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Medical Image Processing of Patients for Skin Cancer Diagnosis Using Artificial Intelligence

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ABSTRACT

Skin cancer represents a serious and growing global public health challenge, with incidence rates increasing steadily across diverse populations. Early diagnosis and timely intervention play a vital role in reducing mortality and improving treatment outcomes. Traditionally, accurate diagnosis has relied on the expertise of trained dermatologists, posing accessibility challenges in resource-limited settings. In recent years, artificial intelligence (AI) technologies particularly deep learning and advanced image processing techniques have emerged as promising tools for assisting in medical image analysis and automated disease detection. This study presents a computer-aided diagnosis (CAD) system based on deep convolutional neural networks (CNNs) designed for the early detection of skin cancer through dermoscopic image analysis. The CNN model was trained and tested on a curated dataset, and achieved a prediction accuracy of 90.5%. The system demonstrates strong potential for identifying malignant skin lesions with high precision, contributing to the rapid, non-invasive, and cost-effective assessment of skin abnormalities. The use of deep learning in this context not only improves diagnostic speed but also offers a scalable solution for screening large populations. These findings underscore the transformative role of AI in dermatological diagnostics and highlight the capability of CNN-based systems to complement clinical expertise. Future work will focus on enhancing model robustness, incorporating multi-modal data, and validating performance through real-world clinical trials.

1. INTRODUCTION

Machine learning, a critical subfield of artificial intelligence (AI), comprises statistical models and algorithms that progressively learn from data to perform specific tasks, including prediction, classification, and pattern recognition. Among its various applications, machine learning has shown remarkable potential in the field of medical diagnostics. In particular, it plays an increasingly important role in the early detection of skin cancer, one of the most prevalent forms of cancer worldwide.

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Despite these advancements, dermatology has been relatively slow to embrace AI technologies compared to other medical specialties such as radiology. One of the primary reasons is the complexity and variability of skin lesions, as well as the need for large, annotated datasets to train robust diagnostic models. Nevertheless, the rapid expansion of AI technologies and their increasing accessibility, even to the general public through smartphones and consumer-grade devices, are paving the way for broader integration of machine learning in dermatological practice.

Artificial intelligence, especially deep learning, offers powerful tools for developing automated systems capable of accurately analyzing dermatological images. Convolutional Neural Networks (CNNs), a class of deep learning models particularly effective for image classification tasks, have shown great promise in assisting with skin cancer diagnosis. By extracting hierarchical features from dermoscopic or clinical skin images, CNN-based systems can classify lesions as benign or malignant with high accuracy.

Early diagnosis of skin cancer is crucial for effective treatment and improved patient outcomes. While dermatologists are highly skilled in identifying skin malignancies, the global shortage of trained specialists limits timely access to expert diagnosis, particularly in under-resourced or remote areas. This underscores the urgent need for developing reliable, automated diagnostic systems that can support clinicians and extend diagnostic capabilities beyond traditional clinical settings.

In this context, machine learning-driven diagnostic tools, especially those based on CNN architectures, can serve as valuable decision-support systems. They can not only enhance diagnostic accuracy but also contribute to faster and more cost-effective screening processes. The integration of such systems into routine clinical workflows has the potential to democratize access to quality healthcare and significantly reduce the burden of skin cancer through early detection and intervention.

2. RELATED WORKS

2.1. Introduction

Skin cancer diagnosis has become a critical area of focus in the healthcare sector, primarily due to the increasing incidence rates and the potential for early intervention to improve patient outcomes. The integration of Artificial Intelligence (AI) into medical image processing has shown promise in enhancing diagnostic accuracy for skin cancer. This literature review synthesizes recent research findings on the subject, highlighting the application of various AI techniques in medical image processing, addressing existing challenges, and identifying knowledge gaps for future exploration.

2.2. Role of AI in Skin Cancer Diagnosis

The landscape of healthcare is increasingly influenced by AI technologies, which facilitate disease diagnosis, including skin cancer. Kumar et al. (2022) emphasize the importance of diverse medical imaging datasets for effective AI systems development, illustrating that comprehensive datasets are essential for accurate disease identification. The integration of various imaging modalities, such as ultrasound and computed tomography, can potentially enhance skin cancer detection capabilities by combining AI's analytical strengths with these advanced imaging techniques [1].

