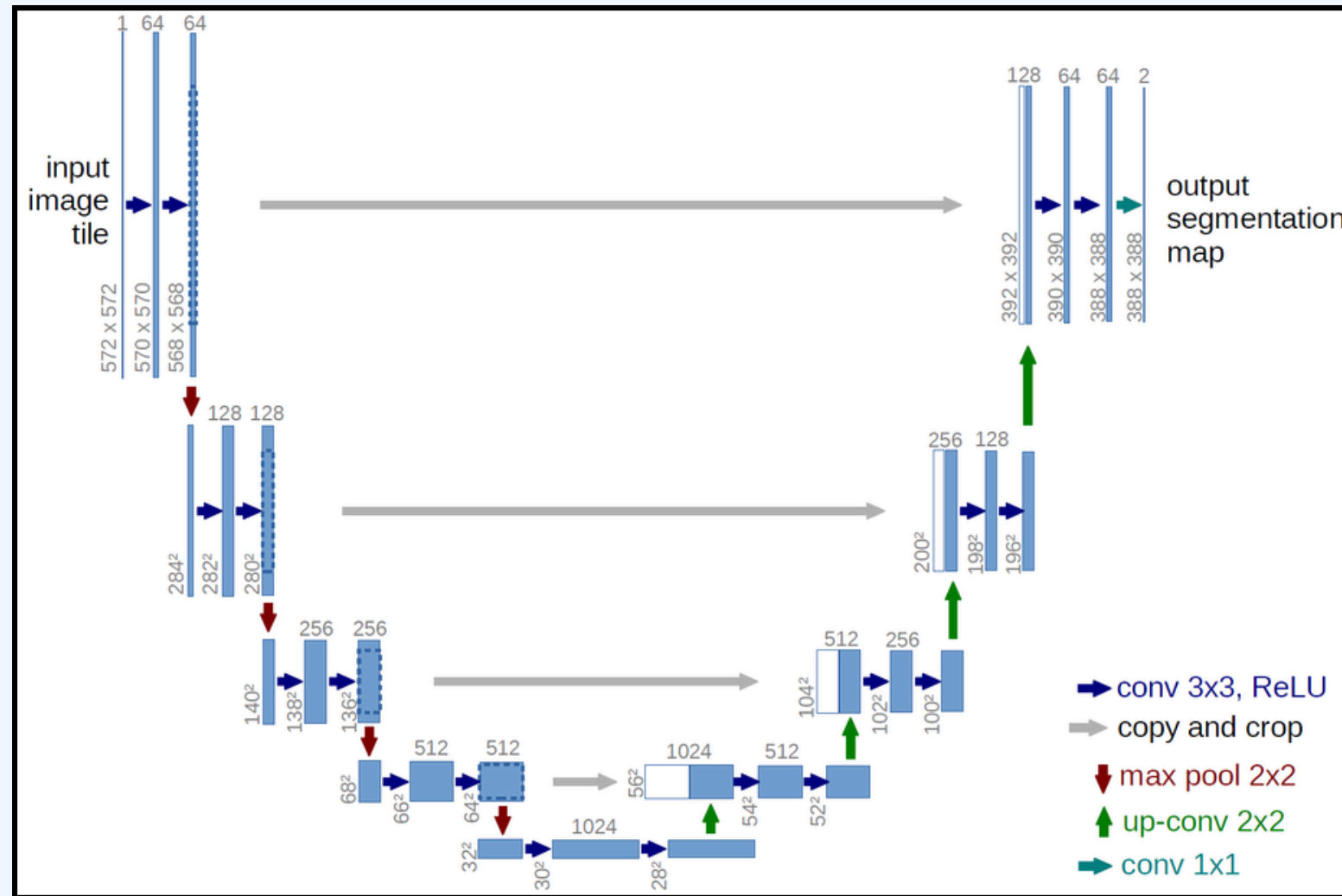


An axial MRI scan of a human brain, showing the cerebral hemispheres and the ventricular system. A large, dark, irregularly shaped mass is visible in the upper right quadrant of the image, which is likely a brain tumor. The tumor appears to be causing some displacement of the surrounding brain tissue. The image is in grayscale, typical of medical MRI scans.

