Active Lesion Prediction in Multiple Sclerosis Using Artificial Neural Network

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June 8, 2023

1 Introduction

Multiple Sclerosis (MS) is an autoimmune disease that effects the central nervous system. On Magnetic Resonance Imaging (MRI), hyperintense brain lesions are seen on T2-weighted (T2w), but not all these lesions are active. Visualization of the active lesions greatly helps in patient management. The most common way to identify active lesions on MRI is to inject gadolinium based (Gd) contrast agent. Active lesions appear hyperintense on post-contrast T1-weighted (T1w) images. Recent studies raised safety concerns with Gd administration. In addition, administration of Gd increases the scan cost. It is, therefore, highly desirable to identify active lesions without Gd administration. In this work, we attempt to automatically identify active lesions using an Artificial Neural Network.

2 Materials and Methods

Anonymized images from 25 MS patients were used in this work. MRI scans on each subject included T1 pre-contrast (T1-pre), T1 post-contrast (T1-post), T2-weighted (T2w), Fluid Attenuated Inversion Recovery (FLAIR), and proton density (PD) sequences. We included the T1-pre, T2w, Flair, and PD images as our input images and subtracted the T1-post from the T1-pre image as our ground truth.

Two neural network (NN) architectures consisting of input, hidden, and output layers were tested to determine the best architecture. We also investigated the effect of sample size on the network performance. The first NN consisted of one input, two hidden, and one output layer, while the second included one hidden layer. The input and hidden layers were followed by ReLU and tanh function respectively. We used mean squared error for our loss function and used the Adam optimizer. The final model predictions were constructed binary images which highlights only pixel values related to MS lesions. We used dice similarity coefficient (dice) to evaluate the performance of our solutions between the predicted image and ground truth. We excluded subjects used for training in evaluating the proposed method.

3 Results

Using the model with two hidden layers and five subjects used for training, we achieved a mean dice score of 0.88 with a standard deviation (SD) of 0.07. In addition, we tested a NN with two hidden layers and trained on one subject, achieving a mean dice score of 0.82 with an SD of 0.06. With one hidden layer and one subjects used for training, we achieved a mean dice score of 0.80 with an SD of 0.04. Lastly, with two hidden layers and one MRI slice used for training, we achieved a mean dice

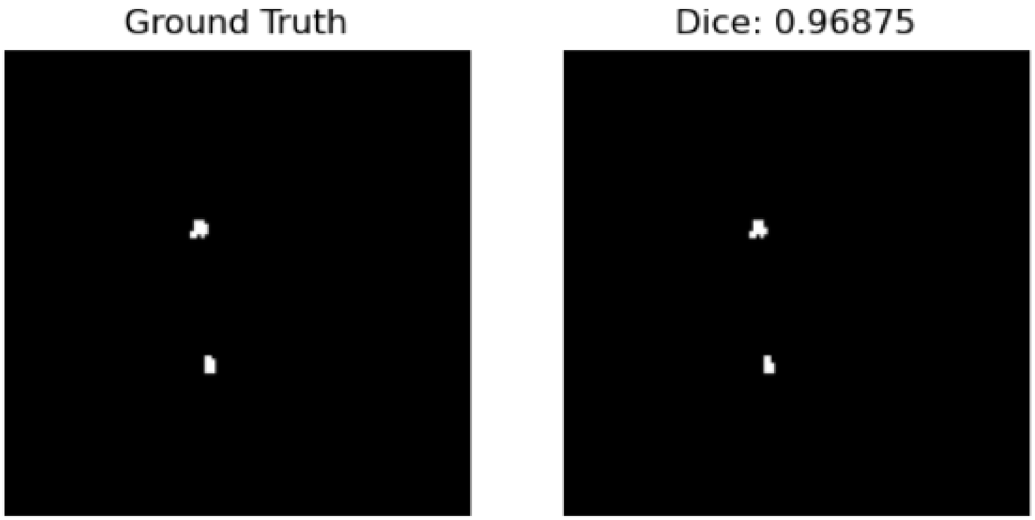

Figure 1: Left Image: The ground truth image or expect results obtained by subtraction of T1-post and T1-pre images. Right Image: Is the model prediction, where the architecture consist of two hidden layers and was trained on one subject. In this example, we tested our solution on one subject and achieved a dice score of 0.97, where zero is the lowest possible score and one, meaning a perfect match, is the highest

