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(Sumit Tripathi)

*Dedicated To My
Family*

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List of Abbreviations

Abbreviation	Details
MRI	Magnetic Resonance Imaging
CT	Computed Tomography
US	Ultrasound
PET	Positron Emission Tomography
LRN	Local Response Normalization
CCN	Cross Channel Normalization
FCN	Fully Convolutional Neural Network
CNN	Convolutional Neural Network
DL	Deep Learning
RELU	Rectified Linear Units
PRELU	Parametric Rectified Linear Units
mIoU	Mean of Intersection over Union
BF score	Berkley First score
BN	Batch Normalization
GN	Group Normalization
CMRI	Cardiac Magnetic Resonance Imaging
GAN	Generative Adversarial Network
SELU	Scaled exponential Linear Unit
NSB	Noise Stifler Block
NIFTI	Neuroimaging Informatics Technology Initiative

MCC	Matthews correlation coefficient
SSIM	Structural Similarity Index Measure
PSNR	Peak Signal to Noise Ratio
PDF	Probability Distribution Function
MSE	Mean Squared Error
WNNM	Weighted Nuclear Norm Minimization
NLM	Non-local Means
DnCNN	Denoising Convolutional Neural Network
LBP	Local Binary patterns
GLCM	Gray Level Co-occurrence Matrix
RF	Random Forest
SVM	Support Vector Machine
PCC	Pearson correlation coefficient
FM Index	Fowlkes-Mallows Index
BCR	Balanced Classification Rate
SARS-CoV-2	Severe Acute Respiratory Syndrome Coronavirus 2
FPR	False Positive Rate
FNR	False Negative Rate
PPV	Positive prediction value
TNR	True negative rate
TPR	True Positive Rate
GM	Geometric Mean
YI	Youden's index

Preface

Biomedical imaging has revolutionized the healthcare system as it helps in analysing the complications in the human body. The advent of computational science and its combination with medical imaging has enabled medical practitioners to provide the best diagnoses. The recent advancement in this combination has proved to be a boon for human lives as complex inner structures of the body can be analysed using these methods. A lot of non-invasive techniques has been devised in the recent past for serving humanity. MRI, Ultrasound, X-ray, Computed Tomography (CT) are the example of such techniques. MRI is an important modality that focuses on providing structural information and detailed characterization of disease. The MR images are further analyzed for finding the diseases such as brain tumour, heart vessel structures etc. For inspecting the pathological and anatomical structural changes in the body, the images are further segmented. The image segmentation aims to present the desired region of interest to the clinical practitioners to diagnose the disease. The advantages of this imaging technique are its non-ionization behaviour and better image quality with high tissue contrast resolution, but it is corrupted with the artefacts. These artefacts result from noise, patient body movement etc., which needs to be removed before analysing the images for the disease diagnosis. The MR images are corrupted with Rician noise, which gets induced because of magnetic coils of the receiver circuitry. Noise removal in MRI is of prime importance as it enhances the visual quality of the images. Biomedical image classification is another important task in the field of biomedical imaging. The image classification task allows the medical practitioner to identify different but related symptoms of the disease. It helps in identifying the features of the diseases in various modalities.

Computer-aided methods play a crucial role in biomedical image processing. The evolution of deep learning has facilitated this analysis by providing accurate and precise results automatically. Deep learning-based techniques have presented the state of the art performance in biomedical image processing. The self-learning property of these methods has eliminated the need for handcrafted features. In such a way, it has provided outstanding solution with reliable results in medical image processing.

The present work is carried out to address the critical issues as stated above that helps in better diagnosis. In this view, the research work has considered the deep learning-based methods for the segmentation and denoising the Magnetic Resonance Images. The methods proposed in this work archives remarkable improvement over their conventional counterparts. This thesis contributes to the necessary theory and implementations to improve biomedical image processing applications such as segmentation, denoising, and classification using deep learning-based methods. Chapter 1 is the introduction of the thesis, which states the current issues, objectives, and thesis contribution. Chapter 2 discusses the theoretical background of image segmentation, denoising and classification. This chapter also gives a brief outline of deep learning and transfer learning-based approaches for various applications of biomedical image processing.

Chapter 3 introduces an enhanced deep learning approach for the segmentation of brain tumour in MR images. This method was implemented using cross-channel normalization, residual connections and parametric RELU in a conventional segmentation network. The obtained results best-preserved the boundary details by explicitly delineating the contour of the tumour region. It produced exceedingly satisfactory results without retraining the network on the different dataset. Chapter 4 presents an end to end trainable segmentation network incorporated using depthwise separable convolution and group normalization for segmentation of public as well as real-time MR images. Moreover, this network also segmented the skin cancer images

with good accuracy and precision. Chapter 5 introduces a deep learning-based approach for the segmentation of real-time noise MR images. In this view, a noise stifier block is introduced between the encoder and decoder of the network. This method produced precise results in the segmentation of cardiac MR images.

Chapter 6 presents an approach for reducing the noisy components in the Magnetic Resonance Image. The motive of the presented approach is to preserve the boundary details while reducing the noisy components. In this regard, a modified deep learning-based approach is presented using depth wise separable convolution instead of regular convolution and local response normalization. This method produced good results without retraining it on other datasets. The proposed method preserved the spatial resolution to a large extent. Chapter 7 introduces a deep learning-based architecture for the classification of covid-19 infected images. Moreover, it also proposes a transfer learning-based approach for efficient classification of covid-19 infection in CT and X-ray images. The features of infection are captured using the well-known deep learning-based models, and these features are further used to train the SVM classifier. The method produced fast and reliable results. In Chapter 8, the thesis's overall contribution and its future directions have been enlisted, which might be of interest for further research in this area.