Brain Tumor Segmentation

By Vincent Niedermayer

Model Architecture



<https://arxiv.org/pdf/1505.04597>

Key additions:

- Batch Normalization
- Dropout (.3)

```
def build_model(self):
    inputs = Input(shape=(self.input_size, self.input_size, 3)) # Default input shape: (256, 256, 3)

    # Encoder - Downscaling
    c1 = Conv2D(self.base_filters, (3, 3), activation='relu', padding='same')(inputs)
    c1 = BatchNormalization()(c1) # Batch Normalization to alleviate overfitting
    c1 = Conv2D(self.base_filters, (3, 3), activation='relu', padding='same')(c1)
    c1 = BatchNormalization()(c1)
    p1 = MaxPooling2D((2, 2))(c1)

    c2 = Conv2D(self.base_filters * 2, (3, 3), activation='relu', padding='same')(p1)
    c2 = BatchNormalization()(c2)
    c2 = Conv2D(self.base_filters * 2, (3, 3), activation='relu', padding='same')(c2)
    c2 = BatchNormalization()(c2)
    p2 = MaxPooling2D((2, 2))(c2)

    c3 = Conv2D(self.base_filters * 4, (3, 3), activation='relu', padding='same')(p2)
    c3 = BatchNormalization()(c3)
    c3 = Conv2D(self.base_filters * 4, (3, 3), activation='relu', padding='same')(c3)
    c3 = BatchNormalization()(c3)
    c3 = Dropout(self.dropout_rate)(c3) # Dropout to alleviate overfitting
    p3 = MaxPooling2D((2, 2))(c3)

    c4 = Conv2D(self.base_filters * 8, (3, 3), activation='relu', padding='same')(p3)
    c4 = BatchNormalization()(c4)
    c4 = Conv2D(self.base_filters * 8, (3, 3), activation='relu', padding='same')(c4)
    c4 = BatchNormalization()(c4)
    c4 = Dropout(self.dropout_rate)(c4)
    p4 = MaxPooling2D((2, 2))(c4)

    # Bottleneck
    c5 = Conv2D(self.base_filters * 16, (3, 3), activation='relu', padding='same')(p4)
    c5 = BatchNormalization()(c5)
    c5 = Conv2D(self.base_filters * 16, (3, 3), activation='relu', padding='same')(c5)
    c5 = BatchNormalization()(c5)
    c5 = Dropout(self.dropout_rate)(c5)

    # Decoder - Upscaling
    u6 = Conv2DTranspose(self.base_filters * 8, (2, 2), strides=(2, 2), padding='same')(c5)
    u6 = Concatenate()([u6, c4]) # Concatenate for skip connection
    c6 = Conv2D(self.base_filters * 8, (3, 3), activation='relu', padding='same')(u6)
    c6 = BatchNormalization()(c6)
    c6 = Conv2D(self.base_filters * 8, (3, 3), activation='relu', padding='same')(c6)
    c6 = BatchNormalization()(c6)

    u7 = Conv2DTranspose(self.base_filters * 4, (2, 2), strides=(2, 2), padding='same')(c6)
    u7 = Concatenate()([u7, c3])
    c7 = Conv2D(self.base_filters * 4, (3, 3), activation='relu', padding='same')(u7)
    c7 = BatchNormalization()(c7)
    c7 = Conv2D(self.base_filters * 4, (3, 3), activation='relu', padding='same')(c7)
    c7 = BatchNormalization()(c7)

    u8 = Conv2DTranspose(self.base_filters * 2, (2, 2), strides=(2, 2), padding='same')(c7)
    u8 = Concatenate()([u8, c2])
    c8 = Conv2D(self.base_filters * 2, (3, 3), activation='relu', padding='same')(u8)
    c8 = BatchNormalization()(c8)
    c8 = Conv2D(self.base_filters * 2, (3, 3), activation='relu', padding='same')(c8)
    c8 = BatchNormalization()(c8)

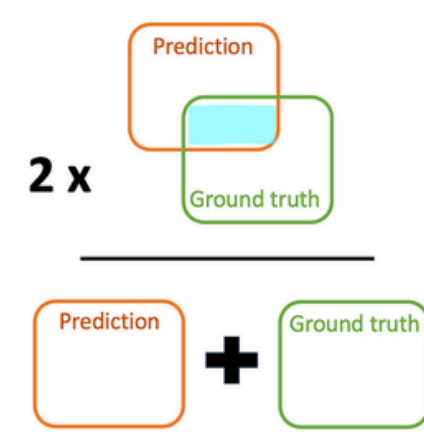
    u9 = Conv2DTranspose(self.base_filters, (2, 2), strides=(2, 2), padding='same')(c8)
    u9 = Concatenate()([u9, c1])
    c9 = Conv2D(self.base_filters, (3, 3), activation='relu', padding='same')(u9)
    c9 = BatchNormalization()(c9)
    c9 = Conv2D(self.base_filters, (3, 3), activation='relu', padding='same')(c9)
    c9 = BatchNormalization()(c9)

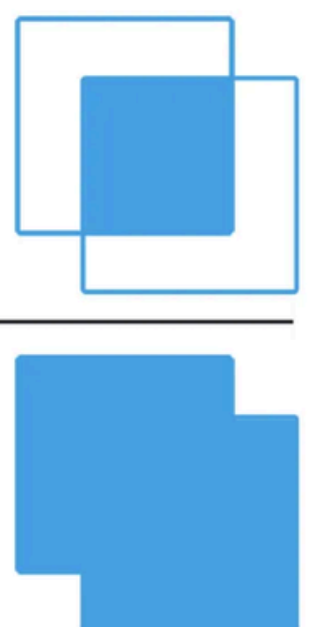
    # Output
    outputs = Conv2D(1, (1, 1), activation='sigmoid')(c9) # Sigmoid activation for prediction

    model = Model(inputs, outputs, name="UNet")
    return model
```

