Journal Publication of International Research for Engineering and Management (JOIREM)
Volume: 04 Issue: 01 | Jan-2026
ISSN (O) 3107-6696

AI-POWERED EARLY DETECTION OF MELANOMA. ADVANCES, CHALLENGES, AND FUTURE DIRECTIONS.

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Abstract - Early and accurate identification of malignant melanoma continues to be a major challenge for clinicians in the field. Traditional diagnostic approaches, including physical examination, histology, imaging, and nodal assessments, are frequently costly, require significant expertise, and can display large variations among clinicians. These factors may result in missed or misdiagnosis, which often significantly affects a patient's prognosis. We examine in detail how the application of AI methods such as machine learning and deep learning can be used to advance early detection and identification of melanoma. We review various AI algorithms, including standard classifiers, ensemble techniques, and complex deep learning models. Hybrid models that combine convolutional neural networks (CNNs) and support vector machines (SVMs) are emphasized in this review, as they show enhanced performance and improved resistance to variations in the diagnostician's input. Better utility of transfer learning and data augmentation approaches is discussed to overcome the challenges posed by small and unbalanced medical datasets. The authors consider the combination of various types of medical information for more effective cancer diagnosis. However, significant obstacles, including model explain ability, privacy safeguarding, and clinical evaluation, still need to be addressed. Extensive efforts are needed to overcome these barriers if AI systems are to be effectively adopted within healthcare environments. We suggest that AI offers the opportunity to revolutionize melanoma care by enabling rapid decision support and individualized treatment plans. Realizing this opportunity will depend on effective partnerships between researchers, clinicians, and industry to bring together advances in technology.

1. Introduction

Skin cancer, particularly malignant melanoma, is known to yield 80% of skin cancer fatalities due to two reasons, namely, its aggressive behavior and ability to metastasize. Early detection is moreover central to increasing survival rates; however, traditional differential diagnostic methods are limited by their reliability and inter-observer variability. To meet these challenges, new diagnostic modalities have evolved that include diagnostic technologies. Recent innovations in imaging, like the Mela Find, are very sensitive and accurate when it comes to melanoma detection and could therefore enhance biopsy choices. Electronic clinical decision support systems offer objective and, therefore, less variable results in terms of inter- and interobservers variations. These systems utilize several feature extractions approaches, such as texture analysis, border smoothness evaluation, and time series analysis of the borders of lesions. Biosensors have also been identified as feasible rapid diagnostic devices in melanoma diagnosis at the point of care. These advancements are about extending and refining the accuracy and reliability of very early detection to finally provide benefits to patients and the healthcare system. The latest research revealed that melanoma detection has a big potential for the development of artificial intelligence (AI). Indices of sensitivity and specificity of melanoma classification from dermoscopic images using a logistic regression approach are satisfactory, equal to 76.36% and 87.04%, respectively. Still, deep learning approaches, especially convolutional neural networks (CNNs), have proven to perform better in terms of accuracy. For example, using the Inception V3 model, it was possible to classify melanoma with an accuracy of 93.74%, a sensitivity of 94.36%, and a specificity of 85.64%. Beyond the detection method, artificial neural networks have also been used in prognosis and treatment response prediction and clinical, dermoscopic, and histopathologic image analysis. Nevertheless, there are problems with data quality and its interpretation. During the process of machine learning, AI has the potential to transform first-stage melanoma diagnostics and even surpass traditional methods with further enhancements to increase the number of saves.

