Machine Learning and AI-Powered Diagnostics for Early Detection of Oral Pre-Malignant and Malignant Lesions

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Abstract. Oral squamous cell carcinoma (OSCC) accounts for over 90% of oral malignancies, with late detection contributing to high mortality rates (5-year survival rate: ~60%). Traditional diagnostic methods, such as visual examination and biopsy, are subjective, invasive, and lack sensitivity for early-stage lesions. This review evaluates the transformative potential of artificial intelligence (AI) in improving early detection of oral pre-malignant and malignant conditions. A systematic analysis of 120+ studies (2018–2023) reveals that AI models, particularly convolutional neural networks (CNNs), achieve an average accuracy of 92.4% in classifying oral lesions, outperforming conventional methods. Key challenges include dataset heterogeneity, model generalizability, and integration into clinical workflows. This paper synthesizes advancements in AI-driven diagnostics, critiques limitations of existing research, and proposes frameworks for scalable, equitable deployment. Contributions include a meta-analysis of performance metrics, identification of clinical validation gaps, and recommendations for federated learning and explainable AI (XAI) adoption.

1 Introduction

1.1 Background & motivation

Oral cancer represents a major global health challenge, contributing to an estimated 177,000 deaths annually worldwide [1]. The prognosis for patients diagnosed with oral cancer is often poor due to the advanced stage at which many cases are identified. Approximately 70% of oral cancer cases are diagnosed at late stages, which significantly reduces the chances of successful treatment and survival [1]. Early detection of pre-malignant lesions, such as leukoplakia and erythroplakia, is critical for preventing the progression to full-blown malignancy. These pre-malignant lesions exhibit variable malignant transformation rates, which can range from 1% to as high as 18%, depending on factors such as lesion type, location, and patient-specific characteristics [2]. This wide variation in transformation rates underscores the importance of early and accurate detection to guide appropriate intervention strategies. Currently, the diagnosis of oral pre-cancer and cancer relies heavily on clinical expertise and visual inspection, often supplemented by biopsy and histopathological examination. However, the diagnostic accuracy of these methods can be significantly influenced by the experience and skill of the clinician. Studies have indicated that the variability in clinical judgment can result in misdiagnosis rates of 20–30%, which may lead to inappropriate treatment plans, delayed interventions, or unnecessary biopsies [3]. This variability highlights the need for more consistent, objective diagnostic tools to improve clinical outcomes and patient care. Artificial intelligence (AI) offers a promising solution to address these challenges. AI-powered systems, particularly those leveraging deep learning techniques, have demonstrated the potential to improve the accuracy and efficiency of oral lesion detection. These systems can analyse large volumes of data, such as medical images or patient history, and identify patterns that may not be immediately obvious to human clinicians. By automating the process of lesion analysis, AI tools can minimize human error, ensure more consistent diagnostic outcomes, and reduce the burden on clinicians, especially in resource-limited settings where access to specialized expertise may be scarce. Moreover, AI systems can offer a scalable approach to diagnosing oral lesions, extending expert-level diagnostic capabilities to underserved populations and improving early detection efforts globally.

1.2 Problem statement

Despite notable advancements in AI-based diagnostic technologies, several barriers hinder their widespread adoption in clinical practice. One key challenge is data scarcity, particularly the limited availability of annotated datasets for rare oral conditions. Another concern is algorithmic bias, as many AI models are developed using non-diverse population datasets, leading to poor generalizability. Furthermore, the lack of real-world validation and integration into existing dental workflows impedes the clinical translation of AI

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tools, leaving a significant gap between research and practical deployment.

1.3 Research gap

While existing reviews have contributed valuable insights into the technical performance of AI in oral cancer diagnostics, they often concentrate narrowly on algorithmic accuracy without addressing broader concerns. Specifically, prior studies [4]–[6] tend to overlook critical aspects such as clinical applicability, ethical and legal implications, and socioeconomic barriers to adoption. Moreover, there is limited exploration of multimodal AI systems that integrate diverse data types (e.g., imaging and genomic information), as well as a lack of focus on longitudinal tracking of patient outcomes, which is essential for assessing long-term efficacy and impact.

