CT Image Hemorrhage Classification and Segmentation by ML Methods

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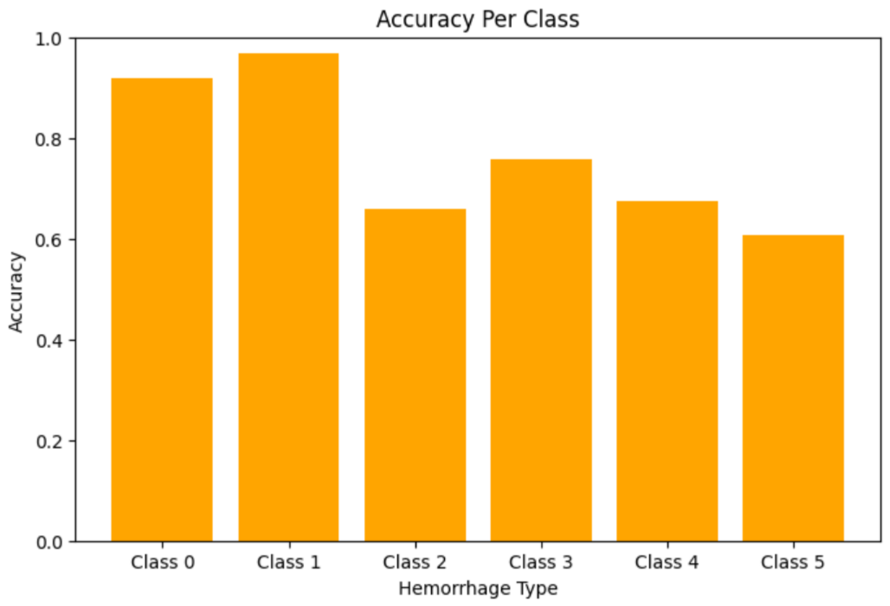
Project Background and Goal

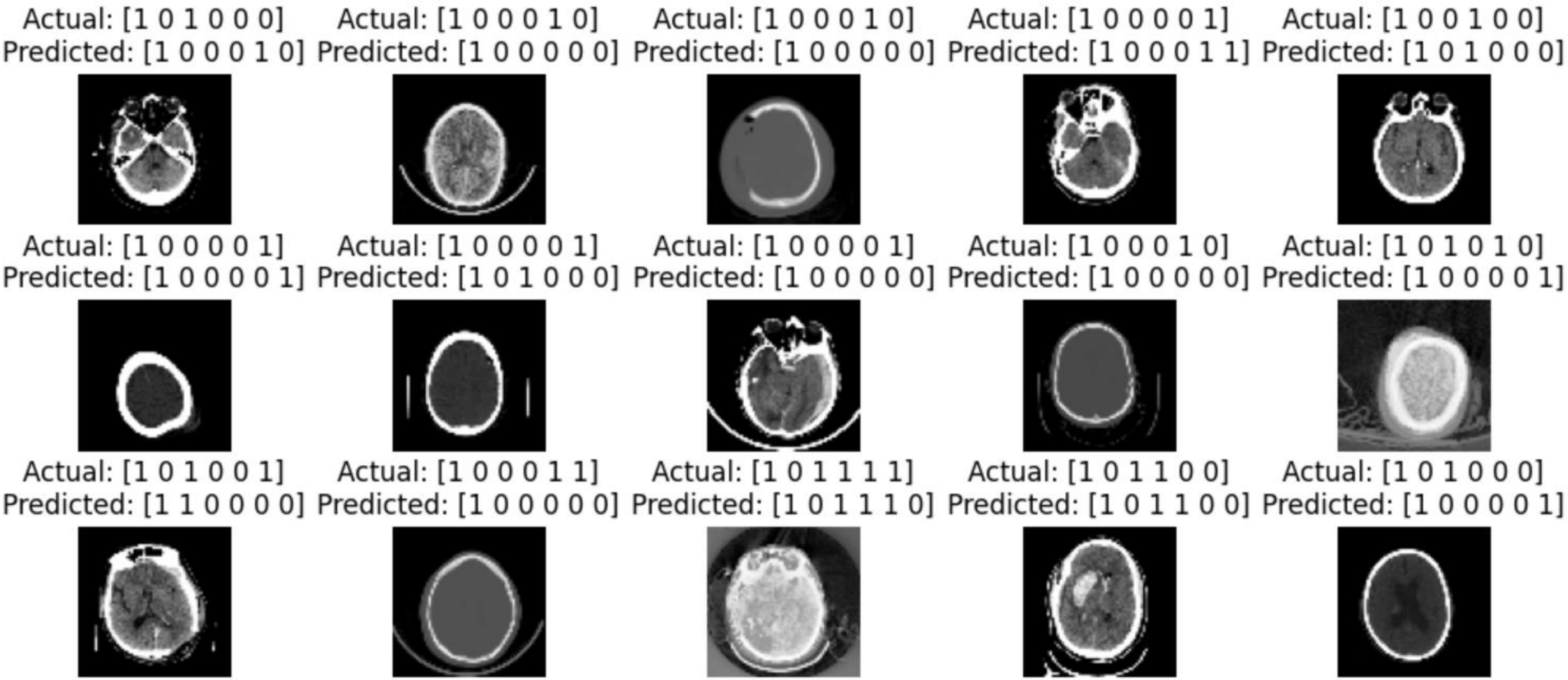
- Zeta Surgical
  - XN partner
  - Improve access to image guidance for emergency and bedside procedures
- Dataset
  - Brain CT scans with different types of hemorrhages (intraparenchymal, intraventricular, subarachnoid, epidural, multi and normal control)
  - Masking data for some images, highlighting hemorrhaged regions
- Goal – apply techniques in ML to perform classification and segmentation of these CT images

