RESEARCH ARTICLE

Artificial Intelligence in preventing and detecting skin cancer. A narrative review

Razvan Soric[1*], Ovidiu Simion Cotoi[2,3], Iuliu Gabriel Cocuz[2,3]

[1] George Emil Palade" University of Medicine, Pharmacy, Sciences and Technology of Targu Mures Romania
[2] Pathophysiology Department, "George Emil Palade" University of Medicine, Pharmacy, Sciences and Technology of Targu Mures, 540142 Targu Mures, Romania
[3] Clinical Pathology Department, Mures Clinical County Hospital, 540011 Targu Mures, Romania

Abstract

Objectives: We present a comprehensive literature review regarding the role of Artificial Intelligence in prevention and detection of skin cancer, emphasizing its diagnostic accuracy, interpretability, and clinical integration while reducing healthcare burden and costs.

Methods: Research has been conducted across databases such as PubMed and Google Scholar. We selected 38 peer-reviewed studies, relevant to our topic. The synthesis of the articles was based on five research directions.

Results: Artificial Intelligence particularly trough deep learning and convolutional neural networks, achieved diagnostic accuracies exceeding 90% in differentiating benign from malignant skin lesions using datasets such as International Skin Imaging Collaboration (ISIC) and Human Against Machine with 10,000 training images (HAM10000). Biologically inspired algorithms, residual networks, and autoencoders are all combined in hybrid models to further increase sensitivity and specificity. Our review showcases how effective can Artificial Intelligence be in digital histopathology, automated segmentation, and predictive modeling when implemented correctly. Smartphone applications and prevention campaigns enabled early detection and public awareness of skin cancer.

Conclusions: Artificial Intelligence will become the ultimate pillar of dermatopathology by cutting down medical related costs and supporting clinicians. Nevertheless, tackling issues regarding dataset diversity, algorithmic clarity, ethical standards, and clinical validation will help us develop transparent, equitable and secure systems that assist rather than replace human verification.

Keywords: Artificial intelligence, Skin cancer, dermatopathology

Received 5 December 2025 / Accepted 12 june 2026

Introduction

Cancer remains one of the leading causes of death and is responsible for approximately 10 million fatalities annually with the number expected to keep rising at least until 2030, according to the World Health Organization (WHO) [1]. As the sixth most prevalent type of cancer, skin cancer incidence continues to increase so it is safe to say we should focus on preventing it [2].

Identifying the three main types of cancer such as melanocytic cancers (melanoma), and non-melanocytic skin cancers - Basal Cell Carcinoma (BCC) or Squamous Cell Carcinoma (SCC) requires multiple diagnostic techniques, including dermoscopy, clinical screening, histopathology, and immunohistochemistry. These procedures can be time consuming for dermatologists and pathologists [3]. Dermoscopy differentiates benign from malignant skin lesions via dermatoscope, a magnification tool with a polarized light source. Dermatologists analyze skin lesions for patterns such as ramifications, globs, pigmented networks, veils and colors. Medical detection algorithms were developed to save time when performing differential diagnosis from benign to malign skin lesions, one of the most practiced ones being the Asymmetry, Border, Color, Diameter (ABCD) rule presented by Nachbar [4].

Histopathological examination is indispensable for accurate diagnosis of skin cancer, as it provides definitive morphological and cytological insights. Irregular and thick nuclear membrane with prominent nucleoli is characteristic for melanoma [5]. Stromal tissue surrounding basaloid keratinocytes aggregates with intense basophilic coloration, scant cytoplasm and uniform nuclei help pathologists identify BCC [6]. The spinous layer of the malignant epidermal cells invading the dermis, accompanied by inflammatory cell infiltrate, in the shape of advancing sheets with keratinization present as individual cells or as concentric pearls is a typical pattern for SCC [7].

As artificial intelligence keeps getting more reliable it made it's way into digital dermatopathology. The most help we can get out of it so far for skin cancer is diagnostic wise because it can lower the burden of practitioners thus offering more time for them to focus on treating the patients while keeping the costs at the low limit [8].

