model

please note that while we found using 30% of our data was better, we will continue with 10% to optimize time efficiency

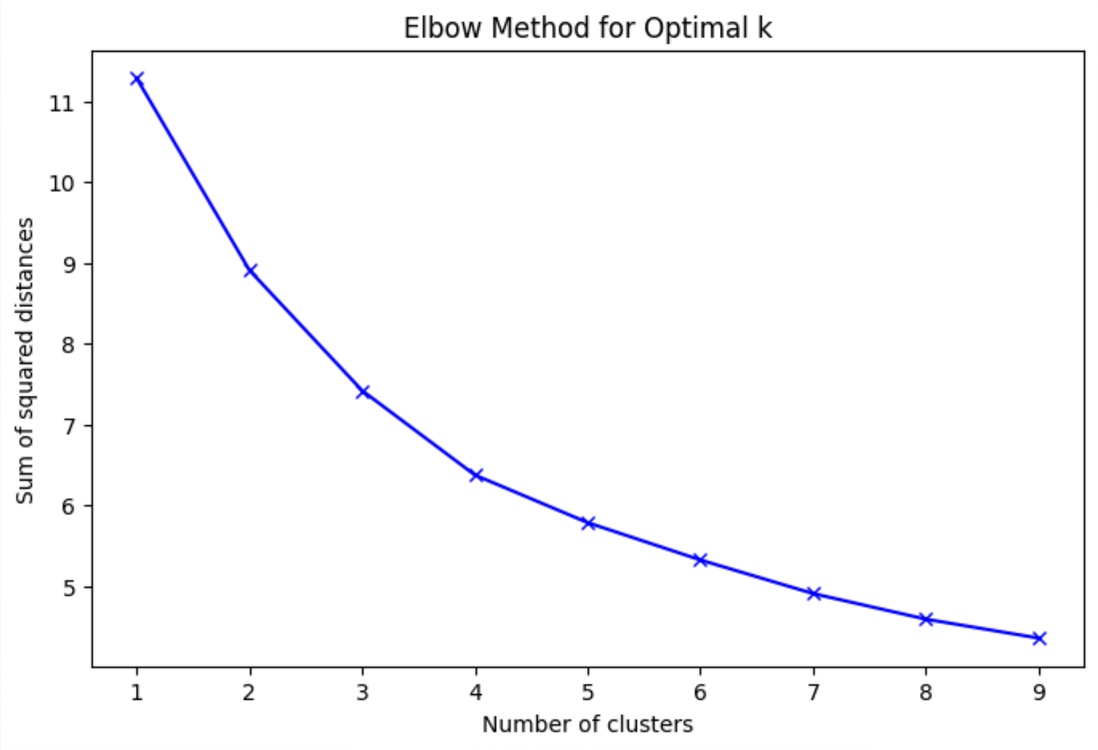
30% did the best

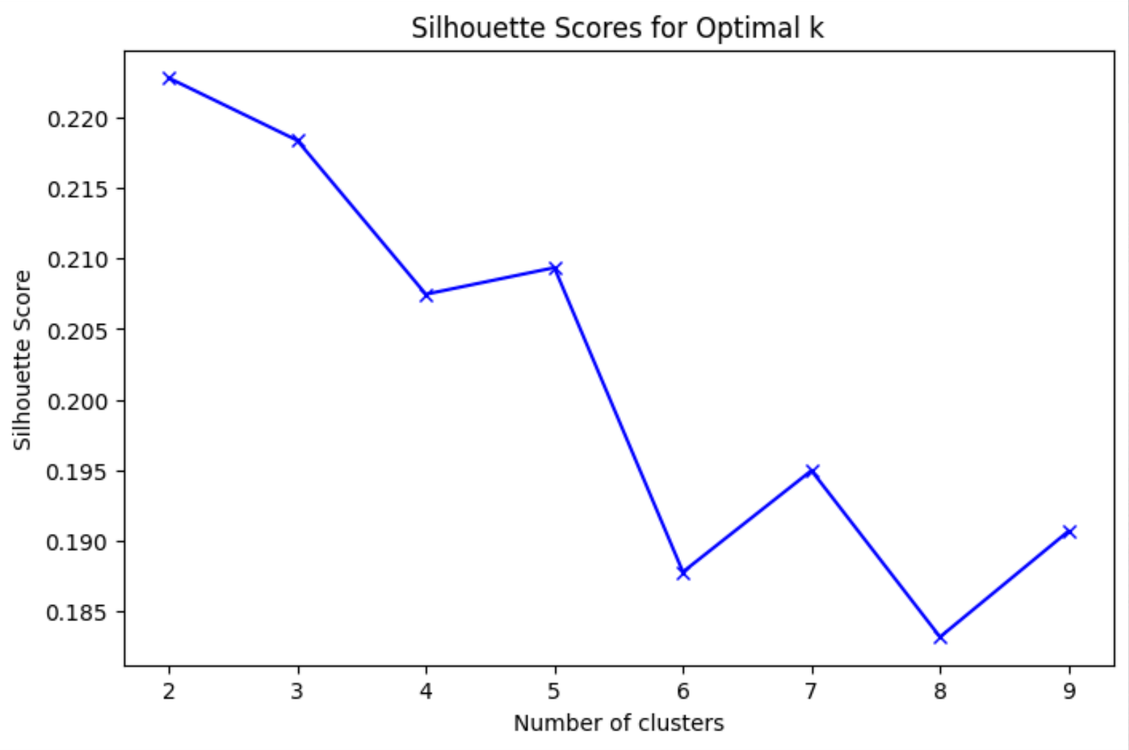




kmeans clustering

0: {'avg_intensity': 32.86749, 'std_dev': 39.523575}