Logistic Regression for Classification

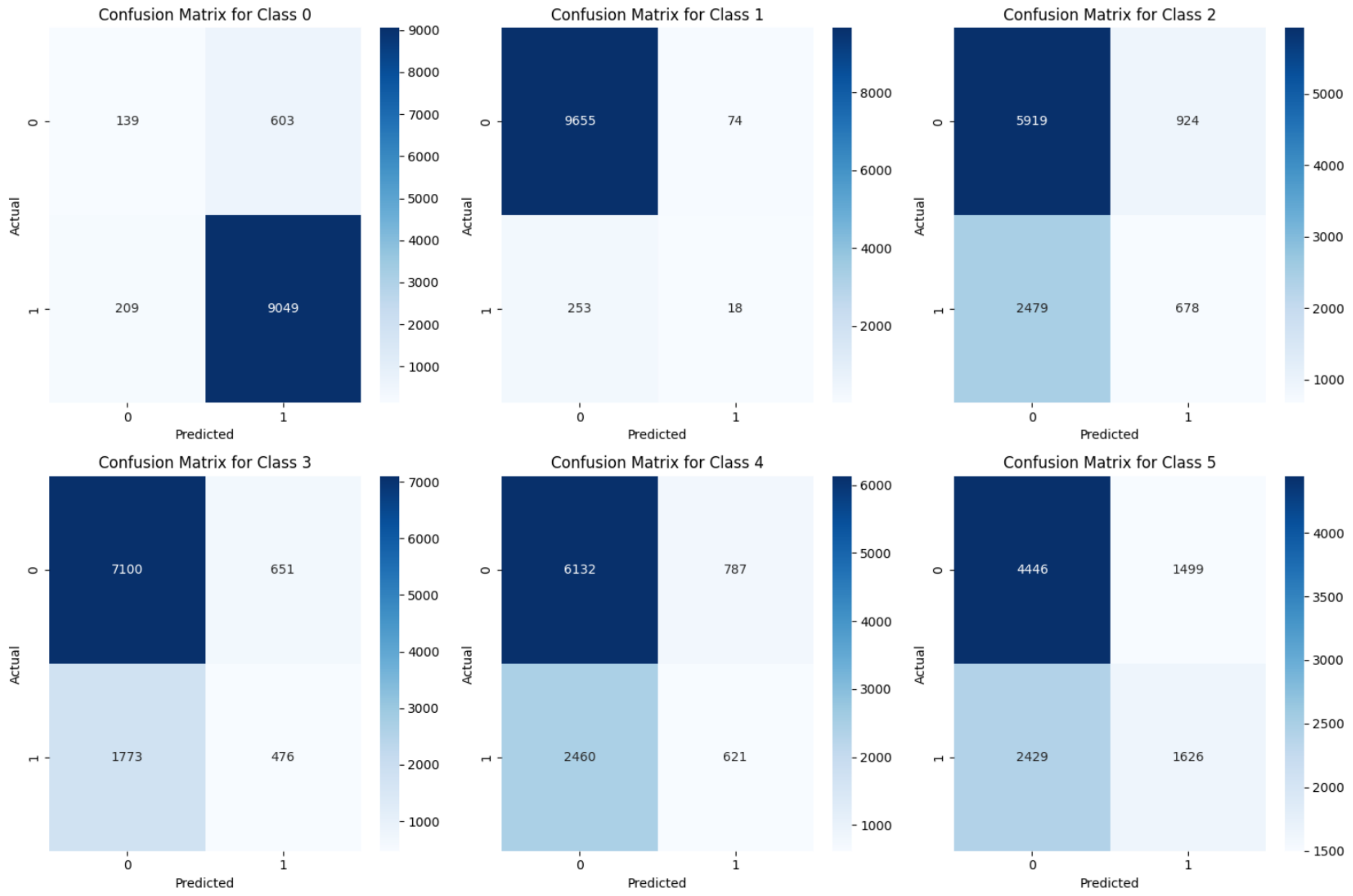
- Used the hemorrhage-labels excel sheet that labeled images from the classes any, epidural, intraparenchymal, intraventricular, subarachnoid, subdural
- Used a random subset of 50,000 images that I loaded in from all windows and classes
- I decided to create an individual binary classification model for each class and combine them
- Total combined model accuracy: ~15%
- Individual model accuracy was good though



