Review Article

# Using the power of artificial intelligence to improve the diagnosis and management of nonmelanoma skin cancer

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Nonmelanoma skin cancer (NMSC), including basal cell carcinoma and squamous cell carcinoma, is the most prevalent type of skin cancer. While generally less aggressive than melanoma, early detection and treatment are crucial to prevent the complications. Artificial intelligence (AI) systems show promise in enhancing the accuracy, efficiency, and accessibility of NMSC diagnosis and management. These systems can facilitate early interventions, reduce unnecessary procedures, and promote collaboration among healthcare providers. Despite AI algorithms demonstrating moderate-to-high performance in diagnosing NMSC, several challenges remain. Ensuring the robustness, explainability, and generalizability of these models is vital. Collaborative efforts focusing on data diversity, image quality standards, and ethical considerations are necessary to address these issues. Building patient trust is also essential for the successful implementation of AI in the clinical settings. AI algorithms may outperform experts in controlled environments but can fall short in the real-world clinical applications, indicating a need for more prospective studies to evaluate their effectiveness in the practical scenarios. Continued research and development are essential to fully realize AI's potential in improving NMSC diagnosis and management by overcoming the existing challenges and conducting comprehensive studies.

**Key words:** Artificial intelligence, nonmelanoma skin cancer, diagnosing and managing

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## INTRODUCTION

Skin cancer is a significant global health issue, accounting for 32.5% of all diagnosed malignancies, with approximately 7.96 million cases reported annually due to UV exposure. While melanoma is relatively rare, it is highly malignant. On the other hand, nonmelanoma skin cancers (NMSCs) are more common but less fatal, boasting a 5-year cure rate of 98.9% when detected early. However, the incidence of NMSCs is on the rise, and they are often misdiagnosed, underscoring the critical importance of timely and accurate diagnosis, which is equally crucial for melanoma.[1,2]

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NMSC represents the majority of diagnosed skin cancer cases worldwide, with an estimated 5 million new cases each year. The two primary types are basal cell carcinoma (BCC) and squamous cell carcinoma (SCC), with BCC being the most prevalent.[3-5]

Genomic studies and molecular profiling have shed light on the biology and progression of keratinocyte carcinomas, such as cutaneous SCC. These investigations have identified driver mutations (TP53, TMEM51, CDKN2A, SNF52F, ZZEF1, and NOTCH1/2) and TP63 gene methylation as the key players in these carcinomas.[6] Similarly, genomic and transcriptomic analyses of BCC have revealed distinct molecular subtypes with unique activation of signaling pathways



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and metabolic processes, highlighting the heterogeneity of these skin cancers. For instance, surface BCCs are associated with PTCH1 and NOTCH1 mutations, and the upregulation of genes such as SPHK1, MTHFD1, and BMS1P20 has been observed.[6]

Diagnosing early BCC lesions can be difficult, often requiring noninvasive diagnostic methods such as optical coherence tomography (OCT) and confocal laser scanning microscopy.[7] Histopathological examination is essential for confirming the diagnosis.[8,9] The primary treatment is surgical removal, including methods such as Mohs micrographic surgery or wide excision with margin control.[10] For superficial BCC, treatments such as photodynamic therapy or topical medications might be used.[7] Advanced BCC may necessitate a multidisciplinary approach, combining radiation therapy with systemic hedgehog inhibitors.[7] In organ transplant recipients, older age at transplantation and the use of immunosuppressants such as cyclosporine and azathioprine increase the risk of BCC.[11] Innovations such as dermoscopy and reflectance confocal microscopy (RCM) improve early SCC detection and monitoring.[12] Treatments for SCC include surgical excision, radiation therapy, and advanced systemic therapies such as EGFR inhibitors and immune checkpoint inhibitors for more severe cases.[12] Socioeconomic factors, such as having public insurance or lower socioeconomic status, are linked to more advanced SCC at the diagnosis.[13] SCC located in the head-and-neck area carries a higher risk of metastasis and mortality compared to other skin regions.[14] Comprehensive clinical evaluation, histological confirmation, and tailored treatment approaches are essential for managing both BCC and SCC, with socioeconomic factors influencing patient outcomes.