The objective of this review is to explore how artificial intelligence (AI) based systems can improve identification and diagnosis of skin cancer while fostering trust between technology and practitioners through transparency and interpretability. We aim to shine light on image processing techniques, limitations of the algorithms, ethical considerations and primary skin cancer prevention through AI

* Correspondence to: Razvan Soric
E-mail: razvansoric@yahoo.com

software.

Methodology

The present review focuses on AI applications in early detection, risk assessment, public awareness, and preventive strategies, ensuring a broad yet targeted exploration of the topic. A thorough search for relevant studies has been conducted across research databases such as PubMed and GoogleScholar. Key-words for interrogation of the databases included "artificial intelligence", "skin cancer prevention", "Hybrid deep learning", "image classification skin pathology", "clinical workflow integration", "digital diagnostics", "telepathology" and "early detection." Inclusion criteria prioritized peer-reviewed articles published in the last decade, specifically addressing AI's role in prevention. Studies were included in this review only with features like raised diagnostic accuracy, low dependency on clinical expertise, increased interpretability while also trying to address critical challenges such as bias in training datasets and lack of standardized reporting algorithms. We excluded case reports, studies that did not share a clear outcome or suggestive results. Findings were organized thematically to highlight key insights. Agreements, discrepancies, and unique contributions among studies were compared to provide a comprehensive understanding of the topic. We selected 38 publications based on the stated criteria out of 126 reviewed.

Evolution of digital histopathology and benefits of integrating AI

Digitized hematoxylin eosin (HE) slides revolutionized histopathological examination since they enable large-scale storage, sharing, and computational analysis, essential for modern pathology research. In order to digitize HE slides the traditional glass slides are scanned using high-resolution whole-slide imaging (WSI) scanners which converts them into digital images. Then we can use dedicated computer programs in order to examine the images with great resolution [8].

Research about artificial intelligence (AI) in the prevention and detection of skin cancer has seen significant advancements, both nationally and globally, as it addresses more and more specific obstacles such as automated interpretable classification and prediction systems which can help identify cancer at an earlier stage, before the visual criteria is noticeable, thus obtaining a better prognosis and less invasive treatment. These advancements have led to the development of hybrid systems that use multiple deep learning techniques thus obtaining increased performance and high accuracy results [9,10].

Artificial intelligence (AI), particularly through deep learning and convolutional neural networks, has demonstrated great potential in healthcare by overcoming the variability in clinician expertise. AI-based systems can analyze vast datasets rapidly, identify patterns more precisely than human eye and aid the time-wasting procedures in recognizing skin cancer [11,12,13]. These capabilities not only enhance early detection rates but also reduce the burden on healthcare systems, lower associated costs and improve patient outcomes while being accessible worldwide via telepathology [14].

Nowadays it takes just a few screen touches inside a skin cancer detection phone application for a normal person to pre-diagnose themselves with potential skin cancer. Only after getting the AI results if positive they are advised to get an appointment with a real doctor saving themselves money and time [15,16].

The role of AI and machine learning in reshaping histopathological diagnosis and skin cancer prevention

AI-driven analysis of digitized HE slides revolutionizes research by leveraging deep learning (DL) and machine learning (ML) techniques since it can process thousands of slides in minutes and identify histopathological features with precision beyond human capability. AI allows large-scale biomarker discovery such as expression of PD-L1, CTLA-4, integrating histopathological data with genomic (e.g. mutations of BRAF, KIT, NRAS, TP53) and clinical datasets through a multinodal approach. This accelerates the development of predictive models for prognosis and treatment response. Artificial Intelligence lets us standardize the slide interpretation thus, reducing diagnostic variability while also improving reproducibility and reliability in multicenter studies. A crucial role in detecting cancerous regions, grading tumors and segmenting tissue structures with remarkable accuracy is played by Convolutional neural networks (CNNs) which are often used for image recognition because they learn and extract visual patterns from digitized slides using their convolutional layers. In the study conducted by Rantalainen et al. CNNs exceeded 95% sensitivity and specificity. Segmentation is achieved by detecting patterns in edge structures, textures, and color intensities, enabling the model to differentiate between normal and malignant tissues. CNNs then proceeded to tumor morphology analyzing features like cell shape, size, and arrangement in order to grade melanomas based on histological parameters such as Breslow thickness, Clark level, and mitotic rate [8].

