Multifaceted Analysis of Carpal Tunnel Syndrome: Simultaneous Ultrasound Median Nerve Segmentation and CTS Classification Enabled by Deep Learning

Background

Carpal Tunnel Syndrome (CTS) is a prevalent peripheral nerve disease in adults, foregrounding the necessity for precise and non-invasive diagnostic methodologies. Ultrasound imaging, known for its safety and non-invasiveness, has become a preferred diagnostic tool for CTS. However, the limitation of ultrasound imaging, characterized by speckle noise, introduces significant challenges in diagnostic accuracy. This noise leads to uneven tissue visualization and diminished tissue boundary contrast, complicating the interpretive tasks performed by clinicians. Therefore, the development of a diagnosis model is urgently needed.

Previous studies have predominantly employed region of interest (ROI)-based approaches, requiring clinicians to manually identify areas for further algorithmic analysis [1][2]. Despite their contributions, these methods often fall short in addressing the clinical needs, primarily due to the pitfalls associated with unclear image quality, which may precipitate segmentation inaccuracies and diagnostic errors [3][4]. Addressing this issue, our research is focused on developing an assisting diagnostic model based on deep learning methodologies. This innovative system aims to transcend the prevalent limitations of ultrasound imaging, furnishing clinicians with quantifiable, objective indicators for both the classification and segmentation of CTS, thereby reducing diagnostic errors.

Method

Our research used 2645 ultrasound images as experimental data, with 1987 images used for training and 636 for testing. The boundaries of the median nerve were guided and annotated by professional medical personnel. Our research combined Bias Field Correction and Multi-Frame Concatenation to develop an image preprocessing algorithm that effectively addresses the blurring issue caused by dynamic movement, resulting in more precise boundaries of the median nerve. The model utilized in our research was a modified version of the Mask-RCNN deep learning architecture, which incorporated Group Normalization techniques to reduce the error rate during the training process. An Attention mechanism module was added to enable the model to focus more on learning task objectives. Based on the characteristics of the diagnostic target, our research optimized the CBAM ratio parameter for the Attention module to achieve the best performance of the model.

Result

The results demonstrated that the proposed method achieved high accuracy in CTS classification, with a 92.9% accuracy, 87.5% sensitivity, 100% specificity, and 93.3% F1 score. Regarding segmentation, the method achieved an average 80.6% Dice coefficient. Further comparison with the YOLOv7 model and the original Mask-RCNN performance showed significant advantages of the proposed method in CTS classification. Specifically, YOLOv7 only attained a 68.1% accuracy, 44.2% sensitivity, 95.8% specificity, and 59.8% F1 score. The original Mask-RCNN showed a 68.4% accuracy, 44.8% sensitivity, 99.6% specificity, and 61.7% F1 score. In summary, our research contributes to developing an assisting diagnostic tool capable of simultaneously achieving efficient CTS segmentation and classification, thereby effectively aiding in the diagnosis and treatment of CTS.

References

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