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A Comparative Study of Vision Transformer Encoders and Few-shot Learning for Medical Image Classification

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Abstract

Computer vision has been significantly impacted by Vision Transformer (ViT) networks. However, most existing deep learning-based methods primarily rely on a lot of labeled data to train reliable classifiers for accurate prediction. This requirement might be impractical in the medical field.

This study explores the application of ViT in few-shot learning scenarios for medical image analysis, addressing the challenges posed by limited data availability. We evaluate various ViT models alongside few-shot learning algorithms, perform cross-domain experiments, and analyze the impact of data augmentation techniques.

Our findings indicate that when combined with ProtoNets, ViT architectures outperform CNN-based counterparts and achieve competitive performance against SOTA approaches on benchmark datasets.

Motivation

- Vision Transformers (ViTs) have emerged as an alternative to CNNs, showing impressive performance on various tasks.
- CNNs struggle with learning long-range pixel relationships due to locality, which ViTs can handle more effectively.
- Medical imaging often has limited labeled data, making it difficult to train deep learning models.
- Few-shot learning (FSL) is a promising approach for handling limited labeled data.

Goal

To our knowledge, ViT architectures have not been used in the field of medical image classification in few-shot learning scenarios. Therefore, given their success in other areas of computer vision, it is important to assess their performance in this area under various conditions.

Contribution

- Investigate the efficacy of various ViT models for few-shot medical image classification.
- Study how different few-shot learning algorithms impact the performance of ViT models.
- Analyze the impact of advanced data augmentation techniques on ViT models.
- Explore the effect of a cross-domain scenario on the performance of few-shot learners.
- framework through experiments when running on the Spark clusters.
- Our methods achieve state-of-the-art performance on challenging medical datasets of few-shot medical image classification

References

- Zhiyong et al., Pfemed: Few- shot medical image classification using prior guided feature enhancement. Pattern Recognition, 2023.
- Rishav et al., Metamed: Few-shot medical image classification using gradient-based meta-learning. Pattern Recognition 2021.
- Yisheng et al., A comprehensive survey of few-shot learning: Evolution, applications, challenges, and opportunities. arXiv preprint arXiv:2205.06743, 2022

Methodology

Problem definition:

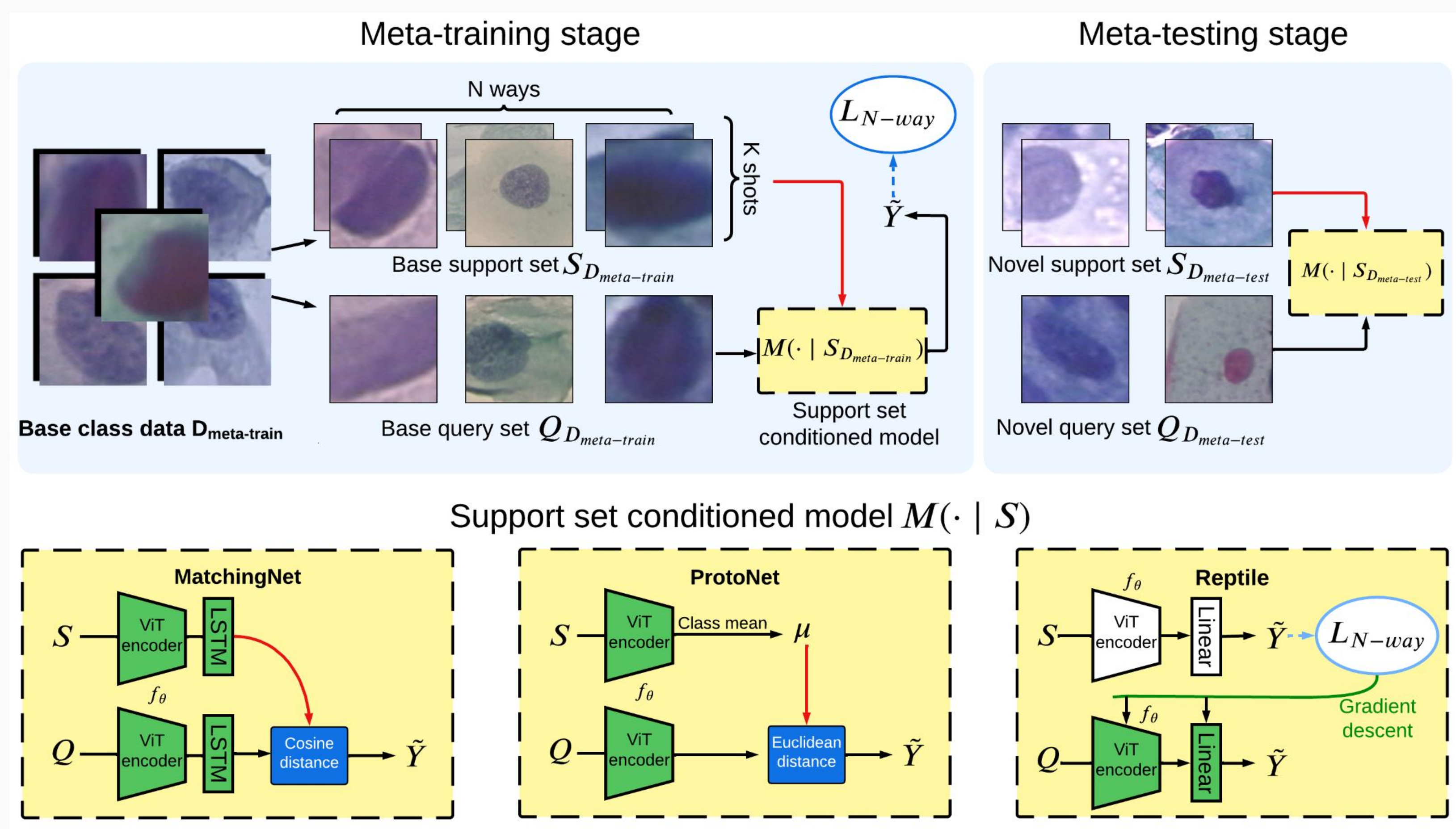
Let D = D_1, D_2, ..., D_n be a collection of n medical datasets, with each dataset D_k consisting of pairs $(x, y)_j$ representing an image and its label.