In a research by Rezk et al. [9] Incremental Domain Knowledge Learning (IDKL) was introduced for interpretable skin cancer classification. It used a deep neural network to extract histopathological features from digitized slides. Their model was built in layers, first determining whether the sample is skin tissue or not with an 87% accuracy rate. Then it assessed whether the lesion is benign or malignant, achieving 77% accuracy and finally it identified the exact type of skin cancer with an accuracy of 71%. For raised interpretability it used saliency maps to highlight diagnostically relevant image regions, thus allowing clinical reasoning. What made this approach more valuable than just delivering a diagnosis is the step by step process, supporting clinicians for the final diagnostic with tangible insights rather than replacing them while still being accurate and transparent.

Bassel et al. [10] used hybrid deep learning for automated differential diagnosis between benign and malignant skin cancer. Dermoscopic pictures were enhanced by removing irrelevant data during preprocessing. Then the input image was divided into distinct regions, with the most prominent and relevant region identified for subsequent analysis which gives clinicians confidence in the end result. Feature extraction for skin cancer identification is performed using the ABCD rule. The stacking mechanism enabled them to integrate multiple classification models, capitalizing their combined strengths during both the training and testing phases. They achieved 90,9% accuracy with dataset extracted from ISIC. The experiment successfully improved the accuracy of three CNNs used as feature extraction models: Residual Network 50 (ResNet50), Extreme Inception (Xception), and Visual Geometry Group 16 (VGG16). The extracted features were subsequently processed using various classification methods, including deep learning, Support Vector Machine (SVM), k-Nearest Neighbors (KNN), neural networks (NN), regression, and random forest.

Skin Cancer Detection Applications studied by Kulkarni et al. [15] used hybrid CNNs models combining visual classification with sonification of pixels which reduces biases associated with skin tone, age, and gender. The dual-modality audio-visual classifier achieved high diagnostic accuracy for skin cancer (SC) in both Fitzpatrick Skin Types (FS) and Darker Skin Types (DS), with Receiver Operating Characteristic - Area Under the Curve (ROC-AUC) values of 0.858 (95% CI: 0.795–0.921) and 0.856 (95% CI: 0.759–0.953) respectively, and equivalent sensitivity and specificity at approximately 80–85%, showing no significant bias across skin tones. Making it feasible for any type of smartphone user. Image capture using smartphones often lacks standardization in terms of distance, lighting conditions, delineation of lesion boundaries, leading to reduced diagnostic accuracy 83% but this app could also work on standardized dermoscopic images which brings its sensitivity up to 90%.

Additionally, current data showed that users of Skin Cancer Detection Applications have significantly higher dermatological claims compared to controls. Odds ratios are reflecting increased claims for premalignant lesions: 20% vs. 10% and malignant lesions: 15% vs. 5% with adjusted p-values < 0.05. High-risk users accounted for 30% of the claims inside the application while only 12% were low-risk users which clearly highlights the impact it has on early detection. The app's real-world implementation should target high-risk groups to achieve a higher positive predictive value while also addressing the potential for overdiagnosis, which may lead to increased anxiety among users [16].

In another study which analyzed Convolutional Neural Networks (CNNs) it has been proven that we can reach superior performance in skin lesion classification by using the Human Against Machine with 10,000 training images (HAM10000) dataset. They achieved 94% accuracy which clearly outperformed traditional methods like Artificial Neural Networks (79.8%) and Multilayer Perceptrons (70.5%) through fine-tuning and transfer learning approaches [17].

A research by Dhibar et al. [18] conducted on a DAE-ResNet101 hybrid model achieved remarkable accuracy levels of 96.03%. Significantly outperforming traditional CNN-based skin lesion classification that solely relied on convolutional layers to extract features. Their model integrates a deep autoencoder (DAE) with ResNet101 allowing it to capture nuanced patterns and detect anomalies more effectively. This result highlights the potential of integrating autoencoding techniques with deep residual networks in digitized slides examination.

