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Survey on Early detection of Skin cancer

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ABSTRACT

Early detection of skin cancer proves crucial for successful treatment because this type of cancer remains the most common form of cancer worldwide. The current traditional diagnostic approach depends on dermatologists performing visual examinations that bring forth subjectivity and occasional mistakes. We carefully examine state-of-the-art ML and DL models to determine their accuracy level together with specification efficiency and computational processing speed. The review outlines current advancements in using ML and DL techniques for diagnosing skin cancer with extensive detail. The paper evaluates the skin lesion classification capabilities of support vector machines (SVMs), decision trees and random forests along with other widely used ML algorithms. The research studies the ways DL transformed dermoscopic and photographic image analysis by enabling lesion identification and segmentation. Studies show an ongoing set of difficulties which primarily stem from insufficient data access and unexplained model processes alongside medical verification requirements. Future research must focus on generating expanded and varied databases and enhancing AI systems' interpretability while integrating these technologies into clinical workflows for early skin cancer detection to advance patient outcomes. The survey identifies current limitations related to scarce model data and unintelligible model outputs and necessary clinical validation. The paper establishes a research agenda that prioritizes developing larger diverse skin cancer databases with interpretable AI systems for clinical application to advance timely accurate detection which benefits patients directly.

KEYWORDS: : Skin Cancer Detection, Machine Learning, Deep Learning, Convolutional Neural Networks, Dermoscopy, Image Analysis, Feature Engineering, Model Evaluation, Clinical Integration

1 INTRODUCTION

Skin cancer has increased substantially since its discovery as the world's leading cancer type due to extended ultraviolet (UV) radiation impacts and ozone layer depletion in addition to climate change effects. For 2023 skin cancer diagnosed 97,160 people in the United States and represented 5.0% of all cancer cases. Statistical data shows skin cancer accounted for 7,990 deaths throughout the year leading to 1.3% of all cancer deaths in the country [1]. Skin cancer includes two main types: Melanoma and Non-Melanoma. Worldwide data from 2018 shows 132,000 reported Melanoma cases and more than one million Non-Melanoma diagnoses. One out of every three cancer diagnoses comes from skin cancer and the World Health Organization (WHO) predicts Americans will experience skin cancer at least once during their lifetime. Scientific studies indicate that a ten percent decrease in ozone would lead to more than 4,500 new diagnoses of Melanoma skin cancer and over 300,000 additional Non-Melanoma skin cancer cases worldwide [2]. Early and precise detection methods for Melanoma are necessary because this cancer type causes 75% of all fatal skin cancer cases.

The detection of skin conditions by physicians through visual examinations remains essential because it shortens treatment processes as well as reduces associated costs. The application of deep convolutional neural networks and artificial intelligence (AI) technology provides faster and more precise methods to assess and determine skin lesion categories [3,4]. Scientists now apply computational methods to dermoscopic images for the diagnosis of skin lesions. Historically automated skin cancer detection systems encountered accuracy and reliability problems until rapid advancements in machine learning and deep learning brought renewed focus on these systems [5–8, 9–14].

Studies extracted geometric features from lesions by applying preprocessing and segmentation techniques to achieve enhanced classification precision [15]. The problem of accurate segmentation remains a persistent challenge. The subtle visual nuances that differentiates benign from malignant skin lesions can be efficiently identified by DL models especially CNNs allowing pixel-level analysis for predicting malignancy [16-18]. Research now focuses on developing optimization algorithms [19] alongside interpretable ML methods [20] to achieve robust multi-class segmentation and classification of skin lesions.

Modern techniques of skin cancer detection through medical image analysis receive investigation in this paper as ML and DL revolutionize the field. The paper aims to demonstrate the benefits of implementing advanced computation methods for diagnostic workflows while making substantial contributions to ongoing skin cancer screening conversations. Our analysis of published research results enables us to reveal current methodological shortcomings in addition to providing new research avenues for medical practice. Our research applies customized state-of-the-art DL and ML algorithms to medical image analysis while using a selected dataset for validation.

The structure of this paper is as follows: A thorough review of published work appears in Section II. Results and conclusions from the review analysis are provided within Section III. This study's fourth section provides suggestions for promising research paths while simultaneously concluding its findings.

2. LITERATURE SURVEY

Machine learning (ML) systems employing dermoscopic images have emerged as important diagnostic tools to detect skin cancer at an early stage during recent years. Medical decision support through these intelligent systems helps dermatologists identify problematic cases while offering essential help to clinicians who have less experience. Such systems help improve patient outcomes through assessment at first encounter and improved monitoring functionality [21, 22].

Research-based skin cancer detection applications operate within two main class divisions which depend on how they extract their characteristics. Systems in the first category operate through clinical-style diagnostic modeling to extract medical indicators such as symmetry and color changes along with abnormal structural details. This second category relies on machine learning methods to locate statistical patterns found in texture and color within images which use human-generated features as inputs [23].

