Histopathology Image Classification using Deep Manifold Contrastive Learning

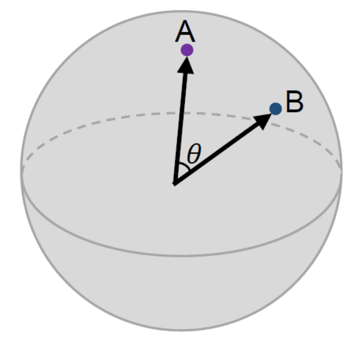
Jing Wei Tan *Won-Ki Jeong*

Department of Computer Science and Engineering, Korea University, Seoul, Korea

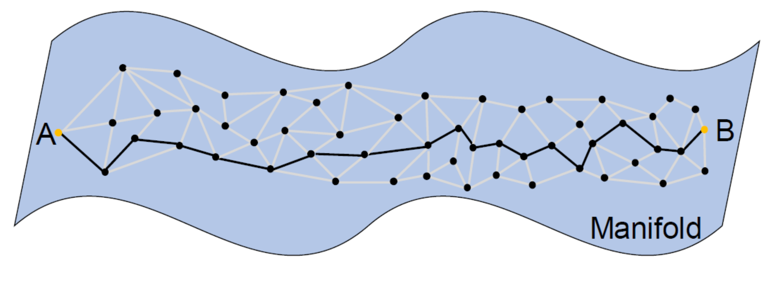
INTRODUCTION

Problems:

1. Multiple instance learning (MIL)
   - Does not require perfect per-patch label assignment.
   - It is important to construct good feature vectors to make the classification more accurate.
2. Cosine distance
   - A commonly used distance metric in contrastive learning
   - Approximates the difference between local neighbors and is insufficient to represent the distance between far-away points on a complicated, nonlinear manifold.



(a) Cosine Distance



(b) Geodesic Distance

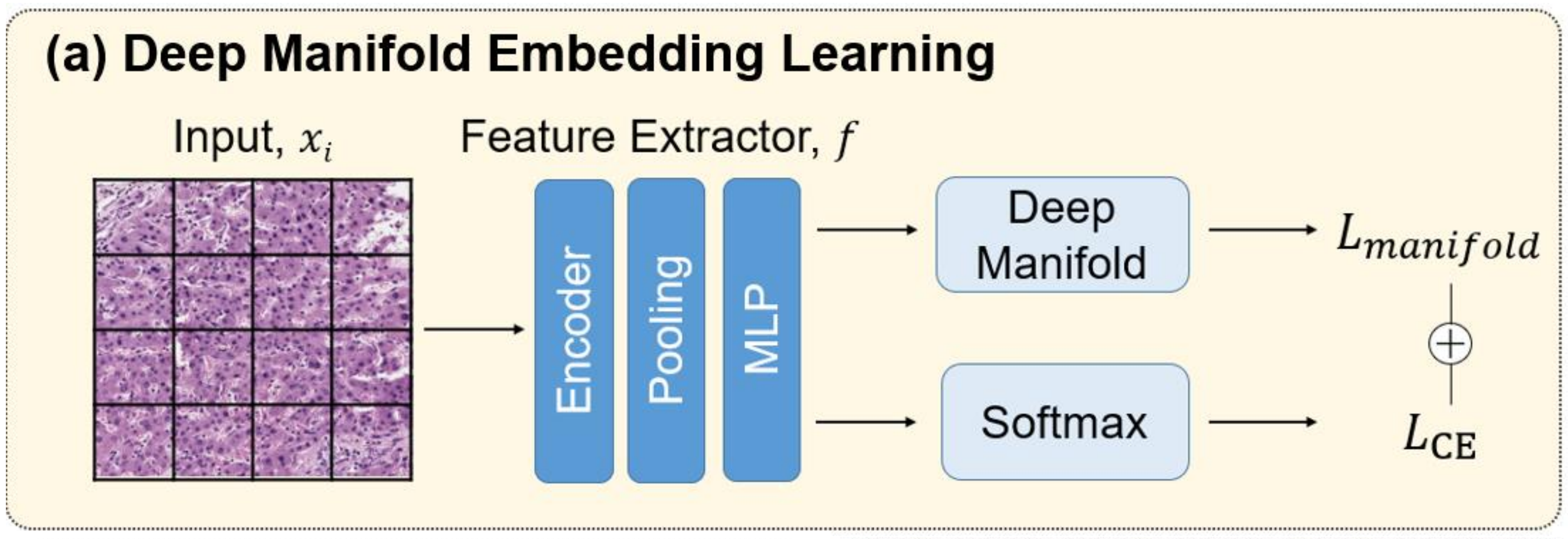
Motivation:

