IDENTIFYING AND LOCATING MULTIPLE SCLEROSIS (MS) LESIONS IN BRAIN MRI SCANS

W.MSCIDS_CVI03.F2 Computer Vision - Group 2

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AGENDA

- Introduction
- Objective
- Dataset
- Methodology
- Evaluation
- Conclusion

INTRODUCTION

- MS affects function in cognitive, emotional, motor, sensory, or visual areas.
- A person’s own immune system attacks their brain and spinal cord.
- According to Walton et al. (2020), MS prevalence has increased in every world region since 2013, with an estimated number of 2.8 million people with MS in 2020 worldwide.

INTRODUCTION

- Volumetric brain MR imaging, as shown in Figure 1, as a common method to treating MS patients.
- The figure only shows one layer - this approach results in **hundreds** of images, making detection or changes very **time-consuming.**
- Diagnosis also influenced by **Inter-** and **Intra-observer Variability** (Conti et al., 2023).

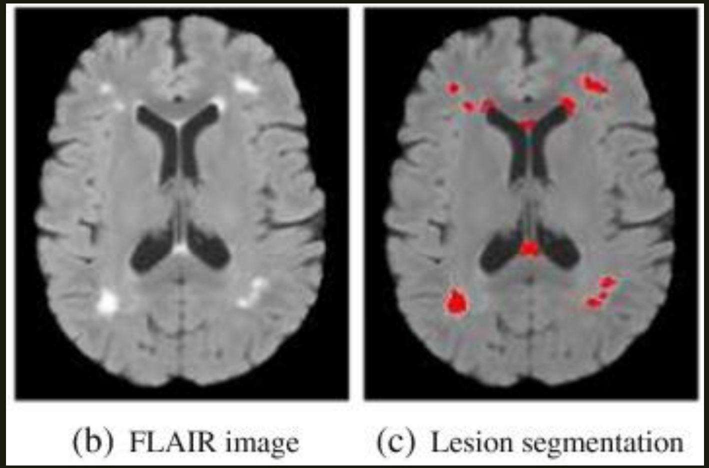


Figure 1. Layer of MRI scan with lesion segmentation (Zhao et al., 2017)

Intra-observer Variability

Consistency of a single expert

Inter-observer Variability

Differences between experts

OBJECTIVE

- Develop an automated machine learning model for accurate segmentation of multiple sclerosis (MS) lesions from MRI scans.
- Evaluation by using the **Dice similarity coefficient**, which measures the overlap between predicted segmentation and ground truth.
  - ✓ Commonly used in medical image applications, which helps with comparison of results

DATASET

- Primary dataset by Muslim et al. (2022)
- Brain MRI scans from 60 patients, confirmed to have MS including manual lesion segmentation
- Provided by Baghdad Teaching Hospital, Iraq
- Each patient folder contains:
  - The patient's brain-scans (T1, T2, Flair)
  - Corresponding lesion segmentation for each of the brain-scans

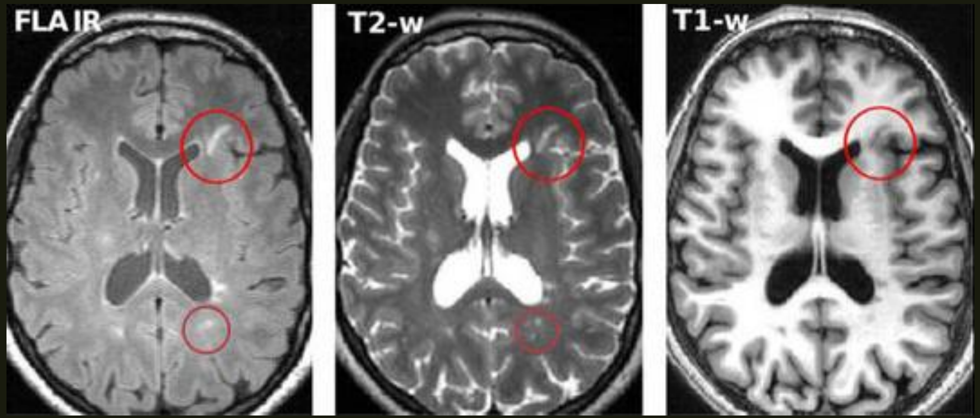


Figure 2. Layer from MRI scan represented in multiple sequences: Flair, T2 and T1 (Ma et al., 2022)

DATASET - EDA

Insights regarding **MRI scan properties**

- Unique Voxel Dimensions: 1
- Unique Image Shapes (HxW): 13
- Unique Scan Orientations: 3