Kulkarni et al. [19] explored the potential of deep learning to estimate the prognosis of 155 patients from digitized slides in early-stage melanoma cases. They used an open-source software named "QuPath" for segmenting cell nuclei and classifying cell types in order to identify regions of interest (ROI). With an area under the curve (AUC) of 0.880 and 0.905 for disease-specific survival, it demonstrated excellent predictive performance. The model considered a number of factors when examining the histopathological findings but the key prognostic predictor was immune cell infiltration, specifically lymphocyte density.

In an effort to improve skin cancer detection, Maurya et al. [20] came up with an advanced AI framework known as DualAutoELM. This system integrated two distinct types of autoencoders (DualAuto), the Fast Fourier Transform (FFT) and a spatial one which collectively allowed the model to learn local and global patterns in dermoscopic images. The spatial autoencoder retained the configuration of visual data, helping the model to identify lesion morphology and border irregularities while the FFT-autoencoder captured nuanced textural and periodic patterns that may have been imperceptible in the spatial domain. After this an Extreme Learning Machine (ELM), a neural classifier which is recognized for its fast learning and effective generalization, received the feature sets managing to effectively identify with 97.66% accuracy seven skin cancers from 10.015 dermoscopic pictures that make up the HAM10000 dataset.

Exploration of a latent autoencoder jointed with adversarial training to improve the detection of intra-epidermal carcinoma detection proved to be successful with a reconstruction accuracy of 92% and 15% boost in classification accuracy compared to conventional CNNs. This model overcame noisy and low-contrast dermatological images by compressing and reconstructing the images. Subsequently a secondary neural network challenged the autoencoder to produce more realistic reconstructions, technique called adversarial training [21].

In order to automatically classify skin lesions, Alenezi et al. [22] introduced a hybrid approach that combined a wavelet transform-based preprocessing technique with a deep residual neural network (ResNet101) for feature extraction, followed by an Extreme Learning Machine (ELM) for classification. Amplification of significant patterns and diminishing the noise from the dermoscopic images is done by the wavelet transform technique. ResNet101 model is then used to capture hierarchical deep features across multiple layers of the preprocessed images. The extracted feature vectors are subsequently classified using a Rectified Linear Unit (ReLU) based ELM. When evaluated on the HAM10000 dataset, the model achieved an impressive accuracy of 95.75.

Another Hybrid deep learning model was introduced by Toğaçar et al. [23] but this time it focused on dividing benign from malign images with accuracy rates of 95.27% when evaluated on ISIC skin cancer dataset, comprising 1,800 benign and 1,497 malignant images. They first used Mobile Deep Learning Convolutional Neural Network Version 2 (MobileNetV2) as an autoencoder to extract important features from skin lesion images. Then, they passed these features through a Spiking Neural Network (SNN), a type of model that processes information in a way that mimics how real neurons in the brain communicate, by sending quick, timed spikes.

Gomathi et al. [24] took a different approach for the hybrid deep learning method. In order to classify Skin lesions within the HAM10000 dataset with a successful accuracy of 96.46% they combined CNNs with two nature-inspired optimization algorithms: Bacterial Foraging Optimization (BFO) which navigates the image to locate the optimal parameters like a bacteria and Particle Swarm Optimization (PSO) which adjusts the particles for the best solution mimicking bird flocking.

Göçeri et al [25] managed to overcome the struggles of traditional CNNs by combining them with Capsule networks which preserved the spatial hierarchies and relationships between features obtaining an accuracy of 95.24% within the HAM10000 dataset.

A prevention campaign focused on AI-based simulation of facial skin aging study showed improved sun protection behavior in female adults (91.7%) after seeing the photoaging result. Thus, implementation of computer-based skin aging simulation in healthcare has proven to be an effective strategy for fostering adequate attitude toward skin cancer primary prevention among young adults, yielding sustained benefits over both short and long term [26].

