Singh Y, Hathaway QA, Erickson BJ. Self-Supervised Learning in Skin Cancer Detection: The Roles of Topological Contrastive Learning with Geometric Analysis. J Dermatol & Skin Sci. 2024;6(2):1-3

Journal of Dermatology and Skin Science

Editorial Open Access

Self-Supervised Learning in Skin Cancer Detection: The Roles of Topological Contrastive Learning with Geometric Analysis

Yashbir Singh[1], Quincy A. Hathaway[2], Bradley J. Erickson[3]

[1]Radiology, Mayo Clinic, Rochester, MN, USA
[2]Department of Medical Education, West Virginia University, Morgantown, West Virginia, USA
[3]Radiology, Mayo Clinic, Rochester, MN, USA

Article Info

Article Notes
Received: June 18, 2024
Accepted: July 17, 2024

***Correspondence:**
*Dr. Bradley J. Erickson, Radiology, Mayo Clinic, Rochester, MN, USA; Email: bje@mayo.edu.

Keywords:
Topological contrastive learning
Geometric analysis
Skin cancer detection
Medical imaging

Editorial

The field of medical imaging has witnessed remarkable advances in recent years, and the Journal of Dermatology and Skin Science has been at the forefront of disseminating these groundbreaking discoveries. Among the most promising developments are advanced artificial intelligence and image processing techniques that hold immense potential for transforming skin disease diagnosis and treatment. Using artificial intelligence for medical applications generally follows one of three approaches: 1) unsupervised learning, (i.e., an algorithm, unassisted, attempts to find patterns within data), 2) supervised learning (i.e., the algorithm is taught, usually through labelled examples, what patterns to find, or 3) self-supervised learning (i.e., the algorithm teaches itself how to create labels from the patterns it finds); if self-supervised learning can be used effectively, it can significantly reduce the number of hours needed to manually curate a data. One application that can help successfully implement self-supervised algorithms is through topological contrastive learning. By examining fundamental differences within images, such as the cell wall structure of melanoma compared to benign melanocytes, topological contrastive learning can extract patterns observed to be present in only malignant cells and begin to extrapolate how these patterns can be classified (e.g. into melanoma or benign cells). Topological approaches, which focus on the connectedness of data points, can also be combined with geometric analyses to better capture shape-based information (i.e., the symmetry or asymmetry present in the cell wall of melanoma).

Topological contrastive learning unveils the intricate higher-order relationships within medical imaging data, enabling early disease detection and accurate classification of complex pathologies[1-3]. By exploring the inherent topological properties of imaging data, this approach reveals patterns and connections that might otherwise go unnoticed, enhancing diagnostic accuracy and facilitating the development of robust, generalizable models. For example, the use of topology and geometry can be used for visual[4] and histological inspection[3] of suspected skin cancer. With multiple medical imaging modalities, topological contrastive learning with geometric analysis could identify unique shape-based data using gross morphology, extracellular matrix, and cellular architecture to predict risk of future malignancy and adverse outcomes. By extracting and analyzing the explicit geometric attributes of imaging data, clinicians can gain novel insights into anatomical structures, paving the way for personalized and effective interventions.

The synergy between topological contrastive learning and geometric analysis presents a comprehensive framework that not only improves diagnostic precision but also fosters the development of interpretable, transparent artificial intelligence driven tools. These tools can enhance clinician understanding and patient trust, reducing diagnostic variability and fostering a collaborative approach to healthcare delivery[5,6]. Moreover, the integration of these techniques with traditional imaging methods opens up new avenues for multi-modal imaging. By converting 2- and 3-dimensional data into n-dimensional shape-based networks and pairing it with functional data (refers to information about the normal or abnormal biological/biochemical processes and functions occurring within the skin tissue itself, beyond just the structural/anatomical imaging data. Combining both structural and functional data aims to provide a more holistic understanding of skin diseases.), researchers can create a more complete representation of patient conditions, enabling a comprehensive approach to patient care. As this field continues to evolve, we anticipate that self-supervised learning techniques, such as topological contrastive learning and geometric analysis, will advance medical imaging and make a significant impact on healthcare delivery worldwide.