Loss Function

- Binary Cross Entropy
 - Initially I only used BCE
- Dice Loss
- IoU Loss
- Total loss
 - $0.4 * \text{bce} + 0.4 * \text{dice} + 0.2 * \text{iou}$

$$\text{Dice} = \frac{2 \times \text{Area of overlap}}{\text{Total area}} = \frac{2 \times \text{Prediction} \cap \text{Ground truth}}{\text{Prediction} \cup \text{Ground truth}}$$


$$\text{IoU} = \frac{\text{Area of Overlap}}{\text{Area of Union}}$$


Training Loop

1. Training Function

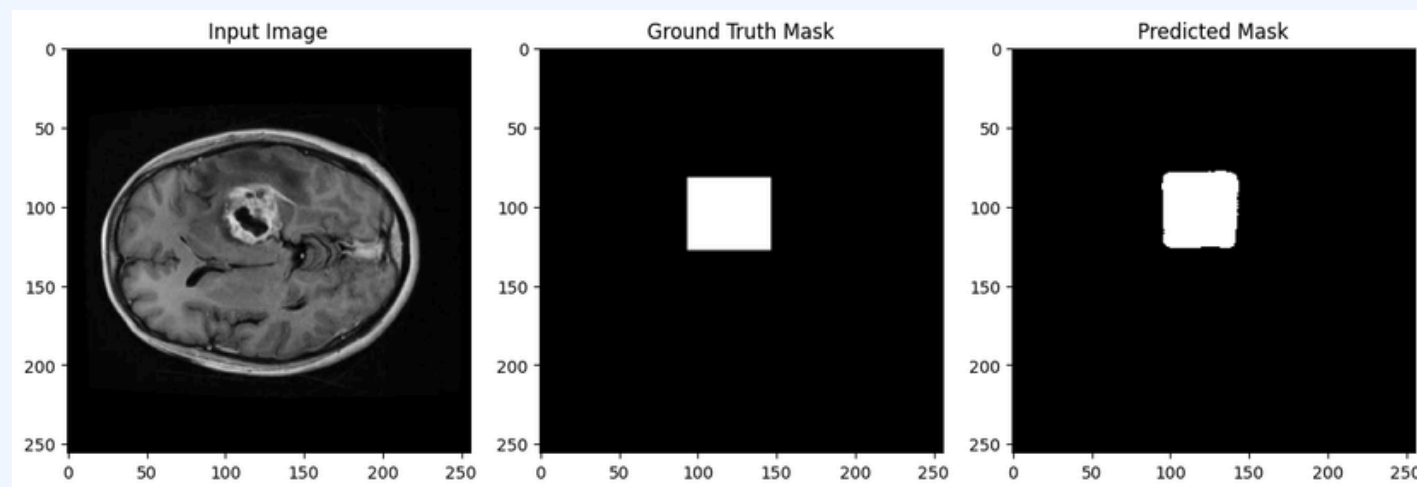
- Adam Optimization Algorithm
- Learning Rate scheduler
- Callbacks
 - Early Stopping
 - Model Checkpoint
 - saves model with best valid acc.

