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Medical Image Learning with Limited and Noisy Data

First International Workshop, MILLanD 2022
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Preface

Deep learning (DL)-based computer-aided diagnostic systems have been widely and successfully studied for analyzing various image modalities such as chest X-rays, computed tomography, ultrasound, and optical imaging including microscopic imagery. Such analyses help in identifying, localizing, and classifying disease patterns as well as staging the extent of the disease and recommending therapies. Although DL approaches have a huge potential to advance medical imaging technologies and potentially improve quality and access to healthcare, their performance relies heavily on the quality, variety, and size of training data sets as well as appropriate high-quality annotations. In the medical domain, obtaining such data sets is challenging due to several privacy constraints and tedious annotation processes. Further, real-world medical data tends to be noisy and incomplete leading to unreliable and potentially biased algorithm performance. To mitigate or overcome training challenges in imperfect or data-limited scenarios, several training techniques have been proposed. Despite the successful application of these techniques in a wide range of medical image applications, there is still a lack of theoretical and practical understanding of their learning characteristics and decision-making behavior when applied to medical images.

This volume presents novel approaches for handling noisy and limited medical image data sets. This collection is derived from articles presented in the workshop titled “Medical Image Learning with Noisy and Limited Data (MILLanD)” that was held in conjunction with the 25th International Conference on Medical Image Computing and Computer Assisted Intervention (MICCAI 2022). The workshop brought together machine learning scientists, biomedical engineers, and medical doctors to discuss the challenges and limitations of current deep learning methods applied to limited and noisy medical data and present new methods for training models using such imperfect data. The workshop received 54 full-paper submissions in various topics including efficient data annotation and augmentation strategies, new approaches for learning with noisy/corrupted data or uncertain labels, weakly-supervised learning, semi-supervised learning, self-supervised learning, and transfer learning strategies. Each submission was reviewed by 2–3 reviewers and further assessed by the workshop’s chairs. The workshop’s reviewing process was double-blind, i.e., both the reviewer and author identities were concealed throughout the review process. This process resulted in the selection of 22 high-quality papers that are included in this volume.

August 2022

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