1: {'avg_intensity': 44.899525, 'std_dev': 49.508053}
2: {'avg_intensity': 63.047462, 'std_dev': 63.520638}
3: {'avg_intensity': 47.403687, 'std_dev': 41.16208}





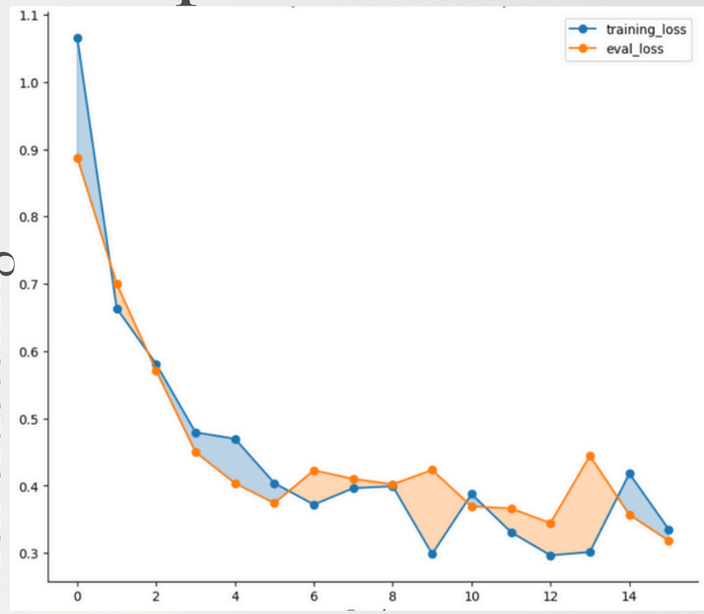
- plotting the sum of squared distances of samples to their closest cluster center
- "elbow" point is where the rate of decrease sharply shifts

