LIVER ULTRASOUND IMAGE SEGMENTATION

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1 Introduction

AI emerges as the current solution with a significant impact on the health sector across the world (Gonçalves & Da Silva, 2024; Supervisor & Hatami, 2024).

Despite its immense impact, African health institutions lack a solution in their facilities, as a result, early detection of disease in ultrasound liver images.

Most African settings rely on ultrasonography as a cost-effective diagnostic technique due to the lack of radiation exposure(Duan et al., 2020). However, analysis and integration of liver ultrasound images require a trained radiologist in areas where expertise services are limited, and delays in diagnosis and treatment can significantly affect patient outcomes (Duan et al., 2020). This poster presents an AI-powered liver ultrasound image segmentation solution under the supervision of the Youth in AI research pilot Lab.

2 Objectives

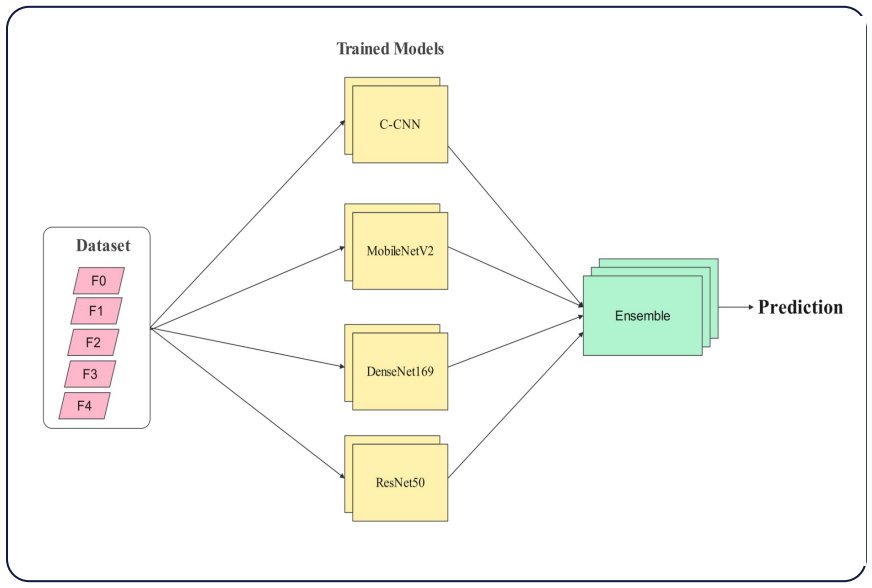
- The focal objective of this project is to develop a mobile-friendly AI model for liver ultrasound image segmentation in real-time, making medical diagnostics tools accessible to remote areas where access to medical tools for diagnostics is limited

3 Methodology

This section presents the methodology of the project.

Dataset ustilized in this porject was collected from a research conducted by (Joo et al., 2023). As illustrated in figure 1,

F0 represents No Fibrosis, F1: Portal fibrosis, F2: Periportal fibrosis, F3: Septal fibrosis, and F4: Cirrhosis



Figurer 1: Architectural diagram

The dataset was train on four defferent models as follows;

- A custom CNN model
- DenseNet169 model
- ResNet50 model
- MobileNetV2 modle

The trained models were ensembled using FLAML to automatically optimize the combination using weighted average of output masks methods.

4 Results

The results obtained from the experiment are presented in this section.

