

Deep kNN for Medical Image Classification

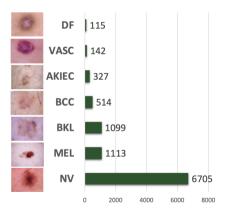
Jia-Xin Zhuang¹, Jiabin Cai¹, Ruixuan Wang¹, Jianguo Zhang², Wei-Shi Zheng¹

¹School of Data and Computer Science, Sun Yat-sen University, China

²Department of Computer Science and Engineering, Southern University of Science and Technology, China.

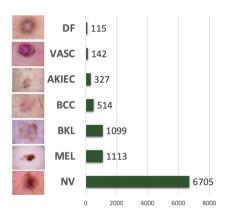
MICCAI 2020

Motivation



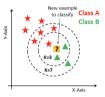
Data imbalance is common in medical diagonsis.

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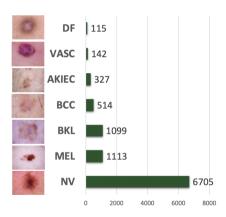


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kNN only use a few neighboring data.

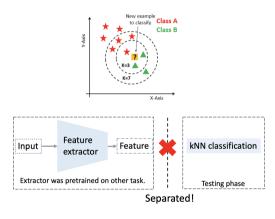


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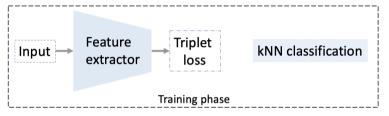


Task irrelevant feature will degrade the performance of kNN.

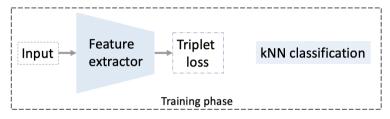
Related work

- ► Feature learning for kNN:
 - ► Traditional metric learning methods: Neighborhood Component Analysis, Large Margin Nearest Neighbor methods.
 - Pretrained Model as feature extractor, such as VGG, ResNet.
 - Triplet based methods.
- ► Alleviate data imbalance:
 - Oversampling, augmentation.
 - Transfer learning, ensemble model.
 - Class Weighting (cost sensitive learning), instance weighting.

Framework of deep kNN (training)

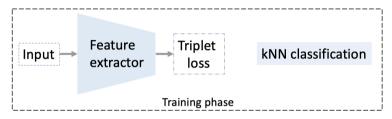


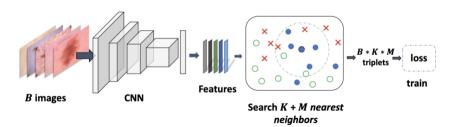
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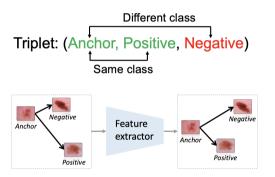


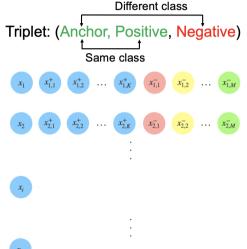


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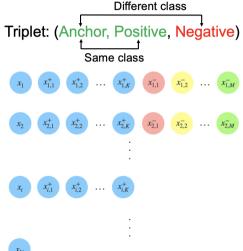






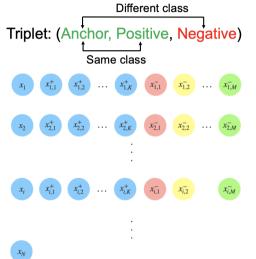


Generate triplets for \mathbf{x}_i :



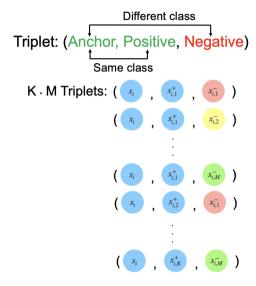
Generate triplets for \mathbf{x}_i :

► K nearest neighbors $\{\mathbf{x}_{i,k}^+\}$ of the same class.



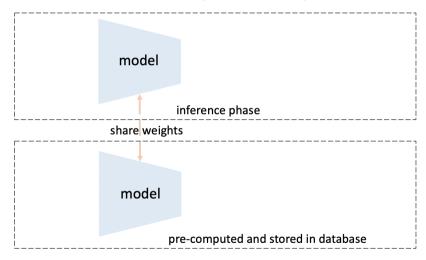
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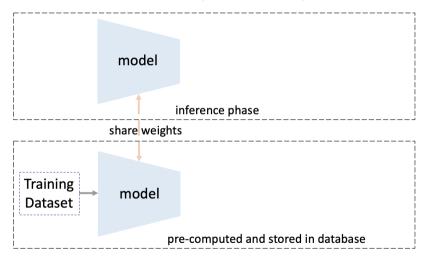
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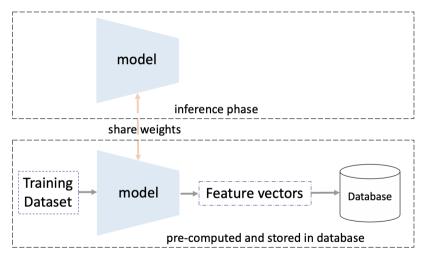