2.3. Challenges in Medical Image Analysis

Despite the advancements in AI applications for skin cancer diagnosis, significant challenges persist. Varoquaux and Cheplygina (2022) discuss systematic issues such as data biases and the incentives driving research, which can hinder the progress of AI in medical imaging. These biases are particularly concerning in skin cancer, where the diversity of imaging data is crucial for training effective AI models. The ongoing efforts to identify and mitigate these biases underscore the necessity for equitable AI systems that can accurately identify skin cancer across various demographics [2].

2.4. Hidden Stratification

Hidden stratification poses another critical challenge in the development of AI models for skin cancer diagnosis. Oakden-Rayner et al. (2019) highlight how certain cancer subtypes may be underrepresented in training datasets, leading to poor model performance on these crucial subsets. This issue is vital, as failing to recognize aggressive skin cancer subtypes can have severe clinical implications. Addressing hidden stratification must be prioritized to ensure that AI systems can accurately detect all relevant skin cancer types [3].

2.5. Methodological Advancements

Significant strides have been made in methodologies for skin cancer diagnosis using AI. Xu et al. (2020) propose a computer-aided approach utilizing convolutional neural networks (CNNs) for image segmentation and classification of skin lesions [4]. Their methodology incorporates median filtering for noise reduction and an optimized feature selection process, showcasing how these techniques can enhance diagnostic accuracy. This approach aligns with the findings from Khan et al. (2021), which evaluate AI-based melanoma detection algorithms, demonstrating high effectiveness in distinguishing between benign and malignant lesions [5].

Additionally, Adegun and Viriri (2020) present a fully automated system for multiclass skin lesion segmentation and classification, which employs advanced deep learning techniques. Their research forms part of a broader effort to leverage AI in improving diagnostic accuracy, highlighting the potential for automated systems to support clinicians in making timely and accurate diagnoses [6].

2.6. Performance Evaluation and Accuracy

The effectiveness of AI systems in skin cancer diagnosis is often measured through performance metrics such as accuracy and sensitivity. Phillips et al. (2019) discuss the importance of these metrics in evaluating AI systems, emphasizing the need for reliable diagnostic tools to improve survival rates in patients with melanoma [7]. Khan et al. (2019) further support this notion, presenting a deep learning approach for precise lesion segmentation, which demonstrates superior performance compared to existing algorithms [5].

Moreover, Jiang et al. (2023) address the challenges of data imbalance in skin cancer detection, proposing a deep learning framework that not only improves diagnostic accuracy but also highlights the potential of AI in saving lives through more effective early detection [8].

2.7. 1. AI-Based Neural Network Approaches

Roffman et al. introduced a multi-parametric artificial neural network that leverages personal health details for early skin cancer detection. Their system achieved high sensitivity and specificity, despite excluding ultraviolet exposure and family history parameters [9].

Tompa and Kabir applied image preprocessing, enhancement, and Otsu-threshold segmentation before classification via a neural network, achieving 97.07% accuracy—though only on a limited dataset [10]. Johandari et al. used first-order texture feature extraction followed by a multilayer perceptron (MLP) classifier, yielding promising results on a 23-image sample [11].

2.8. 2. Hybrid Classifiers and SVM Integration

Sao and Saha normalized and enhanced images, extracted texture features via co-occurrence matrices, and compared classifiers including support vector machines (SVM) and neural networks. Their hybrid model outperformed the individual methods [12]. Zakaria et al. used binary thresholding, feature extraction, and ANN-based classification, demonstrating 97.84% accuracy on 92 images [13].

2.9. 3. Mobile and Convolutional Neural Network (CNN) Methods

Kumar et al. developed a smartphone-based system to detect three types of skin lesions at early stages, reaching 97.4% accuracy [14]. Yandah Noor et al. trained a CNN with data augmentation ("randomizers") achieving 97.49% accuracy in distinguishing benign and malignant lesions [15]. Helker et al. demonstrated that combining patient metadata (age, gender, lesion location) with CNN image features improves classification performance [16]. Brinker et al. reviewed thirteen CNN studies, concluding that CNNs consistently deliver high classification accuracy for skin cancer lesions [17]. Han et al. showed that an R-CNN aimed at keratinocytic skin cancers achieved diagnostic accuracy exceeding that of non-dermatologists [18].