Logistic Regression Results

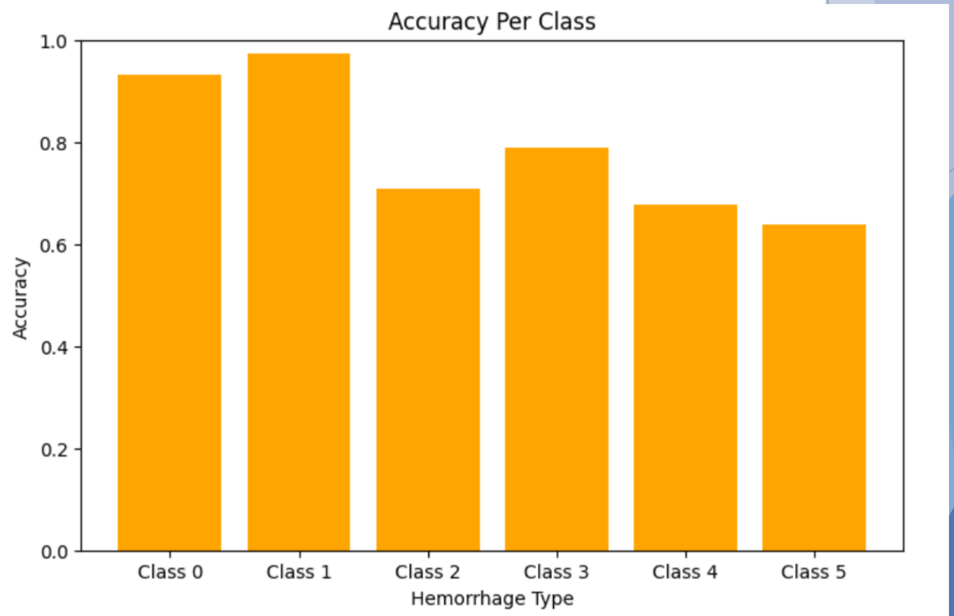


Logistic Regression Results

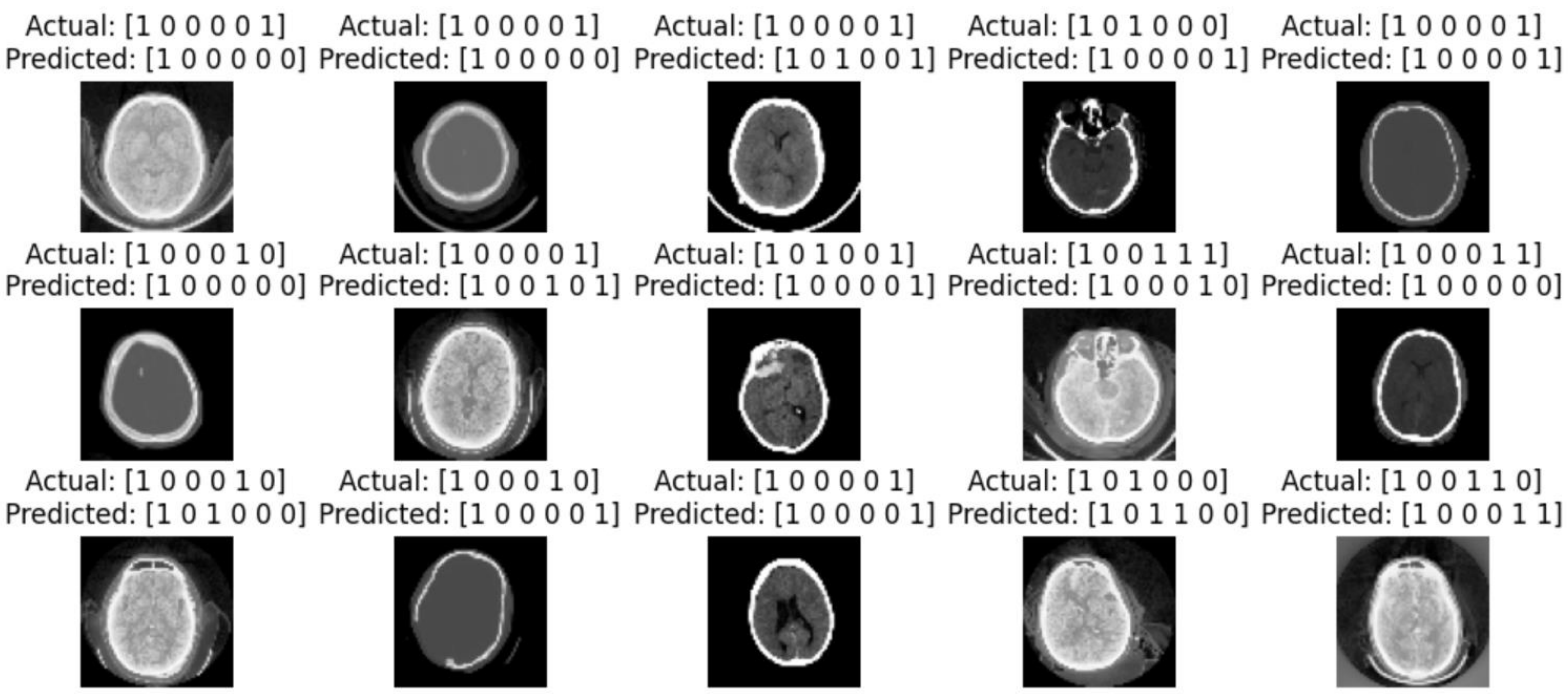


KNN for Classification

- Used the hemorrhage-labels excel sheet that labeled images from the classes any, epidural, intraparenchymal, intraventricular, subarachnoid, subdural
- Used a random subset of 50,000 images that I loaded in from all windows and classes
- I decided to create an individual binary classification model for each class and combine them
- Total combined model accuracy: ~25%
- Individual model accuracy was still very good



KNN Results


Actual: [1 0 0 0 0 1]
Predicted: [1 0 0 0 0 0]
Actual: [1 0 0 0 0 1]
Predicted: [1 0 0 0 0 0]
Actual: [1 0 0 0 0 1]
Predicted: [1 0 1 0 0 1]
Actual: [1 0 1 0 0 0]
Predicted: [1 0 0 0 0 1]
Actual: [1 0 0 0 0 1]
Predicted: [1 0 0 0 0 1]
Actual: [1 0 0 0 1 0]
Predicted: [1 0 0 0 0 0]
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Predicted: [1 0 0 0 1 0]
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Predicted: [1 0 0 0 0 0]
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Predicted: [1 0 1 0 0 0]
Actual: [1 0 0 0 1 0]
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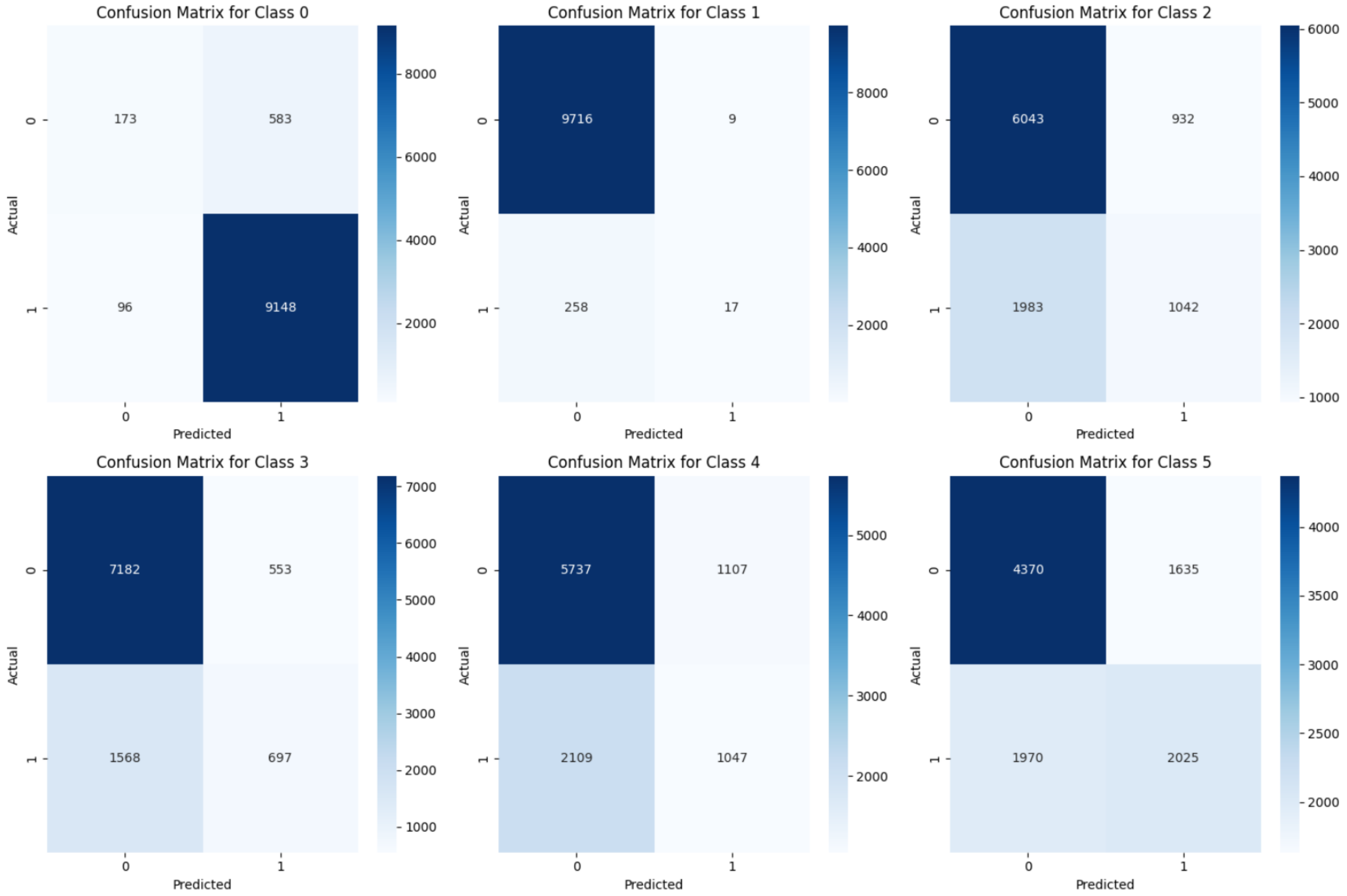
Actual: [1 0 0 0 0 1]
Predicted: [1 0 0 0 0 1]
Actual: [1 0 1 0 0 0]
Predicted: [1 0 1 1 0 0]
Actual: [1 0 0 1 1 0]
Predicted: [1 0 0 0 1 1]