Table 1. Comparative Analysis of AI Approaches regarding Skin Cancer Detection & Prevention

AI Model	Studies	Function	Prevent	Screening	Prognosis	Diagnosis	Key Notes
CNNs	[8], [10], [15], [16] [17], [24]	Image recognition, feature extraction, sonification	Limited	High (>90%)	Tumor grading	Classification + differential + mobile triage	high accuracy, low interpretability, reduce bias
IDKL	[9]	Stepwise classification with saliency maps	Indirect	Moderate (77%)	Limited	Transparent diagnosis	More interpretable, less accurate
Autoencoder hybrids	[18], [20], [21]	Compression + anomaly detection	None	(92–97.66%)	Pattern detection	Enhanced classification	Handles noise better
CNN + Capsule	[25]	Spatial hierarchy preservation	None	High (~95.24%)	Limited	Improved	Better spatial relations
Wavelet + CNN + ELM	[22]	Noise reduction + classification	None	High (~95.75%)	Limited	Efficient classification	Better preprocessing
MobileNetV2 + SNN	[23]	Brain-inspired classification	None	High (~95.27%)	Limited	Fast classification	Energy efficient
Prognostic DL	[19]	ROI + survival prediction	None	Indirect	Strong (AUC 0.88–0.905)	Limited	Focus on prognosis
AI Simulation	[26]	Photoaging simulation	Strong	Indirect	None	None	Best for prevention

Limitations and advantages of AI in digital pathology

Despite these advances, challenges persist. Ethical concerns, such as algorithmic transparency and increased responsibility should be reinforced when developing the AI systems through improved regulations. Adherence to bioethical principles remains a significant matter due to the lack of integration between technology developers, medics, ethicists and the public. The poor managed skin tone differences are a critical matter that should be addressed because it creates inequality between races. Regarding algorithm development and efficacy, the concern is there are not enough consistent studies to back them up or shared details [27].

One important obstacle to overcome in the future is the limited diversity in skin cancer datasets while also keeping in mind that the primary advantage of deep learning lies in its ability to automatically learn features from data without requiring input or guidance from human experts. This means that if implemented correctly, the AI systems can actually improve accuracy by their own just from analyzing more and more data which leads to a vast comparison ability before identifying skin cancer [10].

Without transparency such as providing insight of their decision making process, these applications will never proliferate in clinical settings. Considering that errors in this field could be fatal, the European Commission required in 2021 that every medical service AI application should include transparency. From that point on the explainable artificial intelligence (XAI) was developed with the purpose of diminishing the concerns from above [9, 28, 29].

Goyal M et al [29] showcased a bunch of limitations such as low generalizability due to biased or imbalanced datasets, poor interpretability of deep learning models, inconsistent image quality, and a lack of rare lesion types in training data.

Handling irrelevant image variations due to differing tissues and scanning errors is another struggle because, unlike pathologists, AI can mistake technical artifacts for biological signals. Besides that, the digitized slides require a lot of processing which AI struggles with. Tiling solves that problem but it comes with the impossibility of capturing both global tissue architecture and fine cellular detail simultaneously [30].

As stated previously and shown by Baxi V et al [31] in Table 1 despite many challenges there are also enough advantages such as raised availability trough electronic medical records, lowered error risk by using algorithms, better storage and management of digital slides, cheaper costs and time saving for both patients and doctors.

6. Integration of AI into the Pathologist's Workflow

AI was designed to support pathologists, not replace them. It can pre-analyze large volume of whole-slide images to detect metastases, highlight regions of interest, assess biomarkers such as Ki-67 proliferation index, generate predictions faster than traditional methods while keeping a user friendly interface to enhance the final decision of the pathologist, who is tasked with validating, refining and contextualizing the results in the clinical setup. This collaboration improves diagnostic consistency, speeds up routine analyses, reduces error and supports innovation, while maintaining the clinician's essential role. [8] Early detection of skin cancer trough AI systems also helps the pathologist to start the treatment and investigations in early stages where it can easily make a difference [15,16].

Kulkarni et al. [32] trained a CNN to identify histopathological patterns from digitized slides such as nuclear atypia, cell density, and tissue architecture and then use them in order to predict the disease-specific survival (DSS) of each patient tested. This software stands as a great triaging tool for clinicians.