2.10. 4. Comparative Performance of Classifiers

Latifoglu et al. evaluated several classifiers—MLP (99.8%), pattern-recognition neural networks (98.3%), SVM (96.7%), and k-nearest neighbors (95%)—finding MLP achieved the highest diagnostic accuracy[19] Raja

Subramanian et al. implemented a standard CNN that surpassed their targeted benchmark of 80% accuracy with less than 10% false negatives [20]

2.11. Conclusion

The application of AI in medical image processing for skin cancer diagnosis represents a significant advancement in healthcare technology. Despite the progress made, challenges related to data biases, hidden stratification, and the need for comprehensive datasets persist. Addressing these issues through targeted future research will be essential in realizing the full potential of AI technologies in enhancing skin cancer diagnosis and ultimately improving patient outcomes. Table 1 provides a summary of the application of various algorithms in recent skin cancer detection studies.

Table 1. Summary of the application of different algorithms in recent skin cancer detection studies

Result	Contribution and Limitations	Application	Method/Algorithm
MAPE = 0.71	Using Euclidean distance instead of normalized Euclidean distance	Classification of malignant and benign images	KNN
Accuracy (%) based on ABCD SVM: 89.43, RF: 76.87, KNN: 69.54	Sensitivity (%) SVM: 91.15, RF: 78.43, KNN: 71.32	Specificity (%) SVM: 87.71, RF: 75.31, KNN: 67.76	Feature extraction based on preprocessed images
Accuracy = 92%	Skin color variations may cause failure. Transfer learning is recommended for small sample sizes	Skin lesion segmentation and classification using deep learning methods	SVM, CNN
Lesion Segmentation (Task 1) 75.1%, Dermoscopic Feature Extraction (Task 2) 84.4%, Lesion Classification (Task 3) 90.8%	Development of a multi-scale deep learning network using residual convolutional network	Skin lesion segmentation and classification	Deep Learning model
Accuracy = 100%	Small sample size for digital images and neglecting edge cases	Skin lesion classification as cancerous or non-cancerous	Deep Learning Model - ANN
Accuracy = 95.40%, Specificity = 97.10%, Sensitivity = 90.00%	Reducing overhead costs, more efficient than other convolutional neural network models, faster feature selection	Fully automatic deep learning-based method	Deep Learning and Fuzzy K-Means Clustering
Accuracy = 94.8%, Specificity = 94.17%, Sensitivity = 97.81%, F1_score = 95.8%	Described method is complex and not scalable, resulting in overhead costs	Use of regions with convolutional neural network. Features can be used for deep feature calculation to improve segmentation efficiency	RCNN
Accuracy = 94.29%, Specificity = 93.05%, Sensitivity = 93.77%	Described method is complex and not scalable, resulting in overhead costs	New automatic skin lesion segmentation method using a class-specific learning approach	ResFCN
Accuracy = 86.3%, Specificity = 86.9%, Sensitivity = 87.8%	Feature extraction based on preprocessed image	Data augmentation after preprocessing, using soft bootstrap technique to simulate data	ANN
Accuracy = 96.8%, Specificity = 89.3%, Sensitivity = 95.4%	Several algorithms were compared, and support vector machine performed better than others	Various architectures of artificial neural networks and support vector machines for classifying skin cancer images	SVM and ANN

3. CONVOLUTIONAL NEURAL NETWORKS IN SKIN CANCER DETECTION

Convolutional Neural Networks (CNN) represent an advancement over traditional neural networks. CNNs can be adjusted for different mathematical learning methods such as backpropagation, learning algorithms, and regularization techniques. The hidden layer of a CNN includes convolution layers, nonlinear merging layers, and fully connected layers. CNNs consist of multiple convolution layers followed by several fully connected layers. Three key layers in the construction of a CNN include the convolution layers, merging layers, and fully connected layers. The essential part of a CNN is the convolution layer, which contains various weights for different applications such as image segmentation and multi-dimensional matrices. Figure 1 illustrates the stages of skin cancer detection using a Convolutional Neural Network.

