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Artificial Intelligence-based Image Analysis for Early Cancer Detection: Review

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Abstract

Background: Early detection of melanoma is critical for improving patient outcomes, as late-stage diagnosis is associated with increased mortality. Traditional imaging techniques like reflectance confocal microscopy (RCM), optical coherence tomography (OCT), and dermoscopy require significant expertise, leading to variability in diagnostic accuracy. Artificial intelligence (AI) offers a promising solution to enhance the objectivity and consistency of skin cancer diagnosis.

Methods: A systematic literature review was conducted using PubMed/Medline, Embase, and Cochrane databases, focusing on studies published between 2016 and 2023. The review assessed AI methodologies applied to images of malignant melanoma obtained via RCM, OCT, and dermoscopy. Key search terms included "melanoma," "neural network," and "artificial intelligence."

Results: The analysis revealed a significant advancement in AI-driven techniques for melanoma classification, with deep learning models demonstrating performance equal to or exceeding that of dermatologists. Various studies reported high accuracy rates, with some models achieving an area under the receiver operating characteristic curves (AUC) above 0.90. Notably, methods incorporating diverse datasets showed improved diagnostic reliability across varying skin tones.

Conclusion: AI-based image analysis significantly enhances the early detection of melanoma, offering a robust alternative to traditional diagnostic methods. This review underscores the need for continued research to develop inclusive datasets and refine AI algorithms, ensuring equitable healthcare access and improved patient outcomes.

Keywords: Melanoma, Artificial Intelligence, Deep Learning, Dermoscopy, Early Detection.

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1. Introduction

The identification of late-stage melanoma is linked to worse, perhaps lethal consequences. Timely identification of melanoma is essential to save death and minimize unwarranted invasive interventions,

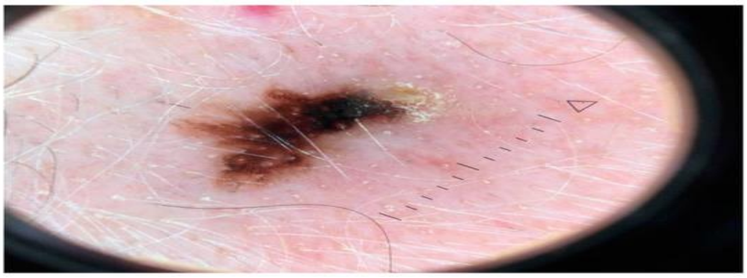

Figure 1. In situ dermoscopy of melanoma reveals blue-white structures, an unusual, thickened network, and an asymmetric reticular pattern.

such as surgical biopsy [1]. In vivo diagnostic imaging modalities have shown considerable effectiveness in the early diagnosis of this lethal skin cancer, especially methods like reflectance confocal microscopy (RCM), optical coherence tomography (OCT), and dermoscopy [2]. RCM uses a diode laser to generate high-resolution pictures in horizontal slices at the cellular level, reaching depths of the papillary dermis, while OCT utilizes near-infrared light to get microscopic images up to 2 mm under the skin's surface [2,3]. Dermoscopy employs a dermatoscope, using either polarized or non-polarized light, to examine patterns and microstructures inside the epidermis and superficial dermis (Figure 1) [4].

Notwithstanding the benefits of these non-invasive imaging techniques, their implementation requires considerable training and experience, resulting in inconsistent diagnosis accuracy. Moreover, the quality of photographs may influence interpretation and diagnostic duration, necessitating an impartial and automated identification approach [5]. Techniques based on artificial intelligence (AI) have been created to evaluate pictures acquired by different imaging modalities, aiming to automate the diagnosis process while ensuring objectivity and consistency in outcomes. AI-based strategies for analyzing non-invasive dermatologic imaging modalities might transform the detection and diagnosis of skin malignancies. Research has shown that machine learning algorithms may reduce the number of artifacts requiring evaluation, accelerate the diagnosis procedure, and decrease the frequency of patient clinic visits [6]. Despite the significant advancement of AI in medical image identification in recent years, its promise for dermatological assessment of skin malignancies remains largely untapped. Accurate algorithms depend on a balanced dataset with diverse inputs to provide exact diagnoses [7]. Consequently, various research investigating machine learning technologies in the analysis of non-invasive dermatologic imaging modalities may exhibit discrepancies in findings because to disparities in algorithm development and picture quality.

