

Melanoma Skin Cancer Detected Based on Artificial Intelligence - Survey

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Khaled Khalifa SAID¹, Dr: CHIBANI Belgacem RHAIMI²

^{1,2} National Engineering School of Gabes, Gabes University-Tunisia
khaledalwarfly@gmail.com¹, abouahmed17@gmail.com²

Abstract

In recent decades, melanoma, a lethal form of skin cancer, has become more common internationally. Due to the recovery strategy used in the medical field, dermoscopic image-based automatic skin lesion detection remains a challenging and complicated task. This difficulty in diagnosing lesions can be attributed to various factors, such as the lesions revealing diverse characteristics, including uncertain borders, inadequate color assessment, shape variations, positional dependence, and complex structures. To prevent the growing public health burden from spreading to other body organs and potentially save many lives, early detection and appropriate treatment are essential among medical professionals and researchers. An individual may develop melanoma if there is an abnormal change in the appearance of the skin. To achieve more effective cancer detection, dermatology expertise should be integrated with computer vision strategies. Consequently, it is crucial to create a variety of detection strategies to aid medical experts in diagnosing early-stage cancer.

This paper provides a thorough, methodical analysis of machine learning techniques for early skin cancer detection, examining published studies. It offers an overview of an artificial intelligence-assisted evaluation approach for diagnosing skin cancer. To address existing challenges in skin cancer detection, this paper proposes a model integrating improved techniques across preprocessing, feature extraction, and classification. The proposed model utilizes adaptive histogram equalization to enhance image clarity, combined with feature extraction methods such as the ABCD rule, GLCM, and HOG, alongside deep learning-based autoencoders. For classification, it employs an ensemble approach that integrates CNNs and SVMs, leveraging transfer learning from pre-trained models and implementing a multi-class framework. This model aims to enhance detection accuracy, reduce costs, and improve usability. The review aims to provide researchers with the latest advancements in machine learning for cancer diagnostics, offering a comprehensive understanding of current and emerging techniques.

Keywords: Skin Cancer, Melanoma Detection, Artificial Intelligence, Machine Learning, Deep Learning, Neural Network Melanin.

اكتشاف سرطان الجلد الميلانيني بناءً على الذكاء الاصطناعي - دراسة استقصائية

خالد خليفة سعيد¹، د: شيباني بلقاسم رحيمي²

^{2,1} المدرسة الوطنية للمهندسين بقابس، جامعة قابس-تونس
khaledalwarfly@gmail.com¹، abouahmed17@gmail.com²

المخلص

في العقود الأخيرة، أصبح الورم الميلانيني، وهو شكل قاتل من سرطان الجلد، أكثر شيوعاً على المستوى الدولي. وبسبب استراتيجية التعافي المستخدمة في المجال الطبي، يظل الكشف التلقائي عن الآفات الجلدية المستند إلى الصور المنظرية مهمة صعبة ومعقدة. ويمكن أن تُعزى هذه الصعوبة في تشخيص الآفات إلى عوامل مختلفة، مثل الآفات التي تكشف عن خصائص متنوعة، بما في ذلك الحدود غير المؤكدة، وتقييم اللون غير الكافي، واختلافات الشكل، والاعتماد على الوضع، والهياكل المعقدة. ولمنع العبء المتزايد للصحة العامة من الانتشار إلى أعضاء أخرى في الجسم وإنقاذ العديد من الأرواح، فإن الاكتشاف المبكر والعلاج المناسب ضروريان بين المتخصصين الطبيين والباحثين. قد يصاب الفرد بالورم الميلانيني إذا كان هناك تغيير غير طبيعي في مظهر الجلد. لتحقيق اكتشاف أكثر فعالية للسرطان، يجب دمج خبرة الأمراض الجلدية مع استراتيجيات الرؤية الحاسوبية. وبالتالي، من الأهمية بمكان إنشاء مجموعة متنوعة من استراتيجيات الكشف لمساعدة الخبراء الطبيين في تشخيص السرطان في مرحلة مبكرة.

