Evaluating Deep Learning Techniques for Segmenting and Classifying Cardiac MRI Images

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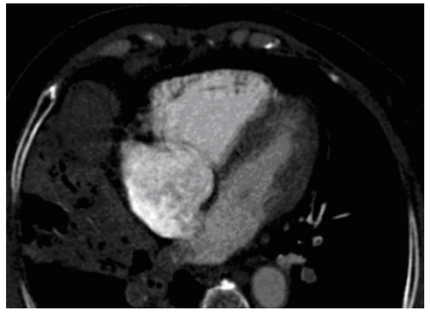
Problem Statement

- Cardiac MRI serves as a gold standard for determining patient cardiac function: stroke volume, left and right ventricle ejection fraction, myocardial wall thickness, and left ventricle mass (Miller et al., 2013).
- Automated cardiac MRI segmentation is a key challenge in the clinical cardiology community as the process is time consuming for doctors requiring need for fully automated characterization.
- Cardiac MRI requires multiple planes of view for complete interpretation, is highly noisy due to dynamic movement of the heart, and highly subjective.



Example of cardiac MRI in 4-chamber plane (Lu et al., 2007)

Overall Approach

- Leverage cutting-edge deep learning methodologies for segmentation of the left and right ventricular endocardium and epicardium, facilitating a comparative analysis with traditional techniques and outcomes.
  - Traditional UNet, UNet++, TransUNet, ResNet, etc.
- Assess the accuracy of deep learning classification models in distinguishing between the five specific heart conditions using relevant features.
  - KNN, Perceptron, Multi-layered perceptron, etc.

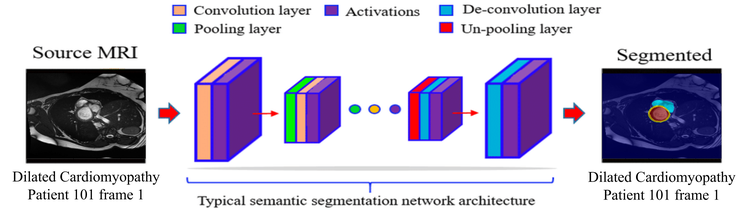
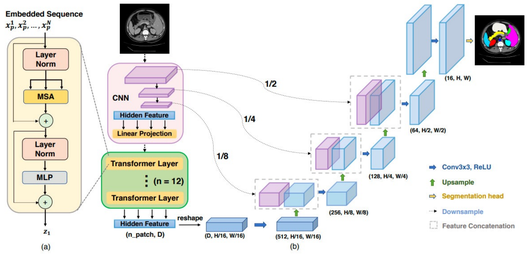


Figure adapted from Altaf et al., 2019

Solution

- Try to outperform previous users/methods in segmentation and classification
  - Last and final leaderboard update was November 2022
- Measure how far state-of-the-art deep learning methods can go at assessing multi-planar CMRI images:
  - Segmenting the left and right ventricles
  - Classifying disease state based on tissue morphology
  - Analyzing cardiac wall thickness and spatial orientation of tissue.
  - Determining model performance via DSC, F1-score, and classification accuracy



Overview of TransUNet (Chen et al., 2021)

Note: We have access to a GPU

Milestones

Segmentation of Ventricles & Myocardium:

I. Traditional UNet Analysis
- Evaluate the performance of the Traditional UNet model.

II. UNet++ & TransUNet Evaluation
- Assess how different UNet variations compare in terms of accuracy and efficiency.

III. Exploration of Various DL Models
- Investigate additional cutting-edge deep learning models for potential improvements (ex. ResNet).

Classification of Pathologies:

I. Perceptron Testing
- Analyze the feasibility of using a single-layer perceptron.

II. MLP Performance
- Test the Multi-Layer Perceptron (MLP) to gauge its effectiveness over the perceptron.

III. More Advanced Methods
- Examine other state-of-the-art deep learning methods to enhance classification results.

Dataset from the Automated Cardiac Diagnosis Challenge (ACDC)
https://www.creatis.insa-lyon.fr/Challenge/acdc/index.html
(Bernard et al., 2018)

References

- O. Bernard, A. Lalande, C. Zotti, F. Cervenansky, et al. "Deep Learning Techniques for Automatic MRI Cardiac Multi-structures Segmentation and Diagnosis: Is the Problem Solved ?" in IEEE Transactions on Medical Imaging, vol. 37, no. 11, pp. 2514-2525, Nov. 2018
- C. A. Miller et al., "Quantification of left ventricular indices from SSFP cine imaging: Impact of real-world variability in analysis methodology and utility of geometric modeling", *J. Magn. Reson. Imag.*, vol. 37, no. 5, pp. 1213-1222, 2013.
- Lu MT, Ersoy H, Whitmore AG, Lipton MJ, Rybicki FJ. Reformatted Four-Chamber and Short-Axis Views of the Heart Using Thin Section (</=2 mm) MDCT Images. Acad Radiol. 2007 Sep;14(9):1108-12. doi: 10.1016/j.acra.2007.05.019. PMID: 17707319; PMCID: PMC2706116.
- Altaf, Fouzia & Islam, Syed & Akhtar, Naveed & Janjua, Naeem. (2019). Going Deep in Medical Image Analysis: Concepts, Methods, Challenges and Future Directions. IEEE Access. PP. 1-1. 10.1109/ACCESS.2019.2929365.
- Chen, J., Lu, Y., Yu, Q., Luo, X., Adeli, E., Wang, Y., ... & Zhou, Y. (2021). Transunet: Transformers make strong encoders for medical image segmentation. arXiv preprint arXiv:2102.04306.