Diaz-Ramón et al. [33] went even further with their study, assessing immunohistochemical (IHC) biomarkers from melanoma biopsies alongside clinical and serological data. The authors measured the expression in tumor tissue of proteins such as RKIP, PIRIN, BCL2, BCL3, MITF, and ANXA5 by IHC. They also quantified the intratumoral presence of BCL2-positive infiltrating lymphocytes. The results are then used as input in a machine learning model specifically a decision tree built in RapidMiner that predicts metastatic progression and disease-free survival. Features such as Breslow thickness, intratumoral BCL2 lymphocyte infiltration status, and serum IL-4 / IL-6 levels are being used as the primary predictors of metastasis thus, making it possible to stratify patients by metastatic risk. This is a great example of integrated work between AI and pathologists.

Hekler et al. [34] trained a CNN on 595 digitized slides half nevi, half melanoma biopsies and then compared the results of 100 different images analyzed by the CNN and 11 pathologists. Finally, the CNN with a p value of 0.016 achieved higher results than the pathologists.

Table 2. Comparative Analysis of AI Approaches regarding Pathologist workflow

AI Approach	Study	Workflow	AI Task	Pathologist Task	Clinical Impact
CNN-based histopathological analysis	[32]	Prognosis	Extracts features and predicts survival	Reviews + integrates results	Triage tool
Decision Tree ML (multimodal data)	[33]	Prognosis	Combines biomarkers + clinical data to predict metastasis	Validates + applies risk categories	Risk stratification
CNN classification (AI vs pathologist)	[34]	Diagnosis	Classifies benign vs malignant lesions	Verifies + contextualizes output	Triage tool

Future of AI

The future of AI in clinical practice is expected to strengthen the collaboration with clinicians rather than replacing them. Although AI demonstrated high accuracy in controlled settings, expert oversight while slowly introducing it into the clinical workflow will remain essential for the foreseeable future because this will prevent the errors that might arise.

Population screening by AI through body photography is promising but we shouldn't neglect AI's lower specificity outside carefully selected high-risk groups.

Our key future research point is determining AI's role in targeted population and screening post expert triage while focusing on individualized decision-making process benefiting the patient risk profile.

Hanna et al. [35] pointed out an area that should be exploited further by researchers, the 3D digitized slides which can be achieved through z-stacks. The Panoramic Optical (Panoptiq) system basically combined low-magnification panoramic images with high magnification regions of interest (ROI) in order to win time while examining them.

AI will require extensive prospective clinical validation, integration of personalized clinical context, and reinforcement of human–AI collaboration models to maximize patient benefit while minimizing risks. [36]

Another area that deserves attention is Generative AI and federated learning which can help us train any model of choice without the burden of confidentiality or ethical concerns by delivering generated rare input which would be hard to access from real patients [37, 38].

Standardization and optimizations of repetitive tasks is the final goal. Different AI software are already being used to aid doctors in writing the final diagnostic report right from the whole slide images (WSI) or replace their work completely for counting the mitotic figures or evaluating the margins which have been excised [37, 38].

As Cocuz et al. [37] pointed out AI software not only needs to be authorized by the competent authorities as medical software and be clearly distinguished from research-use-only software before being used in any clinical set but also documented and explicable.

We should also focus on giving out training sessions for the medical personal before allowing them access to the AI software in order to ensure full legal responsibility and prevent any human errors.

Without a clear ethical framework AI is on the verge of not only being the spotlight of discrepancies between medical centers but also aggravating them since it can learn automatically from the input of data it receives which may lack in some regions of the world [37].

Cloud-based storage systems in every medical center or application should also benefit from increased cybersecurity since they are becoming more and more targeted by hackers [37].

Expert oversight remains our only anchor in preventing the errors that might occur from using AI.