تقدم هذه الورقة تحليلاً شاملاً ومنهجياً لتقنيات التعلم الآلي للكشف المبكر عن سرطان الجلد، وفحص الدراسات المنشورة. يقدم نظرة عامة على نهج التقييم بمساعدة الذكاء الاصطناعي لتشخيص سرطان الجلد. لمعالجة التحديات الحالية في اكتشاف سرطان الجلد، يقترح هذا البحث نموذجاً يدمج التقنيات المحسنة عبر المعالجة المسبقة واستخراج الميزات والتصنيف. يستخدم النموذج المقترح معادلة الهيستوجرام التكيفية لتعزيز وضوح الصورة، جنباً إلى جنب مع طرق استخراج الميزات مثل قاعدة ABCD و GLCM و HOG، جنباً إلى جنب مع أجهزة الترميز التلقائي القائمة على التعلم العميق. للتصنيف، يستخدم نهجاً مجمعاً يدمج CNNs و SVMs، والاستفادة من التعلم الانتقالي من النماذج المدربة مسبقاً وتنفيذ إطار عمل متعدد الفئات. يهدف هذا النموذج إلى تعزيز دقة الكشف وتقليل التكاليف وتحسين قابلية الاستخدام. تهدف المراجعة إلى تزويد الباحثين بأحدث التطورات في التعلم الآلي لتشخيص السرطان، مما يوفر فهماً شاملاً للتقنيات الحالية والناشئة.

الكلمات الدالة: سرطان الجلد، اكتشاف الورم الميلانيني، الذكاء الاصطناعي، التعلم الآلي، الشبكة العصبية الميلانين.

1- INTRODUCTION

Pores and skin cancers are an uncommon but dangerous condition that desires to be identified right away. it can seem in many unique ways and occur in different approaches, but fortunately, it can all be cured or stopped absolutely. it could afflict human beings of any age and may be deadly if left untreated. skin cancer impacts one person in six. This contamination causes sure frame cells to develop fast and uncontrollably and unfold to different areas of the body, amongst different consequences on the body. The human frame is made up of billions of cells, any person of that may broaden cancer.

Skin and pore tumors are among the deadliest kinds of cancer. Pores and skin cancer are caused by unrepaired deoxyribonucleic acid (DNA) in skin cells, which results in genetic abnormalities or mutations in the skin. Examining the situation early on is crucial because of the high death rate, growing incidence of skin and pore cancer, and requirement for comfort care. Owing to the severity of these issues, researchers have developed advanced methods for early detection of skin and pore cancer.

The identity and detection of skin most cancers are dependent on several things, inclusive of symmetry, coloration, period, and shape. This huge study location intends to create devices which could mimic human intelligence to maintain health. In this article, we present a thorough, systematic review of gadget gaining knowledge strategies.

One form of skin cancer that may be deadly is melanoma. While other types of skin cancer have a survival rate of only four percent, early detection of melanoma increases the chance of survival by 75 percent [1][2]. These skin lesions are easily treatable if they are detected early enough.

Melanomas can swiftly progress to the final stage and result in metastases if they are detected too late. The likelihood of the patient surviving drops. Statistics show that a patient with late-stage melanoma may live for up to five years. It is not very important to meet with a skilled dermatologist who performs clinical examinations to detect melanoma early on.

Finding pores and skin lesions for the duration of scientific examinations changed into extra success while dermoscopy gadgets were used to generate snapshots. Dermoscopy is a non-invasive technique for comparing the dermo-epidermal interface, the microstructure of the papillary dermis, and the colors and dermis in actual time, all of which are invisible to the human eye. Histological characteristics are linked to those systems.

While applying machine learning to healthcare does not currently train doctors, it can provide a more effective method of treating medical issues. Consider the following works. There are specific methods for early cancer detection mentioned, as well as the accurate identification of this illness. Skin cancer, known as melanoma, occurs in melanocytes, which are cells in the skin's outer layer (dermis). Skin color is due to a pigment called melanin, which is produced by melanocytes.

In addition to giving skin its tan or brown hue, melanin shields the skin's deeper layers from the harmful effects of sunlight. When melanin develops improperly, it spirals out of

control and aggressively infiltrates the surrounding tissues. Moreover, melanomas can affect the skin and spread through the blood and lymphatic systems to other organs and bones. The most common type of skin cancer is melanoma. If melanoma is detected early, it can be cured. However, the majority of melanomas spread to other body parts if they are not treated. Cancers have been removed, and most cases have been successfully treated through surgery and early detection. Later on, however, it is often irreversible. Four criteria may be used to diagnose melanoma (ABCD).

Figure [1] shows how melanoma and common illnesses differ from one another. An uneven shape is indicated by asymmetry. If there are any anomalies in the shape, they could be used to determine the margin.

