Brain Tumor Detection with Deep Learning

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Introduction

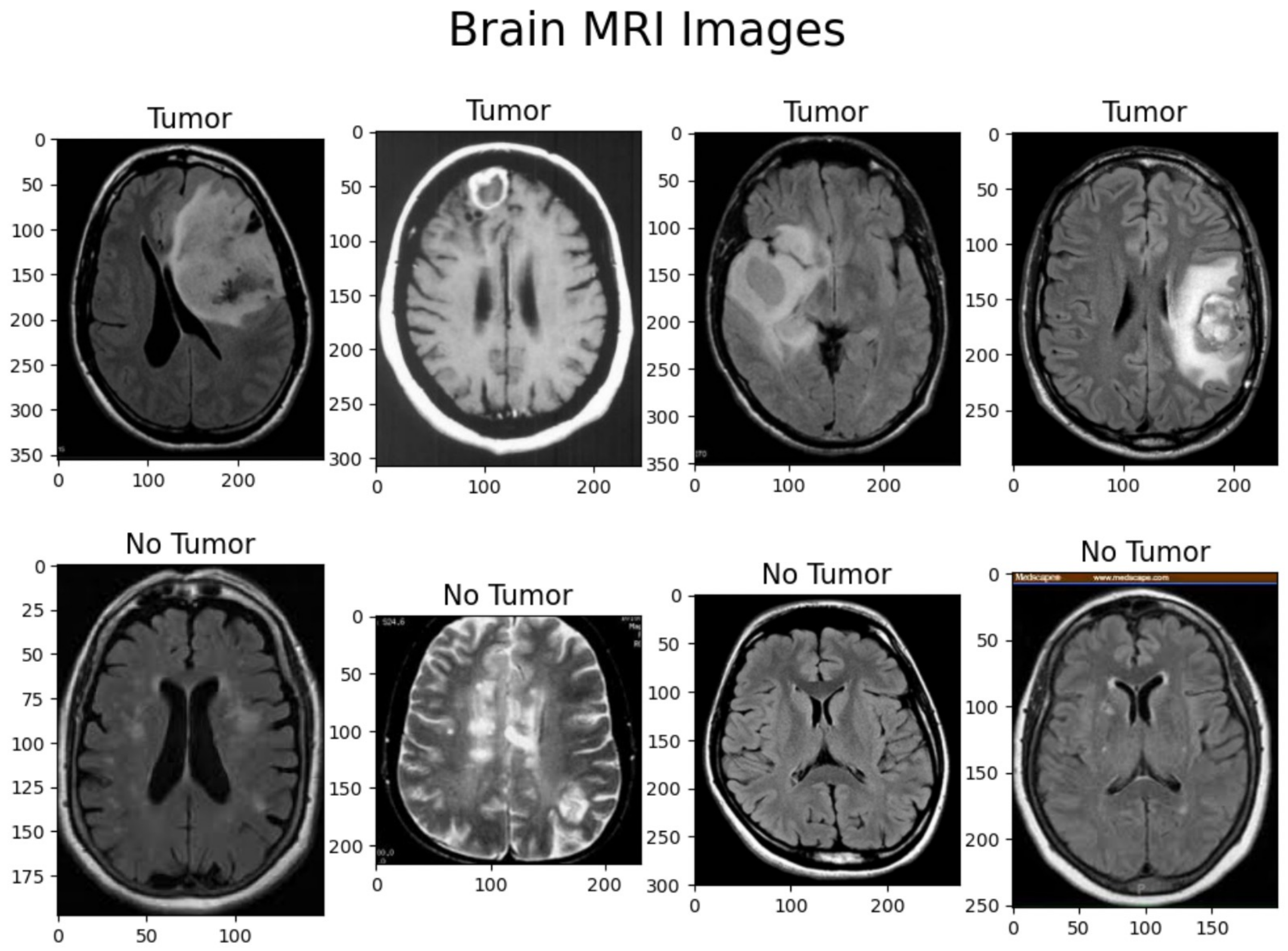
- Machine Learning methods increasingly important in healthcare
- Fast and reliable analysis of imaging tests
- ML tools can help experts in prompt cancer diagnosis

