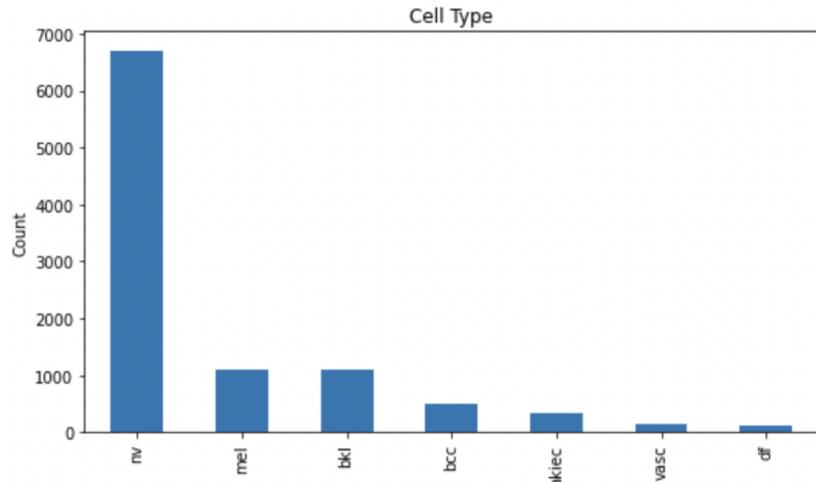
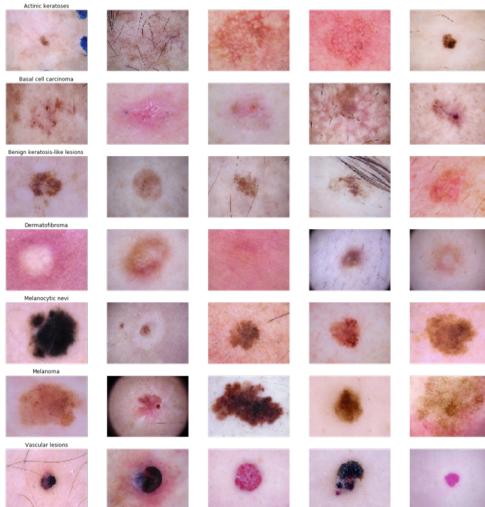


Convolutional Neural Networks for Skin Cancer Lesion Classification

Jon Van Veen, Akash Navani, Laith Abdulmajeid

HAM10000 is a Dataset of 10,000 Skin Cancer Lesions

- Motivation: use a simple image of a lesion to identify skin cancer
- More complicated / higher resolution version of MNIST problem
- 7 classes, highly skewed class distribution--unique challenge



Approaching the Problem

- CNN is obvious architecture choice -- VGG19 network transfer learning
- Started with architecture with fewer layers, increase number of layers later
- Tried replacing dense layers with classifier layers like xgboost and decision tree
- Experimented with common models like VGG and ResNet - around 40% accuracy
- Ended up sticking with a “simpler” custom CNN, and experimenting with hyperparameters

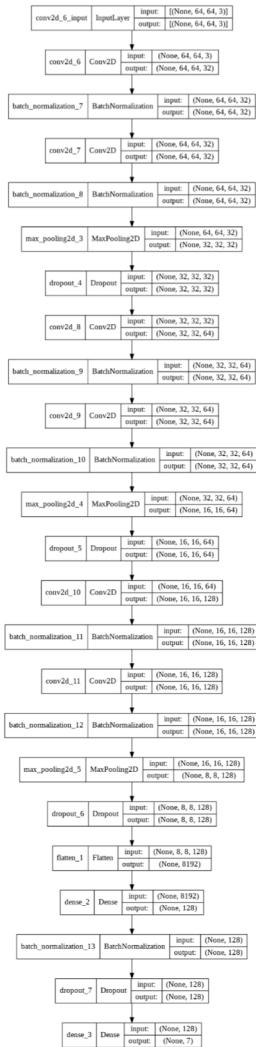
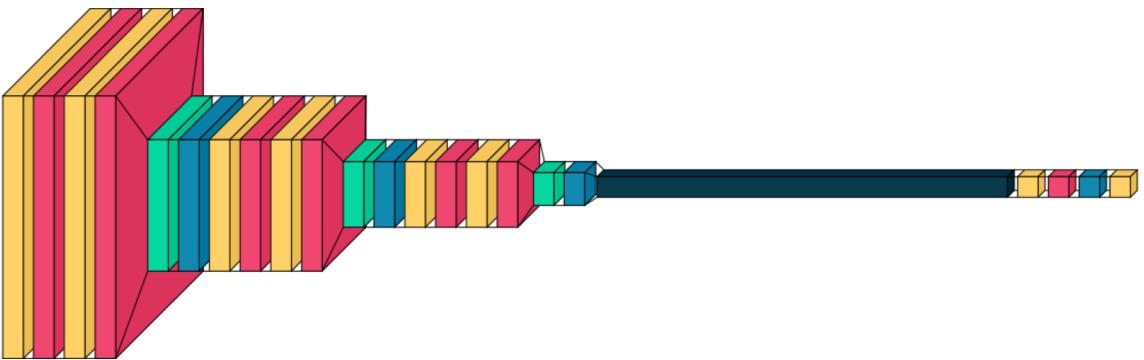
Addressing imbalanced class distributions - three steps

