Deep Learning, Particularly Convolutional Neural Network, Improves Melanoma Detection Accuracy

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Abstract

Background: Melanoma, though rare, is highly fatal due to rapid metastasis. Early detection improves survival rates significantly. Higher Human Development Index (HDI) correlates with better detection and outcomes. Advances in artificial intelligence (AI) and deep learning offer improved accuracy and efficiency in diagnosing melanoma, addressing the need for better methods. Methods: This study utilized a dataset from the International Skin Imaging Collaboration (ISIC), comprising over 23,000 dermatoscopic images. A subset of 640 images (512 for training and 128 for testing) was used to evaluate a proposed convolutional neural network (CNN) architecture. The images were pre-processed to enhance features and remove artifacts, followed by lesion segmentation and classification using the CNN. Performance was compared with k-nearest neighbors (KNN) and support vector machines (SVM). Results: The CNN demonstrated superior performance in detecting and classifying melanoma compared to KNN and SVM. The architecture, consisting of convolutional and pooling layers followed by fully connected layers, achieved high accuracy in distinguishing between benign and malignant lesions. Pre-processing steps, including artifact removal and color enhancement, were crucial in improving detection accuracy. Conclusion: This study highlights the effectiveness of deep learning techniques, particularly CNNs, in melanoma detection. The findings support the integration of AI-driven methods in clinical practice to aid dermatologists in early and accurate detection of melanoma. Future research should focus on refining these techniques and expanding their application to broader datasets.

Keywords: Melanoma, Deep Learning, Convolutional Neural Networks (CNN), Image Processing, Artificial Intelligence (AI)

Significance | This study demonstrated how deep learning, particularly CNNs, improves melanoma detection accuracy, supporting earlier diagnosis and better patient outcomes.

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Introduction

Melanoma, although the least frequent type of skin cancer, stands as its most fatal variant due to its rapid potential to metastasize to other bodily regions (Abbas et al., 2011; Argenziano et al., 2011). Originating from the malignant transformation of melanocytes—cells derived from neural crest neoplasia—melanoma's incidence and mortality rates are intricately linked to the Human Development Index (HDI) (Daghrir et al., 2020). Elevated HDI scores often correlate with improved access to healthcare, facilitating earlier disease detection and treatment, which in turn reduces mortality rates (Ballabio et al., 2019). Notably, data indicates that individuals diagnosed with melanoma at an early stage exhibit a five-year relative survival rate approaching 98%. Conversely, only about 20% to 50% of patients with metastatic melanoma survive beyond five years post-diagnosis (Dalila et al., 2017).

Given these statistics, the implementation of supportive imaging methodologies that enhance and simplify the diagnostic process becomes paramount. These methodologies, inspired by clinical practices employed by dermatologists, encompass a series of steps

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in the automatic identification of melanoma. These steps include pre-processing, extraction of the region of interest, post-processing, and lesion assessment. This pipeline mirrors the traditional pattern recognition system, emphasizing image acquisition, lesion segmentation, and classification techniques (Gautam & Ahmed, 2015; Jadhav et al., 2019). In this context, we propose a novel technique aimed at improving self-examination and early detection of melanoma.

The advent of artificial intelligence (AI) has revolutionized various sectors, notably expediting processes in drug development and material science (Kavitha et al., 2017). Over the past decade, there has been a significant surge in the application of data science approaches across multiple disciplines (Ballabio et al., 2019). For instance, data science facilitates density functional computations, establishing links between atomic and material interactions through quantum mechanics (Gautam & Ahmed, 2015). Machine learning, in particular, plays a pivotal role in structuring property links to represent the mechanics of materials, aiding in the creation of new materials with desired attributes or enhancing existing ones. Its utility extends to pharmacological complex predictions, especially those exhibiting nonlinear behavior.

This paper is structured as follows: Section 2 provides a concise overview of prior research and the visual cues utilized by clinicians in melanoma diagnosis. Section 3 introduces the proposed methodology. Subsequently, Section 4 presents the experimental results and evaluates the efficacy of the proposed approach. The final section offers a discussion and conclusion.

2. System Model

The ABCDE criteria—Asymmetry, Border irregularity, Color variation, Diameter, and Evolution—are widely recognized as effective indicators for diagnosing melanoma. These criteria are instrumental in distinguishing between malignant and benign skin lesions. The process of melanoma detection typically involves several critical steps, including image capture, preprocessing, lesion segmentation, lesion characterization, and lesion classification. While the exact sequence and combination of these steps may vary depending on the specific approach, each plays a crucial role in the diagnostic process.

Most contemporary melanoma detection methods rely on dermoscopic images, which are highly effective for detailed examination of skin lesions. These methods can be broadly categorized into those utilizing traditional image processing and machine learning techniques (Abbas, Celebi, & García, 2011; Argenziano et al., 2011; Daghrir et al., 2020; Ballabio, Todeschini, & Consonni, 2019) and those employing advanced deep learning algorithms (Dalila et al., 2017; Kavitha, Suruliandi, Nagarajan, & Nadu, 2017).

