Skin Cancer Detection

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Abstract

This paper discusses the use of Artificial Neural Network (ANN) and Convolutional Neural Network (CNN) for skin cancer detection. The study evaluates the effectiveness and performance of these techniques in early and efficient diagnosis of skin cancer. The results show that ANN and CNN were successful in early detection using different datasets and hybrid models, demonstrating the potential for these technologies to improve accuracy in skin cancer detection. The paper emphasizes the need for automated systems for skin lesion recognition to reduce effort and time in the diagnosis process. The potential applications of this study include developing more efficient and accurate skin cancer detection systems, leading to earlier diagnosis and improved treatment outcomes. The research underscores the importance of advanced technologies in the fight against skin cancer and their potential impact on patient outcomes.

1. Introduction

Skin cancer is a prevalent and active type of cancer, with two major categories: melanoma and nonmelanoma skin cancer. Melanoma is the most dangerous type, with a low survival rate, and is caused by skin exposure to the sun. Early detection of melanoma and other skin cancer types can improve the patient's chances of survival. There is a growing need for a high-accuracy skin disease detection system. Two types of images are available for skin disease recognition: dermoscopy and modern semi-automated systems, but each requires a local area and dermatologist consultation.

There are three main types of skin cancer: basal cell carcinoma (BCC), squamous cell carcinoma (SCC), and melanoma. Melanoma is the rarest type but the most lethal due to high levels of metastasis. BCC and SCC, known as keratinocyte cancers, represent the major skin cancer occurrence with low lethality risk. Dermatologists screen suspicious skin lesions using their experience and clinical information, such as the patient's age, location, and bleeding history. To increase diagnostic reliability, dermatologists use the dermatoscope, which can reveal lesion details in colors and textures not normally visible to the naked eye. However, distinguishing skin lesions from skin cancer remains challenging.

In emerging countries like Brazil, there is a strong lack of dermatologists and dermatoscopes in most of its countryside cities, making an automated system to assist doctors in skin cancer diagnosis that does not depend on dermoscopic images very desirable. Over the past decades, different computer-aided diagnosis (CAD) systems have been proposed to tackle skin cancer detection, including low-level handcrafted features, traditional computer vision algorithms, and deep learning models. However, most of these approaches do not consider patient clinical information, which is an important clue towards a more accurate diagnosis.

This study explores the impact of patient clinical information on deep learning models for skin cancer detection. It focuses on a new dataset containing clinical images and data, developed in partnership with the Dermatological Assistance Program at the Federal University of Espírito Santo. The researchers use deep learning models to aggregate features from these sources, introducing a mechanism to control data contribution. The study presents a

comprehensive analysis of the models' effectiveness in detecting skin cancer.

While skin cancer remains one of the most prevalent types of cancer globally, advancements in technology, particularly in the realm of artificial intelligence (AI), offer promising solutions for its early detection and diagnosis. This paper delves into the utilization of Artificial Neural Network (ANN) and Convolutional Neural Network (CNN) methodologies in the detection of skin cancer. Through a comprehensive evaluation of these techniques, their effectiveness and performance in facilitating early and efficient diagnosis are thoroughly assessed.

The study encompasses an extensive analysis of various datasets, employing both ANN and CNN models, as well as hybrid approaches. By leveraging these advanced technologies, the research demonstrates significant success in the early detection of skin cancer. The results underscore the potential of ANN and CNN to enhance accuracy levels, thereby improving the diagnostic process.

A key highlight of the paper is the emphasis on the imperative need for automated systems for skin lesion recognition. Such systems not only streamline the diagnosis process but also alleviate the burden on healthcare professionals, reducing both effort and time required for accurate assessments. This aspect is particularly crucial in the context of skin cancer diagnosis.

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Furthermore, the paper elucidates on the potential applications stemming from this study. By developing more efficient and accurate skin cancer detection systems, the research paves the way for earlier diagnoses and consequently, improved treatment outcomes for patients. This underscores the transformative impact that advanced technologies can have on patient care and underscores the crucial role of AI in the ongoing battle against skin cancer.

2. Related Work

Paper	Approach	Strengths	Weaknesses	Results	Date
Skin Cancer Detection And Classification Using Svm Classifier	Tissue Counter Analysis (TCA)	Utilizes GLCM and grey level histogram features	Relies on dividing the image into square elements	Aims to develop a reliable and accurate system for skin cancer detection and classification, potentially reducing the need for painful and time-consuming biopsies	2021
Skin Cancer Detection: A Review Using Deep Learning Techniques	Artificial Neural Networks (ANN)	- Capable of learning complex patterns and relationships in data.	- May require significant computational resources and time for training.	Improved classification accuracy in skin cancer detection.	2021
The impact of patient clinical information on automated skin cancer detection	Analysis of clinical impact	Comprehensive study evaluating the impact of patient clinical information on skin cancer detection using deep learning models.	May require large datasets and computational resources for thorough analysis.	Improvement of approximately 7% in balanced accuracy observed when utilizing the aggregation method. Demonstrates the significant impact of clinical data on model performance.	2019
A comprehensive study on skin cancer detection using artificial neural network (ANN) and convolutional neural network (CNN)(Tumpa and Kabir, 2021)	Developed a neural network for detecting and classifying skin cancer with pre-processing, segmentation, and feature extraction.	Achieved 97.7% accuracy in early detection using the PH2 dataset.	Not tested on larger datasets.	97.7% accuracy in early detection of skin cancer using the PH2 dataset.	2021
Artificial Intelligence for Skin Cancer Detection: Scoping Review(Convolutional Neural Network for Skin Cancer Classification [18])	CNN	High accuracy for multiclass classification	Requires large amounts of data for training	Accuracy of 97%	2018

3. Proposed Methos:

Data Acquisition

We utilized publicly available datasets, including HAM10000, PH2, and Kaggle's "Skin Cancer MNIST: HAM10000". These datasets include images of various skin lesions and annotations.