Moreover, the plethora of AI-driven methodologies used to assess dermatological pictures might obfuscate clinical decision-making in the absence of explicit recommendations. Assessing the practicality of AI in clinical practice, together with the contributions of machine learning, convolutional neural networks, and deep learning, may be complex. Furthermore, it is essential to acknowledge the constraints of AI. Although it has the capacity to transform the field, it may also exhibit bias contingent upon the datasets and training methodology used. For example, datasets used to train AI models may mostly consist of lighter skin tones, leading to less accurate diagnoses for individuals with darker skin tones [8]. Skin tones may influence the outcomes of AI model training, underscoring the need for broad and representative datasets that reflect the patient population. Comparing the diagnostic accuracy of several models trained on distinct datasets is essential for appropriately evaluating their clinical applicability. An unbalanced dataset in neural network training might result in inconsistent performance in the analysis of non-invasive dermatologic imaging modalities using machine learning techniques [9-11]. Consequently, ethical concerns and directives from the Food and Drug Administration (FDA) are essential to guarantee the secure and successful use of AI-based methodologies in clinical environments. These issues underscore the need for a complete assessment of the existing literature about AI-based methodologies to fully comprehend the potential of AI in the non-invasive detection of melanoma. This review seeks to address these problems and enhance comprehension of the present status of the field, with the objective of directing future research aimed at integrating these approaches into therapeutic applications.

This paper aims to assess and delineate the present status of AI in non-invasive skin cancer diagnosis and to synthesize the results of several algorithms. This study offers a thorough examination of the present status of AI in non-invasive skin cancer diagnosis, emphasizes the clinical ramifications of diverse algorithms, and delineates potential avenues for future research. Understanding the present status of the subject is crucial due to the potential of these approaches to enhance patient outcomes and minimize avoidable invasive treatments.

2. Methods

A literature review of PubMed/Medline, Embase, and Cochrane was conducted to identify studies published between 2016 and 2023, examining the use of AI-based methodologies to pictures of malignant melanoma obtained using reflectance confocal microscopy, optical coherence tomography, and dermoscopy. The subsequent search terms employed were: “melanoma,” “neural network,” “diagnosis or detection,” “carcinoma,” “lesion or growth or cancer or neoplasm or tumor or malignant or metastatic,” “computer systems,” “skin cancer detection,” “digital pathology,” “machine or deep learning,” “algorithms,” “artificial intelligence,” “skin cancers,” “diagnostic techniques and procedures,” “dermoscopy,” “reflectance confocal microscopy,” and “optical coherence tomography.”

3. Application of Artificial Intelligence Techniques to Dermoscopic Images

Deep learning has garnered considerable interest in dermatology, especially in the examination of dermoscopy pictures. Dermoscopic pictures of melanoma have been extensively used in the creation and assessment of deep learning models. The majority of studies in our analysis used publicly accessible datasets of dermoscopic pictures of melanoma, which were validated by histopathology, follow-up examinations, expert consensus, or in vivo confocal microscopy confirmation.

Foahom Gouabou et al. introduced a deep learning ensemble technique for precise computer-assisted diagnosis (CAD) of melanoma [12]. This was conducted by evaluating 1113 dermoscopic pictures of melanoma lesions sourced from a public dataset. The suggested system attained an area under the receiver operating curve (AUROC) of 0.93 for melanoma detection, surpassing comparable current approaches in this domain. This research also assessed the decision-making process of the algorithm compared to that of a professional dermatologist in differentiating between benign keratosis and melanoma. The algorithm exhibited improved speed and precision in identifying difficult-to-classify pigmented lesions for the job ($p = 0.90$ for melanoma), while also providing a clear and impartial decision-making procedure. In 2016, Marchetti et al. conducted one of the first studies comparing the diagnosis accuracy of dermoscopic melanoma pictures analyzed by deep learning algorithms with that of dermatologists [13]. This research used five distinct ways to integrate separate automated predictions into "fusion" algorithms. The leading fusion model surpassed the performance of eight seasoned dermatologists. Dermatologists had an average sensitivity of 82% and specificity of 59% in the proper categorization of benign vs malignant lesions. The research revealed that the optimal fusion computer method attained an impressive ROC area of 0.86, indicating a substantial improvement compared to the average ROC area of 0.71 noted among the eight readers in classification ($p = 0.001$).