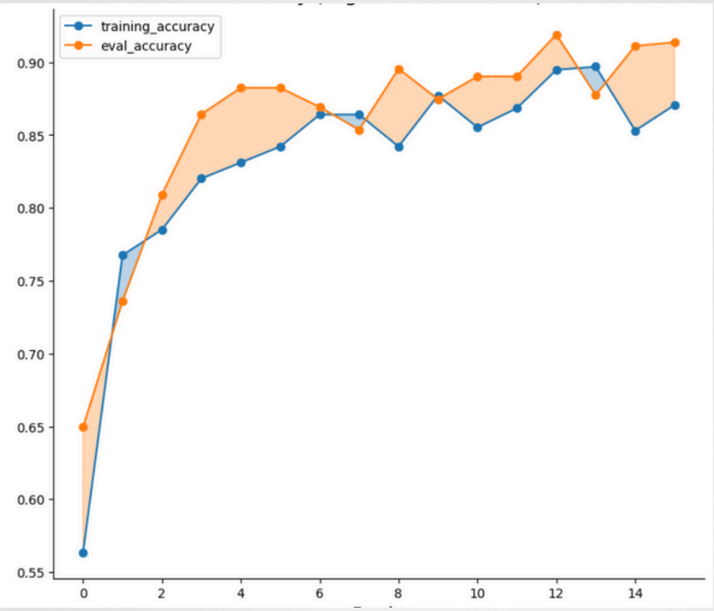
- a(i) = average distance in same cluster (cohesion)
- b(i) = average distance in nearest cluster (separation)
- $s(i) = \frac{b(i) - a(i)}{\max(a(i), b(i))}$

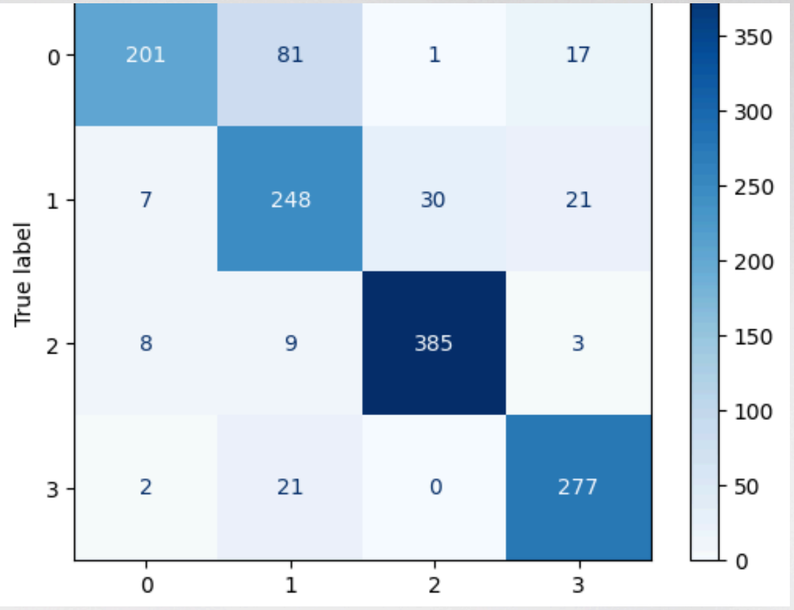
unsupervised learning

please note that while we found using 30% of our data was better, we will continue with 10% to optimize time efficiency