KNN Results



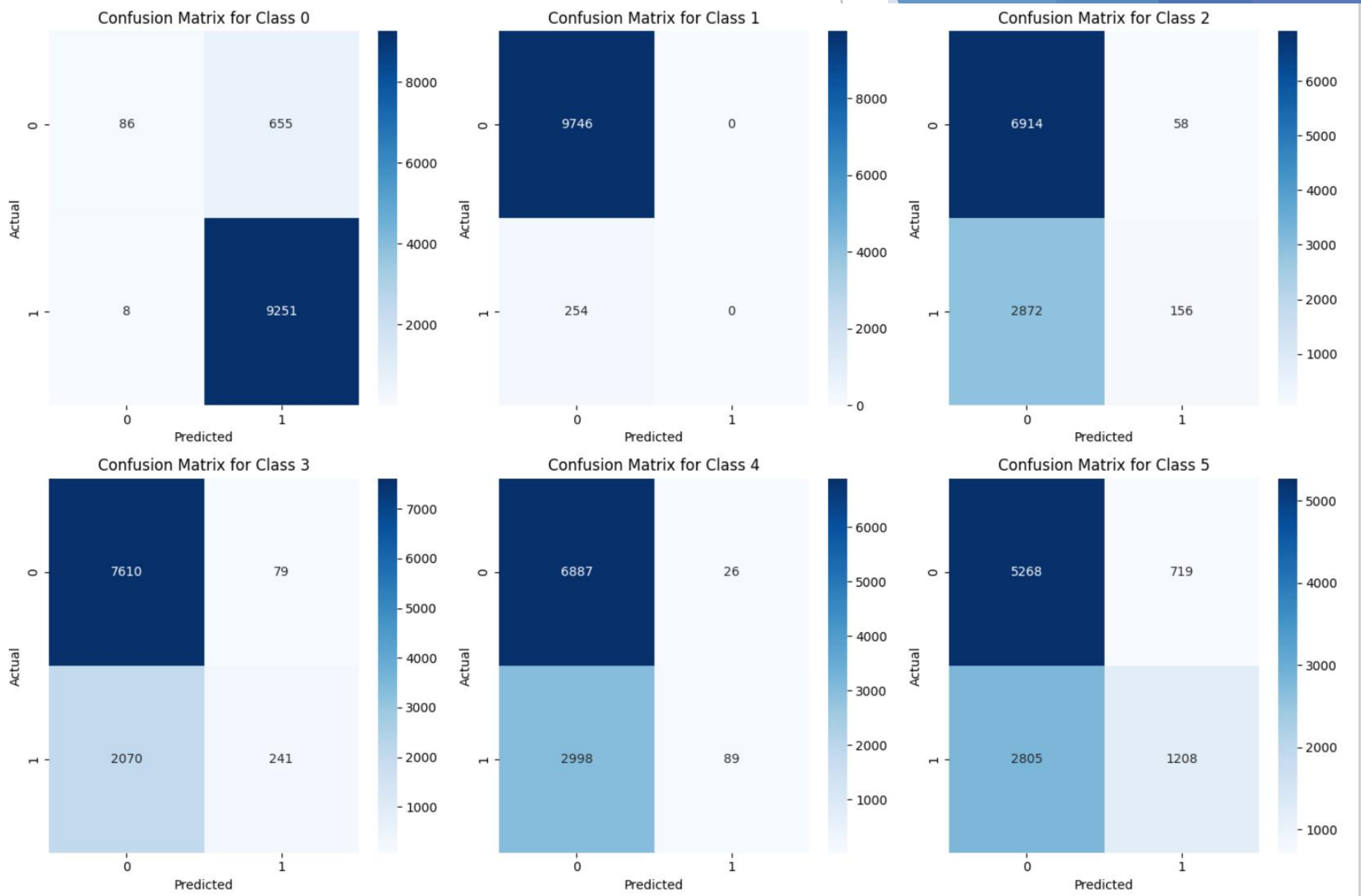
Confusion Matrix for Class 0
173
583
96
9148
Confusion Matrix for Class 1
9716
9
258
17
Confusion Matrix for Class 2
6043
932
1983
1042
Confusion Matrix for Class 3
7182
553
1568
697
Confusion Matrix for Class 4
5737
1107
2109
1047
Confusion Matrix for Class 5
4370
1635
1970
2025
Actual
Predicted

Tree Methods – Decision Tree

Accuracy (overall): 0.1977

Detailed classification report:

	precision	recall	f1-score	support
0	0.94	0.94	0.94	9259
1	0.05	0.06	0.05	254
2	0.36	0.36	0.36	3028
3	0.36	0.36	0.36	2311
4	0.35	0.37	0.36	3087
5	0.46	0.47	0.47	4013
micro avg	0.61	0.62	0.62	21952
macro avg	0.42	0.43	0.42	21952
weighted avg	0.62	0.62	0.62	21952
samples avg	0.58	0.59	0.57	21952