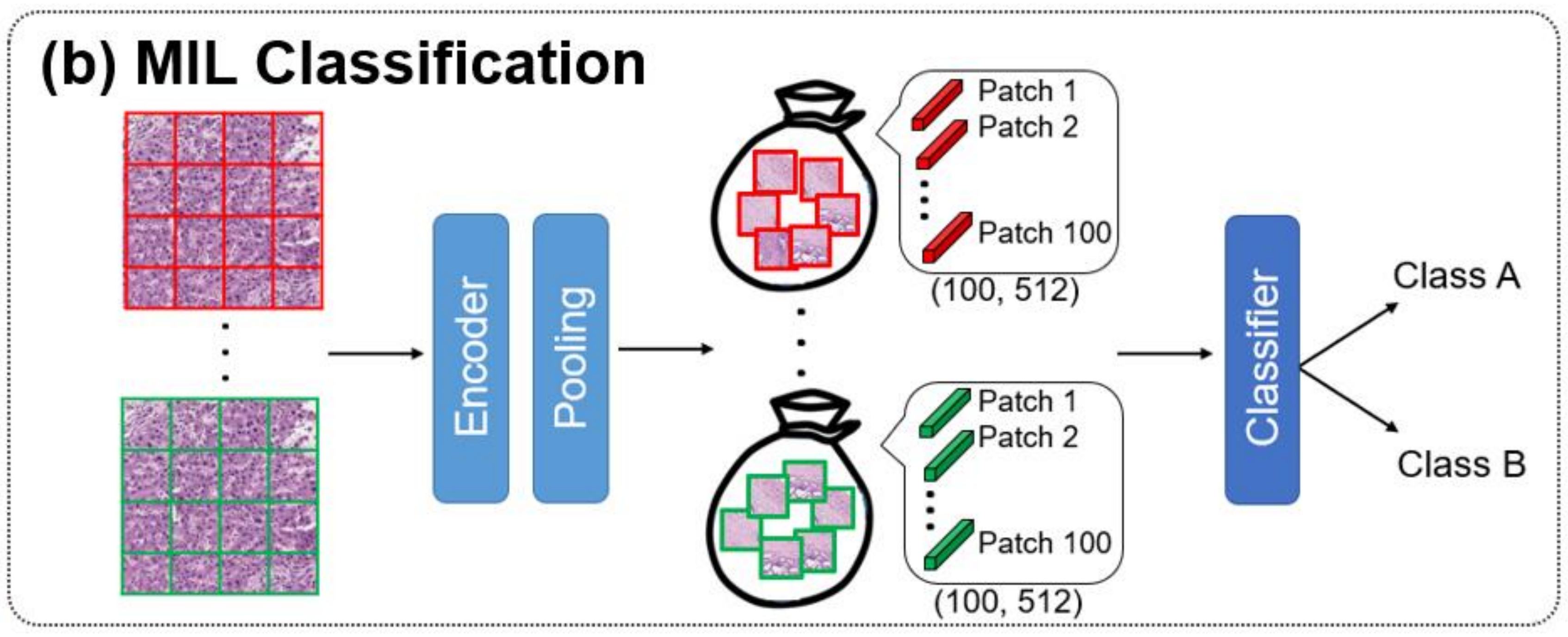
- To extend the current contrastive learning to represent the nonlinear feature manifold inspired by manifold learning.