Topological methods in medical imaging[2] offer a distinct advantage over traditional approaches by capturing the intrinsic shape and structure of data in a robust and invariant manner. Unlike conventional methods that rely solely on pixel or voxel-level information, topological techniques analyze the relationships and connectivity patterns within the data, unlocking a deeper understanding of the underlying structural properties. One key aspect of topological methods is their ability to extract features that are invariant to deformations, rotations, and other transformations. This property is particularly valuable in medical imaging, where variations in patient positioning, image acquisition, and tissue deformations can significantly impact the effectiveness of traditional feature extraction techniques[2]. As mentioned above[4], when using imaging techniques that lack standardization (e.g. fixed pixel size or intensity scale), such as photography of suspected lesions, feature extraction methods less sensitive to these properties are crucial. By focusing on the inherent shape and connectivity patterns, topological methods can overcome these challenges, leading to more reliable and consistent results.

Moreover, topological approaches excel at capturing multi-scale and hierarchical structures, which are prevalent in biological systems and medical imaging data. For instance, in the context of melanoma, histological sections contain structural information on the malignancy (e.g., melanoma) as well as supporting cells (e.g., macrophages) that may have unique interconnections based on distance, architectural distortion, and/or density[6]. Another significant advantage of topological methods lies in their ability to handle high-dimensional and complex data structures. Many medical imaging modalities, such as magnetic resonance imaging (MRI) and computed tomography (CT), generate high-dimensional data that can be challenging to analyze using conventional techniques. Topological methods offer a powerful framework for analyzing and visualizing these complex datasets, enabling the identification of subtle patterns and abnormalities that may be overlooked by traditional approaches[2]. Importantly, newer CT technologies, such as photon-counting detector CT, can improve both spatial resolution and iodine signal offering newer methods for diagnosing metastatic spread of melanoma to the liver[7]. Topological and geometric techniques could improve differentiation between hepatocellular carcinoma, melanoma, and other hypervascular malignancies. The integration of topological methods with other imaging modalities, such as dermoscopy, confocal microscopy, and optical coherence tomography, can provide a multi-modal and comprehensive understanding of skin lesions. By combining the structural and functional information from these modalities, researchers can develop more accurate and robust diagnostic models, leading to personalized treatment strategies and improved patient care[8].

Despite their advantages, topological methods in medical imaging for skin cancer detection face several challenges. These techniques often require significant computational resources, potentially limiting their real-time application in clinical settings. The complexity of topological algorithms can also make them less interpretable for clinicians unfamiliar with advanced mathematics. Additionally, the high sensitivity of topological methods to noise in imaging data may lead to false positives or misclassifications, especially in low-quality or non-standardized images. Furthermore, the lack of large-scale validation studies and the need for extensive training data sets can hinder widespread adoption and integration into existing clinical workflows.

In conclusion, topological contrastive learning and geometric analysis represent a transformative approach to medical imaging that can enhance diagnosis and treatment of skin cancer by identifying unique gross morphological and histopathological properties. By capturing the intrinsic shape and connectivity patterns, these methods can enhance diagnostic accuracy, automate clinical workflows, provide interpretable results using techniques such as Persistent Homology, and enable personalized treatment strategies when combing with genomic omics-based analyses. As the Journal of Dermatology and Skin Science continues to disseminate cutting-edge research in this domain, we urge the scientific community to embrace these developments and pave the way for a future where skin cancer detection and treatment are more precise, personalized, and effective than ever before.

References

1. Baas NA, Carlsson GE, Quick GS, et al. (2020). Topological Data Analysis. Springer International Publishing.
2. Singh Y, Farrelly CM, Hathaway QA, et al. (2023). Topological data analysis in medical imaging: current state of the art. Insights into Imaging, 14(1), 58.
3. Mantovani A & Marchesi F. (2022). A topology perspective on macrophages in melanoma metastasis. Cell Reports Medicine, 3(5).
4. Cheng H, Leamons R & Shami AA. (2023). Modified Topological Image Preprocessing for Skin Lesion Classifications. arXiv preprint arXiv:2308.06796.
5. Sajedi A, Khaki S, Lawryshyn YA, et al. (2024). ProbMCL: Simple Probabilistic Contrastive Learning for Multi-label Visual Classification. arXiv preprint arXiv:2401.01448.
6. Levenson RM, Singh Y, Rieck B, et al. (2024). Advancing Precision Medicine: Algebraic Topology and Differential Geometry in Radiology and Computational Pathology. Laboratory Investigation, 102060.
7. Graafen D, Stoehr F, Halfmann MC, et al. (2023). Quantum iterative reconstruction on a photon-counting detector CT improves the quality of hepatocellular carcinoma imaging. Cancer Imaging, *23*(1), 69.
8. Chen Y, Frias J & Gel YR. (2024, March). TopoGCL: Topological Graph Contrastive Learning. In Proceedings of the AAAI Conference on Artificial Intelligence (Vol. 38, No. 10, pp. 11453-11461).