- Data Augmentation: image data generator to apply rotations, flips, shifts, rescales, etc.
 - Essentially increases diversity of dataset
- Class weights: weight classes with fewer examples more heavily than those with more samples
 - Input to model has more evenly distributed classes
 - Have a higher penalty for misclassification of malignant class labels
- Dropouts to address network overfitting

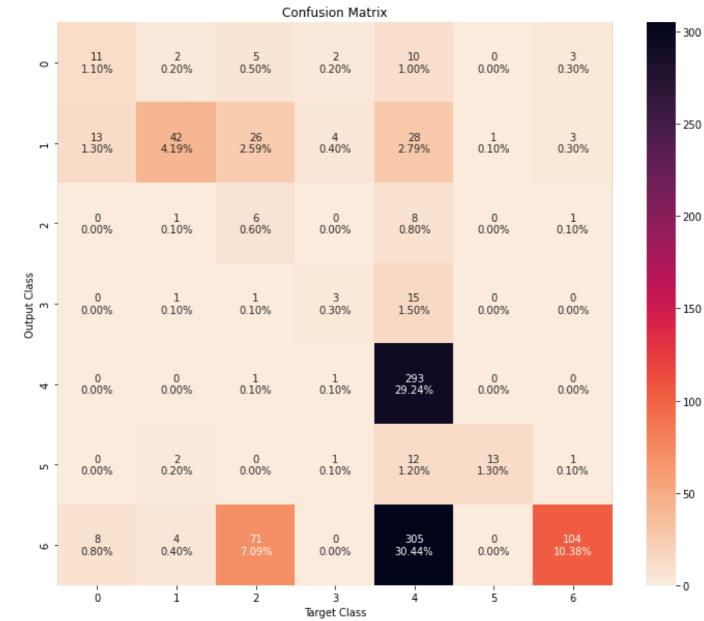
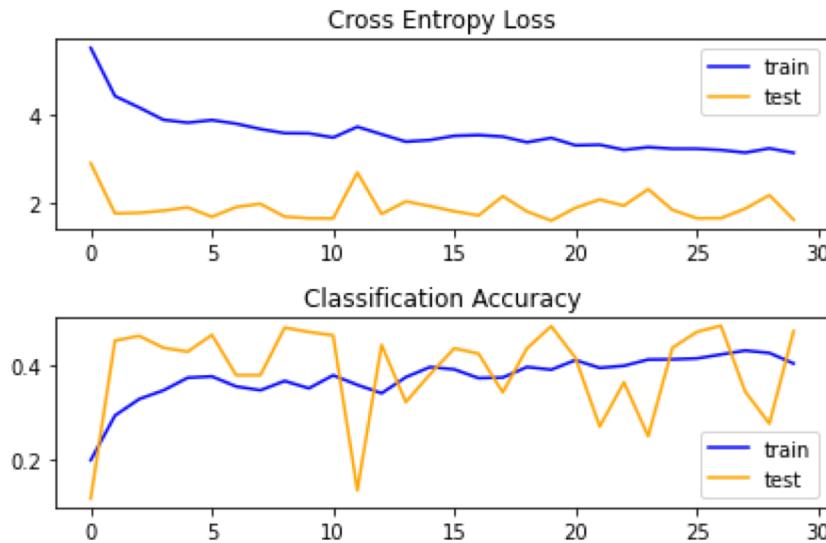
Architecture 1 (Custom CNN)

Color legend:

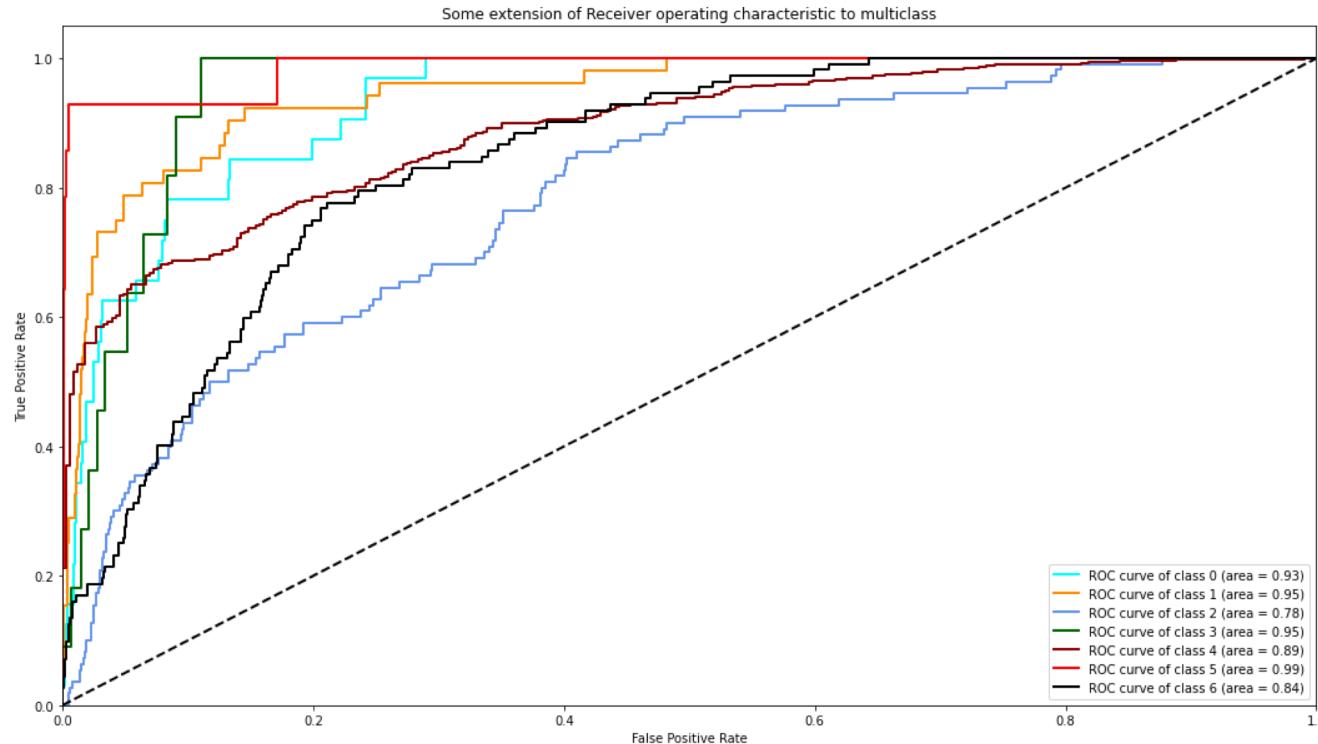
- Yellow: Conv2D
- Red: Batch normalization
- Green: MaxPooling2D
- Blue: Dropout
- Dark Green: Flatten



Architecture 1 (Custom CNN) - Exemplary Loss, Accuracy, Confusion Matrix



Architecture 1 (Custom CNN) - Exemplary Receiver Operating Curve



Architecture 1 (Custom CNN) - Recall

$$\text{Recall} = \frac{\text{True Positives}}{\text{True Positives} + \text{False Negatives}}$$

- Recall for malignant classes is used as a key metric over accuracy, loss or auc-roc

Hyperparameter Adjustment - Performance Comparison

- Changing data augmentation & class weights

Data Aug	Size	weights	dropout	weights	Acc	Recall	Loss	cancer	recall for cancer
y	y	y	0.2	3,8,8	0.5	0.4376884472	1.632410765	148	0.758974359
y	y	n	0.2		0.767465055	0.60998854	0.6540125608	71	0.3641025641
n	y	n	0.2		0.7864271402	0.6411499175	0.7860460877	93	0.4769230769
n	y	y	0.2	3,8,8	0.4381237626	0.3519971084	2.137435436	127	0.6512820513