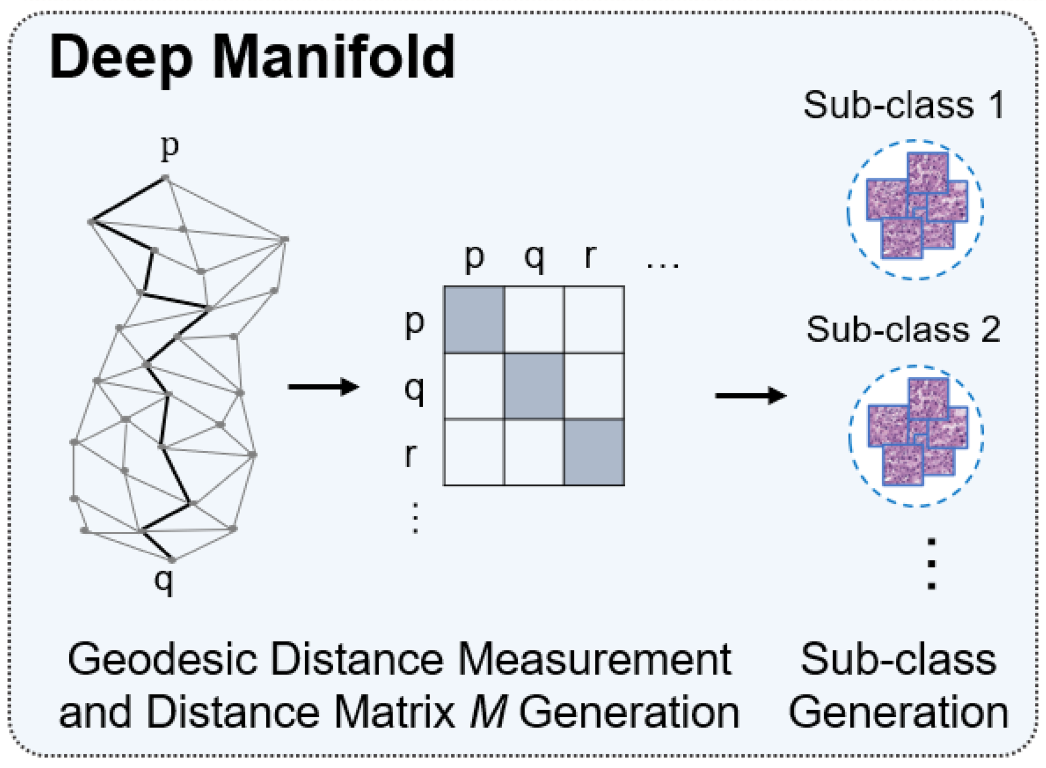
Contributions:

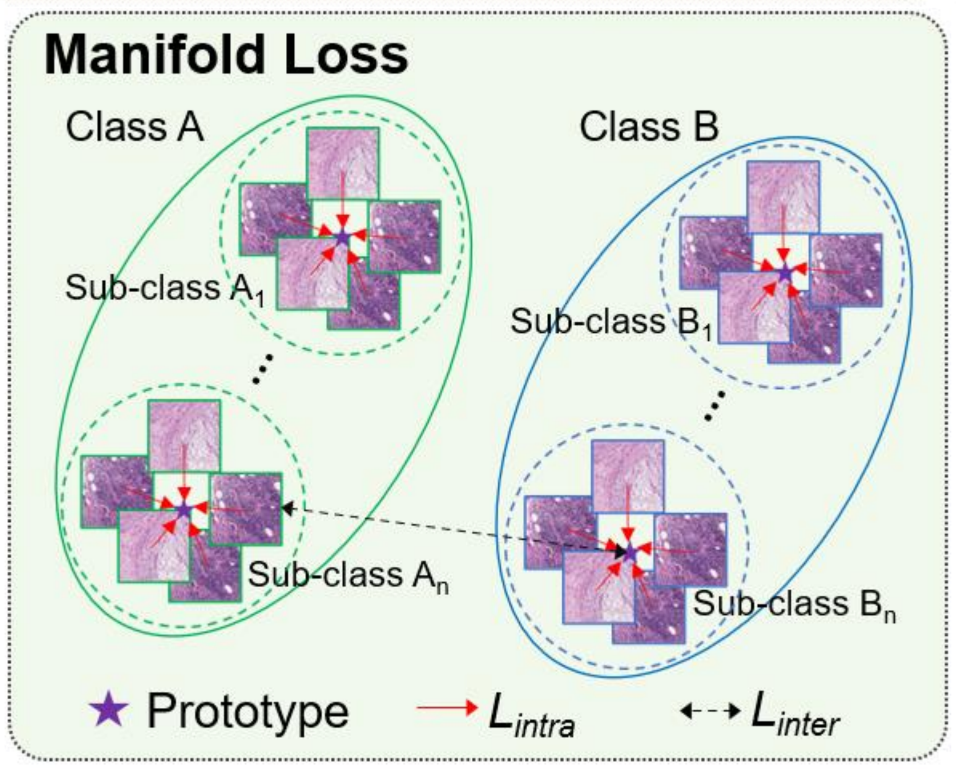
- We introduce **a novel integration of manifold geodesic distance in contrastive learning**.
- We propose **a geodesic-distance-based feature clustering** for efficient contrastive loss evaluation using prototypes without brute-force pairwise feature similarity comparison while approximating the overall manifold geometry well.
- We demonstrate that the proposed method outperforms other state-of-the-art (SOTA) methods with a much smaller number of sub-classes without complicated prototype assignment.