Goal

- Given dataset containing brain MRI scans
- Develop Deep Learning models to identify patients with brain tumor
- Identify best model for the purpose
- ML models can help experts promptly diagnosing brain tumors

The Dataset

- 253 brain MRI scan images
- Grayscale
- 61.4% of images have tumors
- Class imbalance accounted for via weights during training



The Dataset

- Images come in a variety of sizes (width, height)
- Minimum width: 168 pixels
- Minimum height: 150 pixels
- Need to make them uniform before modelling

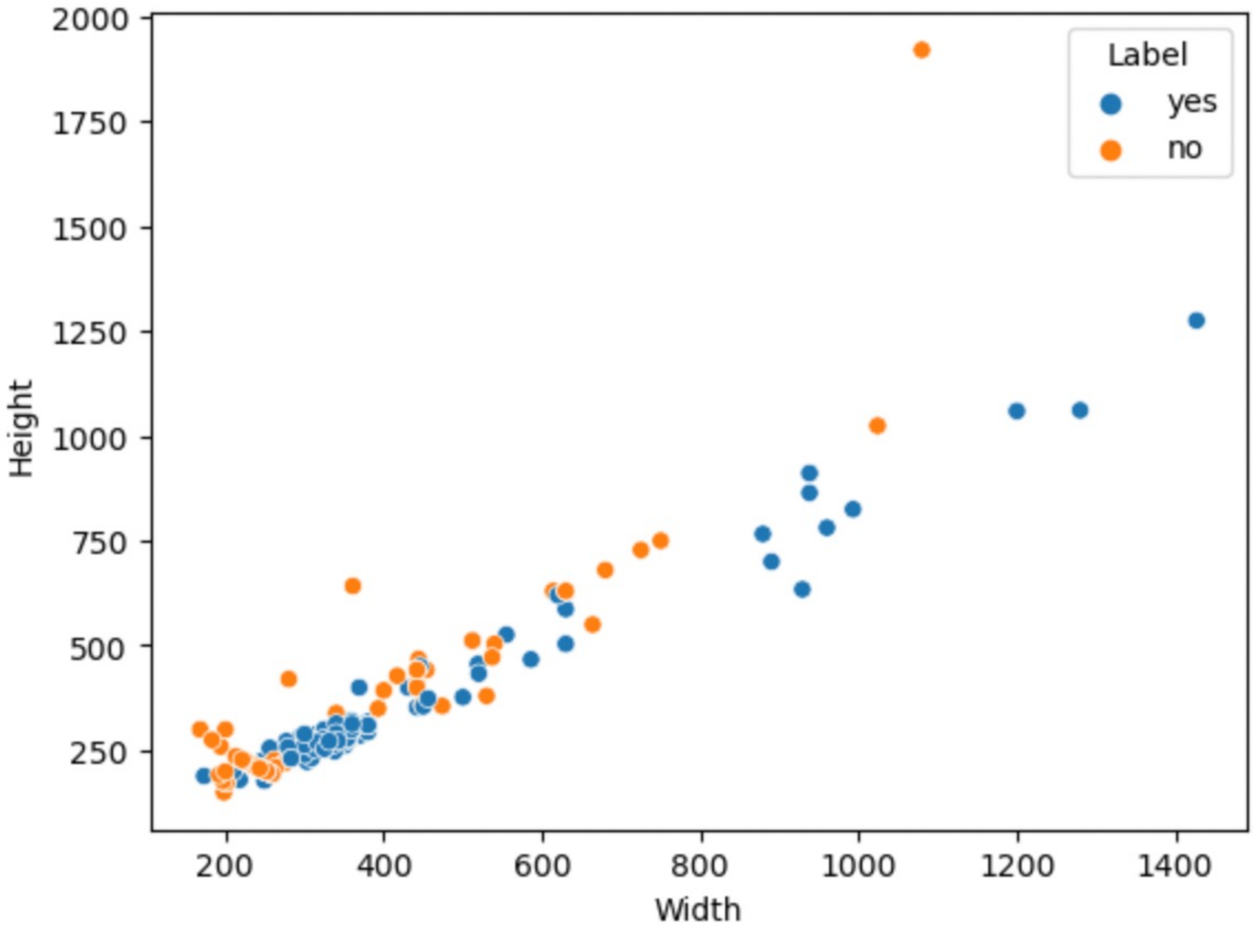
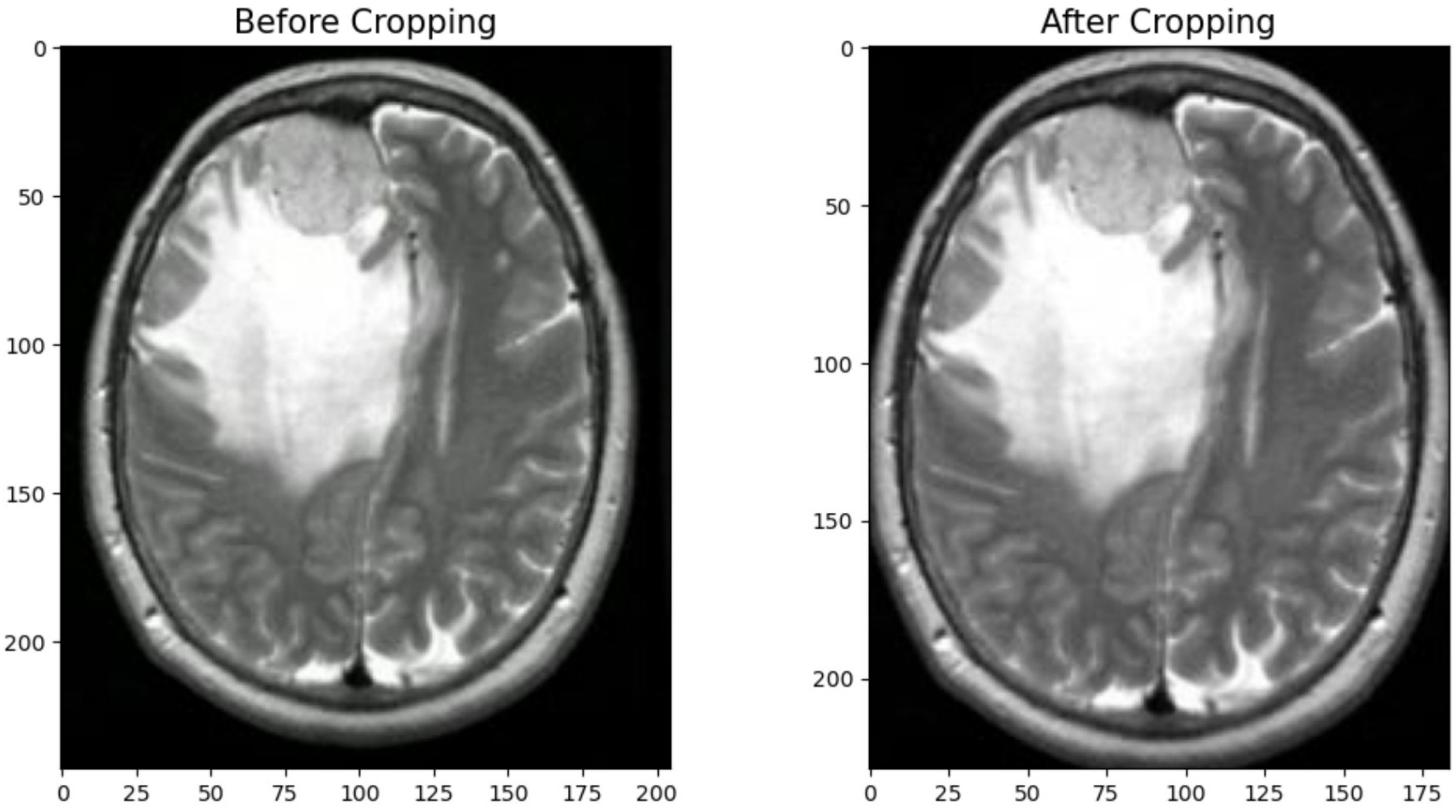