The segmentation of lesions is a critical step following image capture, as it involves isolating suspicious skin lesions from the surrounding healthy skin. This step is considered the most vital in the entire melanoma detection process. For instance, Uzma Jamil and colleagues (2011) introduced an innovative approach that effectively differentiates between the surface of the skin and the underlying layers by applying a gradient filter technique to the image.

Once the features are extracted from the segmented images, a training phase is necessary to develop a model capable of distinguishing between malignant and benign tumors. Support Vector Machines (SVMs) have been widely used by researchers due to their effectiveness and relatively low complexity in generating accurate models (Gautam & Ahmed, 2015; Dalila et al., 2017). However, Dalila et al. (2017) also compare the performance of K-Nearest Neighbors (KNN) and Artificial Neural Networks (ANN), noting that ANN often outperforms KNN. In recent years, the application of deep learning techniques to melanoma detection has become increasingly popular. Unlike traditional pattern recognition algorithms, which heavily depend on the accuracy of the segmentation step, deep learning models can automatically identify skin lesions and learn feature representations from a vast number of skin images.

3. Materials and Methods

The experiments were conducted using a publicly available dataset from the International Skin Imaging Collaboration (ISIC) database, which contains over 23,000 images of skin lesions. For this study, we selected a subset of 640 images, comprising both benign and malignant lesions, all captured using dermatoscopy techniques. Of these, the first 512 images were designated for the training set, while the remaining 128 images were reserved for the testing set. Figure 5 illustrates a selection of these skin lesion images.

The convolutional neural network (CNN) was trained using three distinct methods on the 640 images, each resized to 124 x 124 pixels. Figure 5 also highlights images from both benign and malignant cases, which were predicted by the deep learning model and subsequently diagnosed by medical professionals.

4. Results and Discussion

Table 1 summarizes the results of the three proposed methods, along with the outcomes when these methods were combined. Additionally, the table includes results from applying a K-Nearest Neighbors (KNN) classifier for comparison.

We focus on melanoma, a type of skin cancer that, while potentially life-threatening, can be effectively managed if detected early. Our research explores various deep learning techniques for the early prediction and classification of melanoma using multiple image datasets. These advanced methods are instrumental in enhancing

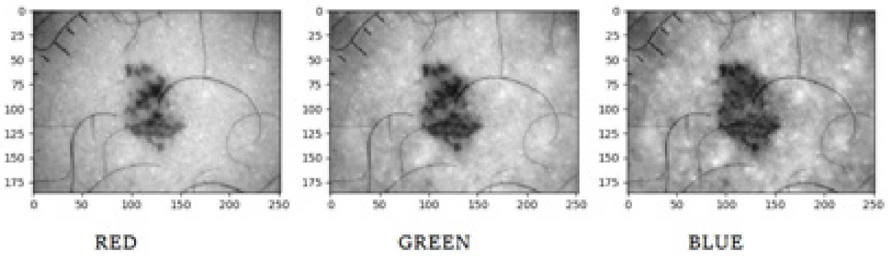

Figure 1. RGB color channels of a lesion on the skin.

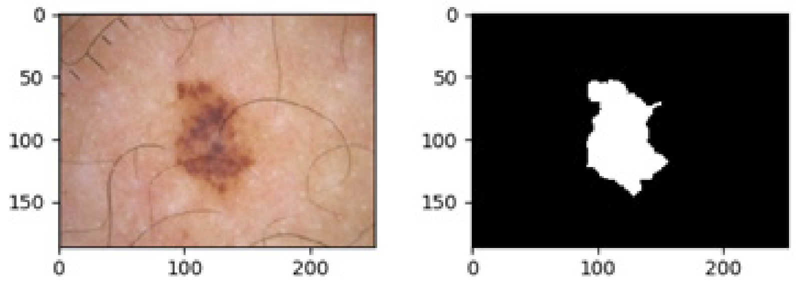

Figure 2. Thresholding is used to segment skin lesions.

