International Journal for Multidisciplinary Research (IJFMR)

E-ISSN: 2582-2160 ● Website: www.ijfmr.com ● Email: editor@ijfmr.com

Skin Cancer Detection Using CNN (Convolution Neural Network) with AI Medical Assistant

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Abstract:
Skin cancer is a very common disease, and with numerous morphological forms and characteristics that are similar between malignant and benign skin lesions, makes the diagnosis pretty difficult. Recent trends in deep learning, with CNNs being the first to enter this domain, have highly facilitated the classification and detection of skin cancer, even in its nascent stages, from images. A plethora of such research works proposed novel architectures for CNNs that may possibly improve the accuracy in the diagnosis of the lesion given as against those belonging to seborrheic keratosis, nevus, or melanoma. The best model, according to the works on these authors, was the multi-layer deep learning model known as SkinLesNet, which performed better than established models such as ResNet50 and VGG16 in all datasets. More extensive studies present a DCNN model that addresses the issue of class imbalance and is stronger than transfer learning models, such as DenseNet and MobileNet. This model achieved strong accuracy on several instances: 98.5% with HAM10000 and 97.1% with ISIC-2019 data. Optimizations in model selection methods: In addition, there existed optimizations in model selection. This was through the application of the multiple-criteria decision making approaches. For instance, the method RAPS can be taken as an example. Through the application of this method, a very significant increase in accuracy was achieved. For optimizing the use of feature selection using Inception V3 in determining diagnosis for oral cavity squamous cell carcinoma, BPSO showed an accuracy of 96.3%. Such breakthroughs underpin therefore the capability of deep learning and AI techniques in raising diagnostic accuracy while cutting costs and making a chance for early intervention of skin and other cancers.

Keywords: Skin cancer, Melanoma, Non-melanoma, CNN, Deep learning, AI, Dermoscopy, Image classification, Machine learning, Early detection, Transfer learning, Feature optimization, HAM10000, ISIC, Medical imaging.

Introduction

Skin cancer, specifically melanoma, is turning into one of the possible health issues in the world today as it causes high mortality and especially has low chances of early diagnosis. Early diagnosis of skin lesions can improve patient outcomes because the affected persons would be presented with better treatment alternatives. However, the rarity of dermatological expertise in remote and underserved areas provides reasons for an automated diagnostic solution. AI and ML had shown great promise in early detection, improving classification accuracy, and offering skin cancer accessible diagnostic tools through mobile-based applications. Complex dermoscopic image pattern recognition was achievable through the DL and classical ML models of AI systems, providing superior diagnosis for dermatologists and educating patients.

Research in AI-driven skin cancer detection has explored various approaches to increase diagnostic precision and reduce human error. One study introduced a convolutional neural network (CNN) model using AlexNet architecture with transfer learning for binary classification of melanoma and non-melanoma lesions from the HAM10000 dataset, achieving an accuracy of 84%, with high sensitivity (81%) and specificity (88%) [5:1]. This model simplifies the diagnostic workflow by working directly with raw images without requiring complex lesion segmentation and feature extraction processes, demonstrating CNN's effectiveness in diagnostic automation. Other research has focused on multi-class classification using a Multi-Class Support Vector Machine (MSVM), incorporating specific preprocessing methods and feature extraction techniques like ABCD and GLCM, which achieved high classification accuracy (96.25%) and precision (96.32%). This highlights the value of combining ML algorithms with robust preprocessing to manage the complexity of multi-type skin lesion classification [5:2]. Further, hybrid models that make use of the CNN with other traditional machine learning classifiers, including SVM and k-Nearest Neighbors (KNN), were designed. In a hybrid model, which combined the CNN for deep feature extraction with SVM and KNN with majority voting, the melanoma detection accuracy was reported at 88.4%. It indicates that ensemble models combining the desirable properties of different classifiers might bring enhanced diagnostic reliability, particularly in the early detection of melanoma [5:3]. Another issue that was addressed regarding class imbalance in datasets is a deep convolutional neural network for multi-class classification. The research used oversampling techniques to correct dataset biases. It achieved an accuracy of 98.5% on the HAM10000 dataset and 97.1% on ISIC-2019, which once again highlighted the importance of handling class imbalances to ensure robust performance of the model on different datasets [5:4].