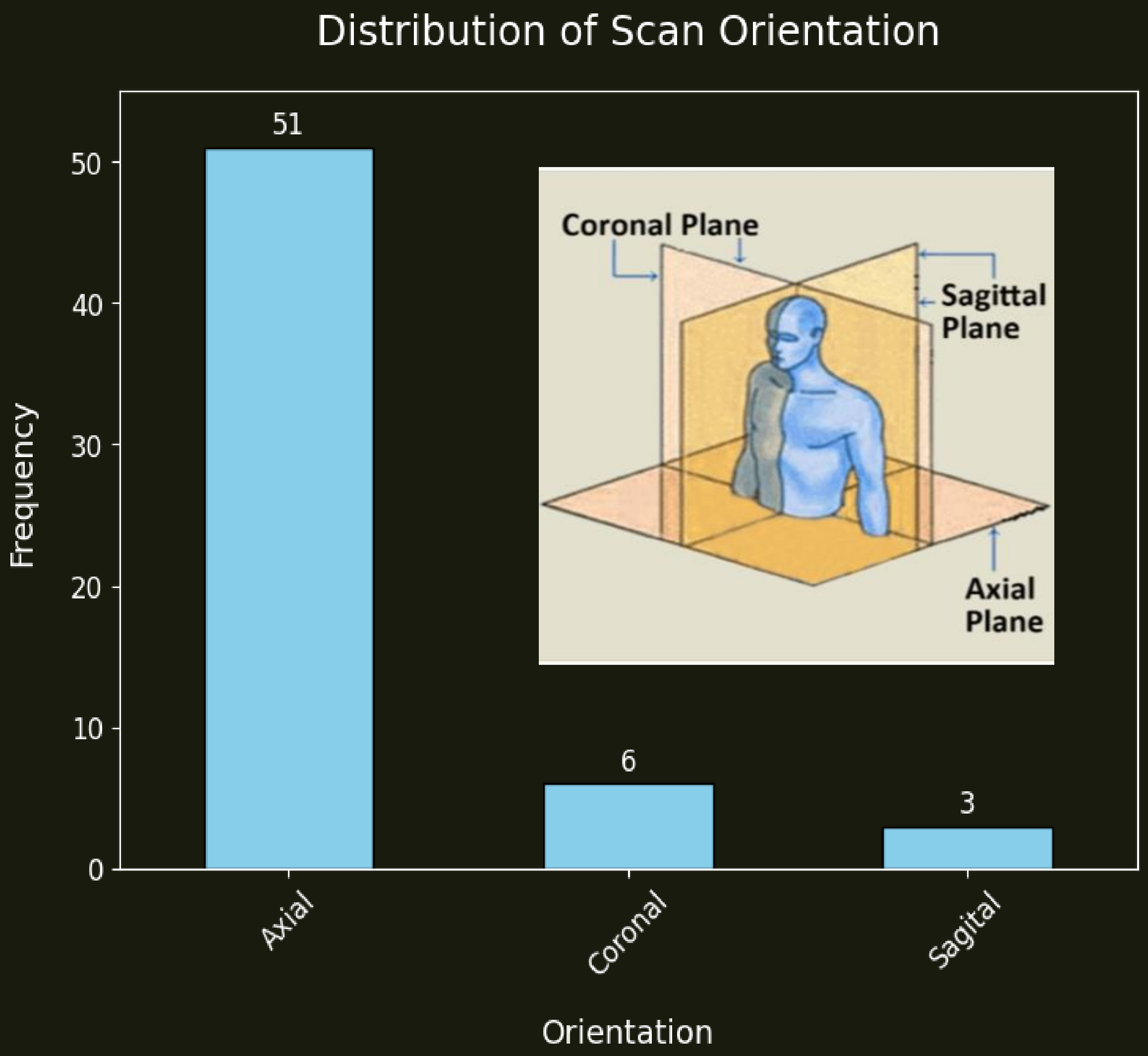


Figure 3. Distribution of scan orientation in dataset

