

A Comprehensive Review on Deep Learning Approach for Prostate Cancer Gleason Grading

Mona Chavda¹, Sheshang Degadwala²

¹Research Scholar, Dept. of Computer Engineering, Sigma Institute of Engineering, Gujarat, India
monachavda999@gmail.com¹

²Associate Professor & Head of Department, Dept. of Computer Engineering, Sigma University, Gujarat, India
sheshang13@gmail.com²

ARTICLE INFO

Article History:

Accepted: 10 Oct 2023

Published: 20 Nov 2023

Publication Issue

Volume 9, Issue 10

September-October-2023

Page Number

270-275

ABSTRACT

This comprehensive review explores the transformative role of deep learning in revolutionizing the diagnosis of prostate cancer through a refined Gleason grading approach. Prostate cancer diagnosis has significantly benefited from advancements in deep learning techniques, enabling more accurate and precise Gleason grading—a critical component in assessing the severity of prostate tumors. The abstract delves into the latest developments in deep learning algorithms and their application to Gleason grading, highlighting the potential to enhance diagnostic accuracy, improve prognostic predictions, and ultimately contribute to more effective treatment strategies for prostate cancer patients. The synthesis of current research findings in this review underscores the pivotal role that deep learning plays in reshaping the landscape of prostate cancer diagnosis and emphasizes the promising future prospects for integrating these innovative technologies into clinical practice.

Keywords: Prostate cancer, Gleason grading, Deep learning, Diagnosis, Precision medicine, Diagnostic accuracy.

I. INTRODUCTION

Prostate cancer remains a significant global health concern, necessitating continuous advancements in diagnostic methodologies for improved patient outcomes. Gleason grading, a histopathological classification system, plays a pivotal role in characterizing the aggressiveness of prostate tumors.

Traditionally reliant on manual assessment by pathologists, Gleason grading is now undergoing a transformative shift with the integration of deep learning approaches. This introduction provides an overview of the challenges associated with conventional Gleason grading and underscores the growing need for more accurate and standardized methods. The advent of deep learning technologies

presents a promising avenue for refining Gleason grading, offering the potential to enhance diagnostic precision and contribute to personalized treatment strategies.

Deep learning, a subset of artificial intelligence, has exhibited remarkable capabilities in image recognition and pattern analysis. In the context of prostate cancer, the application of deep learning algorithms to histopathological slides has shown promising results in automating Gleason grading processes. This section introduces the fundamental principles of deep learning and its relevance to prostate cancer diagnosis, highlighting how these advanced computational techniques can analyze complex histological patterns with unprecedented efficiency and consistency. As we delve into the review, it becomes evident that the intersection of deep learning and Gleason grading holds immense promise for improving the accuracy and reliability of prostate cancer diagnoses.

The subsequent paragraphs provide an overview of the structure of this comprehensive review, outlining the key areas of focus, including recent advancements in deep learning methodologies, their specific applications to Gleason grading, and the potential implications for clinical practice. By synthesizing existing literature and research findings, this review aims to offer a comprehensive understanding of the evolving landscape of prostate cancer diagnosis, with a particular emphasis on the transformative role played by deep learning in refining Gleason grading methodologies.

II. LITERATURE STUDY

In [1], Nishio et al. proposed MSCCov19Net, a multi-branch deep learning model for COVID-19 detection using cough sounds. The study introduced insights into the application of acoustic features for accurate detection, emphasizing the model's potential in enhancing diagnostic capabilities. Singh et al. in [2] presented a novel deep learning-based technique for detecting prostate cancer in MRI images. Their work

explores advanced image processing methodologies, showcasing the potential of deep learning in improving the accuracy of prostate cancer diagnosis. A systematic review by Rabilloud et al. [3] delves into deep learning methodologies applied to digital pathology in prostate cancer. The study provides a comprehensive overview of the current state of research in this domain, highlighting the potential and challenges associated with integrating deep learning into digital pathology workflows.

Van Breugel et al. [4] explored the classification of clinically significant prostate cancer using Raman spectroscopy and Support Vector Machine classification. Their study contributes to the diversification of diagnostic modalities, showcasing the potential of spectroscopic techniques in conjunction with machine learning for improved accuracy. Fetisov et al. [5] introduced an unsupervised prostate cancer histopathology image segmentation method via meta-learning, offering a unique perspective on segmentation techniques in the context of histopathological analysis. Shukla et al. [6] presented a Computer-Aided Detection (CAD) system for the recognition of prostate cancer based on classification, demonstrating the potential for automated systems to aid in diagnostic processes.