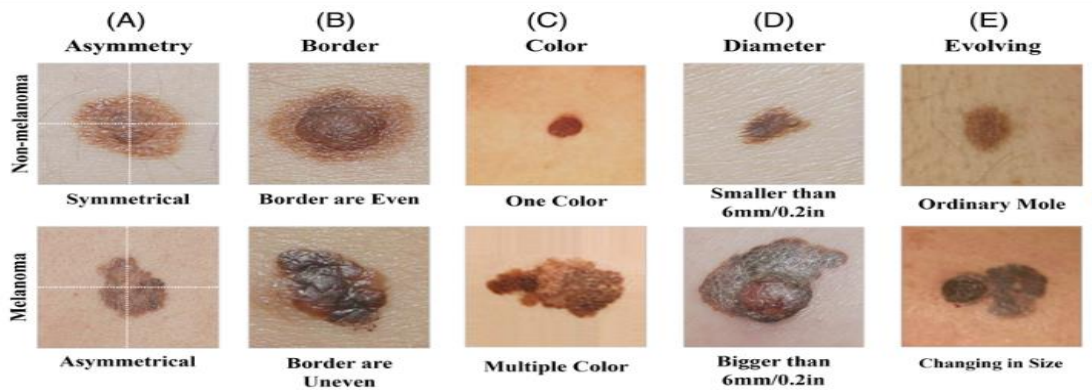


Figure [1] The ABCDEs of Detecting Melanoma

2- STAGES IN MELANOMA

The distinction between melanoma and normal disease is depicted in [1]. Asymmetry denotes an irregular form. The margin may be determined by the shape if any irregularities exist. Five Roman numerals (I to V) and up to four letters (A to D) are used to categorize cancer into stages, with each stage indicating a higher risk. The main factor that determines the stage is specific information about the tumors and their growth, which is tracked in a system known as TNM.

The TNM Staging System includes the extent of the tumor (T), extent of spread to the lymph nodes (N), and presence of metastasis (M).

Subgroups exist within some stages, and they are denoted by the letters A through D. The more advanced the disease and, generally speaking, the worse the prognosis, the higher the number and letter. Stage II is more severe than stage I, for instance, and stage IIIC is more severe than stage IIIB.

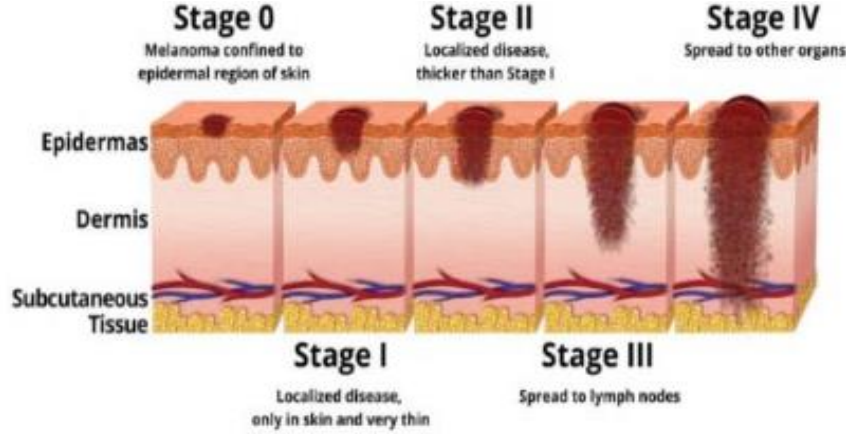


Figure [2] Stages in Melanoma

2-1 Stage 0 Melanoma (in situ)

The malignant tumors are still constrained to the top layer of pores and skin in degree 0 cancer. Most cancer cells have no longer but gotten deeper (into the epidermis), the handiest attaining the epidermis, the skin's outermost layer. melanoma is in situ, a Latin term that means "in place". there is no proof that most cancers have metastasized, or unfold to remote locations along with lymph nodes.

2-2 Stage I Melanoma (localized tumor)

Most cancer cells are present in both the epidermis and the dermis in degree I cancer. stage I melanoma might also or won't have ulcers and has a thickness of up to two mm (Breslow thickness). There may be no proof that most cancers have metastasized, or spread to remote places consisting of lymph nodes. IA and IB are the two subgroups of degree I melanoma.

2-3 Stage II Melanoma (localized tumor)

Thickness of the tumor and ulceration characterize stage II melanoma. Skin and dermis both contain cancerous cells. No proof that the cancer has metastasized, or spread to distant locations such as lymph nodes, has been found. Level II is divided into the IIA, IIB, and IIC subgroups.

2-4 Stage III Melanoma (regional spread)

The degree of ulceration and involvement of lymph nodes represent degree III cancer. stage III melanoma is characterized by the cancer having evolved melanoma deposits inside the skin or dermis alongside the lymphatic vessels before achieving a lymph node, which is known as a transit or satellite metastasis. Most cancers have also unfolded to one or more local lymph nodes. No evidence that most cancers have metastasized, or spread to different places, is present. IIIA, IIIB, IIIC, and IIID are the four subgroups of level III cancer.

