Abstract

In the medical field, timely and accurate diagnosis of disease using multi-modal radiographic images is a very challenging task. The major issues associated with the medical field are a) limited availability of the annotated dataset, b) class imbalance, c) data overfitting issues, and d) under-segmentation and over-segmentation of the lesions. To address these issues, transfer learning-based pre-trained networks are implemented by the researchers. The transfer learning-based pre-trained models have the following advantages a) limited pre-processing pipeline, b) rapid learning, c) time complexity can be adjusted by decreasing the layers, and d) less training dataset required.

Initially, brain MRI scans are examined to diagnose the brain tumor using transfer learning. To address the data overfitting issue associated with the medical field, data augmentation techniques are used on multi-modality radiographic images. In the proposed thesis, wavelet decomposition up to N level along with statistical operation (rotation, translation, shear, etc.) is performed. The performance of the numerous pre-trained deep learning model (VGGs, ResNets, MobileNet, InceptionResNetv2, SqueezeNet, etc.) is compared with augmentation and without augmentation. Further, the impact of various cross-validation techniques, post-processing operations, and optimizers (sgdm, RmsProp, adam) on multi-modality radiographic images is evaluated.

To evaluate the robustness of the proposed methodology, a novel COVID-19 infection is diagnosed using chest radiographic images. The medical field suffers

from class imbalance issues, i.e., unequal samples are available in each class. The class imbalance issue is majorly encountered with the severity of COVID-19 infection from chest CT scans. To resolve this issue, siamese-based networks (P-shot, M-ways approach) with the pre-trained network as the base encoder is implemented. The proposed Siamses-based networks are evaluated on the Indian patients as well.

The proposed classification approach uses deep learning-based techniques for the classification of a variety of diseases, i.e., brain tumor grades (LGG, HGG), brain tumor types (Glioma, Meningioma, and Pitutaory). To segment out the tumor from brain MRI scans, color map-based superpixel technique, and DeepLabv3-based technique is used. To extract the COVID-19 infection patches from the lungs, the novel COVSeg-Net framework is used. Further, the UNet model performance is compared with the COVSegNet model for lesion segmentation.

The pre-trained network used in the diagnosis of the disease is considered a black box for clinicians. Clinicians are interested in the analysis of the reason behind the prediction made by deep learning models. Thus, the XAI approach is used to evaluate the role of numerous features in disease localization. The state-of-the-art XAI techniques that are used in the proposed work are LIME, Grad-CAM, and GradCAM++. Additionally, it refines the prediction made by the deep learning model and extracts the lesion/infection from the localized regions.

In summary, we have proposed a data augmentation-based deep learning framework for disease diagnosis using multi-modal radiographic images. This study evaluates the impact of deep learning-based networks on disease classification, localization, and segmentation from brain MRI and chest CT scans. By analyzing the decision-making process, the XAI tool helps clinicians comprehend the reasoning behind the deep learning model predictions.