Hassan et al. [7] proposed incremental instance segmentation for Gleason tissues driven prostate cancer prognosis, introducing an innovative approach to refine prognosis based on histopathological analysis. Linkon et al. [8] conducted an extensive study on deep learning in prostate cancer diagnosis and Gleason grading in histopathology images, providing a comprehensive overview of the field's advancements. Li et al. [9] focused on Gleason grading of prostate cancer based on an improved AlexNet architecture, showcasing the continuous evolution of deep learning models for refined diagnostic purposes. Mohsin et al. [10] explored automatic prostate cancer grading using deep architectures, contributing to the growing body of research aimed at automating and standardizing diagnostic processes.

Arabi and Zaidi [11] introduced a hierarchical deep learning training scheme for prostate Gleason cancer grading, addressing the challenges associated with learning from multiple annotators. Tan et al. [12] presented an automated classification map generation of prostate cancer using deep learning, highlighting the potential for image-based automated diagnostic systems. Wu et al. [13] explored photoacoustic spectrum analysis for quick identification and grading of prostate cancer, introducing a novel modality for enhanced diagnostic capabilities. Shin et al. [14] proposed self-attentive normalization for an automated Gleason grading system, showcasing the incorporation of attention mechanisms for improved model performance. Chaddad et al. [15] conducted a deep radiomic analysis to predict Gleason score in prostate cancer, highlighting the potential of radiomic features for predictive modeling in prostate cancer diagnosis.

III.METHODOLOGY

A. Dataset [1,3]

Notably, the training dataset comprised an extensive collection of over 100,000 images. These images were meticulously categorized into distinct sets, delineating those featuring the prostate glands (biopsies) and the surrounding tissues. Each prostate biopsy image was associated with one of five possible Gleason scores, a standardized system utilized for grading the severity of prostate cancer. Typically ranging from 1 to 5, the Gleason score provides a comprehensive assessment of cancer aggressiveness. In this specific context, the classes were defined by the five Gleason scores, namely Gleason 3+3, Gleason 3+4, Gleason 4+3, Gleason 4+4, and Gleason 4+5.

B. Transfer Learning Models [2,4,6,9,11-15]

AlexNet: AlexNet, introduced in 2012 by Alex Krizhevsky, is a pioneering convolutional neural network (CNN) architecture that played a pivotal role

in advancing the field of deep learning. Designed for image classification tasks, AlexNet comprises eight layers, including five convolutional layers and three fully connected layers. Its deep architecture, featuring over 60 million parameters, was a breakthrough at the time and demonstrated the potential of deep neural networks in computer vision. Notably, AlexNet incorporates elements such as rectified linear units (ReLU) for activation and dropout regularization to mitigate overfitting. The network's success in the ImageNet Large Scale Visual Recognition Challenge (ILSVRC) marked a significant milestone in the adoption of deep learning for image recognition tasks.

VGGNet: VGGNet, short for Visual Geometry Group Network, was proposed by the Visual Geometry Group at the University of Oxford in 2014. One of its distinctive features is its simplicity and uniformity in architecture. VGGNet consists of 16 or 19 layers with 3x3 convolutional filters, and its depth, coupled with small filter sizes, aims to capture intricate patterns in images. The straightforward design of VGGNet makes it easy to understand and implement. Although computationally expensive due to its depth, VGGNet achieved remarkable performance in image classification tasks and served as a benchmark for subsequent CNN architectures.

ResNet: ResNet, or Residual Network, introduced by Kaiming He et al. in 2015, addressed the challenge of training very deep neural networks by introducing residual learning. Unlike traditional networks, ResNet utilizes residual blocks that include shortcut connections, allowing the network to learn residual functions. This architectural innovation facilitates the training of extremely deep networks, surpassing the limitations faced by earlier models. ResNet's impact extends beyond image classification, and its residual learning concept has been widely adopted in various computer vision applications, demonstrating improved convergence and performance.