The improvement of object detection methods has greatly supported AI in analyzing medical images for melanoma. The first type of traditional object detection relied on regions and was first introduced by Girshick with the R-CNN method. This method used selective search to create region proposals which were then evaluated with CNNs. Though this approach proved very useful, it took too much time and computing power and could not be used effectively in real time. To overcome these issues, Fast R-CNN was created which included a streamlined feature extraction method and added a region of interest pooling stage to make both training and processing easier. Then came Faster R-CNN which introduced a region proposal network (RPN) in place of the external region proposal module, making the detection faster and more efficient. Although these two-stage models gave highly accurate results, they were too slow to handle real-time tasks such as live video analysis or medical diagnostics. Consequently, using only a single detection stage in models like SSD and YOLO became popular. SSD by Liu et al. uses several convolutional filters across feature maps at differing scales which helps catch objects of diverse sizes all at once. YOLO, as introduced by Redmon et al.; considered object detection as a regression task and directly predicted the coordinates of each bounding box and the likelihood of each class from full images. This made the process much quicker without losing much accuracy .Highly accurate and stable models are essential as melanoma is visually complicated and clinically significant. This work assesses different AI methods capable of melanoma detection, comparing their benefits, challenges, and potential usage in clinical scenarios.

Figure 1
Visuals of melanoma skin cancer where the images show an irregularly shaped, asymmetrical mole with uneven borders and varying colors, commonly associated with melanoma.

1.1. Objectives of the Study

The objectives of this research are (a) to conduct a comprehensive study of existing literature related to AI applications for melanoma detection, providing insights into the advancements in this field, (b) to analyze the performance of various machine learning and deep learning models, such as CNN, U-Net, support vector machine (SVM), and KNN, used for the detection and classification of melanoma, (c) to identify the limitations of different AI models employed in melanoma detection and classification, highlighting challenges that hinder their effectiveness in accurate diagnosis, and (d) to explore future directions for improving melanoma identification using AI, suggesting potential enhancements and innovative approaches to advance the field.

1.2. Sections of the Manuscript

This section presents an overview of all sections in the manuscript, as shown in Figure 2.

Introduction: The first section gives information on melanoma as a deadly skin cancer and explains the significance of timely diagnosis. It debates on how the current methods of lesion diagnosis using the naked eye by dermatologists are incomplete and how AI is a disruptive technology. The section culminates by expressing the purpose of the paper as a review of the current AI methodologies in melanoma detection and diagnosis.

Literature review: In this section, there is a review of the literature on previous studies that aimed at using AI in detecting melanoma. It presents major discoveries, past frameworks, and diagnostic tools that have been designed based on ML and DL approaches. It also provides a comparative analysis of various algorithms as well as the methods set in melanoma detection, to provide the historical background of utilization of AI in the specified area.

Methodology: The section describes the systematic way in which the paper was undertaken to conduct the review. This explains how the papers were identified for review, the bibliographic databases in their identification, the search terms used, and the papers included as well as excluded. This section also states the research questions for the review and gives informed information on how the gathered papers were integrated.

Machine learning approaches: This section focuses on a detailed discussion of the usage of the different machine learning algorithms in identifying melanoma, including SVM, RF, and k-NN. How these models are being trained using features extracted from images and how accurately they can distinguish melanoma are also described. It can also contain a topic on feature engineering as well as the strengths and weaknesses of classical ML models.

Deep learning approaches: Different types of machine learning techniques can be used for the identification of melanoma from images, but CNN is more useful. This part examines the modern architectural designs of CNN models like ResNet, Dense Net, and Efficient Net dedicated to melanoma diagnosis. One of them is their capacity to learn to extract features automatically, and the works report the relative performance enhancement arising from the application of these new techniques to classical ML.

Issues, challenges, and research opportunities:

Problems including dataset bias, the relative scarcity of large, diverse datasets, model interpretability, and generalization across different populations are discussed. It also points out the problem of delivering AI into healthcare practice and the numerous legal and moral questions that arise.

As previously, several suggestions are introduced, including the way of increasing model generalization, increasing interpretability, constructing larger and more diverse datasets, as well as developing diagnostic tools for AI in real time. Also, the possible involvement of explainable AI (XAI) and AI–human partnership is also discussed.

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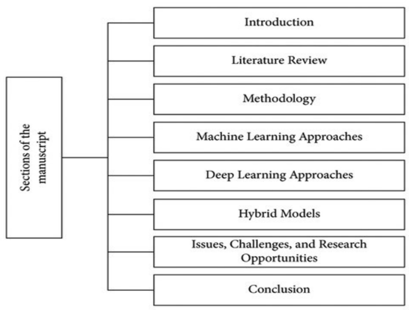

Figure 2
Summary of the sections of the manuscript from Introduction to Conclusion.