Research efforts have significantly improved ML through advanced feature extraction methods like the ABCD rule and 3-point checklist. Modern image analysis now depends heavily on Deep Convolutional Neural Networks (DCNNs) because these networks can automatically extract features from images without requiring expert-designed features for preprocessing.

Saba et al. A DCNN-based system developed by Saba et al. [14] reached 98.4% accuracy in detecting skin lesions across different datasets and demonstrated additional detection rates of 95.1% and 94.8% respectively. Ramya et al. The researchers applied Wiener filtering with adaptive histogram equalization before performing active contour segmentation using features extracted from Gray-Level Co-occurrence Matrix (GLCM) with an SVM classifier. Through their system they attained 95% accuracy and 90% sensitivity alongside 85% specificity.

The authors Premaladha and Ravichandran [25] established an intelligent melanoma classifier that utilized median filtering while incorporating Contrast Limited Adaptive Histogram Equalization (CLAHE) along with Normalized Otsu's segmentation approach. The researchers established a 93% classification accuracy with their hybrid AdaBoost-SVM deep learning system.Bareiro Paniagua et al. [26] introduced a pipeline consisting of preprocessing, lesion segmentation, ABCD-based feature extraction, and classification via SVM. On a dataset of 104 dermoscopic images, their method achieved 90.63% accuracy, 95% sensitivity, and 83.33% specificity.

Khan et al. [27] applied CNNs to dermoscopic images for early-stage melanoma detection, reaching a classification accuracy of 74.76% using texture and color-based features. In contrast, Dai et al. [28] developed a CNN pre-trained on 10,015 smartphone images to optimize latency, reduce power consumption, and enhance privacy, achieving 75.2% accuracy.

3. DEEP LEARNING-BASED APPROACHES

Majtner et al. The system presented by Majtner et al. utilized CNN methods to achieve improved classification accuracy by incorporating preprocessing with CNN feature extraction algorithms. [29] Both segmentation and classification tasks were separated in the network model where segmentation used a symmetric U-Net but classification linked deep residual networks to CNN and recurrent neural networks. The classification method used K-Nearest Neighbors (KNN) as the classification algorithm resulting in 86% accuracy and 99.9% specificity.

Vipin et al. A two-phase melanoma detection framework with segmentation and classification capabilities was proposed by [30] using a refined subset of 7,353 images from the ISIC database. The researchers used a symmetric U-Net model to segment while their classification process relied on deep residual network architecture which combined CNN and recurrent neural network (RNN) models. The proposed architecture delivered 88.7% accuracy and 91% recall as outcome measures.

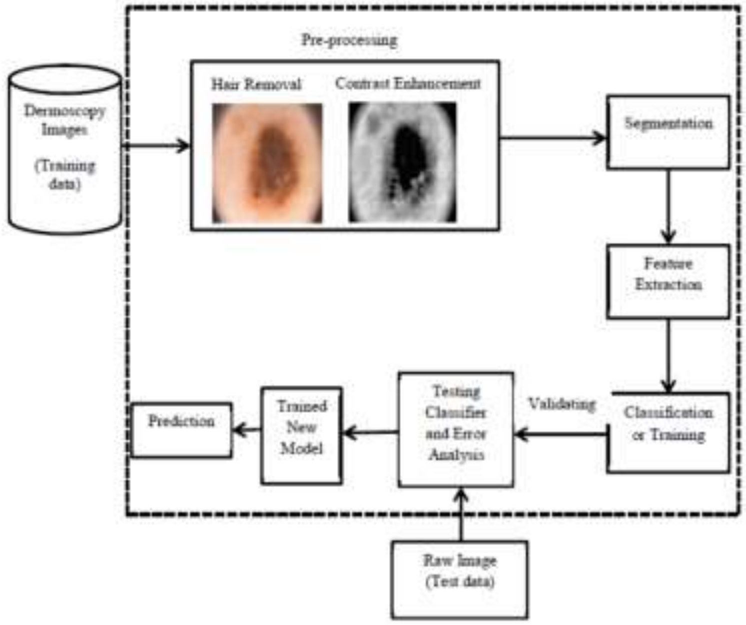

Figure 1: System Architecture

Nasr-Esfahani et al. A CNN model developed by [31] processed 170 non-dermoscopic images for feature detection and classification tasks. The proposed architecture employed convolutional layers together with max-pooling layers and resulted in 81% accuracy with 80% specificity when distinguishing between nevus and melanoma.

Attia et al. Attia et al. [32] created an FCN structure which combined FCN and SegNet through an autoencoder-decoder framework. This model achieved 98% accuracy and 94% specificity during its testing phase with 900 dermoscopic images trained on 375 samples from the ISBI 2016 challenge.

Mukherjee et al. Rephrase the CNN Malignant Lesion Detection (CMLD) architecture through the work of Mukherjee et al. [33] which utilized data from both Dermofit and MEDNODE databases. The analysis revealed promising results through 90.14% and 90.58% accuracy rates when testing on individual datasets while obtaining 83.07% accuracy when processing multiple datasets simultaneously. This showed the difficulties of performing generalizations across datasets.