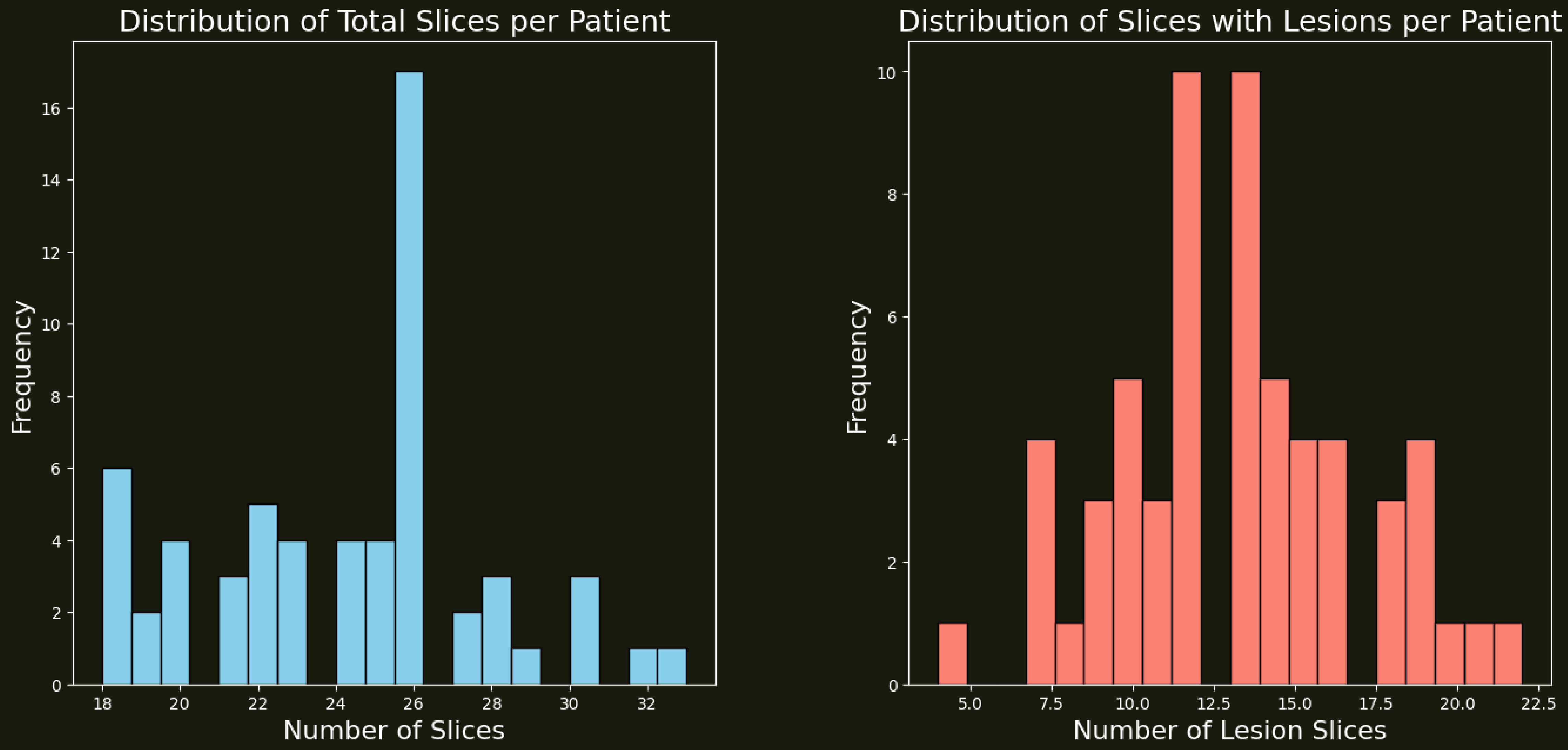
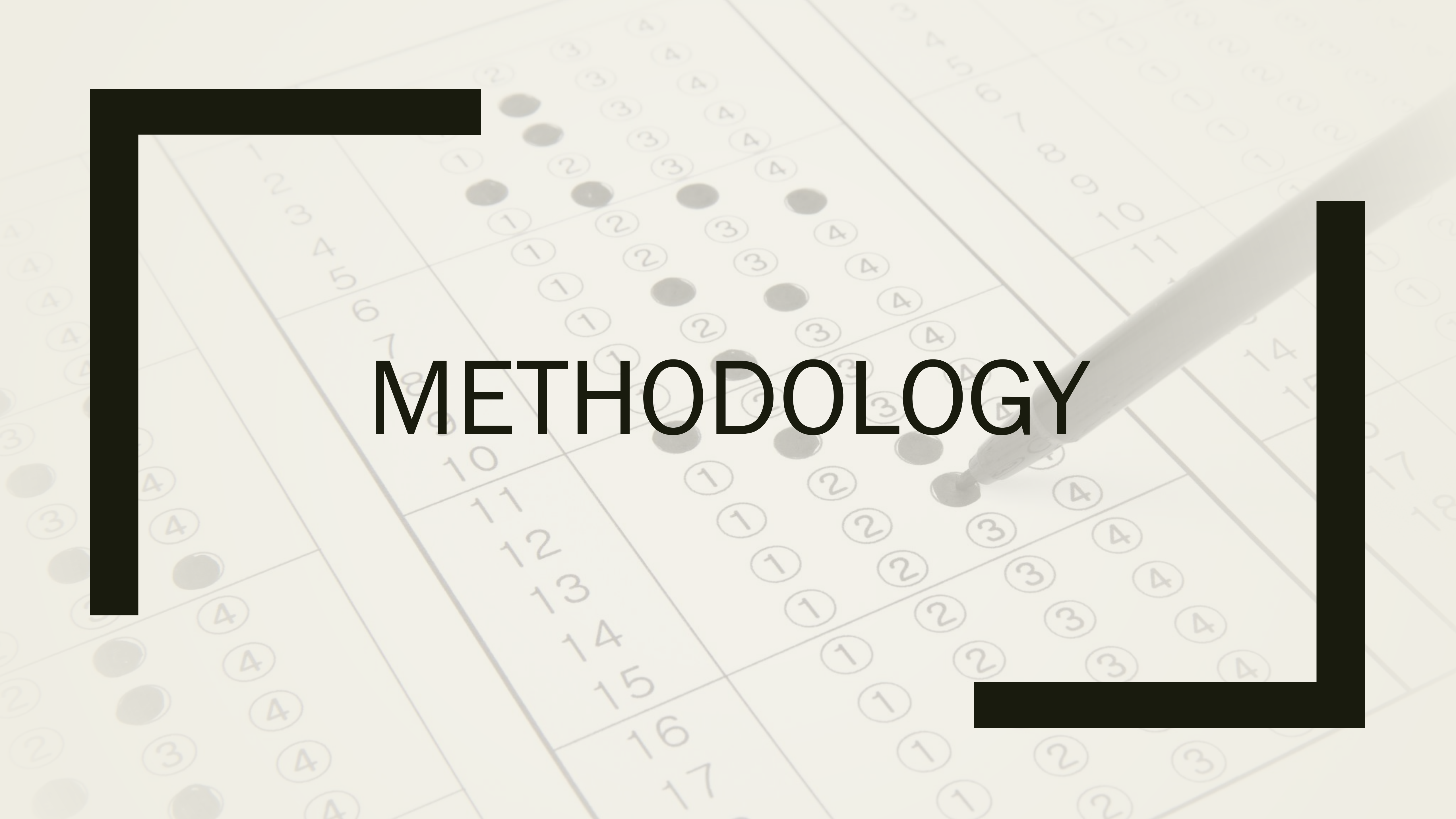