Although NMSCs generally grow slowly and rarely metastasize, they can still lead to significant complications and impact the quality of life, particularly when located on the head and neck.[15-17] Fortunately, NMSCs are highly treatable, especially when detected and removed early.[3-5] Late diagnosis plays a role in the deaths of approximately 65,000 individuals worldwide each year.[18] In addition, the increasing incidence of conditions such as BCC is a cause for concern.[19] Therefore, improving awareness and diagnostic procedures for NMSCs is an important goal.[20] Currently, clinical examination and dermoscopic evaluation are the primary methods used for skin cancer screening.[21] However, research indicates that these techniques have a limited diagnostic accuracy ranging from 75% to 84%.[22,23]

The rising global incidence of NMSC highlights the need for improved screening methods, and artificial intelligence (AI)-based technology holds promise in this regard.[4] AI can assist dermatologists in diagnosing skin cancer by analyzing the visual patterns.[24] Studies show that integrating AI-based malignancy scores and multiclass probabilities into dermatologists' decision-making can significantly improve their diagnostic sensitivity and specificity, with the greatest benefit for dermatologists with less dermoscopy experience.[25] Moreover, AI can perform at the level of experienced dermatologists in evaluating skin malignancies, enabling nondermatologists to triage patients and potentially facilitating patient self-referral, thereby improving access to skin care. Recent advancements allow AI models to integrate clinical data, analyze wide field images, and extract information from whole-slide images without relying on costly human-made annotations.[26] However, the available evidence on the performance of AI techniques specifically for the diagnosis of NMSC is insufficient, indicating the need for further research and synthesis in this area.[24] This study aims to investigate the application and capabilities of AI in the diagnosis and management of NMSCs.

## IMAGE RECOGNITION AND DIAGNOSIS

AI is emerging as a powerful tool to improve the diagnosis of NMSC, addressing challenges faced by healthcare providers and potentially enhancing the early detection and treatment outcomes. Achieving automatic classification of skin cancer is challenging due to the complexity and diversity of skin disease images.

### Artificial intelligence technologies and approaches

Researchers are exploring various AI approaches for diagnosing NMSC. These approaches include using deep learning (DL) techniques with convolutional neural networks (CNNs) and transfer learning to analyze and classify the skin lesions in images.[4,27] Hybrid methods that combine DL with other machine learning (ML) techniques, such as extreme learning machines, are also being investigated to improve classification accuracy.[27] Additionally, spatially offset Raman spectroscopy is being used as a noninvasive technique, combined with AI analysis, to assess the deeper layers of skin tissue for the early detection of NMSC.[28] Furthermore, mobile applications are being developed that utilize smartphone cameras and DL technology to enable remote screening for skin cancer.[4]

### Benefits and considerations

This capability is particularly valuable in supporting general practitioners (GPs), especially in regions with limited access to dermatological expertise, While interest in AI tools is high among healthcare providers, a significant proportion (68%) of surveyed GPs was unwilling to pay for such software, suggesting a need for cost-effective solutions.[29] Furthermore, the noninvasive nature of AI-assisted diagnosis could potentially reduce the need for invasive biopsy procedures,[28] thereby improving patient comfort and reducing associated healthcare costs.[29] These include increased efficiency and speed, advanced visualization for better insight, improved access to remote skin cancer screening, cost-effectiveness, reduction of unnecessary biopsies and procedures, the repetitive nature of self-improvement, greater patient engagement and participation, and enhanced collaboration between specialists and other healthcare providers.

### Artificial intelligence performance and human comparison

Previous studies have also shown that AI-based diagnosis has comparable sensitivity to human doctors, but better specificity and area under the curve (AUC) with AI approaches.[22,23] In addition, the limitations of traditional techniques such as visual, histopathological, and dermatoscope evaluation underscore the potential of alternative approaches, such as artificial intelligence (AI)-based systems, for accurate, noninvasive, and early classification and diagnosis of skin diseases.[30]

### Artificial intelligence-based image recognition systems

AI-based image recognition systems have been developed to automatically identify and classify the types of NMSC from the dermoscopic images. These systems employ ML algorithms and DL techniques to analyze the features such as color, texture, and shape, enhancing diagnostic accuracy and reducing false positives. For example, a study utilizing a CNN achieved diagnostic accuracies of 0.88 for SCC and 0.87 for BCC from dermoscopic images.[31] Thomas and colleagues conducted a study on DL methods for tissue classification to accurately identify the three types of skin carcinomas: BCC, SCC, and intraepidermal carcinoma. They proposed a histopathological environment with 12 meaningful skin classes, achieving classification accuracies ranging from 93.6% to 97.9% and providing interpretable outputs.