2. Literature Review

Melanoma is an aggressive skin cancer that affects people's lives and is a serious concern for public health worldwide as morbidity and mortality rates are growing. Mutations within genetic pathways of discontent predict for those individuals' sensitivity to treatments for melanoma that include radiation, chemotherapy, among others . Melanoma has proven to be increasing with the American Cancer Society estimating thousands of new cases and deaths yearly in the United States . Although progress in treatments like immune checkpoint inhibitors and kinase inhibitors has been made, these issues, like side effects and drug resistance, distort the efficacy of the treatments. Both 1-year and 5-year melanoma mortality rates have shown to differ significantly between countries and across different age groups; most worrisome, several countries have seen a rise in the mortality rates, indicating an increase in this mortality trend, which demands a global concerted effort to respond to this deepening problem. Accomplishments in studying the contributing aspect of sun exposure, besides genes, are important in fighting this increasing menace .

AI has transformed the practice of dermatology, especially in the identification of skin cancer, with improved Ridley accuracy and increased efficiency provided by ML algorithms. AI systems are found to integrate malignant lesions with higher sensitization and specification than traditional methods through the ability of image recognition systems to depict the patterns of the diseases in images. The benefits of AI are that it brings less diagnostic risks, always operates accurately, processes a large amount of data quickly, brings better patient outcomes, provides the possibility of starting working in the early stages of the diseases development, and is built to learn something new from the new data sets in permanent.

These advancements have permanently solidified AI as a vital tool within dermatological practice for the present, and it signifies a major transformation that AI could bring to the specialty.

Machine learning solutions for AI-based melanoma detection have achieved significant interest in the AI community, with SVMs and Random Forests standing as the most mentioned programs. SVMs are good for classifying high-dimensional cases, and it has been widely used in the context of dermatological applications to distinguish between malignant and benign skin tumors from dermo copy images. Previous work has shown that SVMs can reach acceptable levels of classification accuracy and sensitivity, implying that they are helpful tools in melanoma diagnosis. On the other hand, the Random Forests that can use the principle of an ensemble learning model, as it is shown in the article, include several decision trees to improve predictive accuracy and reliability. These algorithms are well suited when it comes to solving data relationships that are intricate and non-linear. This is because the relationship in medical imagery is compounded. odella et al. suggested that Random Forests can enhance diagnostic performance if they incorporated a diverse range of image features for the classification of skin lesions. SVMs and Random Forests have individually significantly advanced melanoma detection using AI-based algorithms, providing credible and effective solutions as compared to conventional methods.

Deep learning is trending in melanoma detection, and the two most used algorithms are CNNs and transfer learning. CNNs, which boast significant image processing performance, have been widely employed in dermoscopic images to diagnose melanoma effectively. These networks can learn grouping and delegation of features from raw image data and provide macro/micro differentiation of skin lesions. Many studies have proved the effectiveness of CNNs with the capabilities of dermo noting level performance in detecting melanoma. Transfer learning utilizes a CNN model pre-trained on large datasets for one problem that is fine-tuned for specific object detection usage for a particular task on smaller datasets. This technique builds upon the knowledge derived from the source domain to enhance the performance in the target domain, a problem associated with a lack of labeled data in medical imaging. There are several risks for employing clinical AI tools for the detection of melanoma, including questions of workflow integration, statutory and ethical issues, as well as trust in AI models. The use of AI in clinical settings means the integration of AI tools into clinical practice, which implies that other systems should be able to engage effectively with the clinicians. Melanoma detection using AI has to be integrated easily with current medical software. The integration process requires educating the users of the healthcare providing organizations regarding the utilization of the AI systems, making the AI-

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recommended information easily implemented into the decision-making process of the clinical setting, and applying feedback mechanisms aimed at enhancing the AI system performance by its practical usage. This integration seeks to improve diagnostic assessment of patients and speed up the process without demanding human effort.