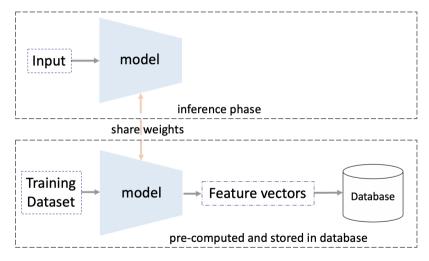
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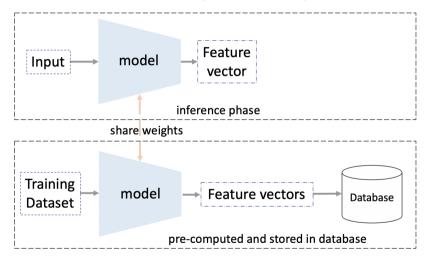
- \triangleright K nearest neighbors $\{\mathbf{x}_{i,k}^+\}$ of the same class.
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- K and M neighbors are used to generate K · M triplets.

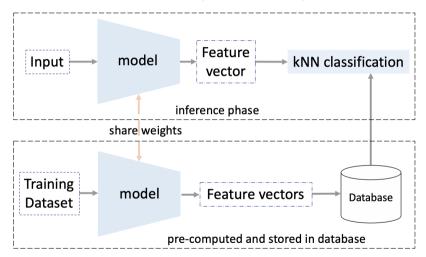












Experiments on baseline

Deep kNN outperforms baselines

Experiments on baseline

Deep kNN outperforms baselines particularly on small classes with a large margin

Datasets		Skin-7		F	Pneumonia SD-198				
Methods	Acc	MCR	RS	Acc	MCR	RS	Acc	MCR	RS
kNN (VGG19, $K_p = 5$)	70.72	30.77	10.34	55.42	55.71	44.97	15.12	13.28	4.17
kNN (ResNet50, $K_p = 5$)	74.41	37.53	34.48	55.52	54.66	39.65	19.11	17.45	12.50
Triplet(ResNet50, $K_p = 5$)	84.29	68.31	67.34	70.00	68.73	66.32	60.17	60.02	47.21
deep kNN (ours, $K_p = 5$)	89.1	78.9	77.3	71.1	69.4	69.0	65.1	64.3	48.3
Weighted-CE(ResNet50) deep kNN* (ours, $K_p = 5$)	88.02	80.21	76.60	71.12	69.11	70.05	61.90	62.40	47.67
	90.3	81.0	80.4	71.6	71.1	70.9	66.4	66.4	51.5

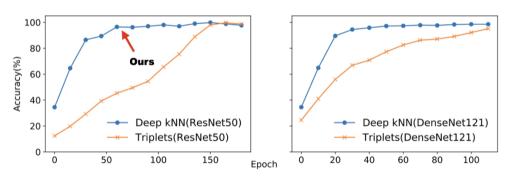
Works with Multilayer perceptron structure

Methods k	NN-basic	NCA	LMNN	MLP + triplets	MLP+CE	MLP+deep-kNN
Acc	64.53	75.06	81.85	77.13	78.85	85.09
MCR	34.49	36.39	61.78	62.22	63.11	66.08
RS	10.34	27.59	62.07	63.43	64.21	67.30

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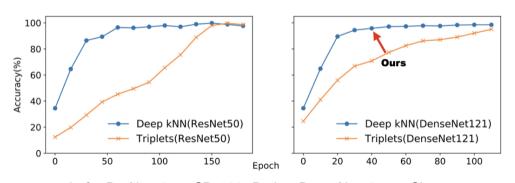
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Faster than traditional triplet loss.



Left: ResNet50 on SD-198; Right: DenseNet121 on Skin-7.

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Models	VGG19		ResNet50		Dense121		SE-ResNet50	
	kNN	deep kNN	kNN	deep kNN	kNN	deep kNN	kNN	deep kNN
Acc	59.16	61.51 +2.35↑	60.17	65.12 +4.95↑	60.54	64.02 +3.48↑	61.85	62.79 +0.94↑
MCR RS	56.33 43.12	61.93+5.60↑ 45.43+2.89↑	57.35 46.01	64.34 +6.99↑ 48.31 +2.30↑	60.12 50.42	65.11 +4.99↑ 52.21 +1.79↑	59.32 50.01	62.27 +4.99↑ 53.12 +3.11↑
K3	45.12	43.43 +2.89年	40.01	40.31 +2.30↑	50.42	32.21 +1.79↑	50.01	33.12 +3.11↑

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Acknowledgement

Thanks for watching.



This work is supported in part by the National Key Research and Development Program (grant No. 2018YFC1315402), the Guangdong Key Research and Development Program (grant No. 2019B020228001), the National Natural Science Foundation of China (grant No. U1811461), and the Guangzhou Science and Technology Program (grant No. 201904010260).