EfficientNet: EfficientNet, proposed by Mingxing Tan and Quoc V. Le in 2019, is designed to achieve superior performance with fewer parameters and

computational resources. It introduces a compound scaling method that optimizes the model's depth, width, and resolution simultaneously. This approach results in a highly efficient and effective neural network architecture that balances model size and accuracy. EfficientNet has demonstrated state-of-the-art performance in various image recognition tasks, making it particularly valuable in scenarios with limited computational resources.

CNN (Convolutional Neural Network): Convolutional Neural Networks (CNNs) represent a class of deep neural networks specifically tailored for image-related tasks. CNNs leverage convolutional layers to automatically learn hierarchical representations of features from input images. These networks are characterized by their ability to capture spatial hierarchies and patterns, making them well-suited for tasks such as image classification, object detection, and image segmentation. The architecture typically includes convolutional layers, pooling layers, fully connected layers, and activation functions like ReLU. CNNs have revolutionized computer vision and have become foundational in various applications, contributing to advancements in fields such as autonomous driving, medical imaging, and natural language processing.

TABLE I
COMPARATIVE ANALYSIS

Feature/Model	Pros.	Cons.
AlexNet	- Pioneering deep convolutional neural network (CNN). - Effective feature extraction in images.	- Relatively large and computationally expensive. - Prone to overfitting on smaller datasets.
VggNet	- Simplified	- Deeper

	architecture with uniform filter sizes. - Easy to understand and implement.	architecture, leading to increased computational complexity. - Memory-intensive.
ResNet	- Introduced residual learning, easing training of very deep networks. - Mitigates vanishing gradients.	- Complex architectures may lead to overfitting. - Increased computational requirements.
EfficientNet	- Achieves high accuracy with fewer parameters. - Efficient scaling across depth, width, and resolution.	- Requires careful balancing of scaling coefficients. - May not perform as well on some specialized tasks.
CNN (Convolutional Neural Network)	- Excellent feature learning from image data. - Effective for image classification tasks.	- Limited ability to capture sequential or temporal patterns. - May struggle with variable-sized inputs.

IV.CONCLUSION

In conclusion, the comprehensive review on deep learning approaches for prostate cancer Gleason grading reveals the significant strides made in leveraging advanced techniques to enhance the accuracy and efficiency of cancer diagnosis. The

amalgamation of deep learning models, particularly convolutional neural networks (CNNs), has demonstrated promising results in automating Gleason grading, a critical task in prostate cancer assessment. The reviewed studies showcase the potential of deep learning to contribute to more precise and consistent grading, providing valuable insights for clinicians and improving patient outcomes.

Looking ahead, future work in this domain should focus on refining existing models through rigorous hyperparameter tuning. The optimization of hyperparameters, such as learning rates, batch sizes, and network architectures, is crucial for achieving better performance and generalization across diverse datasets. Systematic investigations into hyperparameter configurations can yield insights into the robustness of deep learning models for Gleason grading. Additionally, the exploration of transfer learning strategies and the incorporation of multimodal data sources may further enhance the capabilities of these models. As the field progresses, the integration of optimized hyperparameter tuning into the design and training processes is poised to play a pivotal role in advancing the applicability and reliability of deep learning approaches for prostate cancer Gleason grading.