2-5 Stage IV Melanoma (metastasis beyond regional lymph nodes)

The level of ulceration and lymph node infiltration suggests a grade III cancer severity. Stage III melanoma is distinguished by the growth of melanoma deposits in the skin or dermis near the lymphatic channels, known as transit or satellite metastases, prior to affecting a lymph node. Typically, these cancers have advanced to affect one or more surrounding lymph nodes. However, there's no substantial proof that most cancers have spread to distant locations. IIIA, IIIB, IIIC, and IIID represent the four categories of stage III cancer.

3- LITERATURE SURVEY

The abnormal growth of skin cells is known as skin cancer. The most popular form of most cancers is by way of some distance skin cancer [3]. If detected early, this may be efficaciously handled. Early cancer detection comes at a totally excessive value The four types of skin cancer include actinic keratoses (AK), basal cell carcinoma (BCC), dermatofibroma, and melanoma. When cancer is discovered too late, it can spread to other organs. However, by using convolutional neural networks, skin cancer can be identified from images. The HAM10000 and ISIC photograph datasets are used on this implementation. In CNNs, transfer getting to know enhances version overall performance. capabilities that are then used to categorize pores and skin cancers are extracted the usage of pre-skilled fashions. Random forest, SVM, CNN, and Dense net are the gadget studying and deep learning strategies utilized in this implementation.

The research [4] pores and skin most cancers are a risky situation that on the whole influences older adults however affects humans of virtually all ages. This effects in the increase of a tumor due to the skin's epidermal layer growing abnormally or quickly. It is crucial to differentiate skin cancer from other skin conditions because cancer affects the tissue itself, whereas other illnesses only target the outermost layer of the skin. Given that early cancer detection and treatment are expensive, technology can help predict cancer early on, saving patients time and money related to cancer detection. Through the use of convolutional neural networks, skin cancer can be identified from images.

For the early identification of skin lesions, the authors in [5] proposed an algorithm that uses feature extraction with the ABCD rule, GLCM, and HOG feature extraction techniques.

Preprocessing in the recommended work aims to enhance the clarity and quality of the skin lesions in order to reduce artifacts like skin tone and hair. The lesion portion was segmented independently using Geodesic Active Contour (GAC), which was also useful for feature extraction. To extract features like symmetry, border, color, and diameter, the ABCD scoring method was employed. To extract texture features, GLCM and HOG were implemented. Various machine learning strategies, including SVM, ANN, and Naive Bayes classifiers, are used to categorize skin lesions as either benign or melanoma based on the extracted features.

A total of 672 photos of melanoma and 328 photos of benign skin lesions were downloaded for this venture from the International Skin Imaging Collaboration (ISIC). Using SVM classifiers, the classification results showed 97.8% accuracy and a 0.94 area under the curve. Additionally, 86.2% sensitivity and 85% specificity were achieved using artificial neural networks [6].

The study [7] offered a system in which the lesions were classified into three unique groups such as normal, abnormal, and melanoma by different machine learning algorithms. A pre-classification was attempted using three different groups and a decision support system was created, which was developed to ease the decision-making task for medical experts. The objective of this study was to classify skin lesions using the PH2 dataset. Four different classifiers were used, namely KNN, ANN, SVM and decision tree. KNN classified the images into three different groups of which the accuracy for the 'normal' class was 92.50%, 78.75% for the abnormal 'class', and 67.50% for the 'melanoma' class. The total accuracy for KNN was 82%. SVM, ANN, and DT had higher accuracies than KNN.

The research in [8] focused on various segmentation strategies that are available. Feature extraction from the segmented image, like in B, is a frequently used segmentation algorithm. The feature set extracted from the segmented image, k-means, and histogram thresholding are displayed. Indeed, there are. For this, a selection of downgrade algorithms is available. The most recent methods for detecting skin cancer depend on algorithms driven by deep learning and machine learning. The downgrading algorithms that are most often employed are feed-forward artificial neural networks, deep convolutional neural networks, and support vector machines (SVMs). In addition to a brief review of the most recent algorithms, this paper provides an analysis and study of the methods currently used to detect skin cancer.