METHOD









Loss function for Deep Manifold Embedding Learning

$$L_{intra} = \frac{1}{J \cdot I} \sum_{j=1}^{J} \sum_{i=1}^{I} \left(f(x_j^i) - p^+\right)^T \left(f(x_j^i) - p^+\right)$$

$$L_{inter} = \frac{1}{J} \sum_{j=1}^{J} \left(\Delta - D\left(f(Q_j^A), P^B\right)\right)$$

$$L_{manifold} = L_{intra} + L_{inter}$$

$$L_{CE} = -\frac{1}{J \cdot I} \sum_{j=1}^{J} \sum_{i=1}^{I} y_j^i \cdot \log \hat{y}_j^i + (1 - y_j^i) \cdot \log(1 - \hat{y}_j^i)$$

$$L_{total} = L_{manifold} + L_{CE}$$

x_i: An arbitrary patch

x_j^i: *i*-th patch in the *j*-th batch

$f(\cdot)$: feature extractor

p^+: positive prototype of the patch

$f(Q_j^A)$: a set of patch features in batch *j* from class A

P^B: a set of prototypes from the sub-classes of class B

$D(\cdot)$: Hausdorff distance

y: Ground-truth slide-level label

$\hat{y}$: Predicted label

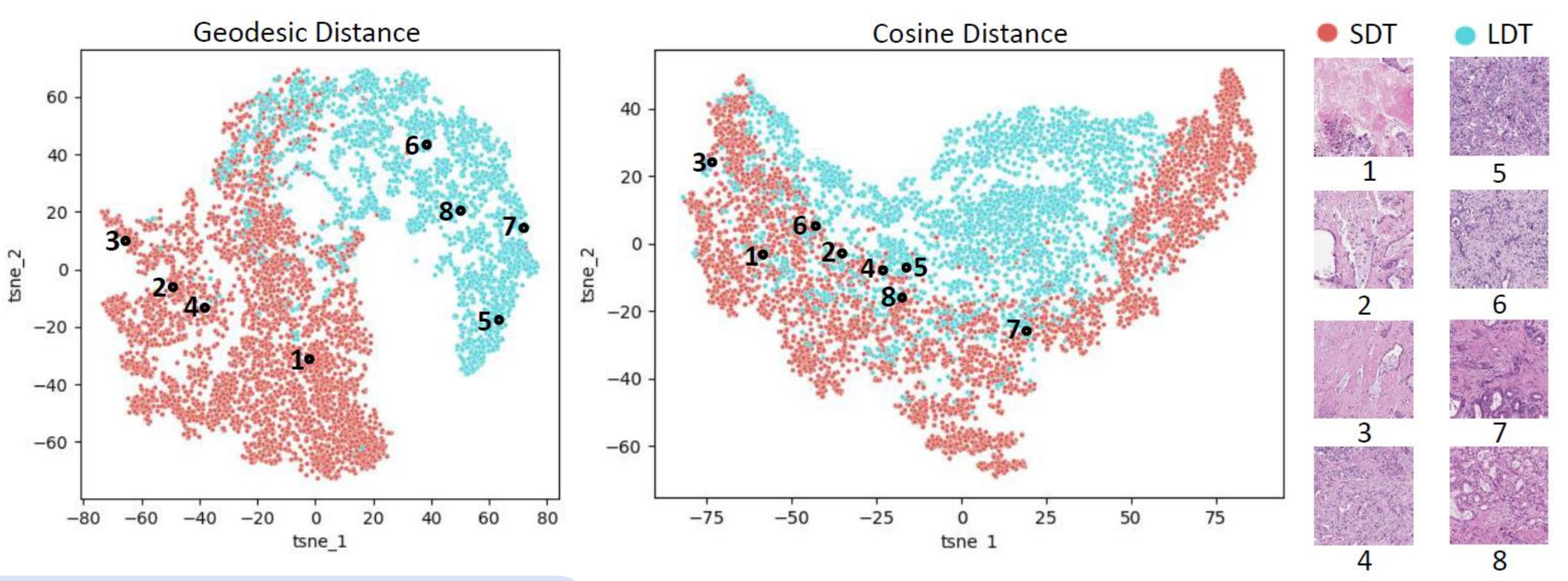
Δ: Margin

RESULT

- Classification performance on Intrahepatic Cholangiocarcinomas (IHCCs) subtype and liver cancer type dataset.

Method	Prototype Number	IHCC Subtype				Liver Cancer Type			
		Acc.	Prec.	Rec.	F1	Acc.	Prec.	Rec.	F1
CNN	NA	0.7315	0.7372	0.7315	0.7270	0.7710	0.7781	0.7719	0.7657
PCL	500-800-1000	0.7386	0.7478	0.7394	0.7354	0.8146	0.7898	0.8146	0.7979
HCSC	2-10-100	0.7230	0.7265	0.7230	0.7231	0.7995	**0.8524**	0.7995	0.7825
Ours	20	**0.7703**	**0.7710**	**0.7678**	**0.7668**	**0.8239**	0.8351	**0.8239**	**0.8227**

- Comparison of geodesic and cosine distance in feature space.



CONCLUSION

- We proposed a novel geodesic-distance-based contrastive learning for histopathology image classification.