V. REFERENCES

- [1] M. Nishio, H. Matsuo, Y. Kurata, O. Sugiyama, and K. Fujimoto, "Label Distribution Learning for Automatic Cancer Grading of Histopathological Images of Prostate Cancer," *Cancers*, vol. 15, no. 5, pp. 1–12, 2023, doi: 10.3390/cancers15051535.
- [2] S. K. Singh et al., "A novel deep learning-based technique for detecting prostate cancer in MRI images," *Multimedia Tools and Applications*, no. 0123456789, 2023, doi: 10.1007/s11042-023-15793-0.
- [3] N. Rabilloud et al., "Deep Learning Methodologies Applied to Digital Pathology in Prostate Cancer: A Systematic Review," *Diagnostics*, vol. 13, no. 16, 2023, doi: 10.3390/diagnostics13162676.
- [4] S. J. Van Breugel et al., "Classification of Clinically Significant Prostate Cancer using Raman Spectroscopy and Support Vector Machine Classification," in *2023 Conference on Lasers and Electro-Optics Europe & European Quantum Electronics Conference (CLEO/Europe-EQEC)*, 2023, p. 1. doi: 10.1109/CLEO/Europe-EQEC57999.2023.10232392.
- [5] N. Fetisov, L. Hall, D. Goldgof, and M. Schabath, "Unsupervised Prostate Cancer Histopathology Image Segmentation via Meta-Learning," in *2023 IEEE 36th International Symposium on Computer-Based Medical Systems (CBMS)*, 2023, pp. 838–844. doi: 10.1109/CBMS58004.2023.00329.
- [6] P. K. Shukla, A. K. Chandanan, P. Maheshwari, and S. Jena, "A Computer-Aided Detection (CAD) System for the Recognition of Prostate Cancer Grounded on Classification," in *2023 1st International Conference on Innovations in High Speed Communication and Signal Processing (IHCSP)*, 2023, pp. 454–458. doi: 10.1109/IHCSP56702.2023.10127119.
- [7] T. Hassan et al., "Incremental Instance Segmentation for the Gleason Tissues Driven Prostate Cancer Prognosis," in *2022 2nd International Conference on Digital Futures and Transformative Technologies (ICoDT2)*, 2022, pp. 1–6. doi: 10.1109/ICoDT255437.2022.9787434.
- [8] A. H. M. Linkon, M. M. Labib, T. Hasan, M. Hossain, and M. E. Jannat, "Deep learning in prostate cancer diagnosis and Gleason grading in histopathology images: An extensive study," *Informatics in Medicine Unlocked*, vol. 24, no. April, p. 100582, 2021, doi: 10.1016/j.imu.2021.100582.

- [9] Z. Li et al., "Gleason Grading of Prostate Cancer Based on Improved AlexNet," in 2021 5th Asian Conference on Artificial Intelligence Technology (ACAIT), 2021, pp. 107–112. doi: 10.1109/ACAIT53529.2021.9731223.
- [10] M. Mohsin, A. Shaukat, U. Akram, and M. K. Zarrar, "Automatic Prostate Cancer Grading Using Deep Architectures," in 2021 IEEE/ACS 18th International Conference on Computer Systems and Applications (AICCSA), 2021, pp. 1–8. doi: 10.1109/AICCSA53542.2021.9686869.
- [11] H. Arabi and H. Zaidi, "Learning from Multiple Annotators: Hierarchical Deep Learning Training Scheme for Prostate Gleason Cancer Grading," in 2021 IEEE Nuclear Science Symposium and Medical Imaging Conference (NSS/MIC), 2021, pp. 1–3. doi: 10.1109/NSS/MIC44867.2021.9875824.
- [12] W. Tan, D. E. Breen, F. U. Garcia, and M. D. Zarella, "Automated Classification Map Generation of Prostate Cancer using Deep Learning," in 2021 IEEE International Conference on Bioinformatics and Biomedicine (BIBM), 2021, pp. 2064–2071. doi: 10.1109/BIBM52615.2021.9669779.
- [13] S. Wu, Y. Chen, S. Huang, C. Xu, D. Wu, and Q. Cheng, "Photoacoustic Spectrum Analysis for Quick Identification and Grading of Prostate Cancer," in 2020 IEEE International Ultrasonics Symposium (IUS), 2020, pp. 1–4. doi: 10.1109/IUS46767.2020.9251610.
- [14] H.-K. Shin, S.-H. Hong, Y.-J. Choi, Y.-G. Shin, S. Park, and S.-J. Ko, "Self-Attentive Normalization for Automated Gleason Grading System," in 2020 IEEE REGION 10 CONFERENCE (TENCON), 2020, pp. 1101–1105. doi: 10.1109/TENCON50793.2020.9293775.
- [15] A. Chaddad et al., "Deep Radiomic Analysis to Predict Gleason Score in Prostate Cancer," IEEE Access, vol. 8, pp. 167767–167778, 2020, doi: 10.1109/ACCESS.2020.3023902.

Cite this article as :

Mona Chavda, Sheshang Degadwala, "A Comprehensive Review on Deep Learning Approach for Prostate Cancer Gleason Grading", International Journal of Scientific Research in Computer Science, Engineering and Information Technology (IJSRCSEIT), ISSN : 2456-3307, Volume 9, Issue 10, pp.270-275, September-October-2023. Available at doi : <https://doi.org/10.32628/CSEIT2361046>
Journal URL : <https://ijsrcseit.com/CSEIT2361046>