Figure 4. Statistical analysis regarding slice properties



METHODOLOGY

PREPROCESSING

- Train-test split: 41 vs. 10 scans
- Brain extraction (Deepbet)
- Resize slices to 256x256
- Min-max normalization to 0-1 within scan
- Select only slices with lesions
- Paired data augmentation:
  rotation, shift, zoom, flip, shear, noise

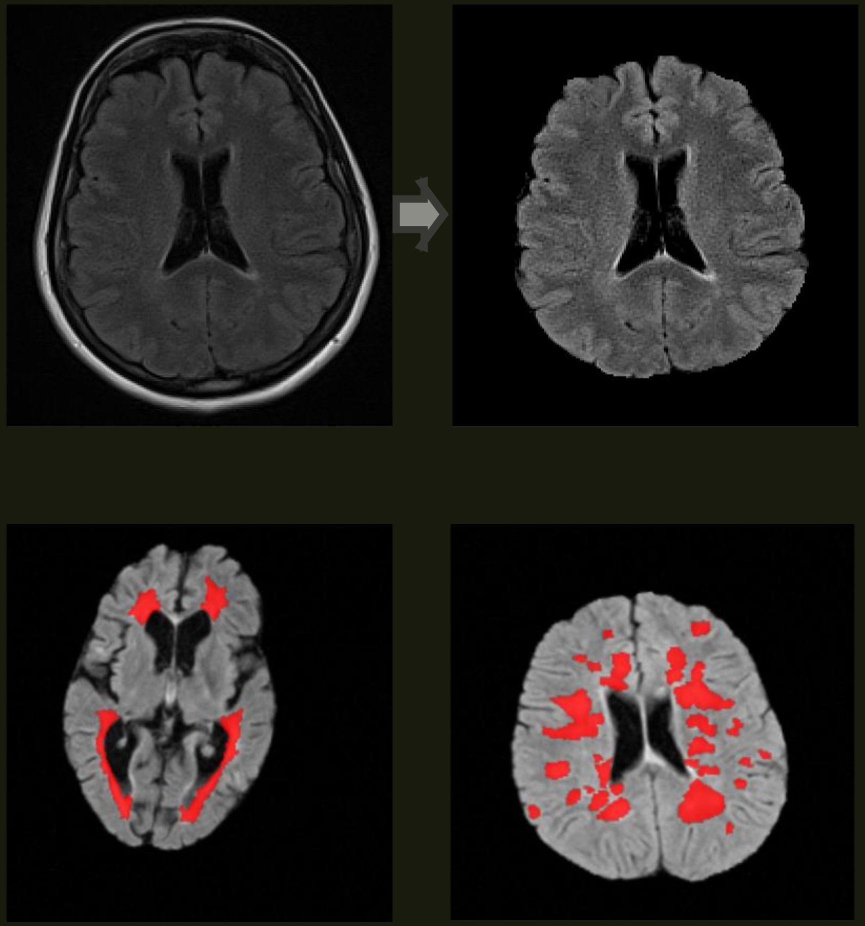


Figure 5. Top: Brain extraction,
Bottom: Augmented slice-mask pairs

U-NET

- CNN, optimized for medical image segmentation
- Input: 256x256 slice
  Output: Segmentation
- Encoder (left): Pretrained ResNet50, MaxPool 2x2
- Decoder (right): Upsampling 2x2
- Skip Connections: preserve fine spatial details and better gradient flow