Datasets are divided into meta-test set ($D_{meta\text{-}test}$) and meta-train set ($D_{meta\text{-}train}$)

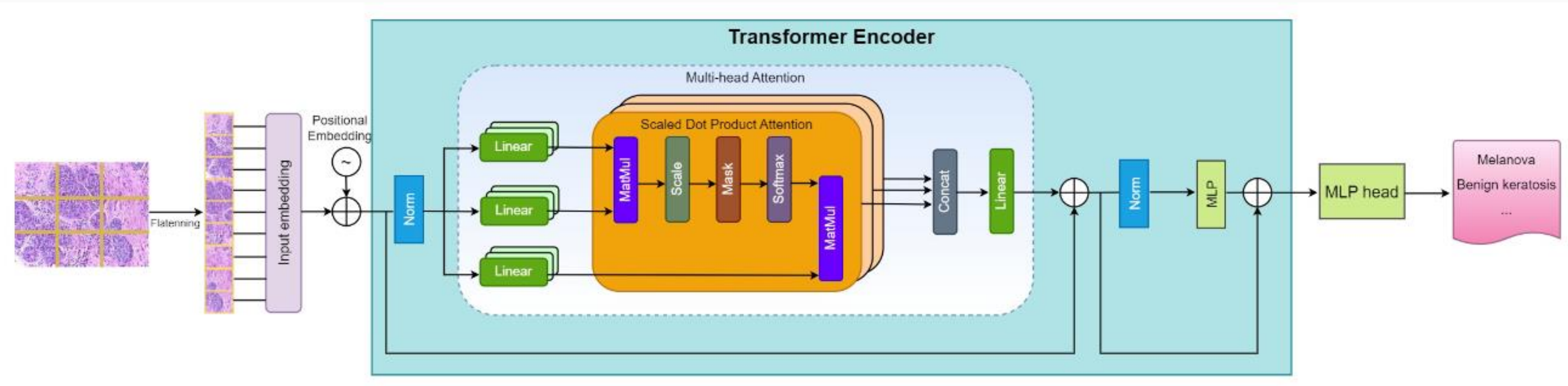
Utilize abundant data in $D_{meta\text{-}train}$ to learn better initial weights (Reptile) or develop effective embedding space (ProtoNet & MatchingNet)

Goal: Improve performance on problems $D_{meta\text{-}test}$ with limited data (novel class data)

Overview of the system pipeline



ViT Encoder:



Results

- **Datasets**: BreakHis (9109 microscopic images of breast tumor tissues from 82 patients with 8 classes), ISIC 2018 (10,015 dermoscopic images of skin lesions across 7 classes), and Pap Smear (917 microscopic images of cervical smears with 7 classes).
- **Experimental Settings**: Pre-trained models obtained from the timm library.
  - ProtoNet: 20 epochs, 500 episodes per epoch, SGD optimizer, learning rate of 10-5 or 10-6, cosine annealing learning rate schedule.
  - Reptile: SGD optimizer, learning rate of 10-3 for inner optimization, learning rate of 10-1 for outer meta-update, 1000 meta-iterations, batch size of 10 tasks, 5 and 50 adaptation steps for each task
- **Evaluation metric**: Accuracy (%) as evaluation metric. 400 episodes randomly selected from novel categories in the test set. Average accuracy rate for image classification.

Algorithm	Model	2-way			3-way		
		3-shot	5-shot	10-shot	3-shot	5-shot	10-shot
ProtoNet	MViT	74.64	76.94	81.50	60.60	64.23	69.23
	ViT_tiny	81.03	83.61	86.52	67.84	71.82	77.68
	ViT_small	**84.35**	**86.70**	89.72	72.10	76.18	81.45
	ViT_base	83.94	86.02	**90.26**	**72.75**	**77.69**	**81.99**
	DeIT_base	72.17	76.53	81.40	57.86	62.38	69.07
	Swin_base	82.49	84.17	89.12	70.75	74.67	79.92
	ResNet50	66.62	68.65	72.81	51.43	53.83	58.34
	VGG16	74.11	78.17	82.11	60.68	64.58	70.84
Reptile	MViT	62.80	67.00	71.80	53.00	54.47	60.33
	ViT_tiny	75.80	78.40	83.50	64.13	68.67	75.13
	ViT_small	70.30	76.10	80.40	63.13	72.13	78.53
	ViT_base	59.30	67.40	72.70	53.27	62.27	70.53
	DeIT_base	72.80	79.40	83.00	61.73	64.73	73.60
	Swin_base	67.30	74.20	81.10	60.60	69.00	75.93
	ResNet50	71.70	72.70	76.50	47.60	51.60	54.93
	VGG16	64.70	72.90	78.60	56.53	62.40	70.67
MatchingNet	MViT	72.41	75.70	78.59	58.79	62.00	65.62
	ViT_tiny	76.66	79.88	83.41	63.42	66.62	71.95
	ViT_small	78.40	81.61	86.34	65.50	70.00	76.47
	ViT_base	79.81	84.19	88.21	67.70	73.30	79.17
	DeIT_base	73.67	77.11	81.60	58.23	62.54	70.47
	Swin_base	72.84	75.60	80.12	58.66	63.09	68.34
	ResNet50	67.99	71.69	75.66	52.93	56.53	61.60
	VGG16	72.20	75.94	79.90	59.76	61.63	67.98

Performance of models using different meta-learning algorithms for ISIC 2018 dataset

Algorithm	Model	2-way			3-way		
		3-shot	5-shot	10-shot	3-shot	5-shot	10-shot
Protonet	MViT	80.84	84.36	86.88	68.04	73.24	78.37
	ViT_tiny	84.65	86.96	88.86	74.33	77.92	81.17
	ViT_small	**92.40**	**94.05**	**94.90**	**86.38**	**89.09**	**90.62**
	ViT_base	92.05	93.26	93.94	85.21	88.48	89.47
	DeIT_base	88.88	89.38	91.22	78.77	81.70	85.28
	Swin_base	85.42	87.56	89.78	75.73	79.88	82.46
	ResNet50	70.49	71.75	69.61	57.74	58.48	59.60
	VGG16	88.75	89.34	91.76	79.04	82.53	85.63
Reptile	MViT	80.60	80.20	84.30	72.00	73.20	78.87
	ViT_tiny	85.60	88.00	90.10	75.27	82.47	86.00
	ViT_small	86.80	90.70	93.90	77.73	82.27	87.00
	ViT_base	77.10	81.50	88.00	70.53	78.27	88.07
	DeIT_base	84.40	87.30	92.50	76.20	82.33	86.27
	Swin_base	81.40	87.20	87.40	80.47	81.53	87.87
	ResNet50	80.90	82.00	89.30	73.67	75.87	81.73
	VGG16	84.90	88.80	93.20	77.73	81.67	88.60
MatchingNet	MViT	80.10	81.97	85.32	67.61	72.27	76.35
	ViT_tiny	86.00	89.09	90.91	77.34	80.92	83.93
	ViT_small	90.84	92.56	94.27	84.74	87.02	89.23
	ViT_base	89.56	89.50	92.10	78.24	82.53	86.33
	DeIT_base	89.25	89.36	91.70	79.43	82.39	85.16
	Swin_base	82.01	83.58	86.94	70.34	74.38	78.27
	ResNet50	76.01	74.46	77.89	59.66	61.23	64.08
	VGG16	87.66	88.30	89.94	77.07	79.60	83.45