- Unlike conventional cosine-distance based contrastive learning methods, our method can represent nonlinear feature manifold better and generate better discriminative features.
- *Limitation*: Extra computation time for graph generation and pairwise distance computation using the Dijkstra algorithm.
- *Future work*: Optimize the algorithm and apply our method to other datasets and tasks, such as multi-class classification problems and natural image datasets.

REFERENCES

1. Guo, Y., Xu, M., Li, J., Ni, B., Zhu, X., Sun, Z., Xu, Y.: HCSC: Hierarchical contrastive selective coding. In: Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition. pp. 9706–9715 (2022)
2. Gong, Z., Hu, W., Du, X., Zhong, P., Hu, P.: Deep manifold embedding for hyperspectral image classification. IEEE Transactions on Cybernetics 52(10), 10430–10443 (2021)
3. Li, J., Zhou, P., Xiong, C., Hoi, S.C.: Prototypical contrastive learning of unsupervised representations. arXiv preprint arXiv:2005.04966 (2020)

ACKNOWLEDGEMENT

This study was approved by the institutional review board of Seoul National University Hospital (IRB NO.H-1011-046-339). This work was partially supported by the National Research Foundation of Korea (NRF-2019M3E5D2A01063819, NRF-2021R1A6A1A13044830), the Institute for Information & Communications Technology Planning & Evaluation (IITP-2023-2020-0-01819), the Korea Health Industry Development Institute (HI18C0316), the Korea Institute of Science and Technology (KIST) Institutional Program (2E32210 and 2E32211) and a Korea University Grant.

hvcl.korea.ac.kr | jingwei_92@korea.ac.kr, wkjeong@korea.ac.kr