1.4 Objectives & contributions

Artificial intelligence (AI) has made significant strides in the field of medical diagnostics, particularly in oral cancer detection. The application of AI methods, especially machine learning and deep learning, has been explored extensively to address the challenges associated with oral cancer diagnosis, which is often delayed due to the reliance on subjective clinical expertise and misdiagnosis [1]. AI-based solutions have the potential to improve diagnostic accuracy, reduce human error, and offer scalable solutions that can be implemented in low-resource settings, thereby ensuring broader access to expert-level diagnostics.

Early Detection and Diagnosis: The integration of AI technologies, including convolutional neural networks (CNNs), transfer learning, and deep residual learning, has demonstrated promise in enhancing the early detection of oral lesions. By analysing medical images, AI models can identify subtle changes in tissue that may not be visible to the human eye, allowing for earlier intervention [4], [5]. AI-based models have been particularly effective in classifying oral lesions as benign or malignant, with studies showing that CNNs outperform traditional diagnostic methods in terms of accuracy and reliability [8].

Reducing Diagnostic Variability: One of the major challenges in oral cancer diagnosis is the variability in clinical judgment. Studies have shown that the diagnostic accuracy of clinicians can vary significantly, resulting in misdiagnosis rates of 20-30% [3]. AI offers a solution to this problem by providing objective, data-driven analysis that minimizes human bias and variability. This leads to more consistent and reliable diagnoses, ensuring that patients receive the appropriate treatment at the right stage of disease [4], [6].

Transfer Learning and Data Augmentation: AI systems, particularly those leveraging transfer learning, have been shown to perform effectively even with smaller datasets. This is crucial in the context of medical imaging, where large annotated datasets may be scarce. Transfer learning allows AI models to leverage pre-trained networks, improving performance in diagnosing oral lesions with limited data. Additionally, synthetic data generation using techniques like generative adversarial networks (GANs) helps augment training datasets, further enhancing model robustness and generalizability [6], [11], .

Multimodal Approaches: The fusion of various diagnostic modalities, such as optical coherence tomography (OCT) images and salivary biomarkers, with AI can further improve the accuracy of oral cancer detection. Multimodal AI models can integrate diverse sources of data to provide a more comprehensive diagnosis, increasing the sensitivity and specificity of detection systems [10]. These systems are particularly beneficial in distinguishing between benign and potentially malignant lesions, which is often a challenging task for clinicians.

AI in Low-Resource Settings: One of the most promising aspects of AI in oral cancer detection is its ability to extend expert-level diagnostic capabilities to underserved or low-resource settings [14]. Federated learning, a decentralized approach to training AI models, has been identified as a viable solution for leveraging data from multiple sources without compromising patient privacy or data security. This can help improve diagnostic outcomes in regions where access to specialized healthcare services is limited .

1.5 Paper organization

The structure of this review is as follows: Sections 3 through 6 provide a detailed synthesis of the existing literature, highlight emerging methodological trends, identify prevailing challenges, and outline prospective directions for future research and clinical application.

2 Related work

2.1 Literature review

Oral squamous cell carcinoma (OSCC) accounts for over 90% of oral malignancies, with late-stage diagnosis contributing to a 5-year survival rate of approximately 60% [1]. Traditional diagnostic methods, such as visual inspection and biopsy, are limited by subjectivity and invasiveness, particularly in low-resource settings where access to specialized care is scarce [3]. Visual inspection, for instance, exhibits moderate sensitivity (64%) and specificity (78%), underscoring the need for more reliable alternatives [7]. Artificial intelligence (AI) has emerged as a transformative solution, with convolutional neural networks (CNNs) achieving accuracies exceeding 90% in lesion classification tasks [8]. For example, ResNet-50 demonstrated robust performance in detecting oral lesions, achieving an AUC of 0.91 in multi-center studies [12]. Despite their efficacy, AI models face significant challenges, including dataset bias and limited generalizability. Models trained on geographically homogeneous datasets, such as those from Indian populations, exhibit performance drops of up to 15% when applied to diverse cohorts . Additionally, the "black-box" nature of CNNs complicates clinical trust, necessitating explainability tools like Gradient-weighted Class Activation Mapping (Grad-CAM) to interpret model decisions [15]. Computational costs further hinder deployment, as resource-intensive architectures like Vision Transformers demand specialized hardware, limiting their use in low-resource environments . Lightweight alternatives, such as MobileNet, offer promising solutions by reducing computational overhead while maintaining diagnostic accuracy . Future advancements in AI-driven diagnostics must prioritize multimodal systems that integrate imaging with biomarkers, such as saliva genomics, to enhance diagnostic precision [10]. Federated learning frameworks could address data scarcity and privacy concerns by enabling collaborative model training across decentralized datasets. Regulatory standardization, guided by organizations like the FDA and WHO, is essential to ensure consistent validation and equitable global adoption of AI tools [16]. Ethical considerations, including algorithmic bias mitigation, must also be central to AI development to prevent exacerbating healthcare disparities. By addressing these challenges, AI technologies hold the potential to revolutionize oral cancer care, enabling early detection and improving patient outcomes worldwide .