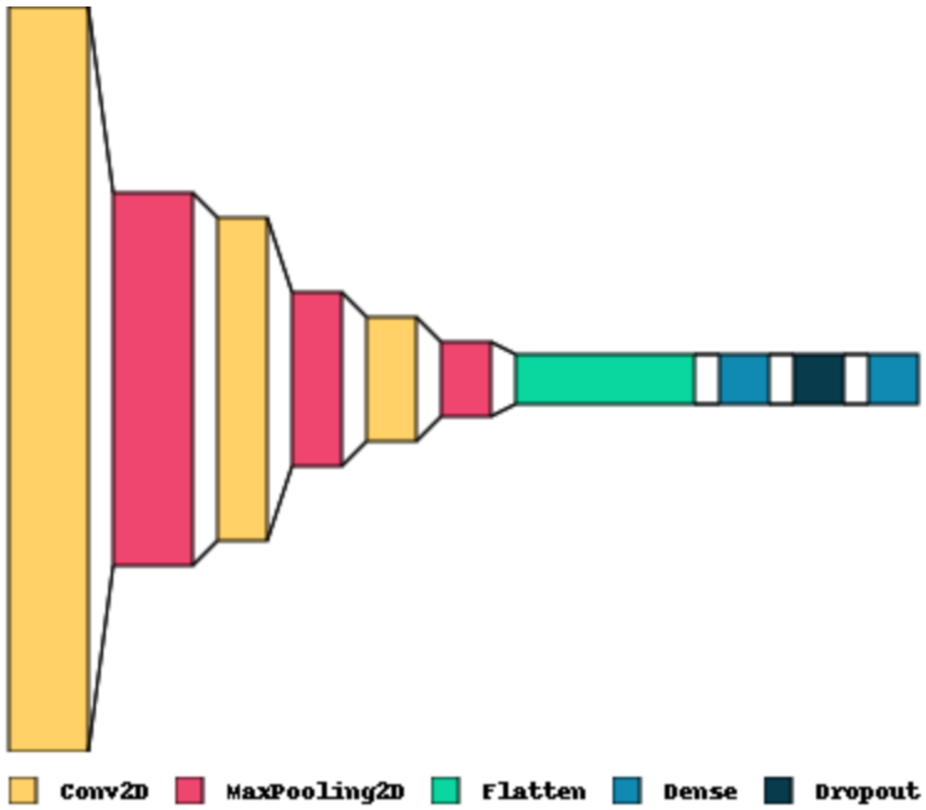
Image Preprocessing

- Brain portion is cropped in all images
- All images reduced to 32x32 pixels
- Images divided into train/validation/test samples with ratios 0.7/0.2/0.1



Model 1: CNN

- **Conv2D:** 16 filters, 3x3
- **MaxPooling2D:** pool size 2
- **Conv2D:** 8 filters, 3x3
- **MaxPooling2D:** pool size 2
- **Conv2D:** 4 filters, 3x3
- **MaxPooling2D:** pool size 2
- **Flatten**
- **Dense:** 8 neurons, activation ReLu
- **Dropout:** 20%
- **Dense:** 1 neuron (output), activation sigmoid