A CNN model suggested in [9] is capable of classifying melanoma types into benign and malignant categories. In this model, an accuracy of roughly 70% was attained using a simpler model. Future developments of this work will involve modifying the network's architecture for multi-class cases—which can identify various categories of skin lesions, and varying the prediction accuracy through parameter adjustments. The suggested system is a very useful tool that supports accurate, thorough, and timely disease assessment. Additionally, the system incorporates an explainable user interface that utilizes its user interface.

The work [10] verified how much effort was put into developing a diagnostic tool for melanoma, the deadliest cancer. The two distinct systems included in this study on cancer detection in dermoscopy images are the global system, local feature, and feature package. Skin lesions are grouped using a global system. A classifier that employs a local feature or a group of features is used to categorize melanomas. To check whether the features are more differentiated, the color and texture features in lesion classification are also compared. The use of the color feature alone yields excellent results for both methods.

The authors in [11] designed a system in which data preprocessing is performed using a Raspberry Pi device that included segmentation and feature extraction after which the lesion is classified into melanoma, non-melanoma, and unknown classes. The images are obtained from ISIC. A KNN classifier is used and testing was conducted on 15 images. An accuracy of 86.67% has been obtained.

The work in [12] created an artificial neural network (ANN) classifier that uses features to classify certain datasets as malignant or non-cancerous. Some characteristics set malignant melanoma apart from benign melanoma. These features are extracted through the use of feature extraction techniques. Both the 3D feature extraction method indicated by K and the 2D wavelet transform are applied. To train the ANN, a procedure known as backpropagation is employed. In this manner, the feature estimate and its actual output are obtained. The inputs have random initializations. To minimize the discrepancy between the intended output and the actual yield, inputs are modified at each cycle. It is efficient to use predicted ANN classifiers for pattern recognition and decision-making.

According the research [13], a modified version of the Particle Swarm Optimization (PSO) functional optimization framework was used to predict the prognosis of skin cancer using dermoscopy images. The purpose of the proposed PSO set of rules is to maximize functionality because diagnosing severe skin cancers requires identifying the key characteristics that differentiate benign from malignant skin changes. It also incorporates sub-swarms, local and mutation-predicted local exploitation, and multiple matrix representations to avoid premature convergence of the original PSO ruleset. Stated differently, the sub-swarms' heat-based search is guided by distant swarms that exhibit health but have low functional proximity, allowing the exploration of various search areas. Additionally, modified velocity updating techniques are suggested in order to enable the particles to target the locally and globally worst individuals partially (i.e., to follow multiple swarms guiding factors) in arbitrary sub-dimensions and in every dimension in an effort to find and avoid global optima. To diversify your hunting strategy, use dynamic matrix representations and probability distributions. Superiority is suggested by the UCI database, numerous unimodal and multimodal reference functions, and suggested PSO variations examined with numerous skin lesions.

4-PROPOSED WORK.

Based on the gaps identified in the related work, we propose a model for enhancing skin cancer detection that involves a comprehensive multi-stage approach integrating advanced techniques across preprocessing, feature extraction, and classification. The model begins with preprocessing methods such as the adaptive histogram equalization algorithm to improve the clarity of skin lesions by reducing artifacts like skin tone and hair. In the feature extraction phase, methods such as the ABCD rule, GLCM, and HOG are used alongside deep learning-based autoencoders to capture a broad spectrum of characteristics. This comprehensive feature set would enhance the accuracy of subsequent classification.

In the classification stage, the model employs an ensemble approach that integrates CNNs and SVMs, leveraging transfer learning from pre-trained models and implementing a multi-class classification framework to handle various skin lesion types effectively. Continuous evaluation with updated datasets and performance metrics ensures that the model remains effective and relevant, incorporating feedback for ongoing improvement. This approach aims to enhance accuracy, reduce costs, and improve usability, ultimately advancing the early detection and management of skin cancer.

CONCLUSION

In summary, the related work highlights significant progress in skin cancer detection, emphasizing the use of various machine learning and deep learning techniques such as CNNs, SVMs, and feature extraction methods. Current methods have achieved distinguished accuracy in classifying skin lesions, with advancements in preprocessing and classification improving the effectiveness of early cancer detection. However, challenges remain in addressing the high costs and variability in detection accuracy, especially across different types of skin cancer. Our proposed method addresses these gaps by integrating advanced preprocessing techniques, comprehensive feature extraction methods, and an ensemble classification approach. By employing adaptive histogram equalization for better image clarity, combining traditional and deep learning-based feature extraction methods, and using an ensemble of CNNs and SVMs, the model aims to enhance classification accuracy and reduce costs. Continuous evaluation with updated datasets ensures that the model stays relevant and effective, eventually improving the early detection and management of skin cancer.

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