score of 0.66 with and SD of 0.07. These results show that increasing the number of hidden layers to two performed better than a single hidden layer. In regards to sample size, increasing the number of subjects used for training yielded better results than training on only one slice or one subject.

4 Discussion

There maybe safety concerns using contrast agent administration, therefore, our solution provides a potential alternative to Gd administration in MS patients. Eliminating the need for contrast administration can reduce the cost of clinical care and increase patient safety. We can further improve the performance of our work by optimizing the hyperparameters of the model and including more subjects during training. While the current study is cross-sectional in nature, it can be easily extended to longitudinal data to follow the disease activity and investigate effect of treatment.

5 Conclusion

In this work, we demonstrated a deep learning approach for predicting active MS lesions on non-enhanced images. These results need to be confirmed on a prospective larger sample size. Our method has the potential to be a viable option for predicting MS lesions in a supervised manner and in other diseases, such as cancer.

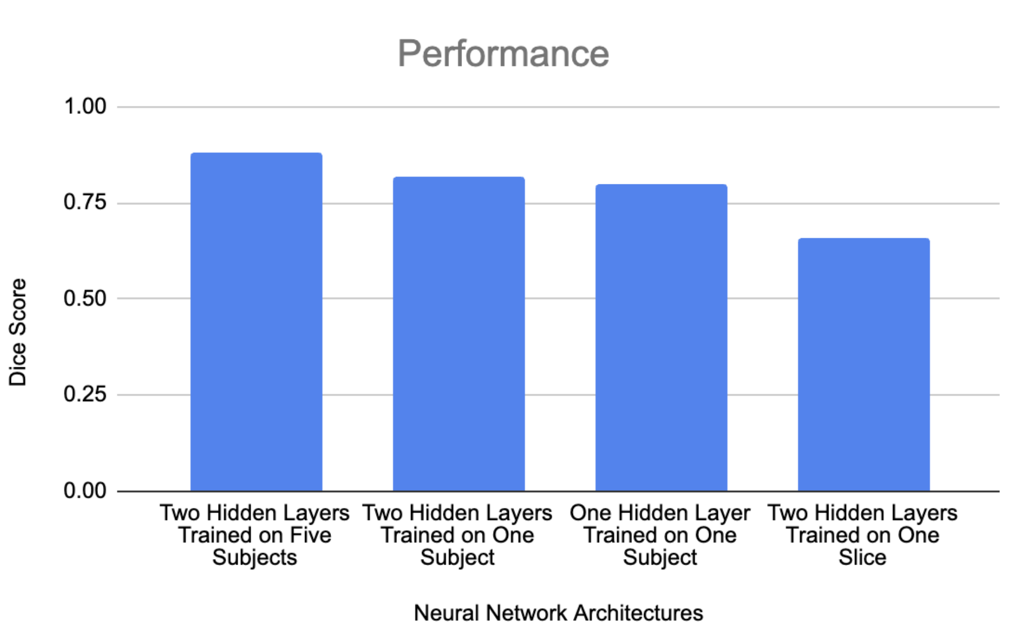

Figure 2: The performance of each neural network (NN) with respect to their mean dice score. NN architecture with one input layer, two hidden layers, and one output layer, is shown to have the highest mean dice score of 0.88 when trained on five subjects. NN with two hidden layers and was trained on one brain MRI image is shown to have the worst performance with a mean dice score of 0.66