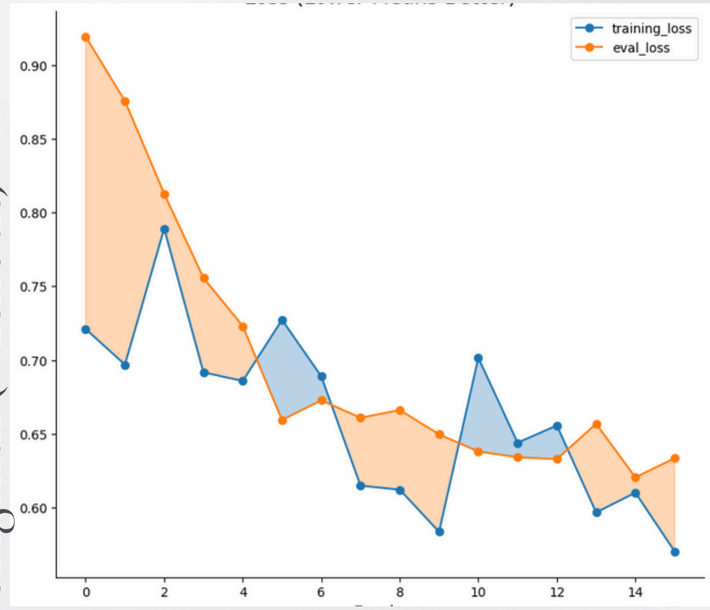
with clustering

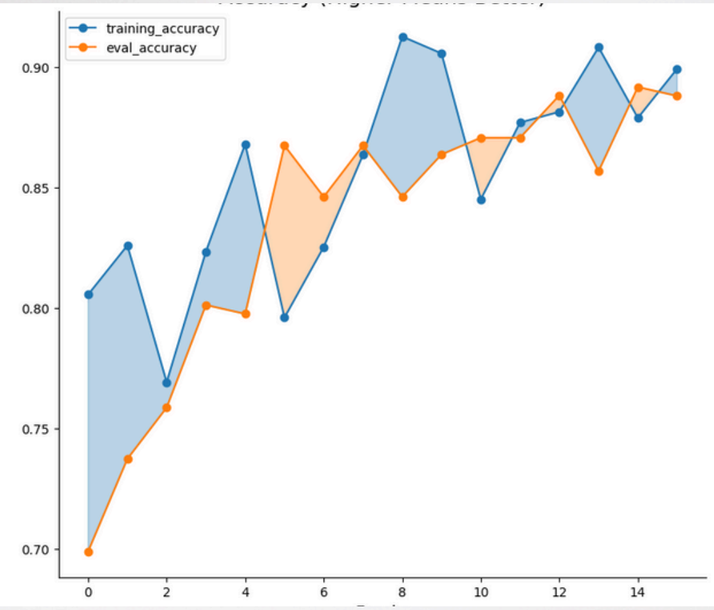


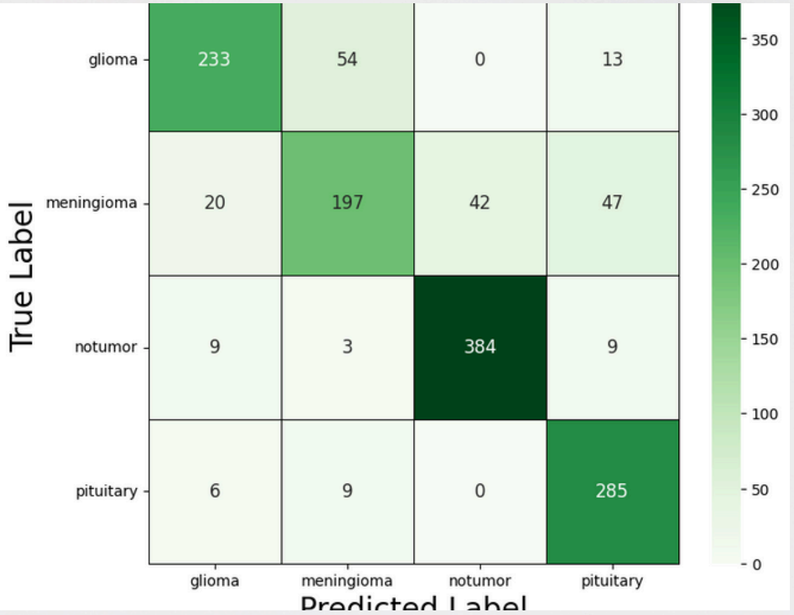




original (without)







parameter fine-tuning

using GridSearchCV, the best parameters are: dropout_rate: 0.0, weight_decay: 0.0, momentum: 0.95, lr: 1e-2

These are the parameters we explored:

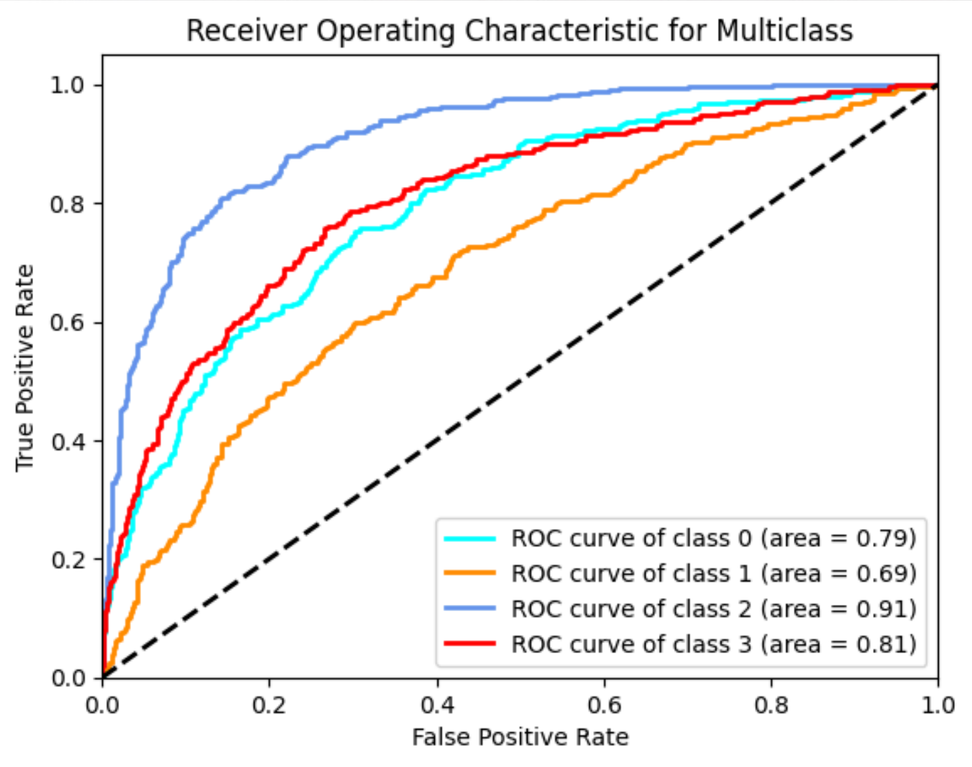
```
param_grid = {
    'dropout_rate': [0.0, 0.1, 0.2],
    'weight_decay': [0.0, 0.001, 0.01],
    'momentum': [0.9, 0.95],
    'lr': [1e-4, 1e-3, 1e-2]}
```

```
Sample 1:
  True Label: 0
  Predicted Label: 1
  Confidence Scores: [0.2502424  0.27024752 0.24365504 0.23585504]
Sample 2:
  True Label: 0
  Predicted Label: 3
  Confidence Scores: [0.2572371  0.23838969 0.19616205 0.3082111 ]
Sample 3:
  True Label: 1
  Predicted Label: 0
  Confidence Scores: [0.26567176 0.2408866  0.23631462 0.25712708]
```