In 2020, Marchetti et al. conducted a comparable investigation in which the top-performing algorithm significantly surpassed eight doctors and nine dermatology trainees ($p < 0.001$) [14]. Xia et al. introduced a two-stage methodology that detects all lesions inside an image, assesses their probability of malignancy, and produces an image-level probability for comprehensive screening [15]. This technique resulted in an AUC of 0.959 using dermoscopic pictures, which increased to an AUC of 0.961 when utilizing a publically accessible dataset from ISIC 2018. This two-stage model shown commendable performance and may be used in a PCP triage for dermatology at scale for photos related to malignancy as a comprehensive end-to-end system. Xin et al. introduced a unique transformer network, SkinTrans, achieving 94.1% accuracy on a clinical dataset of 1113 melanoma dermoscopic pictures, surpassing typical CNN models [16].

In an extensive investigation using several publicly accessible datasets, Singh et al. implemented a segmentation model on four datasets: PH2, ISIC 2017, ISIC 2018, and ISIC 2019, achieving accuracy scores of 99.50%, 99.33%, 98.56%, and 98.04%, respectively [17]. The suggested technique demonstrated much superior sensitivity and specificity in the diagnosis of melanoma lesions. Kaur et al. suggested an automated melanoma classifier using a deep convolutional neural network to precisely differentiate between benign and malignant melanoma [18-23]. Images were collected from the ISIC 2016, ISIC 2017, and ISIC 2020 datasets, where the suggested DCNN classifier attained accuracy rates of 81.41%, 88.23%, and 90.42%, respectively [24]. This model exhibited superior performance relative to existing neural networks, while providing an enhanced foundation for automating the diagnostic procedure.

Naeem et al. introduced a deep learning framework for the multiclassification of skin cancer using dermoscopic images [18]. The melanoma training set included 3,166 photos, accompanied by a validation set of 452 images and a testing set of 904 images. This system demonstrated superior performance relative to four pre-trained classifiers, with an accuracy of 92.18% in melanoma classification. It attained an AUC of 0.9833, a recall of 99.9%, a precision of 92.21%, an F1-score of 91.37%, and an accuracy of 92.21%. Lee et al. presented a collection of deep neural network architectures specifically designed for melanoma identification using dermoscopy pictures [19]. This research yielded a sensitivity of 92.8%, a positive predictive value (PPV) of 78.5%, and a negative predictive value (NPV) of 91.2%. This approach facilitates the implementation of a pre-screening tool in the melanoma diagnosis process, ensuring a delicate equilibrium between computing efficiency and accuracy. Fraiwan et al. used the HAM1000 dataset of dermoscopic pictures to differentiate between melanoma and non-melanoma skin tumors [20]. The melanoma class had a sensitivity of 71% (i.e., recall) and a precision of 43.1%. The maximum accuracy rate recorded in this investigation was 76.7%.

Additionally, Martin-Gonzalez et al. created a deep learning technique to distinguish between benign skin lesions and melanoma in a clinical environment [22]. The analysis was conducted on a dataset of 232 dermoscopic pictures. The nevus group had a markedly lower mean diagnostic threshold (27.12 ± 35.44%) in contrast to the melanoma group (72.50 ± 34.03%), with a p-value of less than 0.001. The area under the ROC curve was 0.813. A diagnostic criterion of 67.33% yielded a sensitivity of 0.691, specificity of 0.802, and accuracy of 0.776. This research notably excluded the use of public databases. Lu et al. developed a deep learning classification algorithm for melanoma diagnosis using dermoscopic pictures from the HAM10000 dataset [23]. This approach achieved a detection accuracy of 100% for melanoma, a sensitivity of 94.05%, and a precision of 97.07%. Vaiyapuri et al. devised an innovative computational intelligence-based method for melanoma identification and classification using dermoscopic pictures, achieving a maximum accuracy of 97.50% [21]. Arshad et al. used the HAM10000 database to build an automated system for multiclass skin lesion categorization, achieving an accuracy rate of 91.7% [25].

