Abstract

Advances in biomedical imaging have greatly enhanced medical diagnosis and research by giving comprehensive insights into biological structures and processes at many level. However, accurate analysis and interpretation of biomedical images might be limited by low contrast, noise, imaging artifacts, and inconsistencies resulting from different acquisition settings. This thesis tackles these problems by creating advanced computational algorithms for multi-scale biomedical image processing, ranging from a cellular microscopy level and going up to an organ macroscopic level, spanning both in vitro and in vivo imaging modalities, specifically Optical Coherence Microscopy (OCM), fluorescence microscopy, and dermoscopic imaging. Organoids—simplified in vitro organ models—are vital for understanding organ development and disease progression, necessitating precise monitoring. At the microscale, Optical Coherence Microscopy (OCM), a high-resolution variant of Optical Coherence Tomography (OCT), IS employed to extract biological information, study growth patterns, and assess therapy effectiveness. However, OCM images usually suffer from speckle noise and poor contrast, which hinder accurate segmentation and tracking. To overcome these limitations, an AI-based segmentation system was developed, employing convolutional neural networks (CNN) combined with heuristic preprocessing techniques to enhance image quality prior to segmentation. The resulting automatic masks were processed by a custom tracking algorithm, enabling precise delineation and longitudinal monitoring across multiple time points. Quantitative assessments demonstrated high accuracy and robustness of the proposed methods on substantial datasets, effectively monitoring organoid growth and evaluating therapeutic responses.

Subsequently, at the tissue scale, fluorescence microscopy plays a crucial role in labeling and visualizing molecular and cellular components, providing essential insights into tissue dynamics and pathology. However, this imaging modality faces significant constraints, including low contrast, excessive noise, and unwanted aut-

ofluorescence. Additionally, many biological specimens are extremely fragile, and high-energy image acquisition can lead to their destruction. Therefore, there is a critical need for methods that enhance low-energy acquisitions to preserve sample integrity while maintaining image quality. To address these challenges, a hybrid image improvement framework was developed, combining deep learning approaches with heuristic methods. This framework incorporates adaptive brightness control, noise reduction utilizing wavelet transforms, and sharpness enhancement. Furthermore, a deep neural network was employed for autofluorescence correction. The enhanced images exhibit significant improvements in contrast and clarity, facilitating more accurate analysis and increasing the accuracy of downstream tasks such as segmentation, all while minimizing energy exposure to delicate samples.

At the macro-scale, dermatological imaging plays a critical role in diagnosing skin conditions, providing essential insights into various dermatological diseases. However, challenges such as uneven lighting and image deterioration can compromise diagnostic accuracy. To address these issues, generative adversarial network (GAN) models were developed for color constancy and super-resolution in digital dermoscopic images. Utilizing a heuristic-driven approach, these models rectify color disparities arising from different imaging settings and enhance image quality by recovering high-frequency details lost due to poor resolution or compression artifacts. Specialized, semi-automatic heuristic algorithms were employed to create appropriate target examples for training the GAN models, thereby improving their ability to generalize across diverse imaging conditions and ensuring more robust performance. The methodologies were validated through quantitative assessments and dermatologist evaluations, demonstrating significant improvements in image consistency, AI analysis, and the accuracy of dermatologists' diagnoses.

Overall, this thesis introduces a set of advanced computational algorithms that enhance biomedical image processing across many dimensions and modalities. These strategies enhance quantitative algorithms for biomedical imaging by addressing issues related to image quality and consistency, thereby increasing accuracy and reliability for better diagnostic and research outcomes. The presented methodologies offer the potential for incorporation into clinical workflow, enhancing the application of computational innovations in practical medical settings.