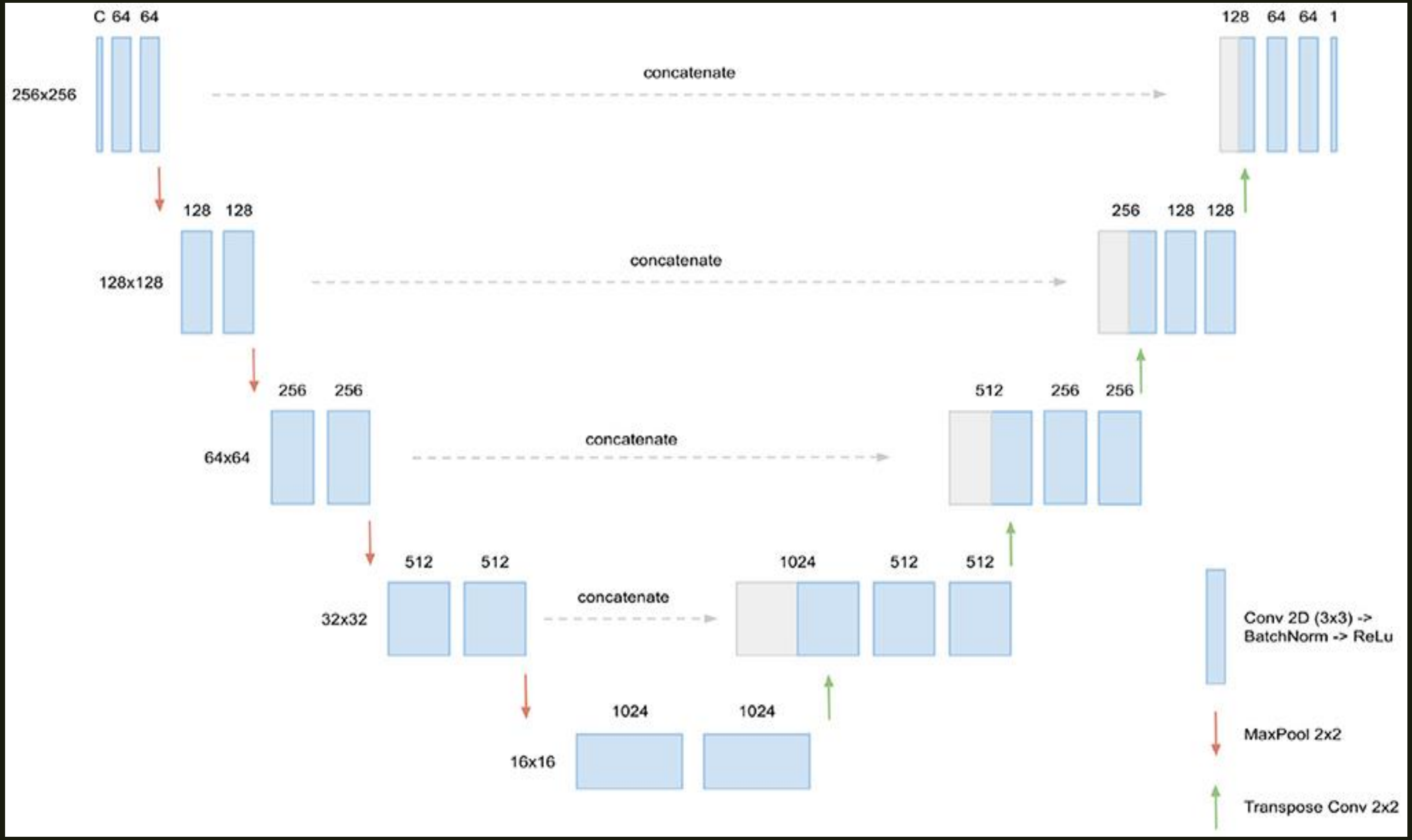


Figure 6. U-Net architecture by Hitziger et al. (2022)

TRAINING

- Dice coefficient: better for imbalanced segmentation than IoU
- Combined loss: dice and crossentropy loss
- Prevent overfitting:
  - Decreasing learning rate
  - L2 regularization
  - Dropout
  - Batch normalization
  - Layer freezing
- Early stopping
- Use best model