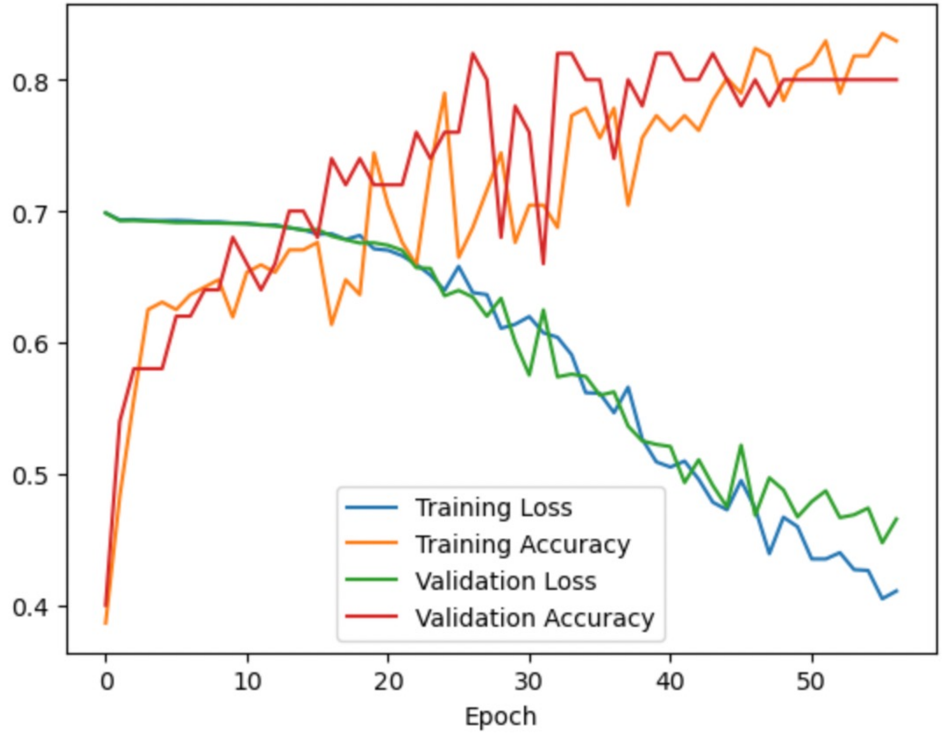
Model 1: Results

On test set:

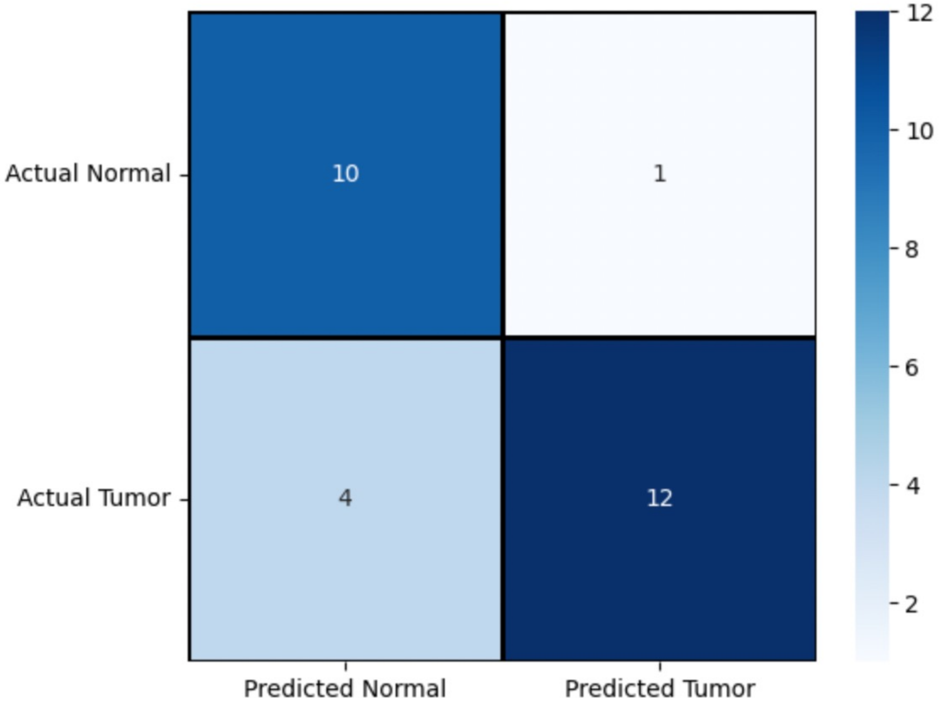
- 81% accuracy
- 92% precision
- 75% recall

Main limitation is low recall.