Xing et al. introduced an innovative Zoom-in Attention and Metadata Embedding (ZooME) network for melanoma identification, using the ISIC 2020 dataset, which comprises 33,126 dermoscopy images [26]. The model attained a 92.23% AUC score, 84.59% accuracy, 85.95% sensitivity, and 84.63% specificity. This model distinctly illustrates an advantage in extracting and using specific pathological information from dermatoscopic pictures while including diverse patient demographics for enhanced prediction. Pham et al. presented an innovative method that improves melanoma prediction on an unbalanced dataset using a restructured CNN architecture and improved algorithms [27]. The training dataset, including 17,302 pictures of melanoma and nevi, is the most extensive dataset used in this context. A thorough comparison was performed between the model's performance and that of 157 dermatologists from 12 university hospitals in Germany, using the same dataset. The results indicated that the suggested method surpassed the performance of all 157 dermatologists and exceeded the state-of-the-art technique, attaining an area under the curve of 94.4%, a sensitivity of 85.0%, and a specificity of 95.0%.

A novel deep learning algorithm introduced by Nawaz et al. was assessed using three established datasets (ISBI 2016, ISIC 2017, and PH2) and shown superior performance compared to existing methods [29]. This technique attained average accuracies of 95.40%, 93.1%, and 95.6% on the ISIC 2016, ISIC 2017, and PH2 datasets, respectively, underscoring its efficacy in skin lesion detection and segmentation. This method integrates accelerated region-based convolutional neural networks (RCNN) with fuzzy k-means clustering (FKM), enabling significant improvements in melanoma diagnosis despite the presence of visual aberrations, including hair, blood vessels, illumination fluctuations, and noise. Kim et al. developed a publicly accessible deep learning method for the classification of malignant melanoma. The suggested method used skin lesion pictures and expert labeling results derived from convolutional neural networks [28]. The U-Net model attained a significant Dice similarity coefficient of 81.1% in comparison to the expert labeling findings. Furthermore, the system exhibited a classification accuracy of 80.06% for malignant melanoma patients. The results underscore the efficacy of the suggested method in precisely detecting and categorizing malignant melanoma [29].

Sayed et al. developed a novel strategy to address class imbalance in datasets for the categorization of skin lesions using ISIC 2020 [30]. This research used a hybrid convolutional neural network architecture combined with bald eagle search (BES) optimization to address this problem. This deep network model for melanoma skin cancer prediction used fewer parameters and attained an overall accuracy of 98.37%, with a specificity of 96.47%, sensitivity of 100%, an F-score of 98.40%, and an area under the curve of 99%. The results indicated that the suggested model was both resilient and efficient, surpassing VGG19, GoogleNet, and ResNet50.

Additionally, Foahom-Gouabou et al. introduced an ensemble of convolutional neural networks (CNNs) using a directed acyclic graph to consolidate binary CNNs, achieving the highest balanced accuracy (76.6%) compared to multiclass CNNs and other pertinent studies on the ISIC 2018 public dataset [31]. This system is distinguished by its hierarchical workflow, which enhances transparency in decision-making and thus facilitates interpretation for dermatologists. Alsaade et al. sought to create a system for diagnosing skin cancer via deep learning and conventional AI machine learning methods [32]. The system was assessed using dermoscopy pictures from two datasets, PH2 and ISIC 2018. The suggested strategy surpassed state-of-the-art techniques for both datasets, with the artificial neural network (ANN) model attaining the best accuracy of 97.50% for PH2 and 98.35% for ISIC 2018, in contrast to the convolutional neural network (CNN) model.

Two studies formulated analogous models using the ISIC 2017 dataset. Iqbal et al. created a deep learning model for the automatic multiclass categorization of skin lesions using dermoscopic pictures from ISIC databases [33]. The suggested deep convolutional neural network (DCNN) method surpassed leading algorithms, attaining 94% accuracy, 93% sensitivity, and 91% specificity in ISIC-2017, with a 0.964 AUROC. This suggested method offers a viable means to automate and accelerate the categorization of skin lesions, thereby conserving effort, time, and human lives. Acosta et al. devised a deep learning methodology including a two-stage procedure using mask and region-based convolutional neural networks (CNNs) with a ResNet152 architecture for lesion categorization [34]. The model achieved enhancements in accuracy and balanced accuracy of 3.66% and 9.96%, respectively, relative to the optimal findings shown in the 2017 International Symposium on Biomedical Imaging Challenge dataset. This model demonstrates a commendable equilibrium among overall accuracy (0.904), sensitivity (0.820), and specificity (0.925).

