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Meta-Learning for Rapid Adaptation and Generalization

in Medical Image Classification

Master's Thesis in Computer Science

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Abstract

This thesis investigates the application of meta-learning approaches for rapid adaptation in medical image classification, with a particular focus on prostate cancer and colorectal cancer detection. Classical deep learning models require large annotated datasets and extensive retraining when applied to new tasks, which is a critical limitation in medical imaging where labeled data is scarce. Meta-learning, or "learning to learn", enables models to acquire transferable knowledge across tasks and adapt efficiently to new classification problems with minimal labeled examples. In parallel, self-supervised learning (SSL) is explored as an independent pretraining strategy to extract rich and generalizable visual representations from unlabeled medical images, without relying on manual annotations. We evaluate state-of-the-art meta-learning algorithms including Model-Agnostic Meta-Learning (MAML) and Prototypical Networks as well as SSL-based approaches, on histopathological image datasets for prostate and colorectal cancer classification. Our proposed approaches demonstrate significant improvements in few-shot adaptation performance compared to conventional transfer learning baselines.

Keywords: meta-learning, few-shot learning, medical image classification, rapid adaptation, prostate cancer, colorectal cancer, MAML, Prototypical Networks, deep learning, convolutional neural networks, self-supervised learning, histopathology.

Résumé

Cette thèse porte sur l'application des approches de méta-apprentissage pour l'adaptation rapide dans la classification d'images médicales, en se concentrant sur la détection du cancer de la prostate et du cancer colorectal. Les modèles d'apprentissage profond classiques nécessitent de grandes quantités de données annotées et un réentraînement intensif lors de l'application à de nouvelles tâches, ce qui constitue une limitation majeure en imagerie médicale où les données étiquetées sont rares. Le méta-apprentissage, ou « apprendre à apprendre », permet aux modèles d'acquérir des connaissances transférables entre différentes tâches et de s'adapter efficacement à de nouveaux problèmes de classification avec un nombre minimal d'exemples. En parallèle, l'apprentissage auto-supervisé (SSL) est exploré de manière indépendante comme stratégie de pré-entraînement, permettant d'extraire des représentations visuelles riches et généralisables à partir d'images médicales non étiquetées, sans recourir à des annotations manuelles. Nous évaluons des algorithmes de méta-apprentissage de pointe notamment MAML et les réseaux prototypiques ainsi que des approches basées sur le SSL, sur des ensembles d'images histopathologiques pour la classification du cancer de la prostate et du cancer colorectal, en démontrant des améliorations significatives par rapport aux approches classiques de transfert d'apprentissage.

Mots-clés : méta-apprentissage, apprentissage par peu d'exemples, apprentissage auto-supervisé, classification d'images médicales, adaptation rapide, cancer de la prostate, cancer colorectal, MAML, réseaux prototypiques, apprentissage profond, réseaux de neurones convolutifs, histopathologie.

Contents

1 Introduction and Medical Background **1**

1.1 Introduction 1

1.2 Prostate Cancer 2

1.2.1 Epidemiology and Clinical Significance 2

1.2.2 Prostate Anatomy and Cancer Zones 3

1.2.3 Histological Grading: The Gleason Score and ISUP Grade Groups . 3

1.2.4 Histopathological Image Analysis in Prostate Cancer 4

1.3 Colorectal Cancer 6

1.3.1 Epidemiology and Clinical Significance 6

1.3.2 Histopathological Tissue Analysis in Colorectal Cancer 6

1.3.3 From Slides to Digital Images: Computational Pathology 7

1.4 Why AI Deployment in Cancer Imaging Is Difficult 8

1.4.1 The Data Annotation Problem 8

1.4.2 Class Imbalance 9

1.4.3 Domain Shift Between Clinical Sites 9

1.4.4 The Few-Shot Learning Formulation 9

1.5 Research Objectives and Thesis Structure 10

1.5.1 Research Objectives 10

2 State of the Art **12**

2.1 Introduction 12

2.2 Artificial Intelligence 12

2.3 Machine Learning 13

2.3.1 Machine Learning Concepts 13

2.3.2 Machine Learning Types 16

2.3.3 Optimization in Deep Learning 16

2.3.4 Key Training Parameters 17

2.4 Convolutional Neural Networks (CNN) 17

2.4.1 Convolutional Layer 18

2.4.2 Pooling Layer 18

2.4.3 Activation Functions 18

2.4.4 Pre-trained Architectures and Transfer Learning 18
2.5 Deep Learning in Medical Imaging: Limitations and Challenges 19
2.6 Meta-Learning 20
2.6.1 Fundamental Concepts 21
2.6.2 Categories of Meta-Learning Approaches 22
2.6.3 Meta-Learning for Medical Image Analysis 29
2.6.4 Domain Generalization and Adaptation in Medical Imaging 31
2.6.5 Challenges and Limitations of Meta-Learning 32
2.6.6 Meta-Learning Benchmarks and Evaluation Protocol 33
2.6.7 Recent Advances in Meta-Learning (Post-2021) 34
2.7 Related Work 34
2.7.1 Deep Learning for Medical Image Segmentation and Detection . . . 34
2.7.2 Foundational Meta-Learning and Few-shot Learning Methods . . . 35
2.7.3 Deep Learning for Prostate Cancer Detection Using Histopathological Images 35
2.7.4 Deep Learning for Colorectal Cancer Tissue Classification 35
2.7.5 Positioning of the Present Work 36
2.8 Self-Supervised Learning 36
2.8.1 Pretext Tasks 37
2.8.2 Contrastive Learning 37
2.8.3 Masked Image Modeling 40
2.8.4 SSL Evaluation Protocols 41
2.8.5 Self-Supervised Learning for Medical Image Analysis 41
2.9 Summary 43