### Artificial intelligence and optical coherence tomography features

A study by Jørgensen *et al*. investigated the combined use of multiple OCT features from BCC and AK lesions and found that ML analysis of these combined features could achieve reasonable classification accuracies for AK and BCC lesions.[32] Dascalu and colleagues conducted a study to evaluate the performance of a CNN in classifying NMSC using dermatoscopic images compared to the images captured by smartphones (SI). The CNN analysis demonstrated that DI had higher accuracy (88% vs. 75%) and sensitivity (95.3% vs. 75.3%) compared to SI, despite having similar features. The results indicate that the use of telemedicine with smartphone images can lead to a significant reduction in diagnostic performance for NMSC compared to traditional dermatoscopy. This is an important consideration for healthcare providers and patients.[33]

### Sensitivity and specificity in artificial intelligence diagnosis

A study by Kuang *et al*. demonstrated that AI-based diagnostic methods for NMSCs have moderate sensitivity, strong specificity, and high AUC performance. The sensitivity was found to be higher for BCC compared to intraepithelial carcinoma, possibly due to more training data available for the basal cell subtype.[24]

### Artificial intelligence in reflectance confocal microscopy

AI has been applied to other noninvasive diagnostic techniques such as RCM, which allows examination of the skin at a cellular level and has reduced unnecessary biopsies by up to 50% in referral centers. AI has been used to automate various RCM analysis tasks, such as identifying the dermal-epidermal junction, evaluating mosaic quality, and differentiating between different types of cutaneous tumors, thereby improving efficiency and reducing subjectivity in RCM interpretation.[25]

### Human dermatoscopic diagnosis and artificial intelligence enhancement

Human dermatoscopic diagnosis of NMSC is currently performed quite well, with sensitivities up to 91% for BCC and 77% for SCC. However, there is still room for improvement in diagnostic accuracy through the use of CNNs in dermatology. Improving NMSC diagnosis using CNNs can help prevent unnecessary biopsies or lengthy surgical interventions, and it serves as a valuable avenue for further research and development in the field of AI in dermatology applications.[33]

### Machine learning and precision medicine

ML algorithms have the capability to store and analyze the large amounts of data necessary for precision medicine, enabling holistic prediction results.[34] Lee *et al*. introduced a holistic risk stratification approach that combines CNN, 3D whole-body photography, and lesion feature assessment for the early detection of melanoma and improved surveillance for high-risk patients.[35,36]

### Optimization of diagnostic processes

The use of AI in managing NMSCs shows significant promise, particularly in enhancing diagnostic accuracy and guiding noninvasive assessments. The DERM-003 study revealed that an AI system could match dermatologist level accuracy in diagnosing NMSC and precancerous lesions. Although DL is also being explored for histopathological analysis, there are currently limited Food and Drug Administration-approved AI devices, primarily in radiology. The Aysa app, which suggests possible diagnoses from images and patient data, could be beneficial for NMSC detection. The interest in AI for skin cancer screening is evident from the vast number of online searches, yet the effectiveness of these tools remains to be thoroughly assessed. In addition, Total Body Dermoscopy systems such as the ATBM Master assist dermatologists by autonomously photographing and categorizing moles, facilitating better monitoring of high-risk patients.[37,38]

### Challenges in automatic classification

Achieving automatic classification of skin cancer is challenging due to the complexity and diversity of skin disease images. Different skin lesions can have significant interclass similarities, which can result in misdiagnosis. Additionally, skin lesions within the same class can vary significantly in terms of color, features, structure, size, and location, making it difficult for classification algorithms to effectively discriminate between subcategories of the same cancer type. Another major challenge is the sensitivity of classification algorithms to the camera devices used to capture the training and test images. The performance of these algorithms often suffers when applied to the images from a different domain compared to the training data. These challenges highlight the need for more robust and generalizable classification algorithms that can effectively handle the inherent variability in skin disease images.[37]