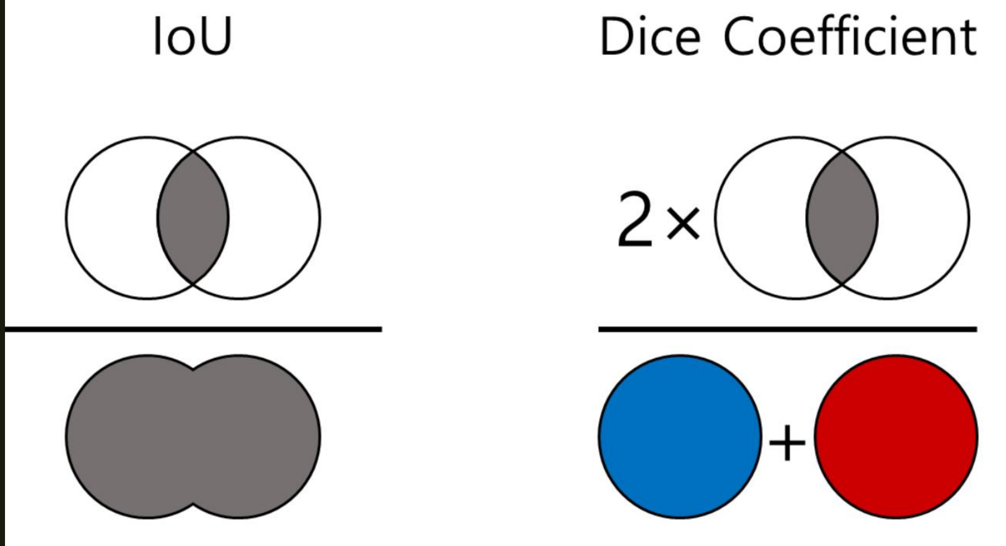
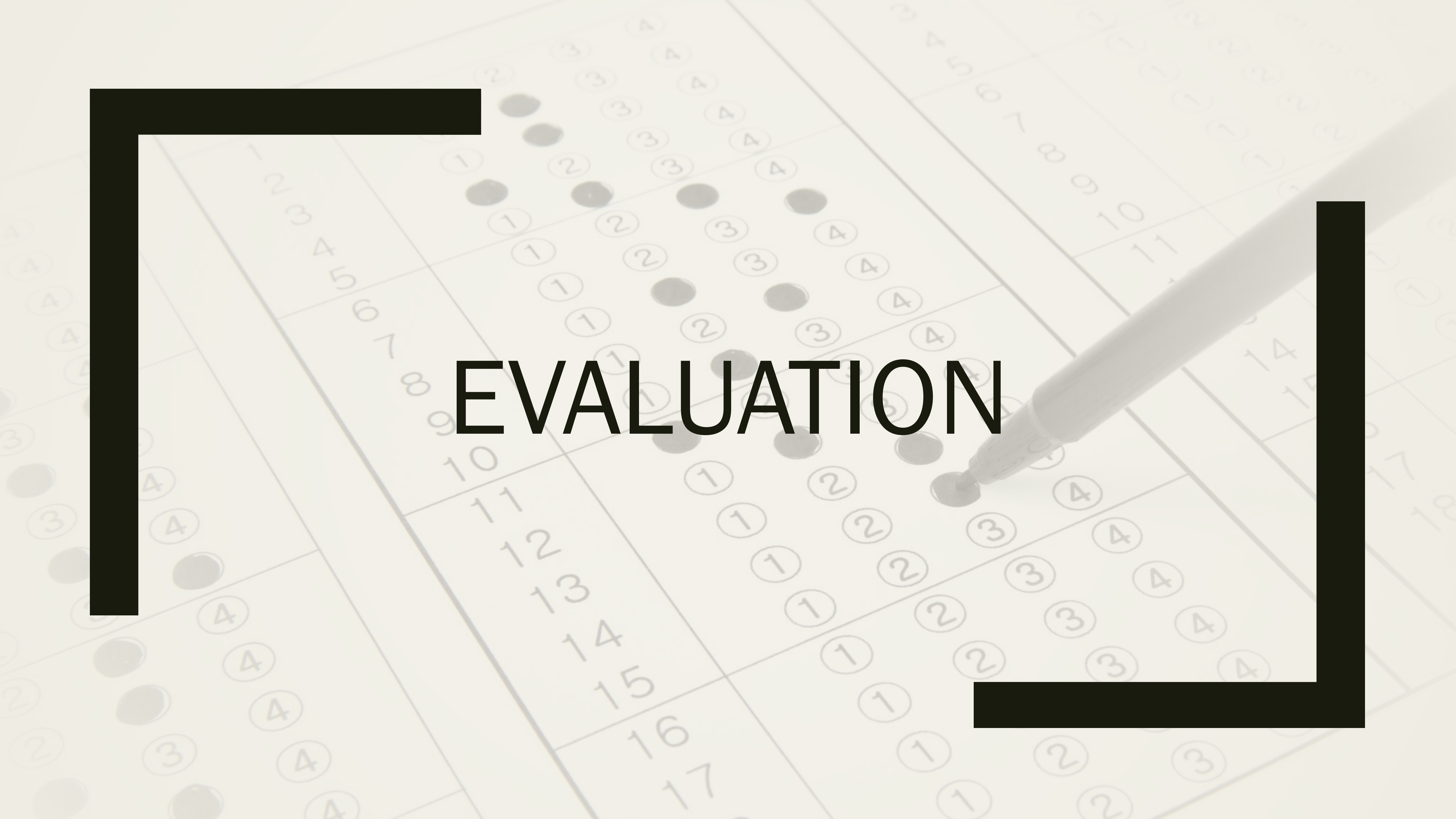


Figure 7. Comparison of IoU and Dice Coefficient (Fakecan, 2023)