Sanketh et al. A CNN architecture developed by Sanketh et al. [34] used two convolutional layers alongside two max-pooling layers for the purpose of early skin cancer detection. A dataset consisting of 2,719 images enabled the model to demonstrate 98% accuracy which validates how simple CNN architectures perform effectively in classification work.

Rahi et al. A CNN model developed by Rahi et al. [35] applied different strides while using max-pooling layers during the training process of 2,967 images. Their method reached 84.76% accuracy but the results suggest that architectural refinement or data expansion could improve these results.

Gulati et al. The research of Gulati et al. [36] relied on AlexNet and VGG16 pre-trained CNN architectures to extract features and perform transfer learning with PH2 dataset information. Transfer learning demonstrated its effectiveness in medical image analysis as VGG16 achieved the most successful results while maintaining 97.5% accuracy and 96.87% specificity.

Daghrir et al. The authors demonstrated a hybrid classification model to integrate CNNs with K-Nearest Neighbors (KNN) and Support Vector Machines (SVM) through their research. [37] The researchers employed their nine-layer CNN system to analyze the ISIC dataset which yielded individual assessment accuracy of 85.5%. The hybrid approach that combined deep learning with traditional methods delivered an overall accuracy of 88.4% while showing slight improvements over CNNs alone.

Table 1. Comparative Analysis of Skin Cancer Detection Methods

Methodology	Dataset(s)	Performance Metrics
DCNN [14]	PH2, ISBI 2016, ISBI 2017	98.4% (PH2), 95.1% (ISBI 2016), 94.8% (ISBI 2017)
Active Contour + GLCM + SVM [24]	ISIC	95% Accuracy, 90% Sensitivity, 85% Specificity

Median Filtering + CLAHE + Otsu + AdaBoost SVM [25]	Skin Cancer & Benign Tumor Image Atlas	91.7% Accuracy, 94.1% Sensitivity, 88.7% Specificity, 0.83 Kappa
Normalized Otsu + AdaBoost SVM [25]	Various Repositories (992 images)	91.7% Accuracy
ABCD Rule + SVM [26]	PH2	90.63% Accuracy, 95% Sensitivity, 83.33% Specificity
CNN [28]	Multi-Source Dermatoscopic Images	75.2% Accuracy, 0.71 Validation Loss
FCRN [38]	ISIC	85.7% Accuracy, 49.0% Sensitivity, 96.1% Specificity, 72.9% Avg Precision
ANN [39]	ISIC	74.76% Accuracy, 57.56% Validation Loss
SVM [40]	ISIC (5341 images)	96.9% Accuracy
GrabCut Segmentation [41]	DermQuest (80 images)	80.0% Accuracy
MobileNet [42]	PH2	92.67% Accuracy
Otsu Threshold Segmentation [43]	1000 Image Dataset	92.7% Accuracy

4. DISCUSSION

The comparative analysis underscores both the strengths and limitations of various machine learning (ML) and deep learning (DL) approaches applied to skin cancer detection. High-performance metrics—such as those achieved by Support Vector Machines (SVMs) and Deep Convolutional Neural Networks (DCNNs)—demonstrate the potential of these models to significantly enhance diagnostic accuracy and support clinical decision-making.

However, the analysis also reveals persistent challenges. Notably, the generalizability of models is hindered by limited dataset diversity, and there is a pressing need for larger, more comprehensive, and annotated datasets that reflect real-world variability. Furthermore, issues related to model interpretability, transparency, and clinical validation continue to obstruct widespread adoption in healthcare settings.

The variability in model performance across different datasets illustrates the importance of standardized benchmarking and evaluation metrics to ensure fair and reproducible comparisons. The exploration of diverse segmentation techniques, image preprocessing methods, and hybrid models reflects ongoing efforts to refine model robustness and diagnostic precision. Together, these findings indicate that while significant progress has been made, considerable opportunities for advancement remain.

5. CONCLUSION AND FUTURE WORK

This survey provides a comprehensive overview of the application of machine learning (ML) and deep learning (DL) techniques for skin cancer detection, highlighting the transformative shift from traditional diagnostic methods to data-driven computational models in early cancer diagnosis. Deep learning architectures—particularly convolutional neural networks (CNNs)—have demonstrated remarkable success in classifying and segmenting dermoscopic and clinical images. However, several limitations still hinder optimal performance and clinical translation. Future directions to address these challenges include the expansion and open access of large, diverse, and high-quality datasets that accurately represent various skin tones, lesion types, and imaging conditions; the development of explainable AI (XAI) models that offer transparent and interpretable outputs to foster trust and clinical adoption; the creation of user-friendly interfaces and validation of ML/DL tools through extensive clinical trials to ensure smooth integration into existing medical workflows; exploration of hybrid approaches combining traditional ML models with modern DL architectures to enhance performance and reliability; and improvement in computational efficiency to support real-time skin lesion analysis, particularly in mobile or point-of-care diagnostic settings.

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