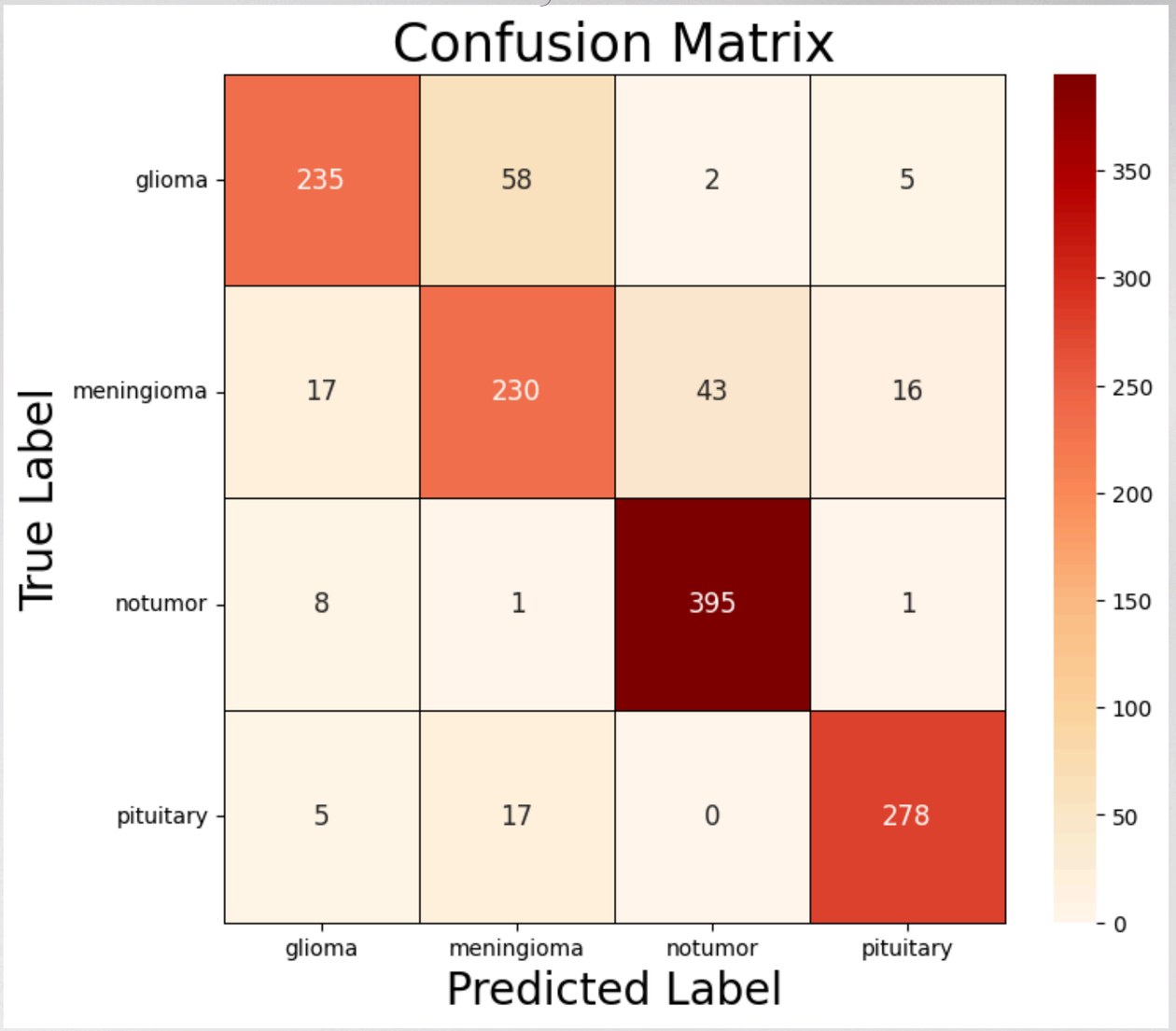
- dropout_rate: regularization technique that randomly drops fraction of neurons during training
- weight_decay: regularization technique that penalizes large weights in the model
- momentum: helps accelerate gradients in theright direction and dampens oscillations
- learning rate: step size taken during optimization

- low confidence scores indicate that the model is unsure about its prediction

final model evaluation



accuracy score: 0.8680396643783371



Classification Report:	precision	recall	f1-score	support
0	0.92	0.67	0.78	300
1	0.69	0.81	0.75	306
2	0.93	0.95	0.94	405
3	0.87	0.92	0.90	300
accuracy			0.85	1311
macro avg	0.85	0.84	0.84	1311
weighted avg	0.86	0.85	0.85	1311

answering the research question

a multi-class classification task that used a pre-loaded EfficietNet Model

- explored how including unsupervised clustering techniques affected the model
- explored different parameters and how to fine-tune them to prevent over-fitting

analysis for the future

want to further analyze this dataset to investigate the feasibility of using symmetry-based methods to estimate the tumor volume from the 2-d MRI scans (a regression task)

thank you!