Brain Lesion Segmentation using 2D UNet

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A Introduction

Current automated lesion segmentation methods for T1w MRIs, commonly used in stroke research, lack accuracy and reliability. The purpose of this project is to implement a deep learning model for better lesion segmentation on brain MRI images. The chosen architecture of this project is U-Net. The dataset used for this project is ATLAS, an open-source dataset of stroke T1w MRIs and manually-segmented lesion masks.
ATLAS 2.0 This dataset consists of T1w MRIs and manually segmented lesion masks that includes training (n = 655), test (hidden masks, n = 300). For this project, training data with masks is used for the validation of model performance. All the raw images are NIfTI files. **Brats17** This preprocessed dataset is from the lab, which consists of around 9000 T1w MRI images of brain tumour and related masks. The pretrained model used in the transfer learning step is trained with this dataset.

B Methods

Preprocessing This step transforms all the NIfIT images into 2D slices. Originally, the 3D images are of the size of 189 x 197 x 233 pixels. The 2D slices are on the x-y plane and each image is padded to be square. To achieve better quality of images, the first and last 50 slices are not chosen because they are more likely to be broken or are just part of skull.

Model Implementation
The main methods for the project are using U-Net with weighted map and transfer learning. This project is implemented in two steps: (1) training and validation with a standard U-Net model with weight maps, (2) transfer learning from tumour segmentation to lesion segmentation. Weighted Dice coefficient is used as the loss function. Dice value, precision and recall are the main metrics.

Training and Validation Process
First, tumour models and lesion models are both trained with similar parameters. Second, parameters of weight strength are manipulated in the training for lesion model.
Due to the similarity between ATLAS and Brats17, the best tumor model is again trained by ATLAS dataset through transfer learning. The last convolutional and activation layers are free to update while the other layers and weights are freezed during the training. In the end, based on transfer the best model from tumour dataset is trained on lesion dataset.
The results section will show the best results of all the training process.

C Results

1. Pretrained U-Net Tumour Model

Hyperparameters:
n base = 8, batch size = 8, weight strength = 1,
dropout ratio = 0.2, batch normalization = $True$, augmentation = $False$.
In the end, the pretrained model reaches Dice value in validation as 92.38%. Several predictions from the validation set are plotted in Fig. 1.

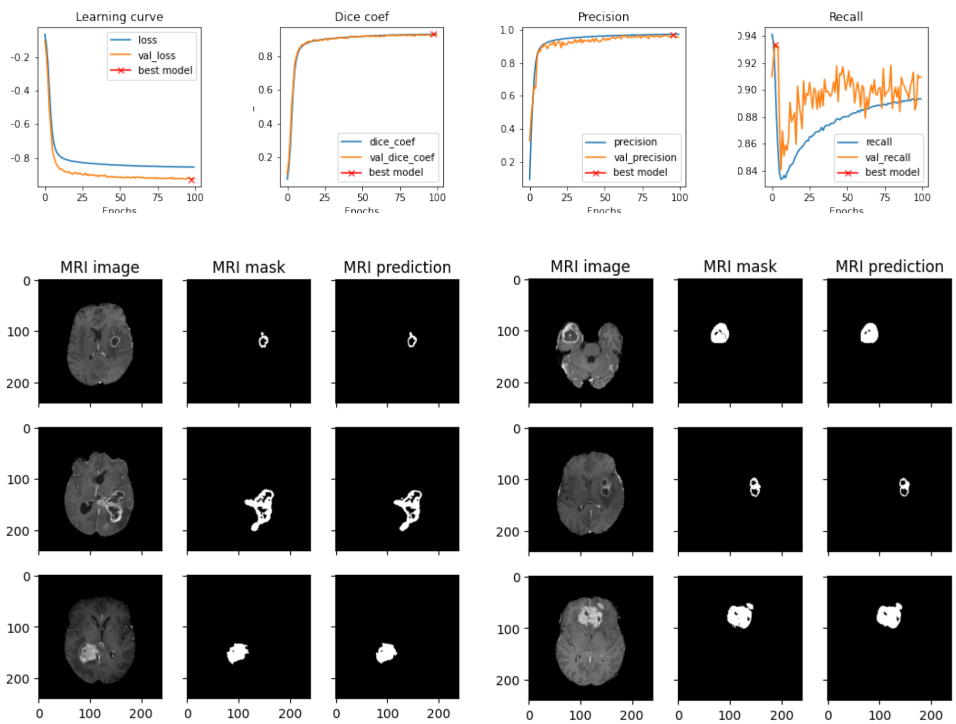

Figure 1: Model history and predictions of pretrained tumour model

2. U-Net Lesion Model:

Hyperparameters:
n base = 8, batch size = 8, weight strength = 1,
dropout ratio = 0.2, batch normalization = $True$, augmentation = $False$.
In the end, the lesion model reaches Dice value in validation as 84.15%. Several predictions from the validation set are plotted in Fig. 2.