In 2017, Tognetti et al. sought to create a deep convolutional neural network, termed iDCNN_aMSL, to assist dermatologists in distinguishing early melanoma from atypical nevi using dermoscopic pictures and clinical data [35]. The model was evaluated against the intuitive diagnoses of dermatologists with varying degrees of expertise and attained the highest accuracy, therefore decreasing the incidence of unnecessary excisions. This model attained an area under the curve of 90.3%, a sensitivity of 86.5%, and a specificity of 73.6%, in contrast to the intuitive diagnoses of dermatologists, which exhibited a sensitivity of 77% and a specificity of 61.4%. It can significantly aid dermatologists in making informed medical decisions, thereby potentially decreasing the incidence of unnecessary excisions [36]. Guo et al. introduced a deep convolutional neural network trained using both cross-entropy and covariance discriminant loss [37]. This method enhances both model outputs and extracted features concurrently, and a novel embedding loss is formulated to more successfully distinguish between melanoma and non-melanoma pictures. The suggested technique attained sensitivities of 0.942 and 0.917 on the ISBI 2018 Skin Lesion Analysis dataset, illustrating its effectiveness in melanoma detection.

R K et al. introduced a deep convolutional neural network for automated melanoma detection that is capable of adapting to various hardware and software constraints [38]. The network was trained using dermoscopic skin pictures from open sources and attained average accuracy, sensitivity, and specificity values of 82.95%, 82.99%, and 83.89%, respectively, when evaluated on a dataset of 2150 images. Minagawa et al. evaluated the efficacy of 30 Japanese dermatologists against a deep neural network (DNN) for the dermoscopic identification of skin cancers across various datasets [39]. The research revealed that dermatologists had a markedly greater sensitivity for malignancy prediction using the Shinshu dataset (Japanese exclusively) than with the ISIC dataset (predominantly fair-skinned), while the deep neural network demonstrated superior specificity compared to human readers. The research indicates that a deep neural network (DNN) might enhance diagnosis accuracy for skin cancers across various skin types and may be more proficient in detecting malignant characteristics after initial evaluations by dermatologists.

Additionally, Nasiri et al. introduced a methodology for the early identification of melanoma using deep learning inside a case-based reasoning (CBR) framework [40]. The DePicT Melanoma Deep-CLASS system employs a sixteen-layer convolutional neural network (CNN) to categorize skin lesions as benign or malignant melanoma. The efficacy of this system was shown using the ISIC Archive dataset, with the suggested technique being successful in malignancy diagnosis, validated in 1796 dermoscopy pictures. Winkler et al. sought to evaluate the diagnostic efficacy of a deep learning convolutional neural network (CNN) for melanoma detection across various melanoma localizations and subtypes [41]. Each group included 30 melanomas and 100 benign lesions with analogous localizations and form. The research indicated that the CNN shown superior performance in superficial spreading melanomas, nodular melanomas, lentigo maligna melanomas, and face solar lentigines, seborrheic keratoses, and nevi. In acrolentiginous melanomas, the CNN exhibited reduced sensitivity, however demonstrated great specificity.

Phillips et al. performed research to evaluate the efficacy of a neural network named Deep Ensemble for Recognition of Melanoma (DERM) in identifying malignant melanoma from dermoscopic pictures of pigmented skin lesions [42]. The DERM model was trained and evaluated using a dataset of 7,102 dermoscopic pictures, which included both melanoma and benign lesions. The results indicated that DERM attained a notable area under the ROC curve (AUC) of 0.93, with a sensitivity of 85.0% and a specificity of 85.3%. The research also conducted a thorough meta-analysis assessing the accuracy of naked-eye examinations, with or without dermoscopy, performed by both specialist and general doctors [43].