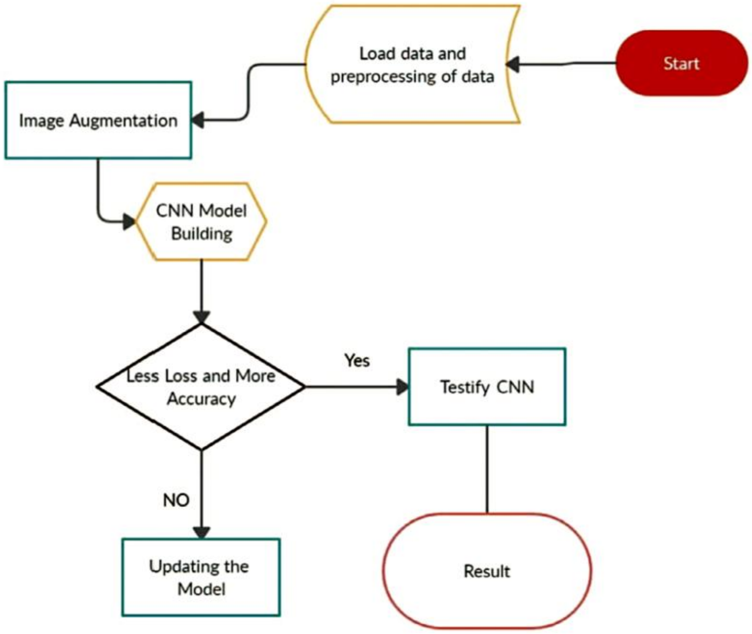

Fig. 1. Stages of Skin Cancer Detection Using Convolutional Neural Networks

4. PROPOSED METHOD

In this paper, we have designed and implemented a machine learning model to predict this dangerous disease. As is well-known, the effectiveness of deep learning has been well-established in various domains and applications. Additionally, in recent years, convolutional neural networks (CNNs) have shown significant power in image processing applications. Therefore, we chose this deep learning model, specifically CNNs, for skin cancer prediction.

As previously mentioned, the proposed system is implemented using convolutional neural networks, which are a branch of deep learning. CNNs, inspired by the human visual system, possess high power in image processing systems. A convolutional neural network is a deep learning algorithm that receives an input image, assigns importance (learnable weights and biases) to each object in the image, and is capable of distinguishing them from one another. In comparison to other classification algorithms, the CNN algorithm requires less preprocessing, as the filters used in earlier methods were manually engineered, while the CNN, with sufficient training, learns these filters autonomously. The architecture of CNNs is inspired by the neural connection pattern in the human brain, particularly from the organization of the visual cortex. Each neuron responds only to stimuli in a restricted region of the visual field, known as the receptive field. A set of these fields overlap to cover the entire visual area.

The architecture of the proposed model consists of two main parts:

- Feature extraction using convolutional layers

- Classification based on extracted features using fully connected layers

The simplified architecture of the proposed model is shown in Figure 2.

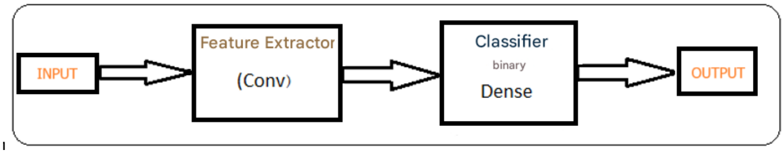

Fig. 2. Proposed Architecture

Our dataset is sourced from Kaggle. The images in this dataset are divided into two categories: 1) benign skin lesions and 2) malignant skin lesions. The dataset contains approximately 10,000 images. While deep learning models typically require large datasets for higher prediction accuracy, this dataset is sufficient for achieving reliable results.