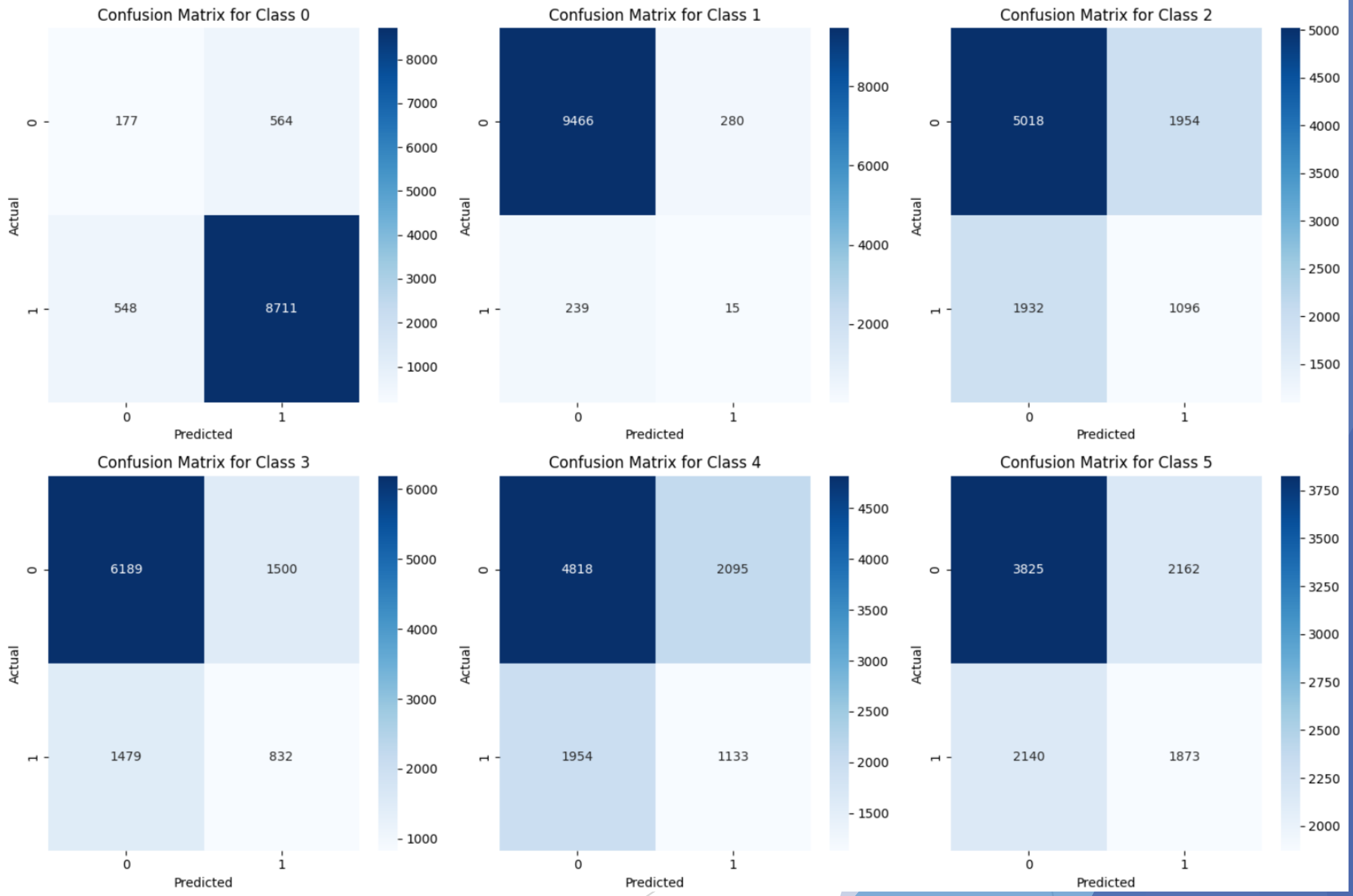


Tree Methods – Random Forest

Accuracy (overall): 0.1194

Detailed classification report:

	precision	recall	f1-score	support
0	0.93	1.00	0.97	9259
1	0.00	0.00	0.00	254
2	0.73	0.05	0.10	3028
3	0.75	0.10	0.18	2311
4	0.77	0.03	0.06	3087
5	0.63	0.30	0.41	4013
micro avg	0.88	0.50	0.64	21952
macro avg	0.64	0.25	0.28	21952
weighted avg	0.80	0.50	0.52	21952
samples avg	0.89	0.48	0.61	21952



QDA Classification

- From 116211 images in dataset 8278 are non-hemorrhoid and the rest have hemorrhoid
- First, we tried to classify images into 7 classes, but QDA didn't converge
- We simplified the problem to detecting hemorrhoid and non-hemorrhoid cases and to balance the number of cases for the two classes we choose randomly 8278 hemorrhoid and 8278 non-hemorrhoid cases.
- We chose only subdural-window to train QDA
- The result accuracy after these simplifications was still very low : %50

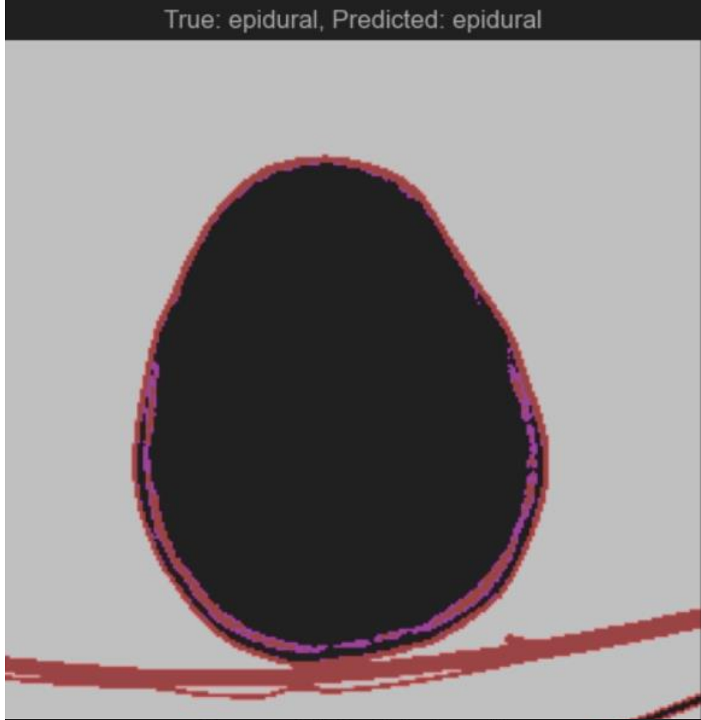
SVM Classification with (Radius Basis Function) RBF Kernel