2. Hyperparameters

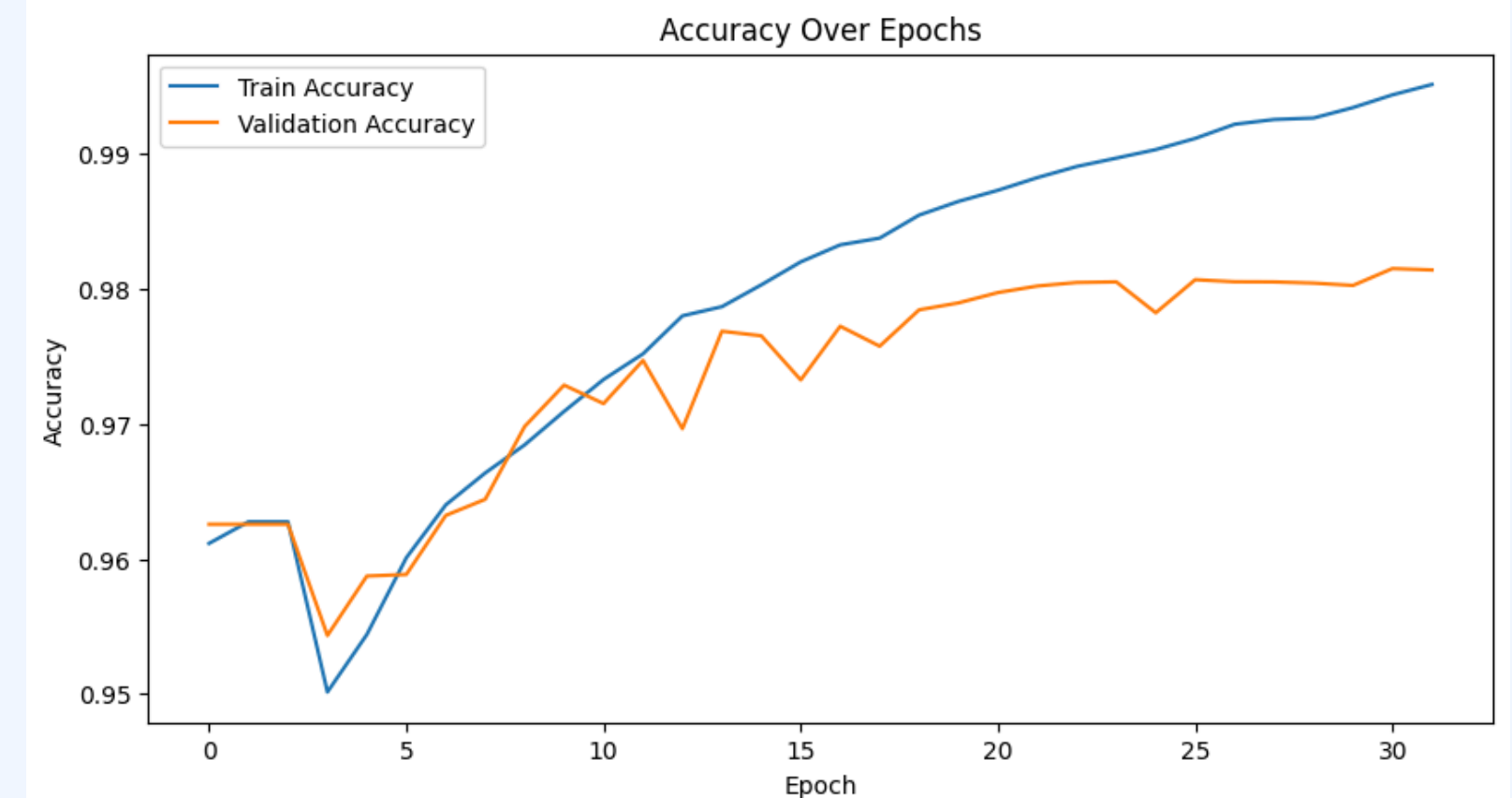
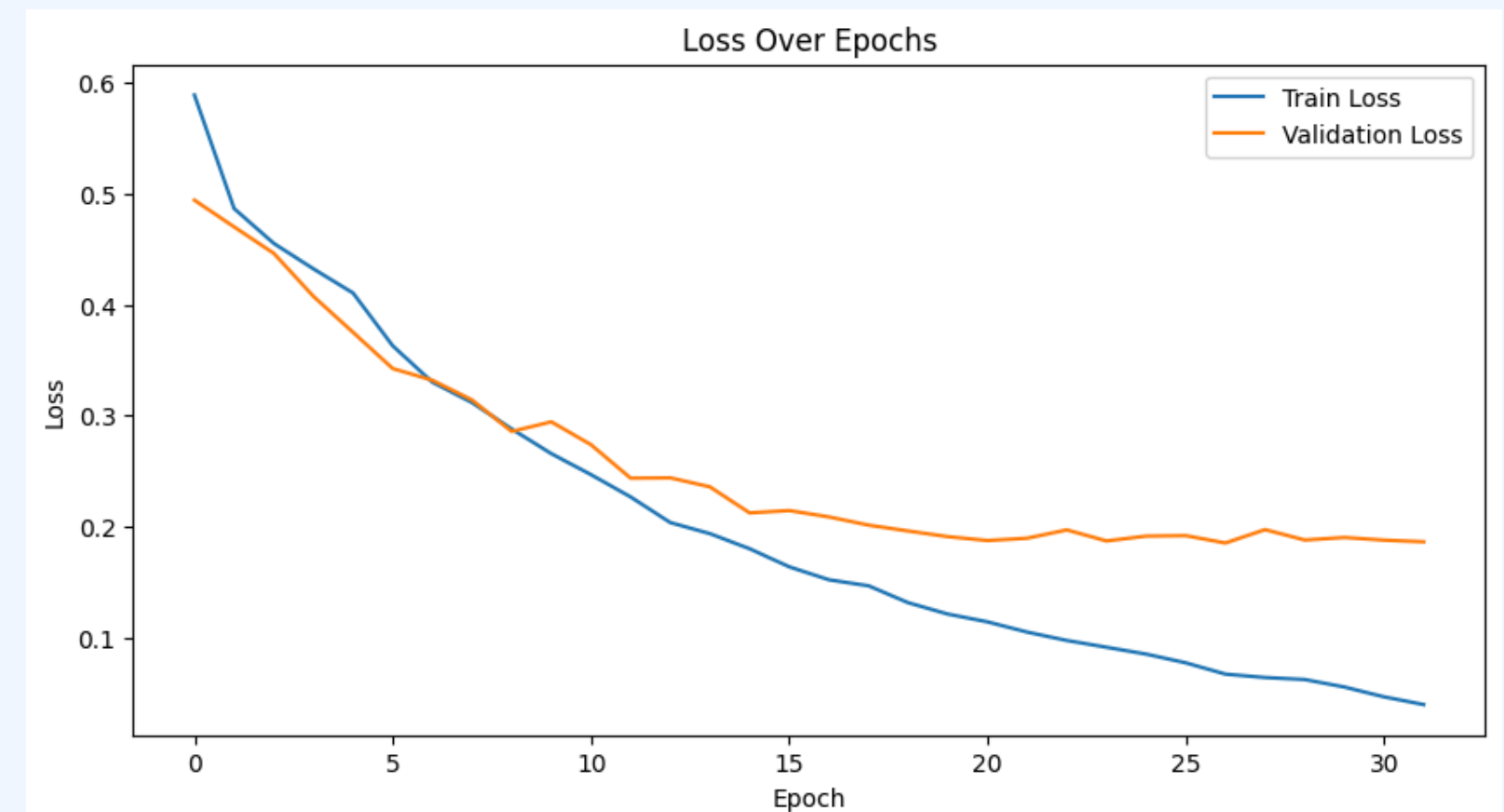
```
INPUT_SIZE = 256
BASE_FILTERS = 64
LEARNING_RATE = 1e-4
EPOCHS = 50
BATCH_SIZE = 16
DROPOUT_RATE = 0.3
DECAY_RATE = 0.9
DECAY_STEPS = 1000
```