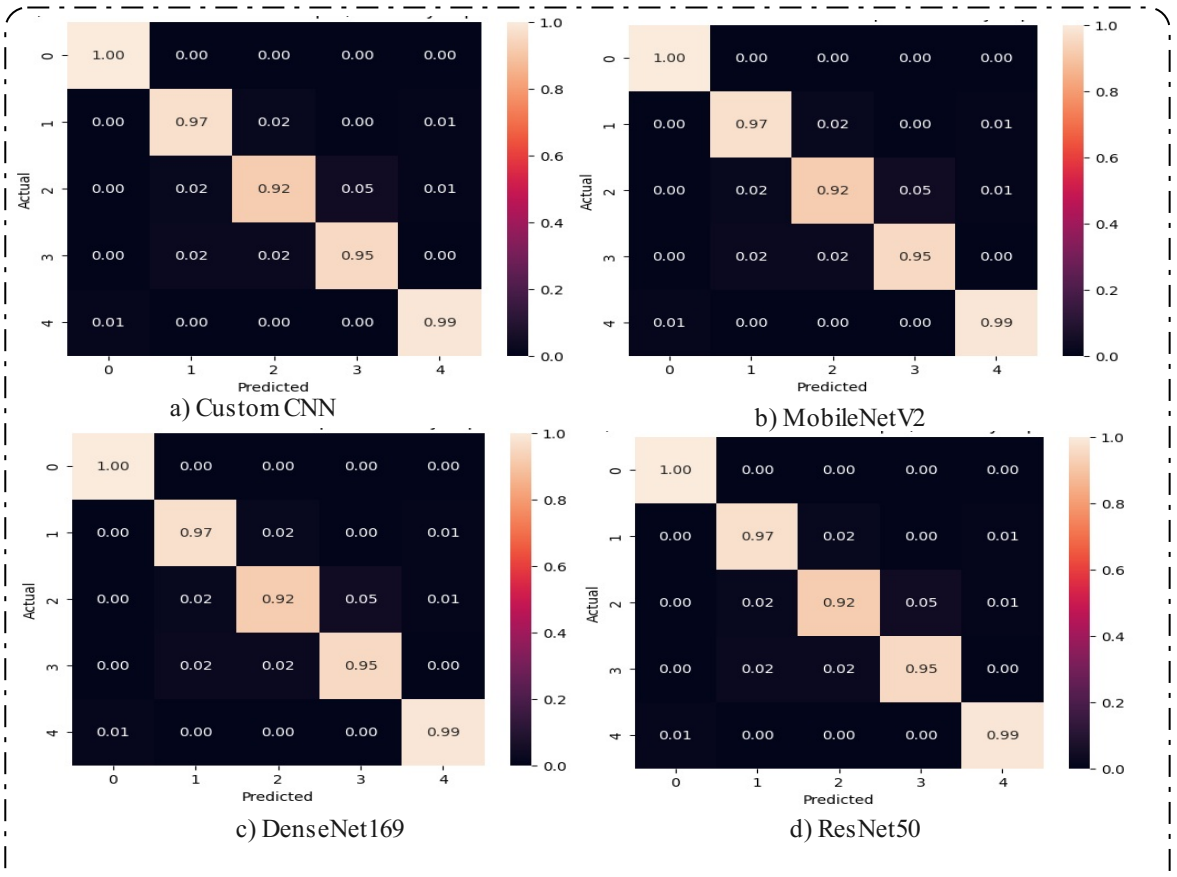
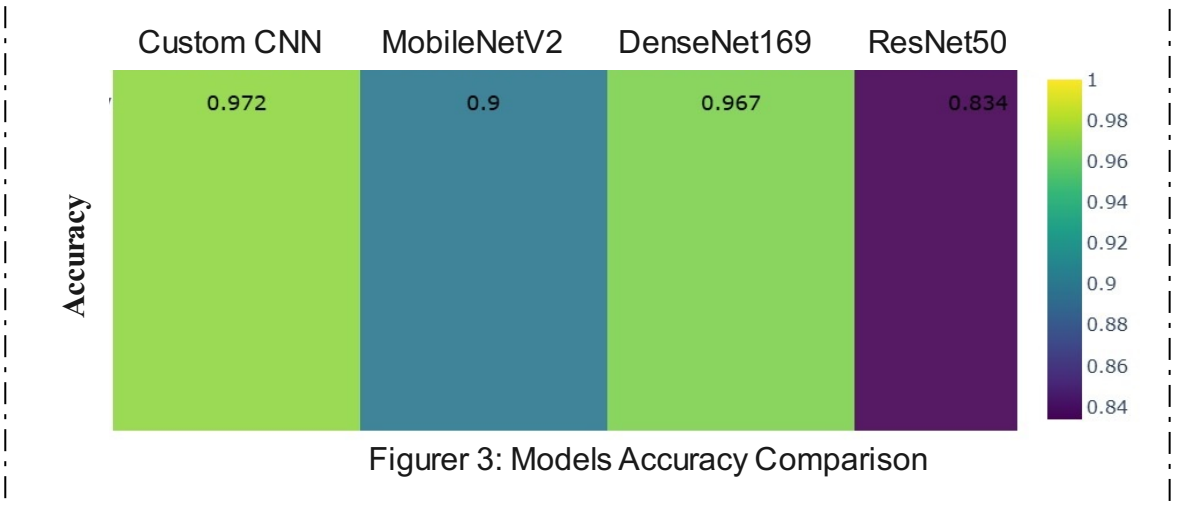


Figure 2: Normalized Confussion Matrics;

0: Normal liver ; 1: Portal fibrosis without septa; 2: Portal fibrosis with few septa; 3: Numerous septa without cirrhosis and 4: Cirrhosis with sharp contrast



Figurer 3: Models Accuracy Comparison

5 Conclusion

- This project successfully demonstrates a deep learning-based solution for liver ultrasound image segmentation using multiple CNN architectures including Custom CNN, DenseNet169, MobileNetV2, and ResNet50.
- The models were ensembled using FLAML, which optimized the output through a weighted average of segmentation masks.
- The ensemble approach enhanced performance and robustness, aiming to deliver an accurate, mobile-friendly diagnostic tool for under-resourced healthcare settings, especially in Africa.

6 Reference

Duan, L., Shao, X., Wang, Y., Huang, Y., Miao, J., Yang, X., & Zhu, G. (2020). An investigation of mental health status of children and adolescents in china during the outbreak of COVID-19. Journal of Affective Disorders, 275, 112–118. https://doi.org/10.1016/J.JAD.2020.06.029

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