False negatives are dangerous for this application



Training History



Confusion Matrix

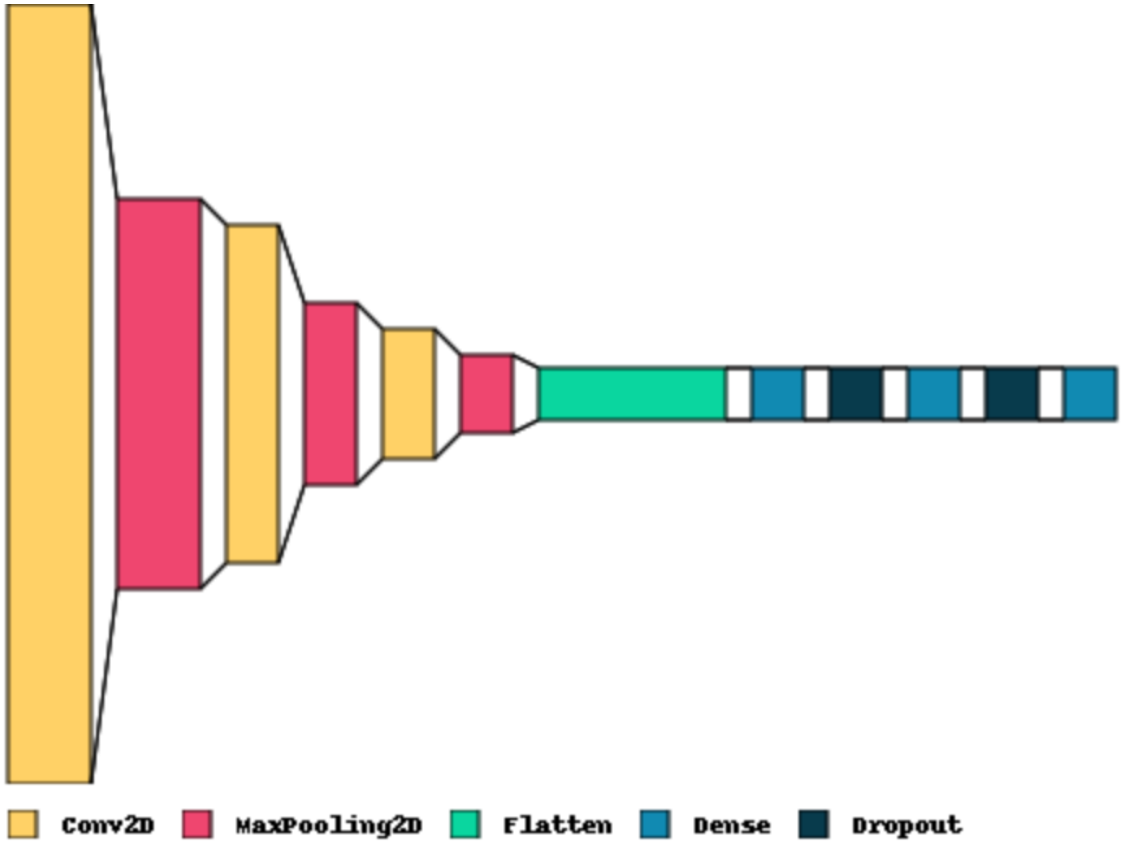
Model 2: CNN + Data Augmentation

Training images augmentation:

- Rotational range 10°
- Horizontal flip
- Vertical flip

Same CNN, but after flatten:

- Dense: 8 neurons, activation ReLu
- Dropout: 20%
- Dense: 8 neurons, activation ReLu
- Dropout: 20%
- Dense: 1 neuron, activation sigmoid

