Abstract

This dissertation investigates how to design artificial-intelligence systems for medical and biologically relevant image analysis that remain accurate, data-effcient, computationally feasible, and reliable in the presence of annotation ambiguity. The work is structured as a cumulative research program that spans custom neural architectures for classification, semantic segmentation, synthetic data generation, and fuzzy uncertainty modeling. These studies culminate in a semi-supervised Transformer framework for hematological semantic segmentation that combines stain-aware preprocessing, pooled-memory global attention, spectral compression, masked supervision, and RGB robust fuzzy C-means regularization within a single training pipeline. Across the dissertation, the results show that domain-adapted architectures and principled data-effciency strategies can outperform generic baselines in small-data scientific settings, while fuzzy modeling improves behavior on ambiguous borders and weakly annotated regions. The final hematological system achieves 99.73% validation accuracy, 99.73% micro-Dice, and 99.46% micro-IoU in a low-label regime, supporting the thesis that effcient long-range context modeling and uncertainty-aware semi-supervision can be integrated into a practical framework for blood-smear microscopy.

Keywords: medical image analysis, semantic segmentation, transformer, semisupervised learning, fuzzy logic, hematological microscopy