3. U-Net Lesion Model from Transfer Learning:

Hyperparameters:
n base = 8, batch size = 8, weight strength = 0.8,
dropout ratio = 0.2, batch normalization = $True$, augmentation = $False$. In the end, the model from transfer learning reaches Dice value in validation as 83.75%. Several predictions from the validation set are plotted in Fig. 3.

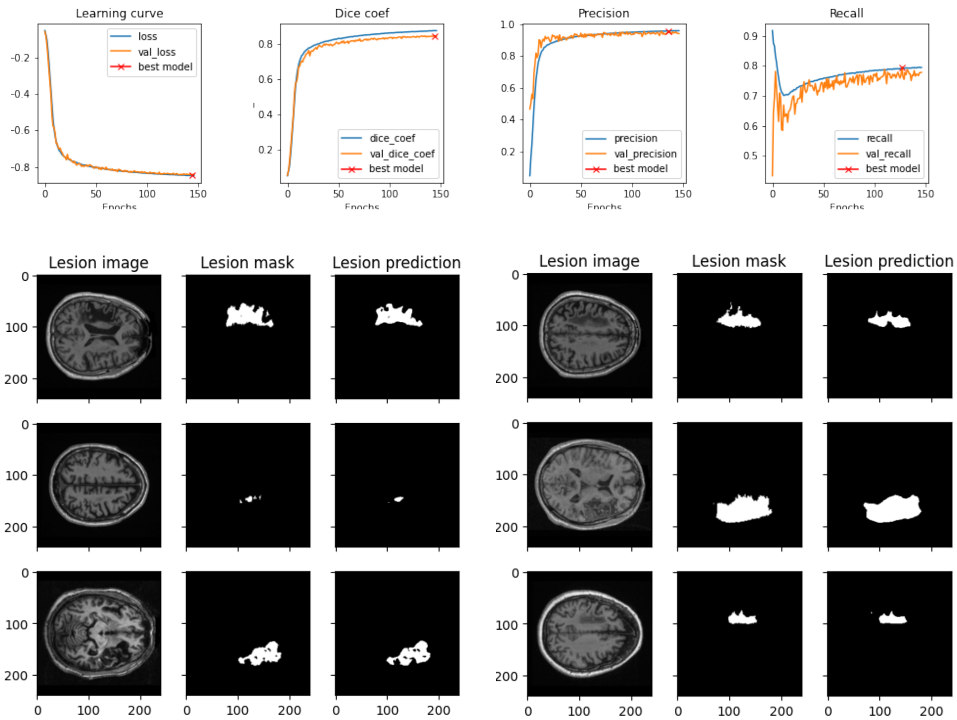

Figure 2: Model history and predictions of lesion model

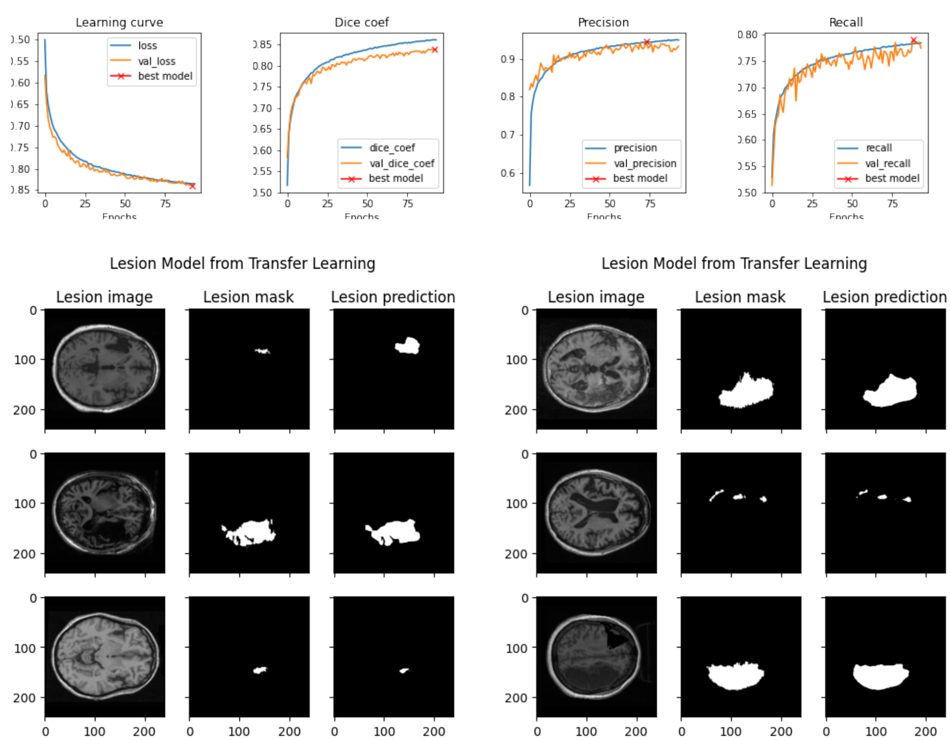

Figure 3: Model history and predictions of the model from transfer learning (This model is still in training by the time of plotting. New result will be updated when finishing.)