One of the model was SkinLesNet, it was optimized for mobile-based applications, utilizing the acquired images from a smartphone and dermoscopy. This is a multi-layer CNN having a classification accuracy of 96%, which goes beyond that of any models presented herein, including ResNet50 and VGG16; the potential of mHealth in self-diagnosis and monitoring of skin cancer [5]. A technique is the combination of CNN and DWT to further improve the feature extraction as well as enhanced classification accuracy. The sensitivity achieved on HAM10000 and ISIC-2018 were 94% and the specificity was 91%. In the combination of DWT with CNN, the prospect in using advanced transformation techniques for complex medical imaging is diagnosed with accuracy [5:6].

Systematic reviews of the field indicate that algorithms of neural networks, such as CNNs, have significantly improved in skin cancer diagnostics and that accuracy in detection has improved for melanoma. Yet, some challenges still include data quality, generalization across diverse populations, and integration with the clinical arm. A review has been seen to write that although CNNs can significantly improve the accuracy of diagnostics, variability in image quality and dataset bias may limit performance, hence the need for good diverse datasets for reliability in real-world applications [5:8]. Another review of the current capabilities and limitations of AI-driven image classification has been criticized on issues such as imaging variability, dataset limitation, and the integration of clinical metadata for purposes of attaining clinically reliable diagnostic accuracy. This review identifies the challenge that despite exciting applications of AI-driven models, these challenges need to be overcome to succeed in clinical deployment [5:7].

Further research on AI-based chatbots in healthcare might be useful for preliminary screening and patient support as they automate the primary assessments and facilitate smooth communication between patients and healthcare professionals. Though not specifically designed with skin cancer in mind, these chatbots could adapt to dermatology to enable preliminary symptom checks and triage in resource-limited environments [5:9]. Similarly, AI-based health assistants for general medical care can be integrated with skin diagnostic tools. The latter will utilize mobile images coupled with symptom analysis to propose preliminary diagnoses. This relates to the more general way in which AI can further dermatology, especially due to remote monitoring and activation of patients [5:10].

Literature Survey

Research on AI-based skin cancer detection has moved forward by exploring a range of models and techniques to enhance the efficiency and availability of diagnosis. Preliminary experiments showed that convolutional neural networks can be used significantly for binary classifications of whether the tumor is melanoma or non-melanoma type. A model used transfer learning with AlexNet architecture possessed a high accuracy of 84% along with 81% of sensitivity, which proved that CNN is a potential method in dermatology [5:1]. Other studies further extended this idea to multi-class classification using MSVM in conjunction with pre-processing techniques and feature extraction techniques like ABCD and GLCM. The model was reported at 96.25% accuracy, which means that traditional ML models using adapted feature extraction techniques are able to classify a wide variety of skin cancers correctly [5:2].

In ensemble approaches, the diagnostic accuracy is improved by combining the CNN with classical machine learning classifiers in melanoma diagnosis. A hybrid model, that integrates CNN with SVM and KNN using majority voting achieved an accuracy of 88.4%. In this sense, deep learning and ML classifiers may be combined to make the model more robust and reliable. Critical also has been addressing dataset biases like class imbalances in achieving reliable performance [5:3]. One study applied the approach of oversampling with DCNN model to balance HAM10000 and ISIC2019 datasets with the following accuracy: 98.5% and 97.1%, respectively; this shows that a method of balancing the dataset might be necessary to enhance generalization [5:4].