Performance of models using different meta-learning algorithms for Pap Smear dataset

Algorithm	Model	FSL	2-way			3-way		
			3 shot	5 shot	10 shot	3 shot	5 shot	10 shot
ProtoNet	ViT_small	Standart	**84.35**	**86.70**	**89.72**	**72.10**	76.18	**81.45**
		CutOut	81.73	85.89	89.22	70.55	**76.23**	81.13
		MixUp	-	-	-	-	-	-
		CutMix	-	-	-	-	-	-
	ResNet50	Standart	**66.62**	68.65	**72.81**	**51.43**	**53.83**	**58.34**
		CutOut	65.52	**68.75**	72.18	49.32	53.81	57.74
		MixUp	-	-	-	-	-	-
		CutMix	-	-	-	-	-	-
Reptile	ViT_small	Standart	76.05	80.30	85.55	**67.50**	**73.15**	77.37
		CutOut	75.30	**80.35**	83.95	64.87	69.97	76.53
		MixUp	**77.50**	79.40	**85.75**	66.20	71.33	77.87
		CutMix	74.85	77.75	85.65	67.40	72.57	**79.63**
	ResNet50	Standart	70.28	**75.78**	**78.83**	54.47	58.22	61.58
		CutOut	68.73	73.60	76.58	**55.70**	59.90	64.67
		MixUp	**70.75**	74.15	78.03	55.00	**60.65**	**64.95**
		CutMix	70.10	74.60	77.95	53.70	58.92	63.62

Effect of different Augmentation techniques on Few-shot classification for ISIC 2018 Dataset

Target	Setting	2-way			3-way		
		3-shot	5-shot	10-shot	3-shot	5-shot	10-shot
BreakHis X100	CD + PN	74.12	78.74	84.11	62.72	68.90	74.72
	Non CD	**80.64**	**83.80**	**87.62**	**69.39**	**75.91**	**81.47**
Pap Smear	CD + PN	**92.22**	**94.12**	94.85	86.22	88.82	90.47
	Non CD	92.40	94.05	**94.90**	**86.38**	**89.09**	**90.62**

Cross-domain ISIC2018-to-BreakHis and -Pap smear

Algorithm	Model	2-way			3-way		
		3-shot	5-shot	10-shot	3-shot	5-shot	10-shot
ProtoNet	ViT_small	**84.35**	**86.70**	**89.72**	**72.10**	**76.18**	**81.45**
	ResNet50	66.62	68.65	72.81	51.43	53.83	58.34
MatchingNet	ViT_small	78.40	81.61	86.34	65.50	70.00	76.47
	ResNet50	67.99	71.69	75.66	52.93	56.53	61.60
Reptile	ViT_small	76.05	80.30	85.55	67.50	73.15	77.37
	ResNet50	70.28	75.78	78.83	54.47	58.22	61.58
	MetaMed[20]	72.75	75.62	81.37	54.83	59.33	69.75
-	PFEMed[6]	81.69	83.87	85.14	66.94	69.78	73.81

Comparison with MetaMed and PFEMed on ISIC 2018

Algorithm	Model	2-way			3-way		
		3-shot	5-shot	10-shot	3-shot	5-shot	10-shot
ProtoNet	ViT_small	80.64	83.80	87.62	**69.39**	**75.91**	81.47
	ResNet50	68.62	72.12	73.31	55.80	60.28	61.88
MatchingNet	ViT_small	76.53	82.09	**88.33**	67.13	72.88	**81.80**
	ResNet50	73.45	76.58	79.14	59.53	62.70	66.98
Reptile	ViT_small	68.10	75.60	81.60	54.40	63.13	72.20
	MetaMed[20]	78.75	81.38	83.88	63.08	66.42	74.08
-	PFEMed[6]	**82.16**	**85.28**	86.90	69.21	75.04	78.93

Comparison with MetaMed and PFEMed on BreakHis