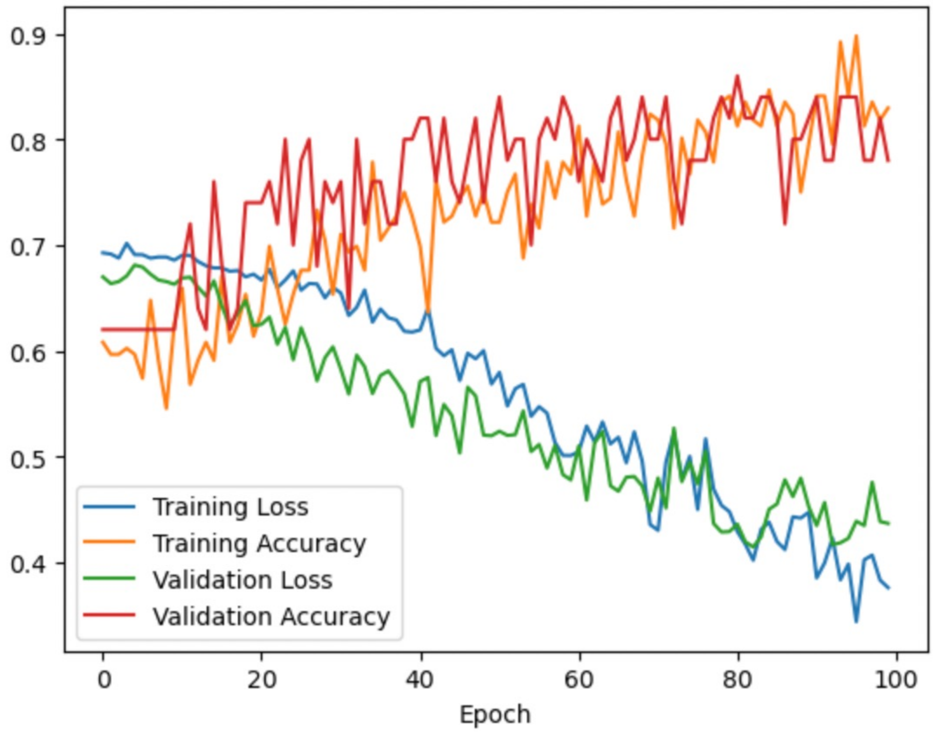


Model 2: Results

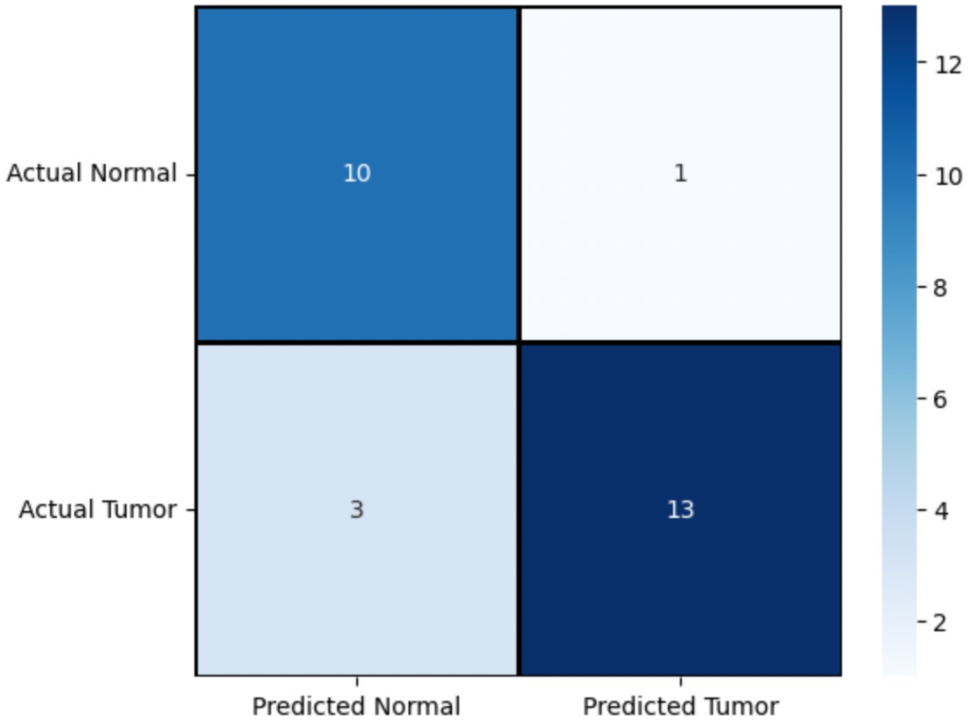
On test set:

- 85% accuracy
- 93% precision
- 81% recall

Better than model 1 in terms of accuracy and false negative rate



Training History



Confusion Matrix

Model 3: Transfer Learning

- Dataset is small, try using transfer learning
- Used pre-trained ResNet50V2 model
- Froze its weights during training
- Used data augmented training set
- Added two dense layers at the end, each with 32 neurons and 20% dropout