The meta-analysis revealed that primary care doctors attained an AUC of 0.83, with a sensitivity of 79.9% and a specificity of 70.9%, while dermatologists reached an AUC of 0.91, with a sensitivity of 87.5% and a specificity of 81.4% [44-50]. The research indicates that DERM may serve as a decision support tool in primary care by offering dermatologist-level advice on the probability of melanoma. Building on their prior research, the same research group undertook a further study to assess the precision of an artificial intelligence system in identifying melanoma in dermoscopic pictures of skin lesions obtained using smartphones and digital single-lens reflex (DSLR) cameras [51]. The method attained a remarkable area under the receiver operating characteristic (ROC) curve of 91.8% in comparison to histological diagnosis. At 100% sensitivity, the algorithm attained a specificity of 64.8%, while physicians obtained a specificity of 69.9%.

Numerous investigations have transcended the conventional binary viewpoint articulated by Brinker et al., Haenssle et al., and Marchetti et al., to pursue multiclass classification endeavors [43,44,46]. In 2019, Brinker et al. evaluated the diagnostic precision of a deep convolutional neural network (CNN) against that of dermatologists in classifying melanoma and nevi pictures [43]. Nine dermatologists evaluated 804 dermoscopic pictures, and the CNN demonstrated superior sensitivity and specificity in lesion categorization compared to the dermatologists. The research found that automated dermoscopic melanoma picture categorization markedly outperformed both junior and board-certified dermatologists. Brinker et colleagues. subsequently built an additional deep learning system on open-source photos, surpassing 136 of 157 dermatologists in the classification of dermoscopic melanoma images [44]. The algorithm was evaluated based on sensitivity, specificity, and receiver operating characteristics, surpassing the performance of dermatologists across all expertise levels.

In a 2020 study by Marchetti et al., computer algorithms from an international melanoma detection challenge surpassed the diagnostic performance of eight dermatologists and nine dermatology residents in identifying melanoma from dermoscopy images, achieving an area under the receiver operating characteristic curve of 0.87, compared to 0.74 and 0.66, respectively [14]. The algorithm exhibited enhanced specificity compared to the dermatologists' total sensitivity, and the incorporation of algorithm classifications augmented both the sensitivity and specificity of the dermatologists. Despite the study's artificial environment lacking a comprehensive range of skin lesions and clinical information, the findings indicate that deep neural networks may enhance human performance in skin lesion categorization.

In a pioneering study that offered supplementary clinical insights to dermatologists, Haenssle et al. evaluated the diagnostic efficacy of a deep learning convolutional neural network (CNN) for dermoscopic melanoma identification against that of 58 dermatologists, comprising 30 specialists [46]. The CNN exhibited superior specificity compared to the dermatologists at same sensitivity levels and attained a bigger area under the curve (AUC) for receiver operating characteristics (ROC) than the dermatologists. The research indicates that dermatologists might gain from the support of a CNN for picture categorization.

Hagerty et al. introduced a unique fusion methodology combining traditional image processing with deep learning to identify melanoma in dermoscopy pictures [45]. The fusion approach integrates three artisanal, biologically inspired image processing modules and one clinical information module with a ResNet50 deep learning network. The fusion strategy, using logistic regression to combine results from both processing arms, attained a classification accuracy of 0.94, surpassing the 0.87 accuracy of the deep learning classifier and the 0.90 accuracy of the traditional image processing classifier. The research advocates for the further exploration and advancement of fusion methodologies for melanoma diagnosis. Li et al. introduced two distinct deep learning approaches to tackle the difficulties in the precise identification of melanoma in dermoscopic pictures [47]. The approaches included lesion segmentation, extraction of dermoscopic features, and categorization of lesions. The suggested deep learning frameworks attained notable accuracies of 0.753 for task 1, 0.848 for task 2, and 0.912 for task 3 on the ISIC 2017 dataset. This research indicates that the dependable automated identification of skin cancers by deep learning networks might enhance the precision and efficacy of pathologists.

Unlike most research in this section, Gareau et al. created a transparent machine learning system to distinguish melanoma from nevi in dermoscopy pictures, along with an interface for sensory cue integration [36]. The interpretable machine learning algorithm surpassed the predominant deep learning method 75% of the time. This research sought to provide a transparent methodology that enhances medical responsibility and trust compared to a CNN, rather than using a deep learning-based technique.