## ROLE OF ARTIFICIAL INTELLIGENCE IN NONMELANOMA SKIN CANCER SCREENING

AI has the potential to revolutionize the screening and early detection of NMSC. AI-based systems can analyze the digital images of skin lesions, such as those obtained through dermoscopy or other imaging techniques, to identify the potential signs of NMSC with high accuracy. Some key ways AI are transforming NMSC screening include:

### Automated lesion detection

AI algorithms can be trained to automatically detect and segment the skin lesions in digital images, helping clinicians quickly identify the areas of concern for further examination.[38,39]

### Improved diagnostic accuracy

AI-powered systems have demonstrated the ability to accurately differentiate between benign and malignant skin lesions, often outperforming human experts in the certain scenarios.[39-41]

### Monitoring and follow-up

AI can be used to track the progression of skin lesions over time, helping clinicians monitor patients for any changes that may indicate the development of NMSC.[40,42]

### Triage and prioritization

AI-based systems can be used to triage patients, identifying those at higher risk of NMSC and prioritizing them for more thorough examination and follow-up.[38,39]

### Accessibility in remote areas

AI-powered mobile screening tools can be deployed in remote or underserved areas, improving access to NMSC screening and early detection.[38]

### Integration with IoT-connected dermascopes

AI-powered computer vision integrated with Internet of things (IoT)-connected dermascopes offers a novel method for early skin cancer detection by identifying the subtle signs of skin cancer in dermatoscopic image analysis.[43]

These integrations are aimed at improving the accuracy, efficiency, and accessibility of NMSC screening, ultimately leading to better patient outcomes and reduced healthcare resource demands.

## ARTIFICIAL INTELLIGENCE REVOLUTIONIZING NONMELANOMA SKIN CANCER MANAGEMENT: FROM DIAGNOSIS TO TREATMENT

NMSC is the most common form of cancer globally. While generally treatable when detected early, effective management relies on accurate diagnosis and personalized treatment plans. AI is emerging as a game-changer, offering significant potential to improve NMSC management across various aspects.

### Optimizing treatment planning and monitoring

1. Personalized treatment strategies: AI algorithms can analyze patient data (imaging and clinical information) to personalize treatment plans, potentially leading to better outcomes
2. Non-invasive treatment support: AI can support the development and optimization of non-invasive treatments, such as topical patches for localized, early-stage NMSC[44]
3. Improved radiation therapy planning: AI has the potential to assist in planning superficial radiation therapy (SRT) for NMSC, enhancing treatment accuracy and efficiency.[45]

### Monitoring patient outcomes

AI-powered systems can significantly aid in monitoring the patient outcomes and detecting recurrences. For instance, an AI-based digital health technology demonstrated an area under the receiver operating characteristic curve of 0.88 for SCC and 0.87 for BCC diagnosis from dermoscopic images, indicating high accuracy in identifying suspicious lesions.[46]

### Effectiveness of image-guided therapy

A study demonstrated the feasibility and effectiveness of using image-guided SRT for early-stage NMSC, achieving a local control rate of 99.2% and a disease-free survival rate of 100%.[47]

### Identifying effective treatments

AI can assist in identifying the most effective treatment options based on patient characteristics and lesion features. AI-based systems can assist healthcare professionals in various aspects of NMSC management, potentially leading to early intervention, improved patient outcomes, and more effective resource allocation.[46,48]

### Diagnostic performance

A study by Kuang *et al*. demonstrated that AI-based diagnostic methods for NMSCs have moderate sensitivity, strong specificity, and high-AUC performance. The sensitivity was found to be higher for BCC compared to intraepithelial carcinoma, possibly due to more training data available for the basal cell subtype.[24]

### Advanced imaging techniques

Study of Courtenay and teammates combined multispectral imaging and AI, specifically using CNNs with a support vector machine activation layer, to achieve up to 90% accuracy in discerning between healthy skin and BCC based on hyperspectral signatures.[49]