Evaluation and Results

Evaluation Metrics:
Loss: 0.2302
Accuracy: 0.9831
IoU: 0.6041
Dice Score: 0.7495



- Ultimately achieved a **test accuracy** of 98.31%
- However, Accuracy and Loss plots show telltale signs of overfitting, and segmentations appear “boxy”



Areas of Improvement

1. Data augmentation

- Shifting, rotating, & scaling
- Implement other brain tumor datasets

2. Hyperparameters fine tuning

- Input Filters
- Dropout rate
- Batch Size
- Decay Rate/Initial LR

3. Loss function

- Weigh scores differently

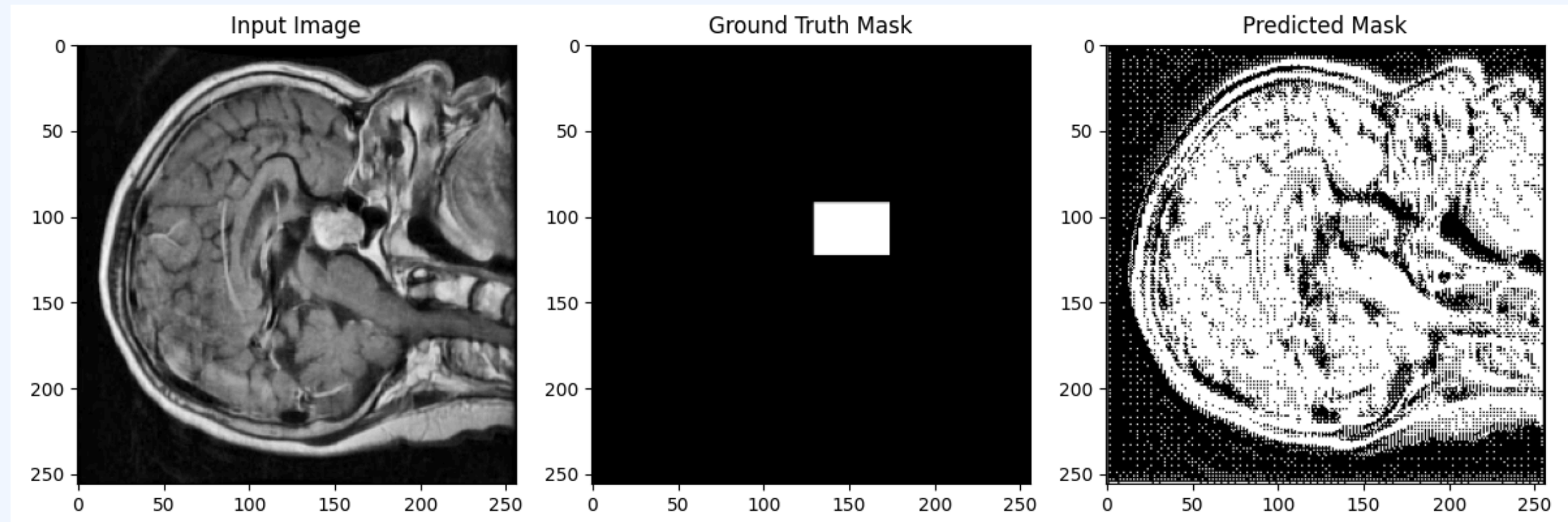
4. Activation functions

- LeakyReLU
- ELU

Thank you

Source code on GitHub:

https://github.com/Aramii0001/UNet_Project/tree/main/src



(It also works for image generation)