4. AI-Driven Methods for Analyzing Reflectance Confocal Microscopy (RCM) Images

Reflectance confocal microscopy (RCM) has become an essential instrument in dermatology for diagnosing skin tumors, including melanoma and non-melanoma skin malignancies, in addition to aiding in the assessment and treatment of inflammatory and infectious skin disorders [52]. This approach enables real-time in vivo viewing of the epidermis to the papillary dermis, with resolution equivalent to histology [53]. Facilitating the dermatologist's ability to conduct a "virtual biopsy" of skin lesions may help minimize superfluous invasive procedures and skin biopsies [54]. RCM enhances the specificity and sensitivity of skin cancer diagnoses, directs biopsies of problematic lesions, and assists in delineating the margins of extensive tumors for accurate surgical excision [52]. It may also be used to monitor the clinical and treatment progression of dermatological conditions.

Notwithstanding its advantages, the subjectivity of this approach and dependence on user interpretation introduce the possibility of diagnostic discrepancies [52]. This presents a potential for AI to enhance the delineation of the dermal–epidermal junction in RCM pictures, while also accelerating the diagnosis procedure and assisting inexperienced users. AI applied to RCM photos facilitates an objective analysis that may diminish human error, boost diagnostic accuracy, and improve the efficiency and reliability of diagnoses. In 2019, Wodzinski et al. introduced a convolutional neural network methodology for the classification of skin lesions using reflectance confocal microscopy (RCM) mosaics [49]. The dataset included 429 RCM mosaics categorized into three classes: melanoma, basal cell cancer, and benign naevi. The categorization of the test set attained superior accuracy relative to medical confocal users. This categorization method serves as an effective instrument for the early, non-invasive identification of melanoma. In 2021, D'Alonzo introduced a poorly supervised machine learning algorithm for segmenting RCM mosaics into "benign" and "aspecific" areas [50]. The deep neural network model attained an average area under the curve of 0.969 and a Dice coefficient of 0.778, demonstrating the viability of spatial localization of certain areas in RCM pictures, hence enhancing the interpretability of the diagnostic decision model for physicians.

5. Application of Artificial Intelligence Techniques to Optical Coherence Tomography (OCT) Images

Optical coherence tomography (OCT) is an interferometric imaging technique first developed for optical imaging, which has since been used for dermatological assessments. This imaging technique offers instantaneous observations of the epidermal layers of the skin [55]. An infrared broadband light source is used to see the skin at depths of 1–2 mm, achieving a resolution ranging from 15 to 3 μm, contingent upon the specific system utilized [55]. OCT is applicable for assessing non-melanoma skin malignancies, inflammatory conditions, parasite infections, and for examining nails [56]. OCT offers a rapid and effective diagnostic imaging modality that may be used alone or in conjunction with other non-invasive imaging methods such as dermoscopy, high-frequency ultrasound, and confocal laser scanning microscopy [57].

Although OCT has been used as an imaging technique for diagnosing basal cell carcinoma and other keratinocyte carcinomas, its application in diagnosing malignant melanoma is still being explored. Preliminary research indicates that OCT may identify diagnostic characteristics of melanoma, including epidermal psoriasiform hyperplasia, melanocytic nests, and vertical icicle-shaped formations, and may aid in the preoperative risk classification of melanoma patients [58]. Nevertheless, while OCT has potential in diagnosing malignant melanoma, its sensitivity and specificity as an independent diagnostic instrument remain unconvincing [59]. Angiographic OCT shows promise in the diagnosis and staging of melanoma by identifying early alterations in vascular shape from dysplastic nevi to melanoma [60]. While conventional OCT has not been used for AI-assisted melanoma detection, a comparable methodology using vibrational OCT was documented in one article identified during our systematic review. Traditional OCT employs near-infrared light to generate detailed, high-resolution images of biological tissues, whereas vibrational OCT integrates traditional OCT with a mechanical vibration stimulus to assess the vibrational characteristics of tissue structures, yielding supplementary insights into tissue composition and function. This approach may be used to see and distinguish certain tissue characteristics, such as the presence of collagen or elastin. This additional characteristic may aid in differentiating melanoma from benign moles. Consequently, whereas conventional OCT delivers high-resolution pictures and assesses the thickness and shape of melanoma lesions, vibrational OCT may give further information that assists in distinguishing melanoma from benign nevi.