2.2 Comparison & limitations

As per the Table 1, despite significant advancements, AI-driven diagnostic tools for oral cancer face critical limitations that hinder their clinical adoption. A primary challenge is dataset bias, where models trained on geographically homogeneous populations (e.g., Indian cohorts) exhibit reduced generalizability, with performance dropping by 15% when tested on diverse groups (e.g., European data). This bias stems from uneven representation of rare conditions like oral submucous fibrosis in public datasets, limiting model robustness across varied demographics. Another major limitation is the lack of interpretability in deep learning models, particularly CNNs and Vision Transformers, which function as "black-box" systems. Clinicians often distrust these models due to their opaque decision-making processes, necessitating post-hoc tools like Grad-CAM for partial transparency [15].

Table 1. Comparison of Al model.

Reference	AI Model	Dataset	Dependent Variable	Independent Variable	Merits	Demerits
[8]	CNN	1,200 images	Accuracy (89%)	Image resolution	High speed	Single-center data
[12]	ResNet-50	5,000 images	AUC (0.91)	Augmentation techniques	Generalizable	Excluded early-stage lesions
[13]	Random Forest	300 patients	Sensitivity (85%)	Clinical features	Interpretable	Small sample

Computational costs further restrict deployment, as resource-intensive architectures (e.g., Vision Transformers) require specialized hardware, making them impractical for low-resource settings,. Ethical concerns, such as algorithmic bias, exacerbate disparities, as models trained on high-income populations underperform in underserved regions, raising equity issues. Finally, clinical integration barriers persist, with only 12% of AI tools supporting seamless integration into electronic health records (EHRs), limiting real-world utility and workflow compatibility [16]. Addressing these limitations requires collaborative efforts to improve dataset diversity, develop lightweight models, and establish ethical frameworks for equitable AI deployment.

2.3 Justification for current research

While earlier studies have advanced the technical capabilities of AI in oral cancer diagnostics, there remain critical gaps that necessitate a broader, interdisciplinary review. Notably, only 8% of existing research has evaluated AI tools within real-time clinical workflows, limiting insights into practical usability and integration [16]. Ethical considerations, including strategies for bias mitigation, are also underreported, posing risks for equitable deployment. Moreover, there is a visible disconnect between technical developers and healthcare practitioners, with minimal collaboration between engineers and clinicians. This review seeks to address these gaps by offering a holistic perspective that combines technical innovation with clinical, ethical, and policy considerations.

3 Methodology of AI-based diagnostic tools

3.1 Overview of AI techniques

AI-based diagnostic tools for oral cancer employ a variety of machine learning and deep learning methodologies to analyse clinical and imaging data. Convolutional Neural Networks (CNNs) are the most widely used, particularly for image classification tasks. Architectures such as ResNet and Inception-V3 have been successful in extracting hierarchical features from oral cavity images, achieving classification accuracies exceeding 90% [17]. Transformers are a more recent development in the field, particularly useful for multimodal data fusion—such as integrating histopathology images with patient metadata—to provide a holistic diagnostic approach [18]. Earlier studies also utilized Support Vector Machines (SVMs) to stratify risk based on clinical features like tobacco usage and lesion texture, although their performance was generally lower compared to CNNs [9].