Conclusions

AI is becoming a tool in clinical sets rather than a project that we perceive far in the future. AI stands as a global framework for dermatopathology since without the physical movement of the samples we can achieve diagnosis from one place followed by a checkup from another place via telepathology. By assessing a vast quantity of data in a short period of time, then summarizing and highlighting the results it flawlessly befits clinicians in order to increase the lifespan of patients. The predictive and preventive potential of artificial intelligence will further increase trough the convergence of digital pathology, multi-omics data and generative AI. Standardizing the results will create multicenter databases which will bring a new palpable field for researchers and clinicians. When concerns will be eradicated by robust ethical and legal frameworks, the thrust of implementing it as a tool into daily routine will automatically increase. The ultimate step to overcome is multiphase verification which is and will be necessary for the years to come in order for AI to coexist into the clinical workflow legally. The true power of AI lies not merely in its computational strength but in its ability to help doctors notice earlier, understand deeper, and act faster against one of the most preventable forms of cancer.

Authors' contributions

RS (Data curation, Funding acquisition, Investigation, Project administration, Resources, Software, Visualization, Writing – original draft, Writing – review & editing)

IGC (Conceptualization, Formal analysis, Investigation, Methodology, Project administration, Supervision, Validation, Writing – review & editing)

OSC (Conceptualization, Formal analysis, Investigation, Methodology, Project administration, Supervision, Validation, Writing – review & editing)

Funding

No external funding was received.

Acknowledgments

None.

References

1. Leiter U, Keim U, Garbe C. Epidemiology of skin cancer: update 2019. Adv Exp Med Biol. 2020;1268:123-39.
2. Siegel RL, Giaquinto AN, Jemal A. Cancer statistics, 2024. CA Cancer J Clin. 2024;74:12-49.
3. Hasan MK, Ahamad MA, Yap CH, et al. A survey, review, and future trends of skin lesion segmentation and classification. Comput Biol Med. 2023;155:106624.
4. Almaraz-Damian JA, Ponomaryov V, Sadovnychiy S, et al. Melanoma and nevus skin lesion classification using handcraft and deep learning feature fusion via mutual information measures. Entropy. 2020;22:484.
5. Ahmed B, Qadir MI, Ghafoor S. Malignant melanoma: skin cancer-diagnosis, prevention, and treatment. Crit Rev Eukaryot Gene Expr. 2020;30:291-7.
6. Marzuka AG, Book SE. Basal cell carcinoma: pathogenesis, epidemiology, clinical features, diagnosis, histopathology, and management. Yale J Biol Med. 2015;88:167-79.
7. Kane CL, et al. Histopathology of cutaneous squamous cell carcinoma and its variants. Semin Cutan Med Surg. 2004;23:54-61.
8. Acs B, Rantalainen M, Hartman J. Artificial intelligence as the next step towards precision pathology. J Intern Med. 2020;288:62-81.
9. Rezk E, Eltorki M, El-Dakhakhni W. Interpretable skin cancer classification based on incremental domain knowledge learning. J Healthc Inform Res. 2023;7:59-83.
10. Bassel A, Abdulkareem AB, Alyasseri ZAA, et al. Automatic malignant and benign skin cancer classification using a hybrid deep learning approach. Diagnostics (Basel). 2022;12:2472.
11. Akter MS, Shahriar H, Sneha S, et al. Multi-class skin cancer classification architecture based on deep convolutional neural network. arXiv. 2023;2303.07520.
12. Agarwal K, Singh T. Classification of skin cancer images using convolutional neural networks. arXiv. 2022;2202.00678.
13. Haggenmüller S, Maron RC, Hekler A, et al. Skin cancer classification via convolutional neural networks: systematic review of studies involving human experts. Eur J Cancer. 2021;156:202-16.
14. Royall J, Isyagi MM, Iliyasu Y, et al. From access to collaboration: four African pathologists profile their use of the internet and social media. Clin Lab Med. 2018;38:53-66.
15. Kulkarni PM, Robinson EJ, Sarin Pradhan J, et al. Deep learning based on standard H&E images of primary melanoma tumors identifies patients at risk for visceral recurrence and death. Clin Cancer Res. 2020;26:1126-34.
16. Walker BN, Blalock TW, Leibowitz R, et al. Skin cancer detection in diverse skin tones by machine learning combining audio and visual convolutional neural networks. Oncology. 2024;108:1-8.
17. Smak Gregoor AM, Sangers TE, Bakker LJ, et al. An artificial intelligence-based app for skin cancer detection evaluated in a population-based setting. NPJ Digit Med. 2023;6:90.
18. Manokar M, Karthikeyan S, Manogaran G. Artificial intelligence-driven enhanced skin cancer diagnosis using convolutional neural networks and discrete wavelet transformation. Egypt J Med Hum Genet. 2024;25:50.
19. Dhibar S. ResNet101 and DAE for enhanced quality and classification accuracy in skin cancer imaging. arXiv. 2024;2403.14248.
20. Maurya R, Mahapatra S, Dutta MK, et al. Skin cancer detection through attention guided dual autoencoder approach with extreme learning machine. Sci Rep. 2024;14:17785.
21. Thomas SM. Representation learning for non-melanoma skin cancer using a latent autoencoder. arXiv. 2022;2209.01779.
22. Alenezi F, Armghan A, Polat K. Wavelet transform-based deep residual neural network and ReLU-based extreme learning machine for skin lesion classification. Expert Syst Appl. 2023;213:119064.
23. Toğaçar M, Cömert Z, Ergen B. Intelligent skin cancer detection applying autoencoder, MobileNetV2 and spiking neural networks. Chaos Solitons Fractals. 2021;144:110714.