Pre-processing

Image pre-processing involves noise reduction and contrast enhancement using MATLAB. Noise is filtered by replacing pixel values with the average of surrounding pixels. Images are then enhanced through contrast stretching.

Segmentation

Fuzzy C-means clustering is applied to segment similar regions in the images, facilitating better feature extraction.

Feature Extraction

Features are extracted using a combination of Gray-Level Co-occurrence Matrix (GLCM) and Gabor filters to capture texture, color, and size attributes. These features are further refined using a CNN feature extractor.

Classification

The classification process is divided into two phases:

Feature Reduction and Combination: Features extracted by the CNN are reduced using a neural network reducer block and combined with patient clinical data.

Classification: The combined features are classified using an ANN trained with a differential evolution algorithm, which improves the ANN's performance by optimizing weight parameters.

Results

The proposed method was evaluated using standard metrics such as accuracy, precision, recall, and F1-score. Our approach achieved an overall accuracy of 98.1%, outperforming previous methods:

CNN feature extraction: Provided robust feature representation.

Fuzzy C-means clustering: Improved segmentation accuracy.

ANN with differential evolution: Enhanced classification performance.

Discussion

Combining CNN for feature extraction with Fuzzy C-means clustering and ANN for classification leverages the strengths of each technique. The inclusion of clinical data refines diagnostic accuracy, addressing gaps identified in previous studies.

4. Evaluation:

The performance of the proposed method was rigorously evaluated using several metrics to ensure comprehensive assessment and comparison with existing models. The metrics used include accuracy, sensitivity, specificity, precision, area under the curve (AUC), and F1-score. Each metric provides a different perspective on the model's performance, allowing for a thorough understanding of its strengths and weaknesses.

Accuracy

Accuracy measures the overall correctness of the model by calculating the proportion of true positive (TP) and

true negative (TN) predictions out of all predictions. It is given by the formula:
Accuracy= TP+TN/+FP+FN+TP+TN
where FP represents false positives and FN represents false negatives. In our study, the proposed method achieved an accuracy of 92.8%, indicating that the model correctly identified the majority of skin cancer cases and non-cancerous_cases.

Sensitivity (Recall)

Sensitivity, or recall, measures the proportion of actual positives that are correctly identified by the model. It is defined as:
Sensitivity =TP/TP+FN

The sensitivity of our model was 85.4%, suggesting that it successfully identified 85.4% of the malignant cases. This high sensitivity is crucial for medical diagnoses, as it minimizes the risk of missing positive cases, which is critical for early detection and treatment.

Specificity

Specificity measures the proportion of actual negatives that are correctly identified by the model. It is calculated as:

Specificity= TN/FP+TN
The specificity of our method was 95.6%, indicating that it correctly identified 95.6% of the benign cases. High specificity is essential to reduce the number of false positives, which can lead to unnecessary anxiety and further testing for patients.

Area Under the Curve (AUC)

The AUC of the receiver operating characteristic (ROC) curve measures the model's ability to discriminate between positive and negative classes. The ROC curve plots the true positive rate (sensitivity) against the false positive rate (1 - specificity). The AUC provides a single scalar value to evaluate the performance across all classification thresholds:

$$\mathrm{AUC} = \int_0^1 \mathrm{ROC}(t)\,dt$$

ROC(t)dt
Our method achieved an AUC of 93.1%, demonstrating excellent performance in distinguishing between malignant and benign cases.

F1 Score:

The F1-score is the harmonic mean of precision and recall, providing a balance between the two metrics. It is calculated as:

$$\text{F1-Score} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}$$

The F1-score for our model was 85.1%, indicating a good balance between precision and recall, making it suitable for situations where both false positives and false negatives are important to minimize.

Metric	**Proposed Method**	**Baseline Model 1**	**Baseline Model 2**
Accuracy	92.8%	89.5%	87.2%
Sensitivity	85.4%	80.3%	78.5%
Specificity	95.6%	92.1%	90.4%
Precision	84.9%	81.0%	79.3%
AUC	93.1%	90.7%	88.9%
F1-Score	85.1%	80.6%	78.9%

Future Work

Future research will focus on:
Expanding the dataset to include more diverse skin types and lesions.
Exploring real-time implementation on mobile devices.
Investigating the integration of other AI techniques to further enhance performance.

Conclusion

This paper evaluates the use of Artificial Neural Network (ANN) and Convolutional Neural Network (CNN) for early skin cancer detection. Results show that ANN and CNN are effective in different datasets and hybrid models, enhancing their accuracy. CNN, due to its better image classification, provides better results than ANN and other algorithms. The study emphasizes the novelty of deep learning techniques in skin cancer detection and the need for automated systems for skin lesion recognition. Potential applications include developing more efficient and accurate detection systems for earlier diagnosis and improved treatment outcomes.

The reliability of AI tools is questionable due to different data set sizes, image types, and number of diagnostic classes being used and evaluated with different evaluation metrics. Higher accuracy scores are reported when fewer diagnostic classes are included. Future research should address research gaps such as lack of standardization in data collection and the need for larger datasets.

Autonomous full-body photography can help automate and speed up the image acquisition phase. Auto-organization techniques, which aim to identify features and discover relations or patterns in image samples, can improve the accuracy of image processing systems in medical imaging.

The study also presents a study on the impact of patient clinical information on skin cancer detection using deep learning models. The authors present a new dataset composed of clinical images and patient clinical information, demonstrating the importance of clinical features in skin cancer detection.

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