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Machine Learning Approach for detection of Leukoaraiosis

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Leukoaraiosis is an essential change in white matter (WM) with aging, indicating ischemic microvascular disease which is now understood to be a significant predictor of risk for Alzheimer's Disease (AD) [1]. Most studies assess leukoaraiosis by its appearance as WM hyperintensities on T2-FLAIR, the fluid sensitive, images; but it is also apparent on T1 weighted MRI, the anatomical images, as WM hypointensities (Fig1). One of the biggest challenges in accessing leukoaraiosis is that there is not a gold standard but many approaches. Lesion Segmentation Toolkit (LST) [2] is the most commonly used white matter hyperintensity detection algorithm used in the research field of neuroimaging; however, the Achilles' heel in this algorithm is only using voxel intensity to segment tissue types in the brain. Another limitation of this tool is that it identifies the area of leukoaraiosis by thresholding the intensity of both T1 and T2-FLAIR images. On the other hand, Freesurfer [3] another widely using neuroimaging software developed in Harvard, identifies subject's brain anatomy maps the subject brain by using a surface-based analysis but only produces white matter hypointensity, which is not that commonly used in clinical diagnosis.

While T1 and T2 appearances may reflect related white matter properties, it might be beneficial to tackle this problem with the help of both sequences. Further, with the current advance in machine learning, U-net neural network architecture seems to overcome the segmentation issue of LST. It allows for precise segmentation of images because it classifies each pixel from inputs [4]. The contracting path of it is used for segmentation while the expansive paths are used to enable precise localization paired with the contextual information from the different paths. This feature in the U-net [5] will be critical in solving the fundamental problem of the project: to identify leukoaraiosis, a white matter disease. Without a doubt, the first thing to do is label each pixel whether it belongs to the white matter region or not. The next step is to identify disease location within the white matter.

An artificial neural network is built using this architecture that takes both T1 and T2-FLAIR images as inputs. It is currently being trained to segment inputs with reliable white matter hyperintensities and hypointensity labels. The result from this step is to generate a probability map from the inputs, WM hypointensities, and hyperintensities, in order to not only accurately determine the presence of leukoaraiosis but also the severity of it. The next step is to add more features to this tool. One of them will be training this model to recognize the region of leukoaraiosis appearance whether it occurs in the front, back, left or right side of the brain. This feature will be a big step forward because the location of leukoaraiosis in the brain reveals different types of Alzheimer's Disease pathology [6].

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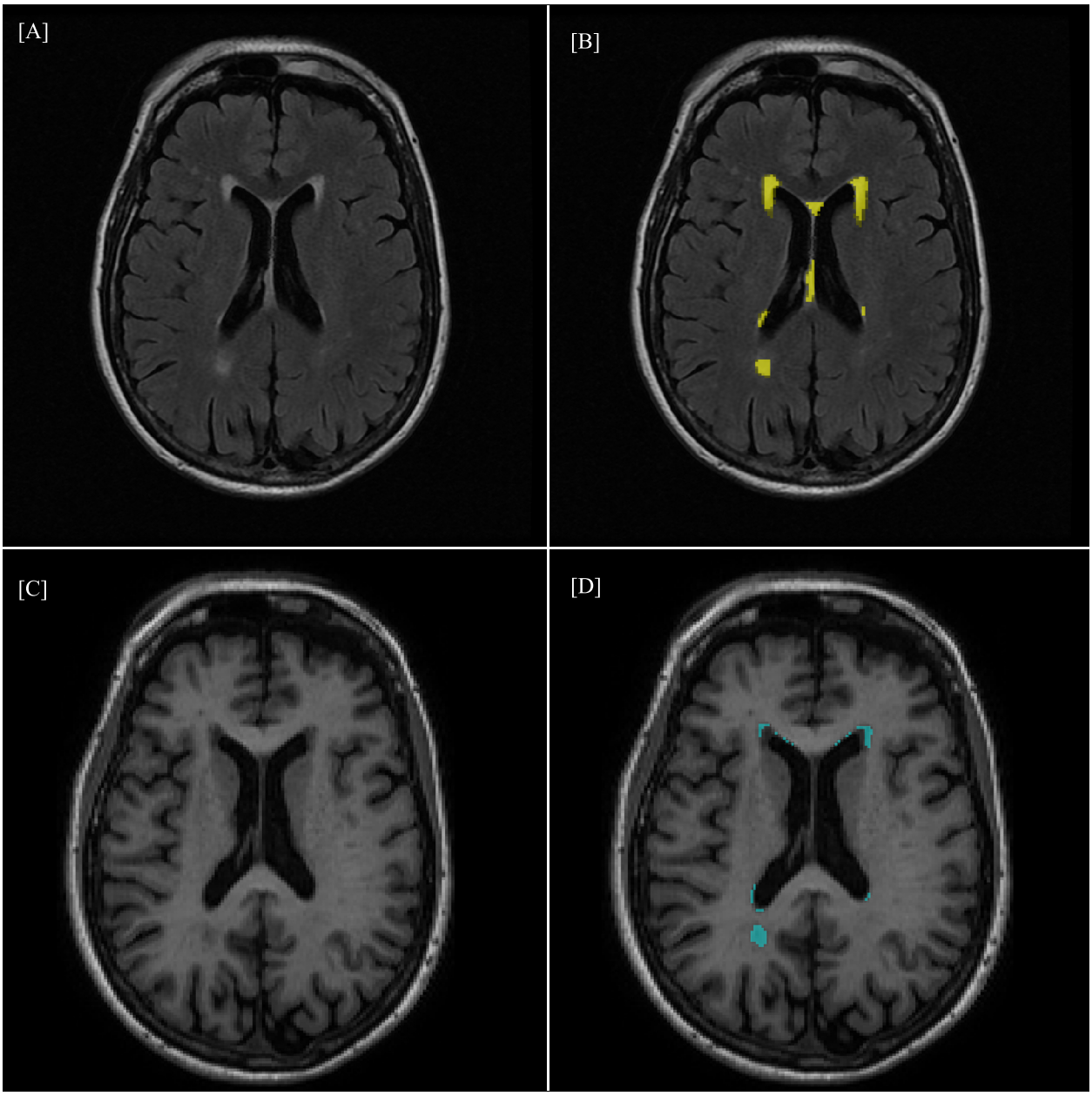

Figure 1. Visualizing T2-FLAIR WM hyperintensity with T1-weighted WM hypointensity on a sample subject in this cohort. [A] and [B] are the T2-FLAIR brain image where [B] colors the WM-hyper regions in yellow. [C] and [D] are T1-weighted image of the same subject. [D] colors WM-hypo regions in blue.

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