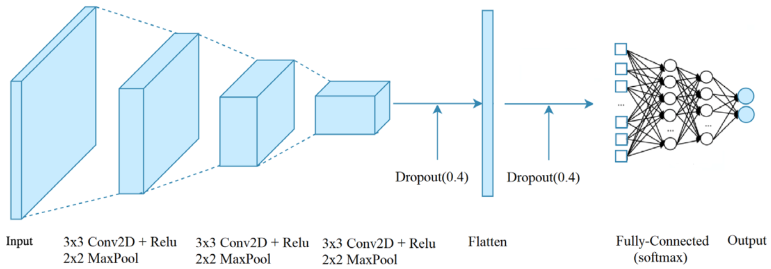

Figure 3. The used deep learning architecture

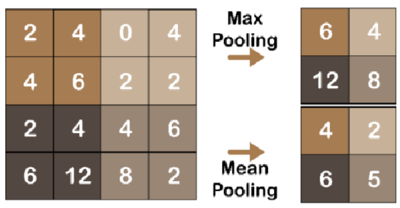

Figure 4. Pooling system diagram

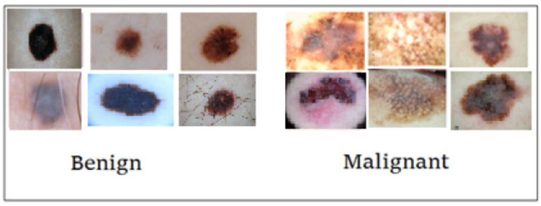

Figure 5. Skin cancer melanoma image samples

Table 1. The accurcy of the distinct methods

Classification Method	KNN	SVM	CNN
The accurcy	56.23%	72.78%	84.45%

early diagnostic capabilities. Dermatologists typically rely on image-based diagnostic techniques to identify melanoma at an early stage by analyzing images of suspicious skin areas. Our findings demonstrate that convolutional neural networks (CNNs) outperform other techniques, such as K-Nearest Neighbors (KNN) and Support Vector Machines (SVM), in accurately detecting melanoma.

Many individuals tend to consult a doctor only when melanoma reaches its advanced stages, making treatment more difficult. Often, skin lesions are perceived as common ailments, similar to any environmental sickness. This highlights the importance of self-examination for any suspicious lesions. In modern medicine, the diagnostic process is increasingly supported by computer-assisted methods. Digital image processing, for instance, simplifies the work of dermatologists and enhances patient outcomes. In this section, we present our proposed strategies that assist both individuals and healthcare professionals in effectively detecting melanoma.

4.1 Challenges in Melanoma Detection

One of the primary challenges in melanoma detection is differentiating between skin lesions and healthy skin. The segmentation process is highly sensitive to the output of the preprocessing phase, which is crucial for accurate identification. Improving image analysis and preprocessing by removing artifacts can significantly enhance segmentation accuracy. Artifacts, such as hair, can obscure important information within the lesion, making it difficult to achieve precise segmentation. Therefore, hair removal is a critical step. Various hair removal techniques have been proposed in the literature to address this issue.

4.2 Hair Removal Technique

We adopted and slightly modified the preprocessing approach for hair detection as proposed by Abbas et al. (2011). Our proposed hair removal method consists of several steps, as illustrated in Figure 2. First, we applied a color enhancement technique focusing on the blue channel of the RGB color model, which improves hair removal and segmentation. Figure 2 shows the differences in gray level values across the three RGB channels. Hairline detection is then performed using the Difference of Gaussian (DOG) derivatives of the blue channel in the dermoscopic images. This method lays the groundwork for subsequent steps in disease detection and prediction, particularly through the application of various machine learning techniques.

4.3 Convolutional Neural Network (CNN) Architecture

The proposed convolutional neural network (CNN) architecture uses entire images resized to 124 x 124 pixels as inputs, making preprocessing a critical step before training the model. As shown in Figure 3, the CNN architecture comprises eight layers. The first three layers are conventional, utilizing 3x3 filters with the ReLU activation function, followed by three pooling layers that reduce the spatial dimensions of the feature maps. These initial layers are responsible for learning feature representations, which involve a combination of linear and nonlinear operations, such as convolution and activation functions. Additionally, the fully connected layer, often referred to as softmax, is depicted in Figure 3, which connects the input, hidden, and output layers of the neural network.

4.4 Pooling Layers

Pooling layers, commonly used after several convolutional layers in CNNs, offer multiple benefits, including the ability to reduce overfitting by gradually decreasing the output volume of the feature maps (Ballabio et al., 2019). The pooling layer accomplishes this reduction by applying either max pooling, which selects the maximum value, or average pooling, which calculates the mean value. Figure 4 provides an example of the pooling process using a 4x4 pixel input image.

5. Conclusion

In conclusion, melanoma, though the least common form of skin cancer, remains the most lethal due to its high potential for metastasis. Early detection is critical, as the prognosis significantly improves when the disease is identified in its initial stages, with survival rates reaching up to 98%. However, the challenge lies in accurately distinguishing between malignant and benign lesions, a task that is often complicated by the presence of artifacts and other image irregularities. Our research demonstrates that deep learning techniques, particularly convolutional neural networks (CNNs), offer a promising solution by providing superior accuracy in melanoma detection compared to traditional methods like K-Nearest Neighbors (KNN) and Support Vector Machines (SVM). These findings underscore the importance of integrating advanced image processing and machine learning techniques into the diagnostic process, ultimately enhancing early detection and improving patient outcomes. As AI continues to evolve, its role in medical diagnostics, especially in conditions like melanoma, will likely become even more critical.

Author contributions

A.R.A. conceptualized the study, designed the methodology, conducted the data analysis, and supervised the project. A.R.A. also collected the data, contributed to the literature review, and wrote, reviewed, and edited the manuscript. The author approved the final version of the manuscript.

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Competing financial interests

The authors have no conflict of interest.

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