### Broader impact of artificial intelligence

AI can have a broader impact beyond diagnostic image analysis. For example, it can predict treatment response, such as radiotherapy for SCC, and identify potential therapeutic candidates for rare skin cancers such as Merkel cell carcinoma.[50,51]

## ARTIFICIAL INTELLIGENCE-POWERED RISK PREDICTION

AI can also be instrumental in predicting the risk of developing NMSC based on patient characteristics and prior skin cancer history. For example, a study identified prior NMSCs, prior BCCs, and prior SCCs as the significant predictors of new NMSC development, while age, gender, and hemoglobin levels were also associated with increased risk.[52] Another study by Roffman and colleagues focused on using an artificial neural network (ANN) to predict and classify NMSC risk based on personal health data. The study showed that an ANN using only personal health data available from the electronic medical records was able to assess NMSC risk with high sensitivity and good specificity, comparable to current approaches that rely on additional data such as UV exposure and family history. However, the combination of additional parameters can further improve the predictive capabilities of the ANN.[53] Personalized risk assessment through AI, analyzing individual genetic and environmental data, enables targeted prevention and treatment strategies.

## CHALLENGES AHEAD AND SUGGESTED SOLUTIONS

### Image quality sensitivity

Current AI algorithms can be easily misled by slight changes in image quality, such as magnification, focus, or anatomical location of the lesion, which may lead to misdiagnosis of rare or unusual cancers, unnecessary procedures in false-positive cases, and delayed diagnoses with false negatives.[54,55] In addition, temporary solutions such as artificial darkening of light-skinned patient images can be explored to improve AI performance. Another avenue worth exploring is the use of genetic biomarkers as alternative diagnostic indicators to compensate for the limitations of visual skin cancer data.[48] However, considering benign lesions can help reduce biases.[55]

### Real-world testing

AI algorithms, such as CNN and image processing, have demonstrated promising results in the analysis of medical images, including skin lesions, to identify potential cancers at early stages. This can lead to more efficient and accurate screening, allowing for earlier intervention and improved patient outcomes.[31]

To truly evaluate the potential of AI algorithms in daily practice, detailed clinical studies in the real-world settings are necessary.[55]

In a recent survey of GPs, 98% reported difficulties in diagnosing NPST, while 86% acknowledged that an AI-based diagnostic tool could be beneficial in primary care settings. Additionally, 83% believed such tools could positively impact their practice. However, a significant 68% indicated they were unwilling to pay for AI software, underscoring the need for cost-effective solutions to support GPs in their gatekeeping role amidst financial constraints in primary care. This highlights the importance of developing affordable AI diagnostic tools that can enhance the efficiency and accuracy of diagnoses while being accessible to healthcare providers.[29]

### Explainability and trust

Additionally, the lack of explainability in AI systems undermines trust and makes it difficult for doctors to identify possible errors or biases.[56,57] Clear guidelines and reporting frameworks, such as the mentioned CLEAR criteria, are essential to address these challenges.[58]

### Patient trust

Patients' low trust in AI at the bedside is another concern that needs to be addressed.[55] While patients understand the benefits of AI-based skin cancer screening, they also have concerns about reduced accuracy and increased anxiety, emphasizing the importance of collaboration between AI and human physicians.[4]

### Generalizability

The generalizability of AI models trained on limited datasets is a major concern.[55] Existing algorithms have been trained on data primarily from Caucasian or Asian patients, highlighting the need for diverse training data. Training algorithms on a wider range of images from different ethnicities can improve their generalization ability.[59-62] Dermatologist involvement is crucial to address the lack of diversity in existing skin cancer image repositories. Their clinical knowledge and direct access to a broader range of patient populations can greatly enhance the quality of the training data.[48] Including patient metadata, such as age, gender, skin type, and anatomical position, in the training data can create a more realistic clinical environment.[63-65]

### Image combination

Combining close-up clinical images with dermoscopic images (combined CNN or cCNN) can provide additional visual cues to improve algorithm performance.[66,67] Moreover, the use of a standard protocol like Digital Imaging and Communication in Medicine (DICOM) is necessary for quality imaging in medical applications.[68]

### Standard protocols

Moreover, the use of a standard protocol like DICOM is necessary for quality imaging in medical applications.[68] Supplementary materials accompanying DICOM can enhance generalizability and facilitate image recovery for future studies.[69] DICOM identification profiles can also help maintain patient privacy in clinical trial studies.[55]

### Pretrained models

Kuang's study on nonmelanoma cancer demonstrated that pretrained models can improve performance, especially for the datasets of limited size. Studies utilizing image enhancement techniques have shown lower sensitivity but higher specificity compared to those without enhancement.[24] Image enhancement techniques can also impact sensitivity and specificity differently.