In this paper, the literature review focuses on revealing several important discoveries about the use of AI in the identification of melanoma, and the outcomes demonstrate the power of the concept. Specifically, these skin lesions that have increasing incidence and mortality rates need to be diagnosed at the earliest stage possible, where application of machine learning and deep learning helps to enhance the accuracy and time of diagnosis. Prior methods are comparative to be invasive and entail subjectivity in contrast to AI, which, specifically through SVMs, Random Forests, and CNNs, provides high sensitivity and specificity. Another type of model also boosts diagnostic.

3. Methodology

This section outlines the methodological approach adopted in conducting the review on the use of AI in melanoma detection. The goal is to establish a standardized research method that embraces a systematic review process for identifying selected research papers, as shown in Figure 3.

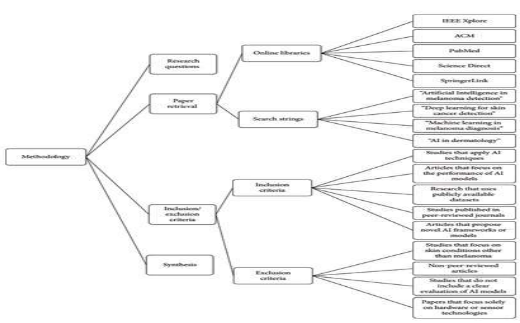

Figure 3
Summary of research methodology of the review.

3.3.1. Inclusion Criteria

Papers that apply machine learning or deep learning techniques for the detection, diagnosis, or classification of melanoma. Papers that concentrated on the accuracy of AI techniques instead of traditional approaches. Papers that utilize publicly available data for melanoma detection. Papers that are published in peer-reviewed journals are presented at highly valued conferences. Research that suggested new AI methods for melanoma detection.

3.3.2. Exclusion Criteria

Studies that focus on skin conditions other than melanoma include melanoma as part of a broader analysis. Non-peer-reviewed articles, opinion pieces, or editorials. The paper has insufficient experimental results and evaluation reports.

3.4. Synthesis

In synthesis, a thorough research procedure was applied to the selected papers for precise extraction of essential findings. The review was organized according to the following themes:

Different AI approaches (i.e., CNNs, SVMs, and decision trees) used for melanoma detection were identified using this protocol. Different models, along with their architecture designs, went through a performance-based comparison analysis. Several obstacles emerged from the research literature, including biased data, uninterpretable models, model generalization problems, and insufficient big datasets. The paper explores solutions that researchers proposed to address these existing problems.The review synthesized future research proposals that involved recommendations to use bigger and more varied datasets while improving the interpretability of models, as well as integrating AI systems in clinical workflows for live melanoma diagnosis.

3.5. Experimental Setup

The experiments in this study were performed on an environment provided by Kaggle that has an NVIDIA Tesla P100 GPU with 16 GB of dedicated VRAM and 13 GB of system RAM. The computers in the lab had enough power to handle the models' training and evaluation. Python 3.8 was used for the experiments, along with widely employed libraries for machine learning and deep learning such as TensorFlow, Kera's, and PyTorch. The evaluation process included classical CNNs as well as sophisticated models such as ResNet50, Exceptions, and YOLOv5/8 models when suitable. Using publicly available data, the models were trained and their performance was measured using accuracy, precision, recall, F1-score, specificity, and sensitivity. A thorough description of the experimental setup, with emphasis on platform, hardware, size of the dataset, models used, and the ways results were measured, has been given to ensure transparency.