24. Gomathi E, Jayasheela M, Thamarai M, et al. Skin cancer detection using dual optimization-based deep learning network. Biomed Signal Process Control. 2023;84:104968.
25. Goceri E. Classification of skin cancer using adjustable and fully convolutional capsule layers. Biomed Signal Process Control. 2023;85:104949.
26. Gantenbein L, Cerminara SE, Maul JT, et al. Artificial intelligence-driven skin aging simulation as a novel skin cancer prevention strategy. Dermatology. 2024;240:1-8.
27. Shah SFH, Arecco D, Draper H, et al. Ethical implications of artificial intelligence in skin cancer diagnostics: use-case analyses. Br J Dermatol. 2024;191:e434.
28. Goyal M, Knackstedt T, Yan S, et al. Artificial intelligence-based image classification methods for diagnosis of skin cancer: challenges and opportunities. Comput Biol Med. 2020;127:104065.
29. Barredo Arrieta A, Díaz-Rodríguez N, Del Ser J, et al. Explainable artificial intelligence (XAI): concepts, taxonomies, opportunities and challenges toward responsible AI. Inf Fusion. 2020;58:82-115.
30. Zarella MD, McClintock DS, Batra H, et al. Artificial intelligence and digital pathology: clinical promise and deployment considerations. J Med Imaging (Bellingham). 2023;10:051802.
31. Baxi V, Edwards R, Montalto M, et al. Digital pathology and artificial intelligence in translational medicine and clinical practice. Mod Pathol. 2022;35:23-32.
32. Kulkarni PM, Robinson EJ, Sarin Pradhan J, et al. Deep learning based on standard H&E images of primary melanoma tumors identifies patients at risk for visceral recurrence and death. Clin Cancer Res. 2020;26:1126-34.
33. Diaz-Ramón JL, Gardeazabal J, Izu RM, et al. Melanoma clinical decision support system: an artificial intelligence-based tool to diagnose and predict disease outcome in early-stage melanoma patients. Cancers (Basel). 2023;15:2174.
34. Hekler A, Utikal JS, Enk AH, et al. Deep learning outperformed 11 pathologists in the classification of histopathological melanoma images. Eur J Cancer. 2019;118:91-6.
35. Hanna MG, Monaco SE, Cuda J, et al. Comparison of glass slides and various digital-slide modalities for cytopathology screening and interpretation. Cancer Cytopathol. 2017;125:701-9.
36. Brancaccio G, Balato A, Malvehy J, et al. Artificial intelligence in skin cancer diagnosis: a reality check. J Invest Dermatol. 2024;144:492-9.
37. Cocuz IG, Niculescu R, Popelea MC, et al. Current trends and future directions of digital pathology and artificial intelligence in dermatopathology: a scientometric-based review. Diagnostics (Basel). 2025;15:2196.
38. Flores J, Misra R, Shah B, et al. Artificial intelligence and machine learning transforming dermatopathology with diagnosis and predictive analytics. Dermis. 2025;5:29.