### Domain shift

DL models often suffer from significant performance deterioration when applied to whole slide images from external test sites, due to domain shift caused by differences in preanalytical variables such as slide scanner and staining. Study of Zhou and colleagues presented a new approach called Multi-Site Cross-Organ Calibration-based Deep Learning (MuSClD), which used WSIs of an off-target organ from the test site to calibrate the training data, mitigating the domain shift without introducing data leakage. Evaluating MuSClD for the automated diagnosis of NMSC subtypes, the approach reduced Wasserstein distances between sites and significantly improved the one-vs-rest AUC performance compared to baseline, demonstrating its ability to compensate for preanalytical variabilities and enhance model robustness.[70]

The limited number of trials identified suggests that despite the potential benefits of AI-based technologies for NMSC screening, there is still relatively little research in this area. Collaborative efforts between AI researchers, dermatologists, and other stakeholders will be necessary to advance the field. Additionally, important ethical considerations, such as patient privacy, algorithm transparency, algorithmic bias, lack of diversity in training data (especially for darker skin tones), and inequality in access and access gaps, should be carefully considered.[4]

### Data availability and diversity

Data availability and diversity play a crucial role in determining the effectiveness of AI models. The performance of these models is strongly dependent on the quality and variety of the training data used.[44]

### Interpretability and explainability

Interpretability and explainability refer to the ability to understand and clarify the reasoning and decision-making processes behind a system or model. Creating AI models that are capable of offering explicit justifications for their actions can foster trust and streamline their incorporation into clinical practice.[71]

### Regulatory approval and integration

AI-powered NMSC screening systems require thorough testing and regulatory approval prior to being widely used in clinical environments. Incorporating these tools into current healthcare processes poses a substantial obstacle.[72]

### Ethical considerations

The integration of AI in healthcare raises ethical concerns, particularly regarding privacy, bias, and the potential for overdiagnosis or overtreatment, especially in NMSC screening. Addressing these issues is crucial as AI becomes more prevalent. User-centered design focuses on creating AI tools tailored to specific user needs, enhancing interpretability and clinical integration through iterative design processes. Explainable AI aims to provide transparent reasoning for AI decisions, fostering trust among healthcare professionals. Collaboration among academics and specialists from the various fields is essential for developing reliable AI solutions for NMSC management. Implementing ethical frameworks prioritizing privacy, fairness, and transparency can effectively address the bias and support responsible AI use in healthcare.[69]

## CONCLUSION: THE ROAD AHEAD FOR ARTIFICIAL INTELLIGENCE IN NONMELANOMA SKIN CANCER DIAGNOSIS AND MANAGEMENT

There are challenges and potential of integrating AI in healthcare, particularly in diagnosing NMSC. Key issues include the lack of sufficient clinical research to validate AI models' effectiveness in real-world settings and the need for patient trust in healthcare professionals using these tools. AI has the potential to enhance early detection and treatment outcomes for NMSC, but various obstacles must be overcome for successful implementation. Collaboration among AI researchers, dermatologists, and other stakeholders is crucial to develop robust models,

**Table 1: Summarize the power of artificial intelligence to improve the diagnosis and management of nonmelanoma skin cancer**