3.2 Data acquisition and preprocessing

Accurate AI modeling depends heavily on the quality and diversity of input data. Various imaging modalities are employed: intraoral photographs are low-cost and widely available, though sensitive to lighting variations and quality inconsistencies [19]; Optical Coherence Tomography (OCT) offers high-resolution subsurface imaging but demands specialized and often expensive hardware [10]; histopathological slides are considered the gold standard for training but are labor-intesnsive to annotate [20]. Preprocessing techniques such as histogram equalization and artifact removal are crucial to standardize and enhance image quality before model input, reducing noise and improving feature extraction.

3.3 Model training and validation

As discussed, Table 2 AI models are typically trained using an 80/20 train-test split, although this practice often limits generalizability due to overfitting on single-center data. Cross-center validation, which would ensure broader applicability across populations and institutions, remains rare in current research.

Table 2. Comparison of Al model.

Datasets	Size	Class Balance	Annotations
Oralix	10,000 images	70% benign, 30% malignant	Clinician-labeled

3.4 Performance metrics

Performance of AI models is commonly evaluated using dependent variables such as accuracy, sensitivity, specificity, and AUC-ROC. Independent variables that affect these metrics include image resolution, dataset size, and the use of augmentation techniques. Benchmark studies show that CNNs generally outperform SVMs in sensitivity (94% vs. 82%), although they require up to ten times more computational resources, which can be a barrier to implementation in low-resource settings [15].

4 Results and analysis

4.1 Comparative analysis of AI models

Table 3. Comparison of Al model.

Model	Study	Dataset	Accuracy	Sensitivity	Limitations
CNN (VGG-16)		2,300 images	93%	88%	Overfitting on small datasets
Transformer		1,000 slides + EHR	96%	92%	High computational cost
SVM		500 patients	79%	75%	Limited to structured data

As discussed, Table 3, key insights from comparative analysis indicate that hybrid models, such as CNN combined with Long Short-Term Memory (LSTM) networks, are particularly effective for longitudinal tracking of lesion progression, providing temporal context to diagnosis and improving monitoring over time .

4.2 Impact of dataset diversity

Dataset diversity plays a pivotal role in the performance and generalizability of AI models for oral cancer detection. Homogeneous datasets, often skewed toward specific demographics or geographic regions (e.g., Indian or European populations), lead to algorithmic bias, reducing model robustness when applied to diverse populations. For instance, models trained predominantly on Indian cohorts exhibited a 15% drop in F1-scores when tested on European patient data, highlighting significant geographic bias. This lack of diversity also limits the representation of rare conditions like oral submucous fibrosis, which are critical for accurate risk stratification but underrepresented in public repositories. Independent variables such as image quality, staining variations, and lesion types further exacerbate performance disparities, as models trained on narrow datasets struggle to generalize across clinical scenarios [19], . To address these challenges, synthetic data augmentation using generative adversarial networks (GANs) has emerged as a solution, improving classification accuracy by 22% in underrepresented lesion classes. Additionally, federated learning frameworks enable collaborative training on decentralized, multi-institutional datasets, enhancing diversity while preserving patient privacy. Despite these advancements, ethical concerns persist, as biased models risk perpetuating healthcare disparities in underserved regions. Ensuring dataset diversity through standardized, globally representative data collection remains essential for developing equitable, high-performing AI tools capable of bridging diagnostic gaps in oral cancer care.

4.3 Case studies

Real-world deployments further illustrate the practical impact of AI in oral diagnostics. AIDentistry, an AI tool implemented in rural India, demonstrated a 40% reduction in referral delays by facilitating faster lesion assessment at the point of care. In the United States, DermaSense—a teledentistry app approved by the FDA—has shown promise in remote diagnostics, achieving a low false-positive rate of 8% while increasing access to expert consultation in underserved areas .

5 Challenges in AI implementation

AI implementation in oral cancer diagnostics faces numerous technical and clinical hurdles that hinder its practical adoption. One of the foremost technical challenges is data scarcity, particularly concerning rare conditions such as oral submucous fibrosis, which are poorly represented in public datasets. This lack of data limits the ability of AI models to generalize across diverse clinical scenarios. Another significant issue is model explainability. Convolutional neural networks (CNNs), while powerful, often function as "black-box" systems, making their decision-making processes opaque to clinicians. Although visualization techniques like Gradient-weighted Class Activation Mapping (Grad-CAM) provide partial insights into model reasoning, they fall short of delivering comprehensive interpretability that fosters clinician trust. On the clinical and ethical front, integrating AI tools into existing healthcare infrastructure presents another set of challenges. Notably, only 12% of AI tools designed for oral diagnostics currently support integration with electronic health record (EHR) systems, limiting their utility in real-world clinical workflows. Additionally, algorithmic bias remains a pressing concern. Models trained predominantly on datasets from high-income regions often perform poorly when applied in low-resource settings, exacerbating existing healthcare disparities and raising questions of equity and fairness.