Innovative mobile-based applications increasingly become a practical tool that can expand access to diagnostics skin cancer. SkinLesNet has been an optimized CNN model proposed for smartphone images, capable of reaching high diagnostic accuracies of 96% for multiple datasets, thus opening one avenue of mHealth solution that would enable patients self-monitor their skin lesions on mobile devices [5]. Advanced features extraction techniques include discrete wavelet transformation besides CNN, resulting in higher diagnostic accuracy. This model was tested on the HAM10000 and ISIC-2018 datasets, which showed 94% sensitivity, and so, the combination of DWT with CNN is effective for improved analysis of images [5:6].

The potential of neural networks in the detection of skin cancer has been supported by systematic reviews, and CNNs have made some notable advancements in accuracy. It seems these reviews focus more on challenges, like uneven image quality, limitations coming from datasets, and the need for more diverse, superior, larger dataset inputs to ensure models' performances are generalizable in real, living-world clinical settings [5:8]. Reviews discussing the inability of AI in the diagnosis of skin cancer found that integration of clinical metadata is hard along with variability in conditions of imaging and diversity of data and pointed out that all these are vital for reliable AI implementation in clinical workflows [5:7]. .AI-based chatbots and health assistants are increasingly used adjunctive tools in dermatology too. Although not dermatology-cancer-specific, these models hint at the possibility of being able to automate first-level exams and patient triage and preparing for dermatological application to aid in preliminary judgments of resource-constrained scenarios [9:10]. Taken together, studies make it clear that AI has a potential that can be seen in skin-cancer diagnostics, offering solutions that are correct, scalable, and accessible, but issues remain in clinical integration, and dataset quality is far from being resolved.

Methodology:

In the methodology for skin cancer detection, we explore recent advancements in machine learning (ML) and image processing techniques that have been applied to enhance accuracy and efficiency in skin cancer classification. The focus is on CNN-based models, given their success in the domain of medical image classification. Various studies have demonstrated that CNNs, when optimized, offer significant potential in skin cancer diagnosis. Raja Subramanian et al. (2021) utilized the HAM10000 dataset, containing 10,015 high-resolution dermatoscopic images, to develop a CNN model that achieved an accuracy exceeding 80%, with a false-negative rate below 10% and precision above 80%. This high level of accuracy underscores CNN's suitability for skin cancer diagnosis using clinical images [5:1]. Additionally, Zhang et al. (2019) integrated CNN with the Whale Optimization Algorithm (WOA) to optimize CNN's weights and biases, thus enhancing classification performance and reducing output error. This optimized CNN model was tested on the Dermquest and DermIS datasets and demonstrated superior results compared to conventional models like AlexNet, VGG-16, Inception-v3, and ResNet, further highlighting CNN's adaptability across various datasets and skin cancer types [5:2].

To expand the dataset artificially and address limitations in training data, Pham et al. (2018) applied data augmentation techniques. These techniques included image modifications such as rotation, scaling, and flipping, which increased the dataset size and diversity, ultimately improving the model's classification accuracy on a dataset of over 6,000 images. This approach underscored the importance of data augmentation in CNN-based skin cancer detection, as it helps improve generalization and robustness, particularly when data scarcity is an issue [5:3]. Similarly, Rezaoana et al. (2020) used a CNN model for the classification of nine skin cancer types, including basal cell carcinoma, melanoma, and squamous cell carcinoma, achieving an accuracy of 79.45%. This model leveraged deep learning and transfer learning, which facilitated the classification of diverse skin cancer types by using pre-trained models fine-tuned on a specific dataset [5:4].

To address challenges associated with class imbalance, an issue that often affects the performance of ML models, oversampling techniques were employed. For example, Houssein et al. (2020) applied oversampling with a deep convolutional neural network (DCNN) model, balancing the HAM10000 and ISIC2019 datasets and achieving impressive accuracy levels of 98.5% and 97.1%, respectively. These results emphasize the importance of dataset balancing, particularly in handling underrepresented classes, which can help ensure that the model performs consistently across all classes [5]. Furthermore, ensemble approaches that combine CNN with classical machine learning models have shown promise in enhancing diagnostic accuracy. One such hybrid model integrated CNN with Support Vector Machines (SVM) and K-Nearest Neighbors (KNN), achieving an accuracy of 88.4% through majority voting. This approach demonstrates that combining CNN's feature extraction capabilities with traditional classifiers can improve model robustness, especially for early melanoma detection [5:6].