| Paper | Study design | Methodology | Main findings |
|---|---|---|---|
| Nonmelanoma skin cancer diagnosis: A comparison between dermoscopic and smartphone images by unified visual and sonification DL algorithms[34] | Retrospective, noncontrolled | Comparison of dermoscopic images and smartphone-captured images for nonmelanoma skin cancer diagnosis using a dual convolutional neural network | The DL algorithm had higher accuracy, sensitivity, and AUC when analyzing dermoscopic images compared to smartphone images<br>The accuracy of the algorithm was 88% for dermoscopic images but only 75% for smartphone images, a statistically significant difference |
| Preoperative AI-driven fluorescence diagnosis of nonmelanoma skin cancer[73] | A prospective, observational study | Using a laser-based diagnostic device (DSL-1) to measure fluorescence spectra from BCC lesions and surrounding normal skin, and then using a DNN with 3 dense layers as a binary classifier to determine whether the spectra correspond to cancer or normal tissue | The AI-driven fluorescence diagnosis method using the DSL-1 device correctly predicted BCC lesions, with an average sensitivity of 62% and average specificity of 83% |
| Effectiveness of an image analyzing AI-based digital health technology to identify non-melanoma skin cancer and other skin lesions: results of the DERM-003 study[46] | Prospective, multi-center, single-arm, masked study | Images were analyzed by the DERM AI algorithm, which generates a numeric output reflecting its confidence in the lesion type. Patients and lesions that did not meet the inclusion criteria were excluded from the ITT population, and lesions without a final diagnosis or AIaMD result were excluded from the PP population | The AIaMD demonstrated high accuracy in detecting SCC and BCC, with AUROC values around 0.88–0.89 across different camera types |
| Deep convolutional neural support vector machines for the classification of basal cell carcinoma hyperspectral signatures[74] | A retrospective study and supervised binary classification study using hyperspectral images to distinguish between BCC and healthy (H) skin samples | Using convolutional neural networks and support vector machines to build a classification model and evaluated the model's performance using various metrics like accuracy, AUC, and kappa statistic | The CNSVM architecture achieved up to 90% accuracy and an AUC of 0.9 in classifying BCC and healthy skin hyperspectral signatures |
| Interpretable DL systems for multi-class segmentation and classification of nonmelanoma skin cancer[75] | A retrospective observational study, with the authors creating multiple datasets with different levels of downsampling (2x, 5x, 10x) from a preexisting collection of 290 H and E slides | DL algorithms for medical image diagnosis, creating ground-truth segmentations, training networks with specific optimization techniques, and performing automatic surgical margin clearance calculations | DL methods can be used to accurately segment and classify nonmelanoma skin cancers (BCC, SCC, IEC) in high-resolution histological images |
| A novel cumulative level difference mean based GLDM and modified ABCD features ranked using eigenvector centrality approach for four skin lesion types classification[23] | Noncontrolled, observational study | Evaluating the performance of a new automated skin lesion classification system that classifies four skin lesion types (malignant melanoma, malignant BCC, benign BKL, and nevi) using a novel texture feature (CLDM) combined with a modified ABCD feature set | The proposed CLDM texture features, when combined with the modified ABCD features and ranked using the eigenvector centrality approach, achieved outstanding performance in classifying four skin lesion types with 100% accuracy, sensitivity, and specificity using cubic SVM |
| Predicting nonmelanoma skin cancer via a multi-parameterized artificial neural network[53] | Retrospective observational study | Using a randomly split training and validation dataset from the NHIS 1997–2015, with further testing on the NHIS 2016 datase | The ANN model developed by the authors was able to predict NMSC risk with high sensitivity and decent specificity<br>The ANN model was able to stratify individuals into different risk categories (high, medium, low) based on their predicted NMSC risk |

BCC=Basal cell carcinoma; DNN=Deep neural network; NHIS=National Health Interview Survey; CNSVM=Convolutional neural support vector machine; ANN=Artificial neural network; NMSC=Nonmelanoma skin cancer; SCC=Squamous cell carcinoma; AUC=Area under the curve; DL=Deep learning; AI=Artificial intelligence; AUROC=Area under the receiver operating characteristic curve; SVM=Support vector machine; ABCD=Asymmetry, border, color, diameter; CLDM=Cumulative level difference mean; BKL=Benign keratosis-like lesions; IEC=Intraepidermal carcinoma; DSL-1=Diagnostic spectral laser 1; AIaMD=Artificial intelligence as a medical device; PP=Per protocol population utilizing diverse datasets and ethical frameworks. Additionally, combining AI with advanced imaging techniques can improve diagnostic accuracy. Continuous learning systems can further refine AI capabilities, aiding professionals in identifying patients who would benefit most from specific treatments Table 1.

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### Conflicts of interest

There are no conflicts of interest.

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