This review used a detailed outline of how the process was carried out to make it more transparent and reproducible. We first found about 300 articles, but after removing doubles, we ended up with only 220. Screening of the articles was done in three different phases. The review process includes looking at the title, abstract, and the full text of the paper. Each article had to meet all the inclusion requirements to be used in the

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ISSN (O) 3107-6696

analysis. A total of 84 peer-reviewed research papers made up the final dataset. A sample Boolean search query used in various online libraries was: (“artificial intelligence” OR “deep learning” OR “machine learning”) AND (“melanoma” OR “skin cancer”) AND (“detection” OR “classification”). From each study, we gathered the AI approach, the name of the dataset, how many samples there were, the metrics (accuracy, sensitivity, specificity, F1-score), and what clinical impact the research had. Two separate reviewers read through every article to help maintain consistency. If there were disagreements about how to select or extract data, we discussed them and came up with an agreement. Quality was determined for each study by checking its methodology, the extent of evaluation it includes and how easy it is to confirm its results. All studies contributing to the final analysis had clear steps and measurements. Following this structure increases the trustworthiness and dependability of the outcomes.

Advances

Deep Learning Models:

Convolutional Neural Networks (CNNs) excel at identifying complex patterns and subtle anomalies in dermoscopic images, improving detection accuracy.

Ensemble Methods & Hybrid Models:

Combining different deep learning approaches or integrating models like CNNs with Support Vector Machines (SVMs) can further boost accuracy and resistance to diagnostic variations.

4. Machine Learning Approaches

4.1. SVMs

Using SVMs in an automated system has been so effective in detecting malignant lesions, especially in enhancing early detection in melanoma diagnosis. SVM classifiers have always proven to be dynamic concerning recognition accuracy, and other researchers use Wavelet features to achieve up to

87.7% recognition accuracy [47] . Compared with other classifiers, it is also evident that SVM has better performance at an average melanoma recognition rate of 82.5% . Figure 4 illustrates the segmentation results of melanoma skin lesions as presented by Rashad and Takruri , demonstrating the effectiveness of their proposed method in delineating lesion boundaries.

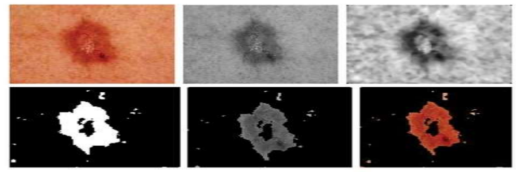

Figure 4
Visual representation of melanoma segmentation.

Due to these reasons, several feature extraction techniques have been incorporated into the SVM algorithm. For example, the texture analysis based on the calculation of Gray Level Co-occurrence Matrix (GLCM) included an accuracy of 82.7% as shown in Reference. Surprisingly, experiments revealed that utilizing six significant attributes is enough to classify melanoma, proving the superiority of SVM regarding the processing of applicable data for precise diagnosis.

4.2 Random Forest

Multiple studies confirm that Random Forest Improvements enhance the performance of melanoma detection systems for diagnosis. For instance, the Random Forest model had a promising level of accuracy of 94.34% in categorizing the tumors; it separated between the benign and malignant diseases (S et al., 2019). This shows that the proposed technique, Random Forests, can enhance the diagnostic results of melanoma. Even though other approaches like Mahalanobis distance learning give sensitivity rates more than 99%, Random Forests remain viable. The basic understanding and the versatility that they afford when it comes to tackling a range of medical imaging tasks put them in good stead when it comes to noting melanoma.

Damian et al. introduce a method for skin lesion analysis that uses color features (C) and Hu (H) moments to distinguish between benign nevi and malignant melanoma lesions. Random Forest serves as the classification method for this approach. A total of 23 features derived from colors are extracted from the data set using minimum and maximum RGB intensity levels, together with the Hu moment analysis. The Random Forest (RF) classifier proves effective for distinguishing benign from malignant skin lesions according to the results depicted in Figure 5.

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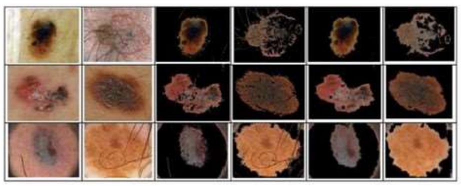

Figure 5
Classification results of melanoma using Random Forest model.