Hyperparameter Adjustment - Performance Comparison

- Changing dropout rate

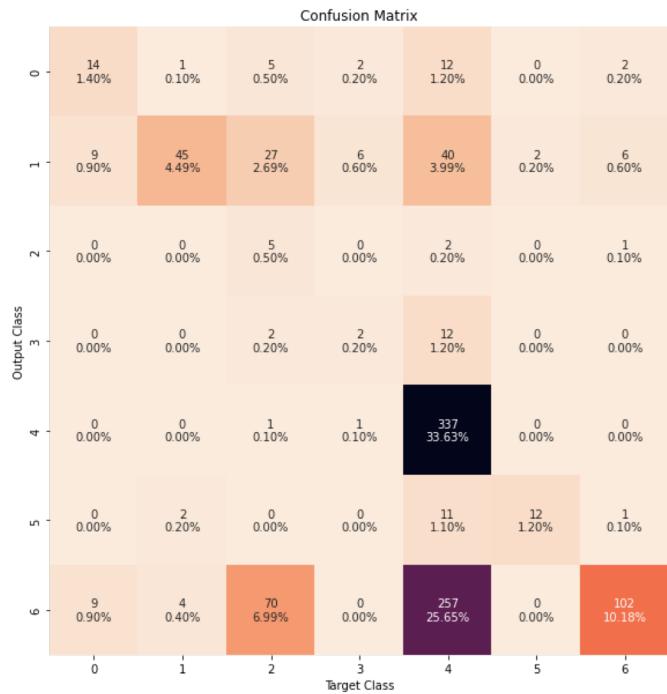
Data Aug	Size	weights	dropout	weights	Acc	Recall	Loss	cancer	recall for cancer
y	y	y	0.2	3,8,8	0.5	0.4376884472	1.632410765	148	0.758974359
y	y	y	0.25	3,8,8	0.5159680843	0.4512328871	1.458364964	161	0.8256410256
y	y	y	0.3	3,8,8	0.2874251604	0.389135138	1.991754651	146	0.7487179487
y	y	y	0.4	3,8,8	0.382235527	0.3020589518	1.93186903	152	0.7794871795
y	y	y	linear inc	3,8,8	0.4810379148	0.4509781951	1.584651947	150	0.7692307692

Hyperparameter Adjustment - Performance Comparison

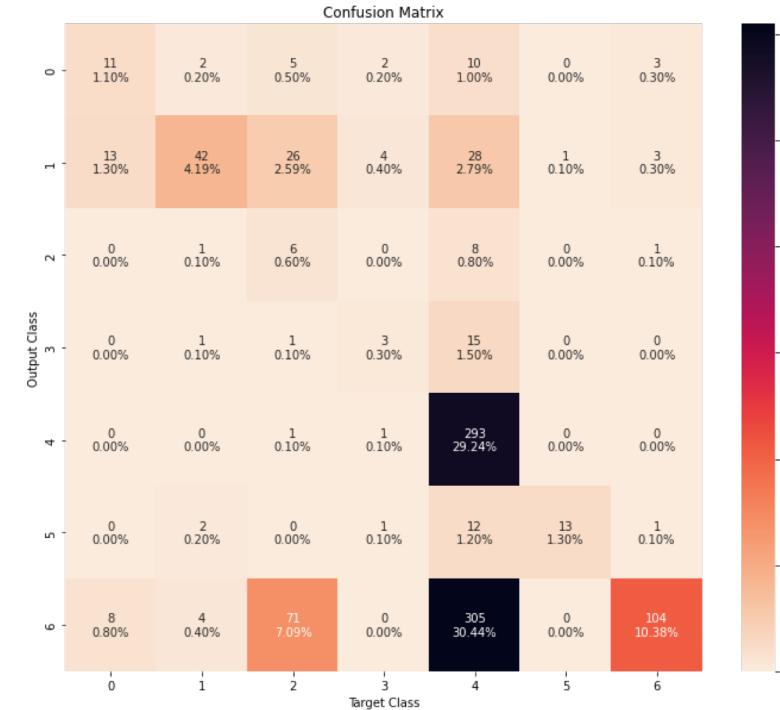
- Further experimentation with cancerous class weight multiplier

Data Aug	Size	weights	dropout	weights	Acc	Recall	Loss	cancer	recall for cancer
y	y	y	0.25	8,4,2	0.5049900413	0.4138706765	1.310278535	106	0.5435897436
y	y	y	0.25	6,6,6	0.4790419042	0.4739038394	1.498404026	152	0.7794871795
y	y	y	0.25	3.75,5.4,11.7	0.4710578918	0.4100265725	1.533285499	157	0.8051282051

Final comparison: class 0,1,6 weight multiplier



Weight multiplier = 3, 8,
8



Weight multiplier = 3.75, 5.4, 11.7

Potential Improvements

- Longer training times -- due to Google Colab restrictions, limited to ~30 epochs
 - Image classification tasks typically require longer training periods
 - Sometimes running out of memory just loading the images
- Combining different network architectures with hyperparameter tuning
 - Was difficult in this project due to Colab limitations

Questions?