5. IMPLEMENTATION

Python is one of the most widely used programming languages in the field of artificial intelligence, offering a rich collection of powerful libraries for implementing AI systems—particularly in machine learning and neural networks. Accordingly, in the present work, Python was employed to implement the proposed system. The TensorFlow library, which is specifically designed for the development of deep neural networks, was used due to its flexibility and high performance. However, to simplify programming and enhance the usability of TensorFlow in building deep learning models, the Keras library was utilized. Keras is widely adopted in most deep learning applications. Therefore, in this study, Keras was used to implement the convolutional deep neural networks.

6. 6. EVALUATION

To arrive at an optimized model, two sets of experiments were conducted. In the first set, a fixed classifier model (a single layer with 32 neurons) was used while various parameters of the convolutional network were modified. In the second set, the parameters of the classifier model were optimized based on the best-performing parameters from the first set of experiments. Before initiating these evaluations, it was essential to define a key parameter: the evaluation metric. In this study, accuracy was chosen as the evaluation metric. Accuracy is calculated as the percentage of correctly classified instances out of the total number of classifications, i.e., the number of test samples.

7. RESULTS

Based on the results of multiple experiments, the classifier model consisting of two layers with 128 and 256 neurons, respectively, was selected as the final model. It is worth noting that, due to the absence of significant overfitting, there was no need to apply regularization techniques or adjust the learning rate. Therefore, optimization of the initial model was concluded at this stage. Instead, additional experiments were conducted by modifying the dimensions of the convolutional filters. The results indicated that a 3×3 convolutional filter was the most suitable for our dataset, achieving an accuracy of 45.90%.

Figure 3 and Figure 4 illustrate, respectively, the accuracy learning curve and the loss learning curve of the model with the two-layer classifier consisting of 128 and 256 neurons.

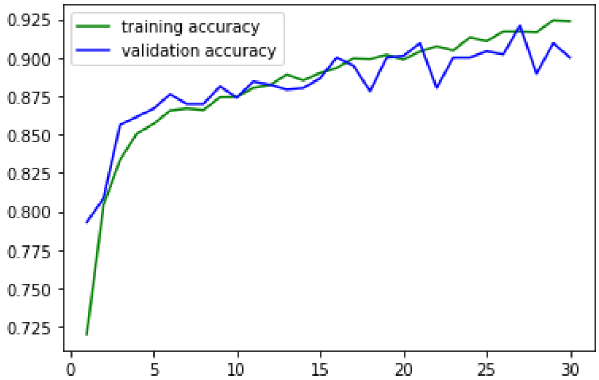

Fig. 3. Accuracy learning curve of the model with a two-layer classifier consisting of 128 and 256 neurons.

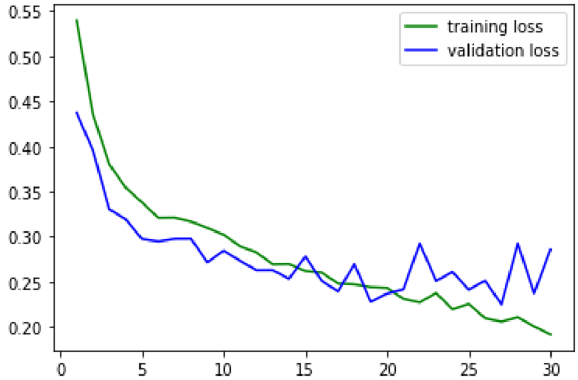

Fig. 4. Loss learning curve of the model with a two-layer classifier consisting of 128 and 256 neurons.

8. CONCLUSION

In this study, using a convolutional neural network, we achieved a prediction accuracy of 90.5% for the early detection of skin cancer. Various experiments were conducted by changing the number of layers and neurons, and the optimal values for these parameters were identified. To build an optimized network with maximum accuracy, the system was divided into two main components: feature extraction and classification. The optimal parameters for each component were determined separately. Additionally, convolutional filters of different sizes 3×3, 2×2, and 4×4 were evaluated on our dataset. The outcome of these efforts was the attainment of a 90.5% accuracy rate.

Declaration

We acknowledge that we used ChatGPT to enhance the academic writing of our manuscript while ensuring the originality and integrity of our work.

Transparency Statement

The data supporting this study are available upon reasonable request to the corresponding author, subject to ethical and confidentiality considerations.

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Declaration of Interest

The authors declare that they have no competing interests.

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