5.3. U-Net for Image Segmentation

In the diagnosis of melanomas, U-Net emerged as a popular architectural design for image segmentation. Segmenting skin lesions from dermoscopic images is important for diagnosis and therapies; hence, its proficiency is vital. The encoder–decoder used in the U-Net made it ideal because it offers accurate localization and context that is necessary in segmenting skin lesions. Computer research conducted on its efficiency reveals that it has an efficient performance with an average of Dice coefficient of 0.93 and 0.87 on PH2 and datasets respectively to confirm efficient melanoma segmentation. Nazi and Abir's U-Net architecture is shown in Figure 6, where melanoma can be detected and segmented. The figure outlines the full process, proving that the model can determine different elements of lesions at different scales and segment missing melanoma areas in the image, demonstrating the U-Net's ability to handle varied lesion boundaries in dermoscopic images.

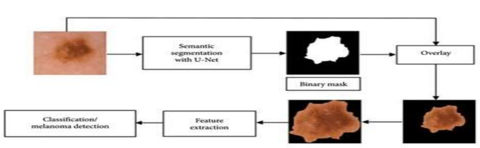

Figure 6
Illustrative representation of melanoma detection and segmentation using U-Net.

6. Hybrid Models

6.1. CNN and SVM Hybrid Models
The detection of melanoma in dermo copy images has become more effective through the adoption of modern research methods that fuse CNNs and SVMs into single systems. These combined procedures take the benefit of the classical machine learning model and deep learning to enhance the diagnostic capabilities and classification accuracy.

For example, Keerthana et al. put forward a CNN-SVM that offered considerably is a much higher performance compared to basic CNN models. This model leverages the fact that the CNN does not require user intervention to extract detailed features from dermoscopic images, apart from the SVM for classification purposes. The major advantage of the proposed hybrid model is that it is built with an integration of the form feature extraction that is associated with CNNs and the powerful classification features offered by the SVMs to yield an improved performance.

8. Issues, Challenges, and Research Opportunities

8.1. Challenges
Nonetheless, several limitations and still existing challenges have arisen that continue to hinder the increased implementation of the AI-based melanoma detection solutions:

8.1.1. Data Limitations
The performance of AI models, therefore, directly depends on the quality and variety of lessons and data given to these applications. Most clinical trials utilize brief sets of skin lesions as their test subjects and fail to represent all population diversity in the United States. This leads to overfitting and poor ability to generalize when used in actual real-life clinical situations.

8.1.2. Performance Variability
Structure in AI models depends heavily on selected algorithms in addition to their data elements, together with performance metrics. Clinical application of AI systems becomes unstable due to possible discrepancies in diagnosis precision resulting from study-specific variations in selection methods.

8.2. Future Directions
The current approaches of AI in detecting melanoma are still developing rapidly, while the following are the future predictions and prospective as well as prospects, thereby improving detection accuracy of melanoma with better results of patients' prognosis in addition to overcoming the current issues. These directions include:

8.2.1. Enhanced Data Collection and Sharing
For enhancing the performance as well as the ability of the model to generalize, there is a strong demand that arises for data sets of larger size and from different population groups, including different skin types, at different stages of melanoma. Healthcare institutions should cooperate mainly with researchers and technology developers, as well as share data, but in the right and ethical manner so that subjects' rights and privacy are covered.

9. Conclusion

This systematic review has evaluated the current landscape of

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AI techniques used for melanoma detection, providing insights into their methodologies, datasets, performance metrics, and clinical applicability. According to the findings, AI is becoming increasingly significant in helping increase the reliability of melanoma classifications. It is thanks to CNNs' ability to identify useful details from images that they are chosen repeatedly for top performance in analyzing dermoscopic and clinical photos. SVMs, Random Forests, KNN, and group models helped a lot, especially along with efforts to select the most relevant features or to use combined methods. It is also observed that techniques such as transfer learning, data augmentation, and using multimodal data tend to noticeably improve the strength and flexibility of AI models, mainly when the datasets are small and uneven. Many investigations depended on ISIC, PH2, and Derm7pt, though some researchers are still concerned.

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