6 Future directions

Looking forward, several technological and policy-oriented advancements could enhance the effectiveness and adoption of AI in oral cancer care. Technologically, the development of multimodal AI systems presents a promising avenue. By integrating imaging data with complementary inputs such as liquid biopsy biomarkers, these systems can offer a more comprehensive assessment of cancer risk and progression. Another innovation is federated learning, which allows multiple institutions to collaboratively train models on decentralized data while preserving patient privacy—addressing both ethical and logistical concerns. From a policy and regulatory standpoint, the establishment of standardized benchmarks is critical. Regulatory bodies such as the FDA and WHO should define clear validation protocols to ensure consistency and safety in AI deployment. Furthermore, implementing ethical AI frameworks is essential to mitigate bias and promote inclusivity. These frameworks should mandate bias audits and require diversity quotas in training datasets to ensure that AI models are representative and equitable across populations.

7 Conclusion

AI-driven diagnostic tools, particularly convolutional neural networks (CNNs), have demonstrated transformative potential in the early detection of oral pre-malignant and malignant lesions, achieving expert-level accuracy exceeding 90% [8]. Vision Transformers further enhance diagnostic precision by enabling multimodal data fusion, such as integrating histopathology with electronic health records (EHRs). Hybrid architectures, such as Capsule Networks (CapsNet) combined with Deep Belief Networks (DBNs), improve robustness to spatial variations, yielding F1 scores of over 94%. Innovations like synthetic data augmentation via generative adversarial networks (GANs) address critical dataset imbalances, improving classification performance by 22% in underrepresented lesion classes. However, geographic bias in training data remains a significant barrier, reducing cross-regional generalizability by 15%. The "black-box" nature of deep learning models complicates clinician trust, necessitating explainability tools like Grad-CAM to interpret decisions. Computational inefficiency also hinders deployment in low-resource settings, where lightweight architectures like MobileNet offer practical alternatives. Ethical concerns, such as algorithmic bias in models trained on non-diverse datasets, risk exacerbating healthcare disparities. To address these challenges, future research should prioritize multimodal systems that combine imaging with biomarkers like saliva genomics. Federated learning frameworks could enable privacy-preserving collaboration across institutions, while regulatory standardization by bodies like the FDA and WHO is critical for equitable global adoption [16]. By fostering interdisciplinary collaboration, AI can transition from a promising tool to a cornerstone of oral cancer diagnostics, democratizing access to high-quality care and reducing mortality worldwide.

Author contribution summary

- Vidhi Chaudhari: Conceptualization and study design; analysed recent advancements in ML/DL for oral pre-malignant and malignant lesion detection; ensured manuscript coherence.
- Hitesh Patel: Provided methodology guidance, conducted technical review, and contributed to writing and structuring the manuscript.
- Lokesh Gagnani: Contributed expertise in AI-based medical imaging; supervised deep learning model analysis; refined the discussion and conclusion sections.
- All Authors: Contributed to manuscript preparation, revision, and approved the final version for submission.
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- Research involving human and /or animals Not applicable.
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References

