Chapter 9

Conclusion and Future Scope

The main objective of this thesis is to provide a deep learning-based solution to determine the stroke's main cause and quantify it. In this work, B-mode ultrasound images of common and internal carotid arteries are used for experiments. Further, three types of databases are used to avoid biases. The atherosclerotic plaque segmentation in ICA and CCA images has a very low percentage error. The proposed methods are efficient and shows remarkable improvements over pre-existing method. These AI-based methods are automated, reliable, and accurate. Thus, based on the results and performance numbers the systems can be used for clinical applications. This chapter discusses the major finding of each chapter and the future scope of the present study.

9.1 Significance of the Research

The significance of this research lies in its deep impact on the field of medical imaging and stroke diagnosis. By harnessing the power of deep learning algorithms, this thesis has introduced innovative and efficient methods for the segmentation of atherosclerotic plaques in common and internal carotid arteries. These advancements hold the potential to revolutionize the strokes diagnosis and treatment. The development of hybrid deep learning models, optimization of computational resources, and the exploration of multiple artery segments from diverse datasets not only improve the accuracy of plaque detection but also reduce biases, making these methods highly reliable for clinical use. Furthermore, the quest for explainability in deep learning, as addressed in this research, aligns with the growing need for transparent and interpretable AI systems in healthcare. This work serves as a foundation for future research in stroke diagnosis and paving the way for more precise and efficient tools that can assist cardiologists and radiologists and enhance patient care.

9.2 Conclusion

Chapter 3 introduces the concept of hybrid deep learning (HDL) segmentation models. These HDL models are compared with SDL models. Three SDLs (UNet, UNet+ and SegNet) and two HDLs (SegNet-UNet and SegNet-UNet+) were used with CE-loss and DSC-loss functions. Further, the CE-loss function is the best loss function for plaque area segmentation. In this work, moderate to high-risk ICA ultrasound images were used. All performance indices, such as AUC, CC, ACC, DSC, JI, FoM, and MAD, prove the system's ability to segment the ICA plaque area. These models lay the foundation of HDL models. However, the model size is large and takes longer to train. The difference between predicted and ground truth plaque area is minimal. The algorithms were trained and tested on one segment on the artery i.e. ICA with high risk plaque only. The algorithms need to test on other segment of artery such as CCA which lays the foundation of next chapter. Further, the developed model should be compared against some commercial model to check the performance in clinical settings.

The previous chapter uses HDL models for ICA plaque segmentation only. Therefore, to check the feasibility of the HDL models with other artery segments, CCA ultrasound images are used in chapter 4. The same UNet and SegNet-UNet models performed segmentation of low to moderate-risk plaque from CCA ultrasound images. Further, both models' results are compared with a commercial segmentation model AtheroEdge 2.0 (AtheroPoint LLP, Roseville, CA, USA). HDL model results are fascinating and outperform the commercial model results. The results of SDL, HDL, and AtheroEdge 2.0 models are validated by the performance metrics such as FoM, CC, AUC, and statistical tests such as paired t-test, Bland Altman's plot, and power analysis. Visual results of segmentation show a slight difference between predicted and ground truth plaque areas. Present chapter demonstrates that the algorithms work fine for both segments of artery i.e. ICA and CCA. However, the algorithms were tested on datasets from one geographic region which may present a bias in the system. Therefore, the next chapter requires research which overcomes the bias originating from demographics of the patients.

Both works in previous chapters suffer from data selection bias, i.e. data collected from the same ethnicity and centre. Thus, to make our system bias-free, chapter 5 introduces the unseen segmentation model. In this work, the segmentation model uses the Japanese database for training and the Hong Kong database for testing and vice-versa for two unseen experiments, respectively. Further, both investigations are compared with a mixed database experiment. As hypothesized earlier the mixed data experiments yield high-performance indices compared to the unseen data experiments. Also, the FoM, mean area error, and AUC numbers favour the HDL model. Conclusively unseen data experiments remove the biases originating from data selection. So far, the model is free from data selection, demographics bias. However, the clinical application also requires a fast, robust, low computation model. Therefore, the next chapter is built up on the foundation of low computation, low memory, low training time models.

Previous UNet models suffer from large memory sizes, high training time, and large training parameters. Therefore, those models are difficult for web, cloud, or Android applications. Thus, in chapter 6 few novel HDLs are presented with new features. Three novel HDLs such as Inception-UNet, Squeeze-UNet and Fractal-UNet, are proposed in this work. These models show equal performance to the SDL models. Further, all models were compared with an autoencoder-based network. This work utilized ICA and CCA databases both. Also, the system is validated on an unknown database from Hong Kong. Thus, this work is a bias-free study of a multi-ethnic, multicentre, multi-segment artery database. Also, as desired, the models show low training time, low memory size, and low training parameters. More advanced models incorporating the advance feature extraction capabilities are still required. The requirement of next chapter is built upon this fact.

In chapter 7, an attention-based new mechanism of feature extraction is presented. The attention-based mechanism can enhance the features in the spatial domain. This attention-based mechanism is deployed in the UNet model in place of skip connections. Thus, a complete attention based UNet model performs the CCA and ICA image segmentation. The attention based UNet model can segment the critical images of the CCA and ICA ultrasound by focusing on plaque areas. Visual results confirm the ability of the attention-UNet model. In chapter 8, B-mode ultrasound images of transverse CCA section are localized using a faster RCNN-based method. The method used two sets of ultrasound images from Ultrasonix and Toshiba's scanner. These images show the CCA cross-section, which is clearly localized by the Faster RCNN-based method. The method used ResNet50 backbone architecture.

9.3 Future scope

The proposed algorithms can be improved in the future by adding the following extensions to the current work.

(1) The current models lack the explainability part of the DL models. Most of the DL technique applications show black box nature, where input signal/image is provided, and the output is derived. No, explanation or interpretation of the output is given. Thus, different methods can be deployed to enhance the explainability of DL feature maps, such as gradient class activation map and SHAP (SHapley Additive exPlanation) visualization tool. Also, a feature map of individual layers can be seen, and the effect of varying depths of convolutional filters can be analysed. Using these techniques, we can avoid the black-box nature of the DL models.

(2) In the present thesis, only one artery segment, either ICA or CCA, is used for model development. We can add diversity to the model by adding the multiple artery segments such as ICA, CCA, and bulb area from multi-ethnic, multicentred, and multidevice data. By doing so, the bias in the system will be reduced, and the results will be more reliable.

(3) To enhance the clinical applicability of the proposed algorithms, future work can explore the integration of clinical data such as patient demographics, medical history, and risk factors. Combining clinical information with imaging data can provide a more holistic view of the patients' condition and aid in the personalized diagnosis and treatment planning.

(4) In chapter 6, we introduced new hybrid DL models to reduce the computational cost, memory sizes, and training time. Similarly, we could explore other segmentation models with additional features and reduced computational cost and training time.

(5) All the models presented in this study use binary masks or coordinates of the region of interest. These pieces of information guide the system in a supervised manner to determine the ROI. However, with a significantly large number of images preparation of binary masks will be challenging. Therefore, in such situations, an unsupervised or semi-supervised algorithm can be used to develop the model.

(6) Real time application of the proposed model will be another exciting area of research. Implementing the developed model on portable ultrasound device or integrating them with existing workflow can assist the healthcare professionals during patient examinations.

(7) Ongoing research should focus on enhancing the robustness and generalization capabilities of the models. Evaluating the algorithms on diverse and challenging datasets from different geographic regions and patient populations may ensure their reliability in various clinical settings.