3 Datasets and Implementation Tools **44**
3.1 Introduction 44
3.2 Dataset Description 44
3.2.1 NCT-CRC-HE-100K 44
3.2.2 SICAPv2 46
3.3 Dataset Grouping 47
3.3.1 NCT-CRC-HE-100K 47
3.3.2 SICAPv2 47
3.3.3 Episode Configuration 47
3.4 Preprocessing 48
3.5 Data Augmentation 49
3.6 Data Balancing 49
3.7 Implementation Frameworks and Tools 50
3.7.1 Python 50

3.7.2 PyTorch . . . 50
3.7.3 Torchvision . . . 50
3.7.4 Higher . . . 50
3.7.5 NumPy . . . 51
3.7.6 Scikit-learn . . . 51
3.7.7 Matplotlib . . . 51
3.7.8 Seaborn . . . 51
3.7.9 Pillow . . . 51
3.7.10 Kaggle . . . 51
3.8 Model Evaluation Metrics . . . 52
3.8.1 Accuracy . . . 52
3.8.2 Recall . . . 52
3.8.3 Precision . . . 53
3.8.4 F1-Score . . . 53
3.8.5 Confusion Matrix . . . 53
3.9 Summary . . . 53

4 Experiments and Results **55**
4.1 Introduction . . . 55
4.2 Experimental Setup . . . 55
4.3 Experiment 1: ProtoNet on NCT-CRC-HE-100K (In-Domain) . . . 56
4.3.1 Configuration . . . 56
4.3.2 Algorithm: Prototype Classification . . . 56
4.3.3 Test Results . . . 57
4.4 Experiment 2: ProtoNet on SICAPv2 (In-Domain) . . . 59
4.4.1 Configuration . . . 59
4.4.2 Algorithm: Early Stopping on Small Datasets . . . 59
4.4.3 Test Results . . . 59
4.5 Experiment 3: ProtoNet Cross-Domain (CRC → SICAPv2) . . . 60
4.5.1 Configuration . . . 60
4.5.2 Test Results . . . 62
4.6 Experiment 4: SSL (MoCo v2) Cross-Domain . . . 64
4.6.1 Configuration . . . 64
4.6.2 Algorithm: MoCo v2 Self-Supervised Pre-training . . . 64
4.6.3 Test Results . . . 65
4.7 Experiment 5: MAML on NCT-CRC-HE-100K (In-Domain) . . . 66
4.7.1 Configuration . . . 66
4.7.2 Algorithm: MAML Inner Loop via `higher` . . . 67
4.7.3 Test Results . . . 67

4.8 Experiment 6: MAML on SICAPv2 (In-Domain) . . . 68
4.8.1 Configuration . . . 68
4.8.2 Algorithm: Partially Frozen with Dropout Head . . . 69
4.8.3 Test Results . . . 69
4.9 Experiment 7: MAML Cross-Domain (CRC → SICAPv2) . . . 70
4.9.1 Configuration . . . 70
4.9.2 Algorithm: Cross-Domain Adaptation at Test Time . . . 71
4.9.3 Test Results . . . 71
4.10 Comparative Analysis . . . 73
4.10.1 Overall Performance Comparison . . . 73
4.10.2 ProtoNet versus MAML . . . 74
4.10.3 In-Domain versus Cross-Domain Performance . . . 74
4.10.4 Embedding Space Visualizations . . . 75
4.10.5 Statistical Significance . . . 76
4.10.6 Error Analysis . . . 76
4.10.7 Ablation Study . . . 76
4.10.8 Key Findings . . . 77
4.11 Limitations . . . 78
4.12 Summary . . . 78

Glossary of Abbreviations **79**

A Algorithm Pseudocode **81**
A.1 Siamese Networks . . . 81
A.2 Matching Networks . . . 81
A.3 Reptile . . . 81
A.4 Meta-SGD . . . 81
A.5 Gradient Descent . . . 81
A.6 Stochastic Gradient Descent (SGD) . . . 82

B Consolidated Hyperparameter Table **83**

C Misclassified Patch Examples and Error Analysis **84**
C.1 Experiment 1: ProtoNet on CRC (5-way 5-shot) . . . 84
C.2 Experiment 2: ProtoNet on SICAPv2 (2-way 5-shot) . . . 85
C.3 Experiment 3: ProtoNet Cross-Domain (CRC → SICAPv2) . . . 85
C.3.1 Benign patches misclassified as cancer . . . 86
C.3.2 Cancer patches misclassified as benign . . . 87
C.4 Experiment 4: SSL Cross-Domain . . . 88
C.5 Experiment 5: MAML on CRC (5-way 5-shot) . . . 88