In 2022, Silver et al. investigated the use of vibrational optical coherence tomography (VOCT) combined with machine learning to non-invasively distinguish between normal skin and various skin malignancies [48]. The findings indicated that machine learning, in conjunction with the height and position of the VOCT mechanovibrational peaks, can effectively distinguish between normal skin and various malignant lesions, including melanoma, achieving sensitivity and specificity rates of 83.3% and 77.8%, respectively [48].

6. Conclusions

The bulk of research used deep learning models on dermoscopic pictures, showing that AI-based techniques perform equally or better than traditional approaches in melanoma detection. The incorporation of AI into clinical platforms may profoundly affect regions with inequalities in melanoma incidence and elevated death rates, including rural areas and poor nations. Nonetheless, ethical, legal, and patient privacy concerns associated with the use of AI must be addressed prior to clinical integration. This is the first review synthesizing the results of AI-trained analyses for melanoma diagnosis with non-invasive imaging modalities. This information will facilitate the future development of AI-driven diagnostic tools for melanoma and enable algorithm improvement. Subsequent studies should broaden the datasets to include photographs of all skin tones and races, to create more robust, dependable, and clinically relevant algorithms. Our results highlight the need for ongoing endeavors in the advancement and assessment of AI-driven methodologies for the early identification of melanoma.

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تحليل الصور المستند إلى الذكاء الاصطناعي للكشف المبكر عن السرطان: مراجعة

الملخص

الخلفية :يُعد الكشف المبكر عن الميلانوما (سرطان الجلد) أمرًا حاسمًا لتحسين نتائج المرضى، حيث يرتبط التشخيص في المراحل المتأخرة بارتفاع معدلات الوفيات. تتطلب تقنيات التصوير التقليدية مثل الفحص المجهري العاكس بالليزر (RCM) وتصوير التماسك البصري (OCT) والدرموسكوب خبرة كبيرة، مما يؤدي إلى تباين في دقة التشخيص. يوفر الذكاء الاصطناعي (AI) حلاً واعدًا لتعزيز موضوعية وثبات تشخيص سرطان الجلد.

الطرق : تم إجراء مراجعة منهجية للأدبيات باستخدام قواعد بيانات PubMed/Medline و EmbaseوCochrane، مع التركيز على الدراسات المنشورة بين عامي 2016 و2023. تناولت المراجعة منهجيات الذكاء الاصطناعي المطبقة على صور الميلانوما الخبيثة التي تم الحصول عليها باستخدام RCM و OCTوالدرموسكوب. تضمنت المصطلحات البحثية الرئيسية "الميلانوما"، "الشبكة العصبية"، و"الذكاء الاصطناعي."

النتائج :أظهرت التحليلات تقدمًا كبيرًا في تقنيات الذكاء الاصطناعي لتصنيف الميلانوما، حيث أظهرت نماذج التعلم العميق أداءً يوازي أو يتفوق على أطباء الجلد. أبلغت الدراسات عن معدلات دقة عالية، حيث حققت بعض النماذج مناطق تحت منحنى خصائص المستقبل (AUC) أعلى من 0.90. ولاحظت النتائج أن الطرق التي تعتمد على مجموعات بيانات متنوعة أظهرت موثوقية تشخيصية أفضل عبر درجات لون الجلد المختلفة.

الاستنتاج :يعزز تحليل الصور المستند إلى الذكاء الاصطناعي الكشف المبكر عن الميلانوما بشكل كبير، مما يوفر بديلاً قويًا للطرق التشخيصية التقليدية. تؤكد هذه المراجعة على الحاجة إلى مواصلة البحث لتطوير مجموعات بيانات شاملة وتحسين خوارزميات الذكاء الاصطناعي، لضمان الوصول العادل للرعاية الصحية وتحسين نتائج المرضى.

الكلمات المفتاحية :الميلانوما، الذكاء الاصطناعي، التعلم العميق، الدرموسكوب، الكشف المبكر.