EVALUATION



BASE MODEL

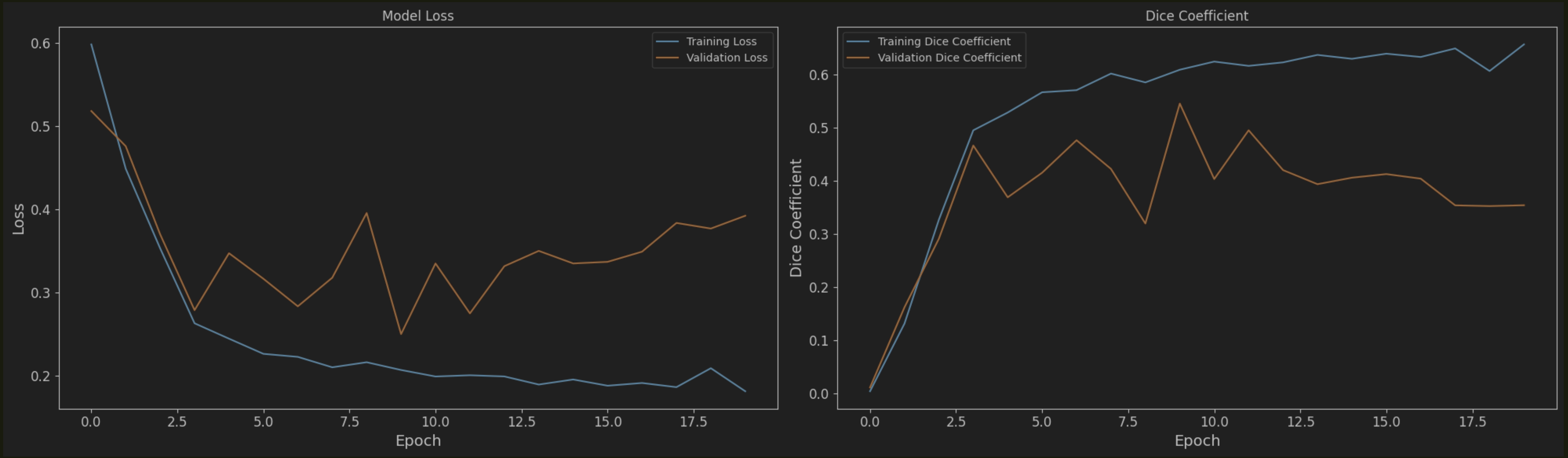


Figure 8. Training using default ResNet50 architecture

- Model overfits after a couple of epochs

PARAMETER TUNING

- Optimizing the following Params:
    - Dropout
    - Regularization (L2)
    - Learning rate