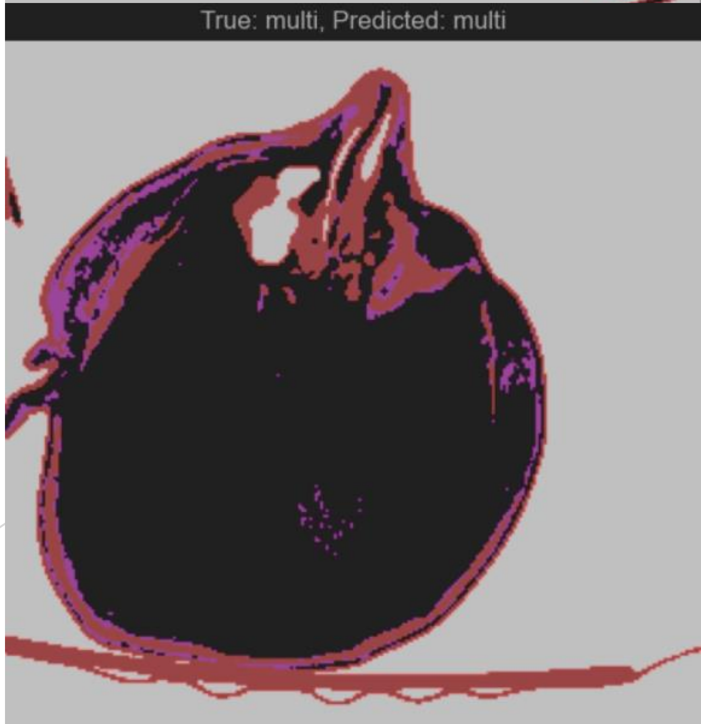
- We start with previous setup we used for QDA where we just classify subdural-window images to hemorrhoid and non-hemorrhoid cases:

Class	Precision	F1-score
Non-Hemorrhoid (0)	%81	0.71
Hemorrhoid (1)	%70	0.77

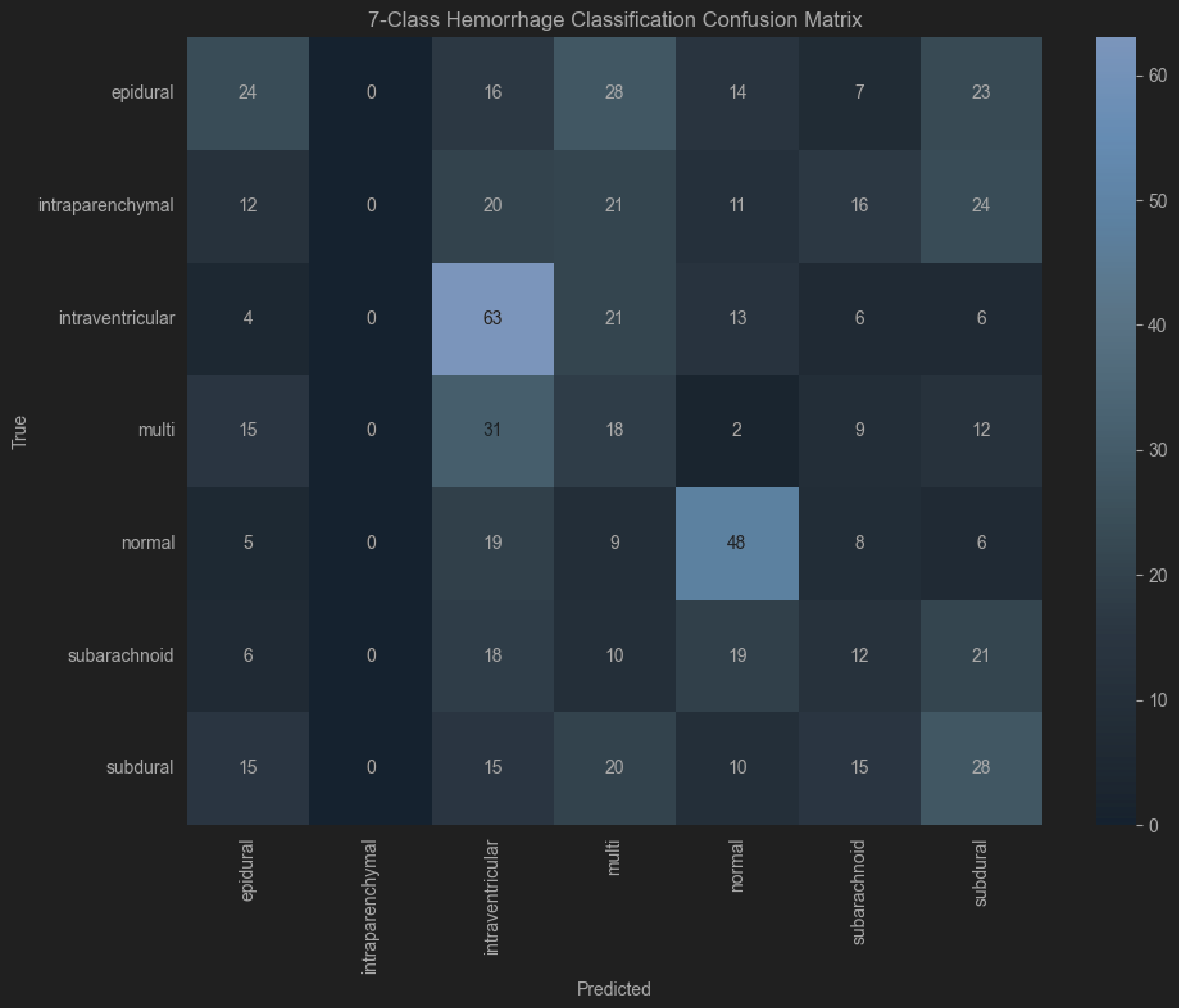
Neural Net Techniques for Classification