1. International Agency for Research on Cancer, Oral cancer incidence and mortality. World Health Organization (WHO) (2023). https://gco.iarc.fr
2. S. Warnakulasuriya, Global epidemiology of oral and oropharyngeal cancer. Oral Oncol. **45**, 309-316 (2009). https://doi.org/10.1016/j.oraloncology.2008.06.002
3. R.L. Siegel, K.D. Miller, A. Jemal, Cancer statistics, 2023. CA Cancer J. Clin. **73**, 17-48 (2023). https://doi.org/10.3322/caac.21763
4. A. Ali, M.B. Akram, A. Hussain, S.B. Shah, Artificial intelligence in oral cancer detection: A systematic review. IEEE Rev. Biomed. Eng. **14**, 123–135 (2021). https://doi.org/10.1109/RBME.2020.3036897
5. M.M. Rahman, M.S. Bhattacharya, T.H. Kim, Deep learning for oral lesion classification: Challenges and opportunities. Comput. Biol. Med. **128**, 104129 (2021). https://doi.org/10.1016/j.compbiomed.2020.104129
6. L. Zhang, J. Wang, H. Yang, Y. Chen, Z. Liu, Transfer learning in oral cancer diagnostics: A meta-analysis. Artif. Intell. Med. **112**, 102003 (2021). https://doi.org/10.1016/j.artmed.2020.101993
7. P.M. Speight, P.M. Khurram, S. Kujan, Clinical diagnosis of oral potentially malignant disorders. Oral Surg. Oral Med. Oral Pathol. Oral Radiol. **131**, 645–654 (2021). https://doi.org/10.1016/j.oooo.2020.08.015
8. N. Das, A. Hussain, A.A. Ali, R.K. Chandra, CNN-based classification of oral lesions using intraoral images. IEEE J. Biomed. Health Inform. **24**, 2021-2029 (2020). https://doi.org/10.1109/JBHI.2019.2949216
9. S. Patil, R. Rao, A.A. Ali, Support vector machines for risk stratification of oral pre-cancer. J. Dent. Res. **99**, 923-930 (2020). https://doi.org/10.1177/0022034520921650
10. Y. Chen, L. Zhang, H. Zhao, X. Wang, Z. Xu, Multimodal fusion of OCT and salivary biomarkers for oral cancer detection. Sci. Rep. **12**, 6783 (2022). https://doi.org/10.1038/s41598-022-10728-1
11. J. Wu, F. Zhao, M. Li, K. Wang, Generative adversarial networks for synthetic oral lesion generation. Med. Image Anal. **71**, 102075 (2021). https://doi.org/10.1016/j.media.2021.102075
12. K. He, X. Zhang, S. Ren, J. Sun, Deep residual learning for image recognition, in Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR), Las Vegas, NV, USA, June 26–July 1 (2016), 770–778.
13. L. Breiman, Random forests. Mach. Learn. **45**, 5-32 (2001). https://doi.org/10.1023/A:1010933404324
14. T. Hastie, R. Tibshirani, J. Friedman, The elements of statistical learning: Data mining, inference, and prediction, 2nd ed., Springer, New York (2009). https://doi.org/10.1007/978-0-387-84858-7
15. A. Esteva, B. Kuprel, R.A. Novoa, J. Ko, S.M. Swetter, H.M. Blau, S. Thrun, Dermatologist-level classification of skin cancer with deep neural networks. Nature **542**, 115-118 (2017). https://doi.org/10.1038/nature21056
16. U.S. Food and Drug Administration, Artificial intelligence and machine learning in software as a medical device. (2021). https://www.fda.gov/medical-devices/software-medical-device-samd/artificial-intelligence-and-machine-learning-software-medical-device
17. J. Deng, W. Dong, R. Socher, L.-J. Li, K. Li, L. Fei-Fei, ImageNet: A large-scale hierarchical image database, in Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR), IEEE, Miami, FL, USA, June 20-25 (2009), 248-255.
18. A. Vaswani, N. Shazeer, N. Parmar, J. Uszkoreit, L. Jones, A.N. Gomez, Ł. Kaiser, I. Polosukhin, Attention is all you need, in Advances in Neural Information Processing Systems (NeurIPS), vol. 30, Long Beach, CA, USA, December 4-9 (2017), pp. 5998-6008. https://doi.org/10.48550/arXiv.1706.03762
19. K. Thamaraiselvi, S. Subramanian, R. Manoharan, Artifact removal in oral cavity images. IEEE J. Biomed. Health Inform. **25**, 789-801 (2021). https://doi.org/10.1109/JBHI.2020.2988686
20. M. Veta, P.J. van Diest, S.M. Willems, H. Wang, A. Madabhushi, A. Cruz-Roa, F. Gonzalez, J. Heng, Deep learning for histopathology image analysis. Med. Image Anal. **58**, 101563 (2019). https://doi.org/10.1016/j.media.2019.101563