Parameter	Value
Dropout	0.1
Regularization (L2)	2.3e-5
Learning rate	2.2e-4

Table 1. Optimal parameters for final model

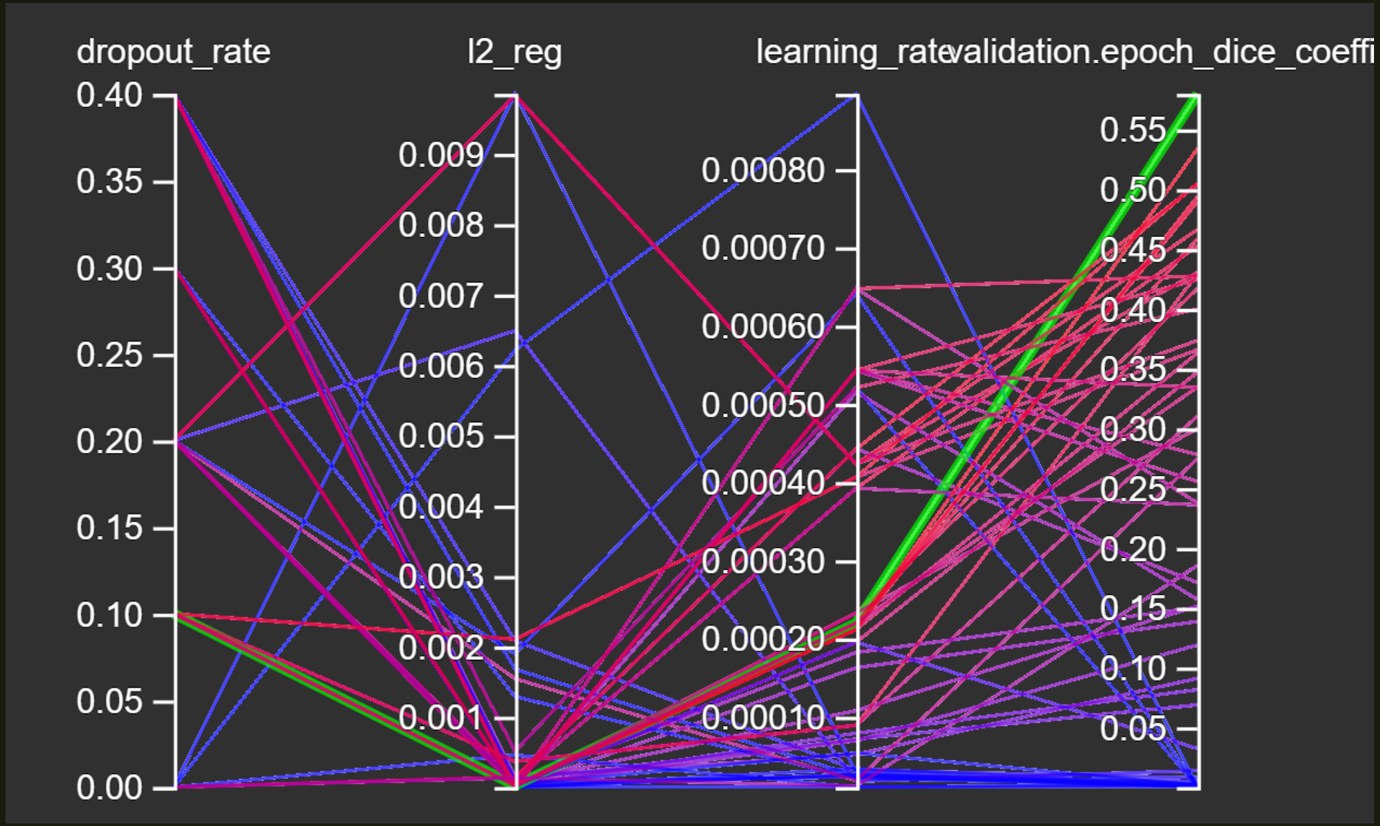
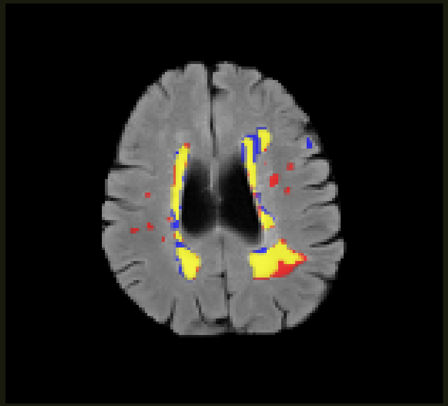
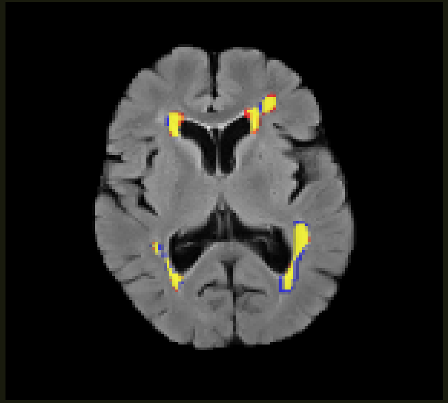


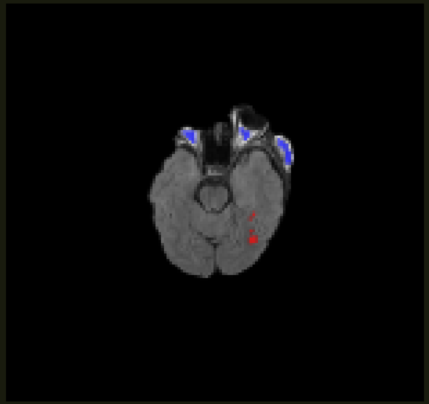
Figure 9. Tensorboard tuning overview

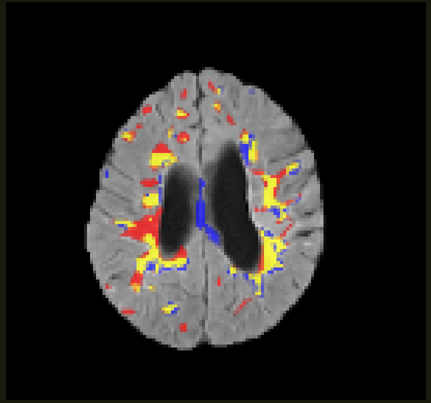
Good Predictions





Potential for Improvement





- Wrong predictions around the eyes and the ventricles

Lesion Mask

Predicted Lesion

Overlap (correct prediction)

MODEL PERFORMANCE COMPARISON

Model	Dice Coefficient
DeepScan (McKinley et al., 2020)	0.6
CLAIMS (La Rosa et al., 2022)	0.49
Segmentation of multiple sclerosis lesions using deep neural networks (Sasko, 2021)	0.6
Best model from our group	**0.59**

Table 2. DSC study comparison

CONCLUSION

CONCLUSION

- Complex MRI scan preprocessing represented a critical challenge in this project
- We successfully trained a U-net model to predict MS lesions on MRI scans
- The quality as well as the quantity of MRI scans makes a big difference
    - Model tends to overfit on small amount of training data
    - Difficult to acquire a large amount of high- quality MS MRI scans
    - Large differences between scans adds another difficulty (e.g. voxel sizes, masks)

THANK YOU

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Code on Github: https://github.com/rportm/cv_hslu_24