- Bone, Brain and Subdural Windows (no max contrast) combined as RGB images (approx. 2000 of each type)
- 7-classes: epidural, intraparenchymal, intraventricular, multi, normal, subarachnoid, subdural
- Down-sampled to 256x256 images (original 512x512)
- Basic CNN - Test accuracy: 0.1502 (almost random)
- CNN with ResNet-50 - Test accuracy: 0.3029 (2x random)
  - “Dead-neuron” effect for intraparenchymal
- Drop multi – Test accuracy: 0.3140 (~2x random)
  - Class prediction disparities persist
- 2-class - Test accuracy: 0.7054
- CNN with xception base (7 class) - Test accuracy: 0.6586



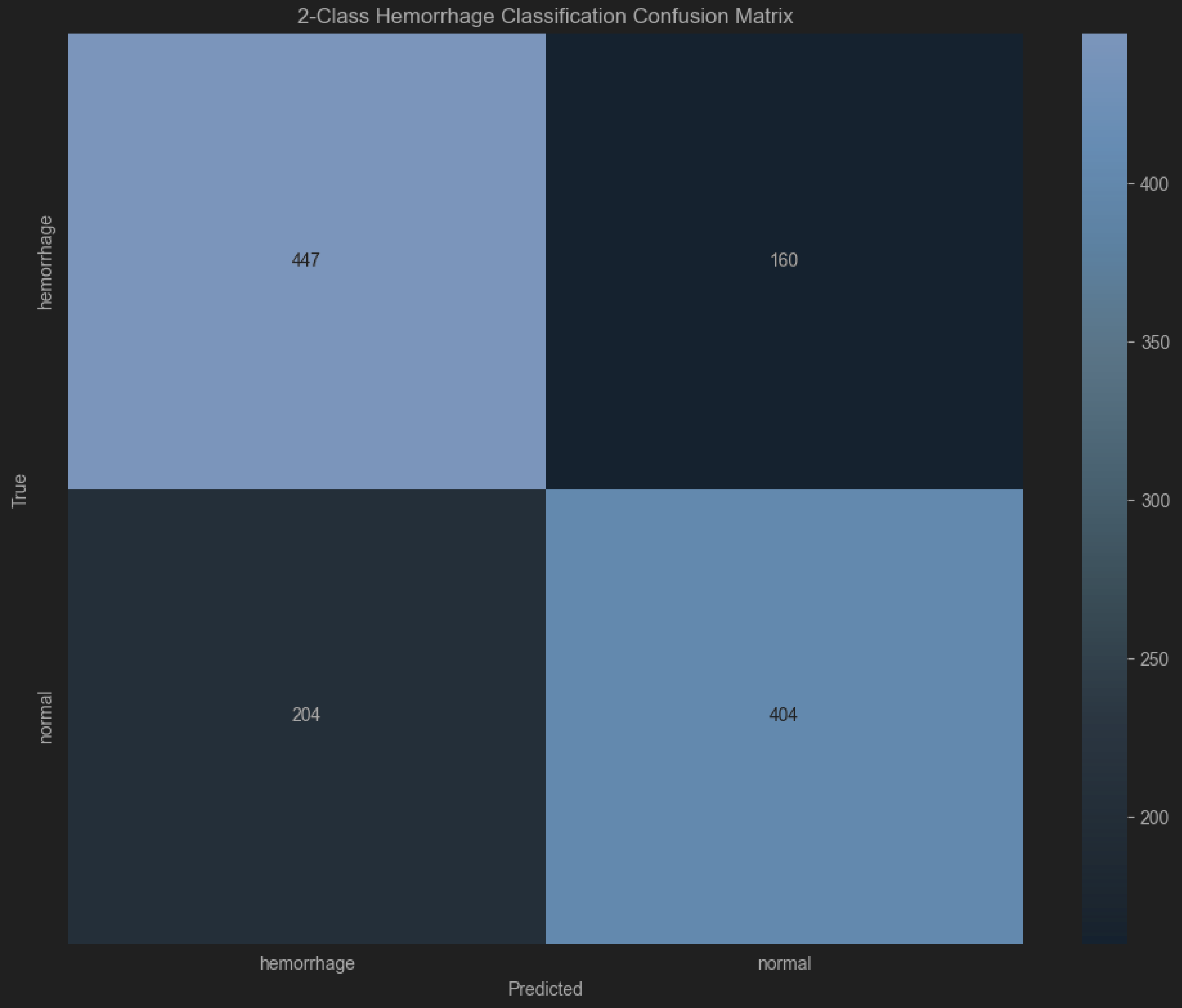


7-Class Confusion Matrix

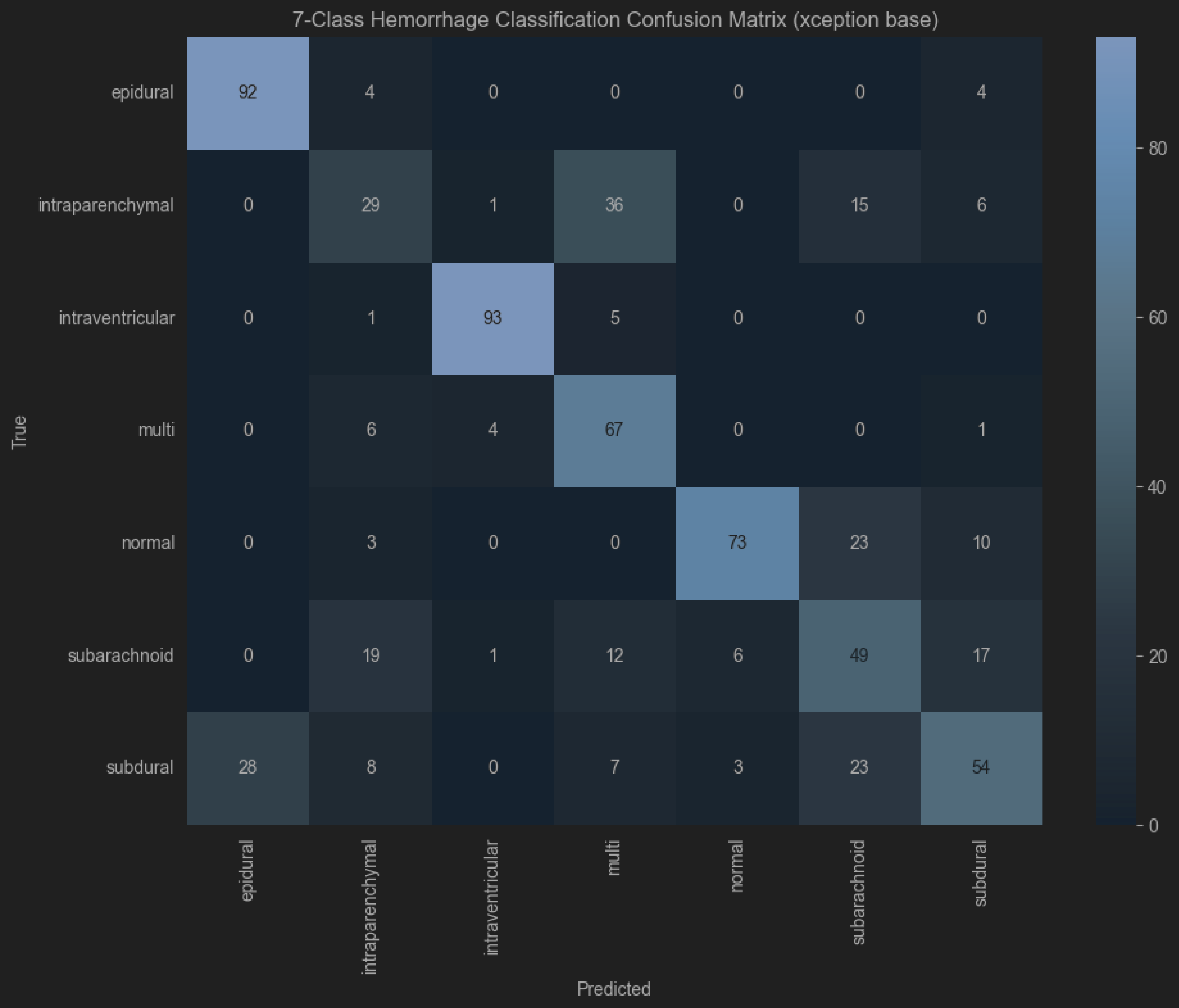


6-Class Confusion Matrix

2-Class Confusion Matrix

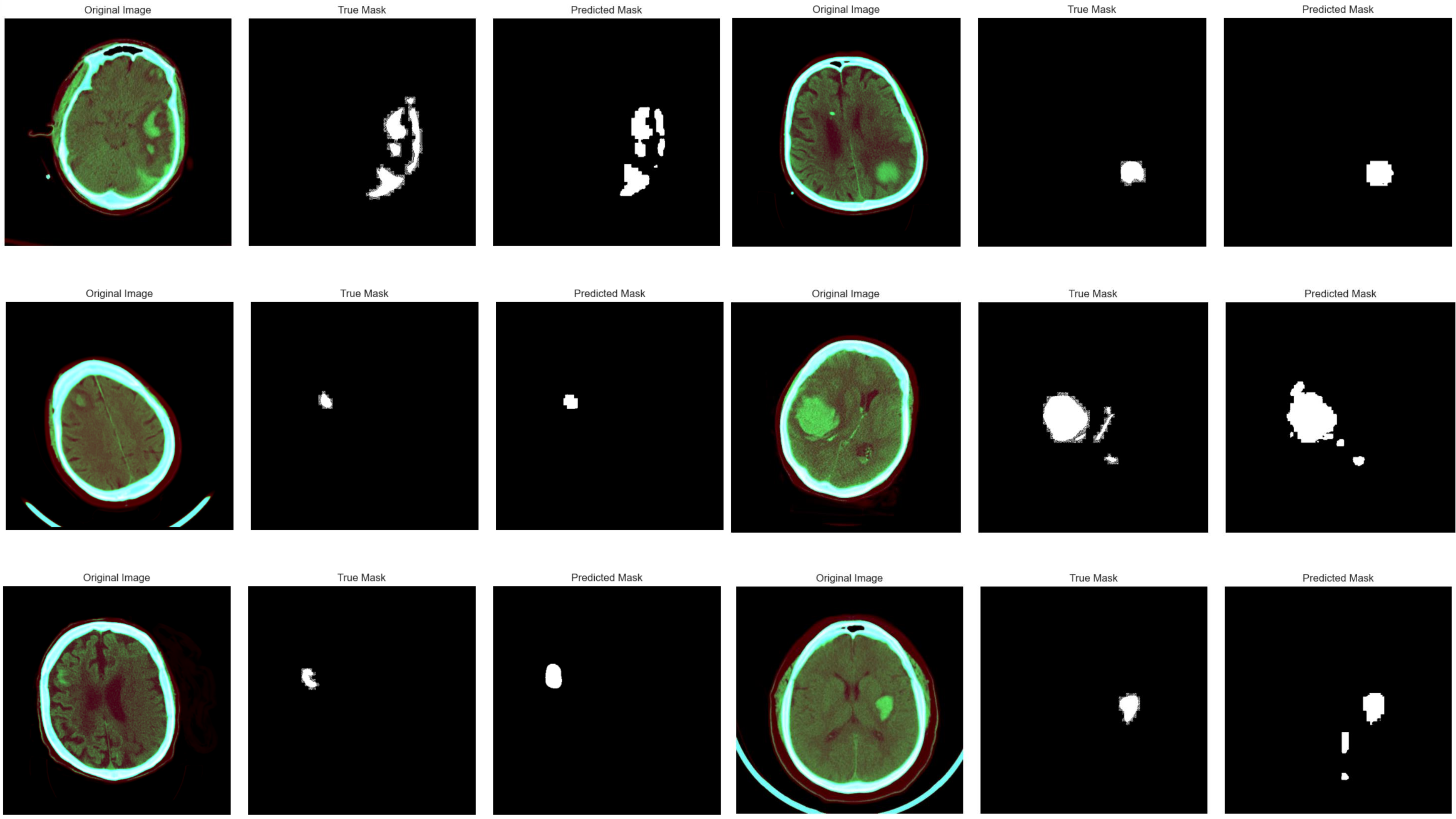


7-Class Confusion Matrix (xception)



Neural Net Techniques for Segmentation

- Mask Generation: Binary and Quaternary
- Bone, Brain and Subdural Windows combined as RGB images (max contrast omitted)
- General Difficulties:
  - CPU & GPU constraints and batch processing
  - Quaternary / non-binary masks and blank images
- Simple U-NET approach – struggled and predicted empty images or overly large regions
- Pretrained Base Model (ResNet-50)
  - Test Accuracy: 0.9894, Precision: 0.7732, Recall: 0.7165


Original Image
True Mask
Predicted Mask
Original Image
True Mask
Predicted Mask
Original Image
True Mask
Predicted Mask
Original Image
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Original Image
True Mask
Predicted Mask
Original Image
True Mask
Predicted Mask