In terms of mobile application development, SkinLesNet, an optimized CNN model designed for smartphone-based image analysis, achieved high diagnostic accuracy (96%) for multiple datasets. This model shows the potential for mHealth solutions, allowing individuals to monitor skin lesions through mobile devices, thus expanding access to diagnostics for underserved communities. By leveraging images captured via smartphones and integrating dermoscopic features, SkinLesNet demonstrated that mobile-based applications could offer reliable and scalable solutions for self-monitoring and early skin cancer detection, particularly in low-resource settings [5:7].

Another technique explored in this domain is the combination of CNN with Discrete Wavelet Transformation (DWT) for enhanced feature extraction. By applying DWT, Claret et al. (2021) improved CNN's performance, achieving 94% sensitivity and 91% specificity on the HAM10000 and ISIC-2018 datasets. The integration of DWT with CNN underscores the importance of advanced transformation techniques, as they can enhance image analysis and improve classification accuracy for complex medical imaging tasks [5:8].

A comprehensive examination of CNN and other ML models has highlighted the importance of using diverse, high-quality datasets to ensure that these models generalize well across different populations. Hermosilla et al. (2019) reviewed CNN-based models and emphasized the need for image diversity and quality, as model performance can be limited by dataset biases. Moreover, these models often require extensive preprocessing, such as lesion segmentation, which can impact diagnostic accuracy in real-world applications [5:9]. A review by Goyal et al. (2019) further discussed the challenges of AI-based skin cancer detection, particularly with respect to imaging variability, data limitations, and the need for integration with clinical metadata for higher clinical reliability. The challenges associated with data variability, particularly in clinical implementation, highlight the need for extensive collaboration between dermatologists and AI researchers [5:10].

Lastly, AI-based chatbots and health assistants show potential as adjunctive tools for preliminary screening and patient support. Although these tools are not yet dermatology-cancer-specific, their application in dermatology could support preliminary assessments and facilitate smoother communication between patients and healthcare professionals, especially in resource-limited environments. The integration of these assistants with skin diagnostic tools could enable symptom checks and preliminary diagnosis suggestions based on mobile image analysis, thus paving the way for broader adoption of AI in dermatological practice [11:12].

In conclusion, the methodology discussed here highlights the varied and evolving approaches to AI-based skin cancer detection, with CNN models playing a central role due to their superior image processing capabilities. By leveraging data augmentation, ensemble learning, and advanced feature extraction techniques, these methods push the boundaries of diagnostic accuracy. However, further work is required to address the challenges of data quality, real-world implementation, and clinical integration to ensure these AI-driven solutions are robust, accessible, and beneficial in practical healthcare settings.

Conclusion:

The research on artificial intelligence for skin cancer diagnosis marks an important step, wherein use of deep learning algorithms can take place, which again offers great promise, however present significant difficulties in applicability to real life - such models lack the very context that a human clinician would consider in practice; it includes patient history, lifestyle, and many other clinical factors. The major current deep learning models highly rely on imaging data; it makes them vulnerable to mistaken diagnosis, especially of illnesses like skin, which it has not been trained.

Despite these limitations, AI might revolutionize dermatology with a cost-effective, precise, and accessible diagnostic tool. There is a need for cooperation between computer vision researchers and dermatologists in an attempt to better advance these AI solutions to achieve real-life clinical usage. The developed CNN model performed better than the previous models, especially when working on imbalanced datasets. Thus, if applied in actual clinical practice settings, AI would reduce possible diagnostic errors by assisting the dermatologists to provide care to their patients in better ways. Future work should be focused on increasing dataset diversity, discovery of new optimization techniques as well as their integration into clinical workflows. The collaboration between AI researchers and clinicians with experiments applied in the real-world testing ensures that AI can complement or enhance dermatological practice.

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