PREFACE

Medical imaging, in conjunction with image processing, has been invaluable over the decades. With the exponential growth in data size and the availability of robust computational infrastructure, the training of deep neural networks for disease detection has become feasible. However, it's important to note that despite its effectiveness, this approach demands substantial computational power, which has posed a significant limitation for many researchers due to its associated costs.

To address this challenge, we have employed an alternative technique known as Deep Transfer Learning in our research. Our work is structured into two main segments: Medical Image Classification and Medical Image Segmentation.

In the first part, we have endeavored to develop methods for precise differentiation between COVID-19 and various pneumonia types using chest X-ray and CT images. We pursued this goal through two distinct approaches: a) Multiclass classification (Covid-19, Normal, Viral Pneumonia, Bacterial Pneumonia), and b) Binary Class Classification (Covid-19 vs Normal).

In the multiclass classification problem, we utilized chest X-rays to identify Covid-19 and various Pneumonia types, employing a transfer learning-based model based on the pre-trained VGG-16 classifier network. We presented our model through three case studies: Case (i) – four-class classification, Case (ii) – three-class classification, and Case (iii) – two-class classification, demonstrating robust performance across these scenarios. In the Binary Class classification problem, we introduced an efficient methodology for precise COVID-19 infection identification using CT and X-ray images. We utilized a depthwise separable convolution-based MobileNet-V2 model for feature extraction, followed by SVM classification. Our approach achieved impressive accuracies of 99.42% for CT images and 98.54% for X-ray images, with MCC scores of 0.9852 and 0.9657, respectively. These results, supported by Youden's index, signify a significant improvement in diagnosis efficiency.

Upon conducting a comprehensive literature review, we identified the importance of age and gender-specific metadata in chest X-ray datasets for accurate COVID-19 identification. Unfortunately, our selected dataset lacked such information, as it was initially compiled during the early stages of the COVID-19 pandemic when detailed demographic data was not widely available. It's worth noting that the dataset landscape has since evolved, with more comprehensive datasets now accessible. However, these larger datasets come with increased computational demands and time constraints.

While our primary emphasis was on the adult chest X-ray dataset, we acknowledge the inherent dissimilarities between adult and pediatric datasets. We are committed to delving deeper into this discrepancy by leveraging expanded datasets and enhanced computational resources.

To underscore the importance of age and gender-related biases in the realm of medical imaging and to validate our model's performance concerning age-related nuances, we took a deliberate step of acquiring a smaller dataset sample from Kaggle, specifically denoted as the children's chest X-ray dataset. This dataset comprises 1400 images, meticulously partitioned into training (1120 images) and testing (280 images) sets, encompassing three distinct classes: Normal, Viral Pneumonia, and Bacterial Pneumonia. Our model's performance in this context yielded noteworthy results: Accuracy = 67.83%, Precision = 78.79%, Recall = 81.25%, and F1-Score = 79.99%. These metrics underscore a marked variance in model performance across different age groups, thereby underscoring the significance of accounting for these factors when striving for model generalizability.

However, it is essential to acknowledge that the pursuit of training on multiple datasets, each representing diverse age groups, genders, and races, and potentially accounting for pre-existing medical conditions, entails increased computational demands and costs. Our primary research focus has centered on paving the way for automated diagnosis, serving as an initial step. The subsequent phase would involve extensive research on various datasets stratified by age, gender, demographics, and health conditions, ultimately culminating in the development of a more universally applicable model capable of delivering robust results across a spectrum of age and gender variations.

In the second part of our work, we addressed the challenge of accurate biomedical image segmentation. Traditional manual labeling by experts is time-consuming and prone to errors. To overcome these limitations, we proposed a cascade of conventional and deep learning methods. Seed Region Growing, Random Walker, and K-Means clustering were used to outline regions of interest, and the generated masks were leveraged to train a deep learning model for final segmentation.

Our proposed method was validated for left ventricle segmentation in cardiac magnetic resonance images (ACDC Dataset) and cross-validated on an unseen dataset. Moreover, we tested the segmentation pipeline with a reduced number of images at different levels (Degree I, II, and III). Evaluation metrics, including Dice score, Jaccard index, and Hausdorff distance, showcased the effectiveness of our weakly supervised approach, with competitive results compared to state-of-the-art supervised methods. Our proposed method paves the way for unsupervised biomedical image segmentation with minimal manual intervention.

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