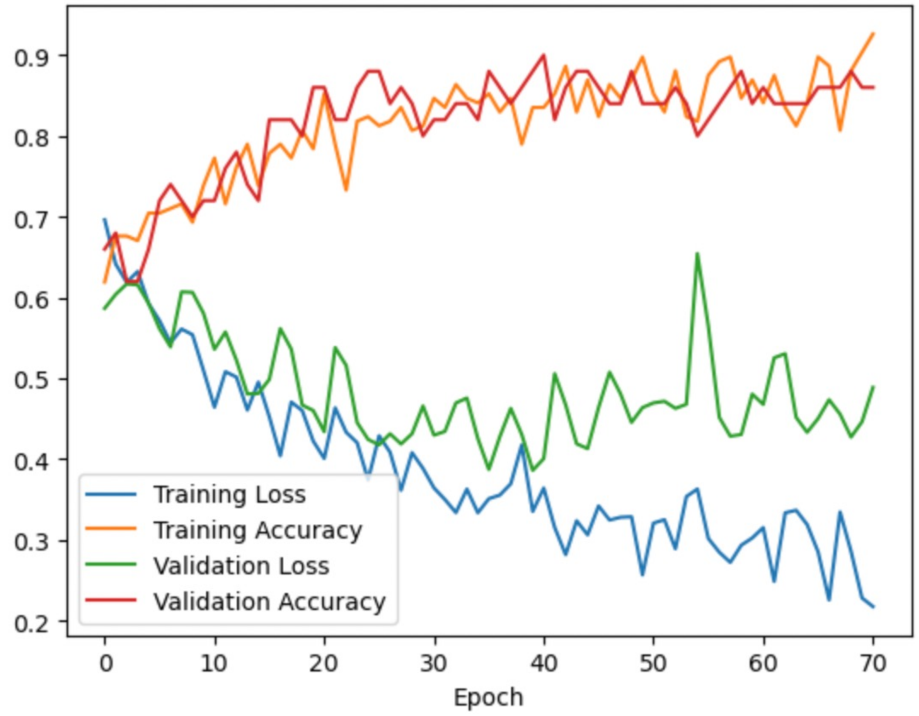
Model 3: Results

On test set:

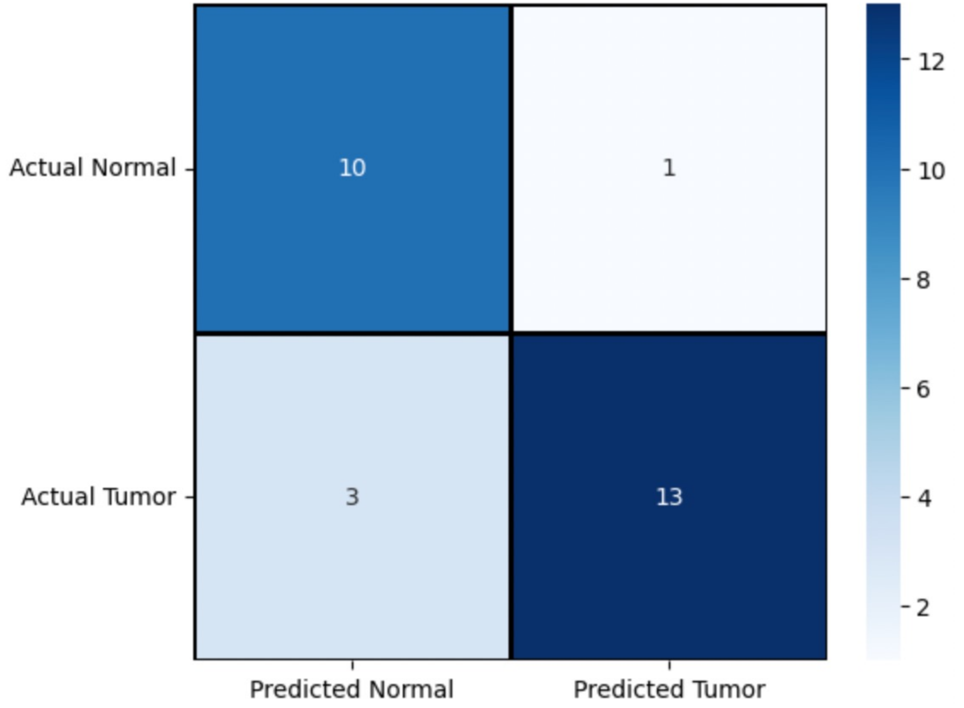
- 74% accuracy
- 80% precision
- 75% recall

Worst model in terms of accuracy

More tuning might be beneficial



Training History



Confusion Matrix

Conclusions

- Model 2 achieves best accuracy (85%), while maximising recall (81%)
- Higher recall means fewer false negatives, which are dangerous in this application

Future prospects:

- Small dataset: more data and stronger augmentation could be beneficial
- Explore more complex image pre-processing
- More hyperparameter tuning might improve performance
- Transfer learning promising: need more experimenting and hyperparameter tuning