## **Introduction**

Automated systems for detecting and analysing skin diseases, particularly melanoma, have highlighted the potential of deep learning and machine learning in improving diagnostic accuracy. However, these technologies are still evolving and face challenges in achieving clinical adoption.

This review explores advancements in deep learning, machine learning, and computer vision techniques for skin cancer detection. By synthesizing findings from key studies and highlighting existing gaps, it provides insights for enhancing diagnostic systems and guiding future research.

## **Overview of Skin Cancer and Conventional Methods**

*Skin cancer, including melanoma, is a global health concern. Early detection improves survival rates, but traditional methods, such as dermatological examination and biopsies, are resource-intensive and inaccessible in underserved areas.*

*Dermoscopy has enhanced visual diagnosis, but its reliance on expertise limits widespread application. This gap underscores the need for automated systems that leverage advancements in computer vision and machine learning.*

## **Datasets for Skin Cancer Detection**

Datasets play a critical role in developing robust and accurate models for skin cancer detection. Two prominent datasets frequently used in research are:

1. **[1]ISIC** **Archive**: The International Skin Imaging Collaboration (ISIC) Archive is one of the largest public databases of dermoscopic images. It provides a wide range of annotated images for training and testing machine learning models.
2. **[2]HAM10000**: This dataset comprises over 10,000 multi-source images of skin lesions, including both benign and malignant samples. Frequently used in Kaggle competitions, HAM10000 serves as a benchmark for evaluating the performance of skin cancer detection algorithms.

The quality and diversity of datasets like these are instrumental in ensuring model generalization and robustness. However, challenges such as class imbalance and limited representation of rare lesion types persist.

## **Image Processing and Deep Learning Techniques**

Preprocessing techniques, such as segmentation and contrast enhancement, improve the quality of skin lesion images for analysis. Studies like [5]“**Detection and Classification of Melanoma Skin Cancer Using Image Processing Techniques**” emphasize the role of these methods in boosting accuracy.

Deep learning, particularly convolutional neural networks (CNNs), has emerged as the leading approach for skin cancer detection. For instance, [6]“**Dermatologist-Level Classification of Skin Cancer with Deep Neural Networks**” demonstrated the efficacy of CNNs in achieving dermatologist-level accuracy. Additionally, transfer learning models, as explored in the GitHub repository [7]“**Skin-Cancer-Detection-using-Transfer-Learning-with-PyTorch**,” provide practical frameworks for adapting pre-trained architectures like VGG16.

A systematic review by [4]*"****Skin Cancer Detection: A Review Using Deep Learning Techniques****"* consolidates findings from key research papers, emphasizing lesion parameters such as symmetry, color, and shape in distinguishing benign and malignant skin cancers. The review provides insights into various deep learning tools, frameworks, and evaluation methods, further underscoring the importance of early detection.

Similarly, [3]*"****Detection of Skin Cancer Based on Skin Lesion Images Using Deep Learning****"* highlights the application of CNNs and transfer learning models (Resnet50, InceptionV3, and Inception Resnet) on the ISIC2018 dataset. The study integrates preprocessing steps like ESRGAN for image enhancement and augmentation, achieving accuracy rates of up to 85.8% with InceptionV3. The innovative use of ESRGAN as a preprocessing technique showcases the potential of advanced image processing methods in improving classification performance.

While CNNs deliver impressive results, challenges such as overfitting and computational requirements persist.

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## **Machine Learning Approaches**

Traditional machine learning methods, such as SVM and KNN, offer alternative approaches for skin cancer detection. The study [8]“**Skin Cancer Classification Using Image Processing and Machine Learning**” highlights the importance of feature extraction and handling class imbalance to enhance performance.

Comparatively, deep learning models generally outperform traditional approaches, but SVM and KNN remain valuable for smaller datasets or simpler classification tasks.

## **Research Gaps and Future Directions**

Despite the progress made in skin cancer detection, several gaps remain:

**Dataset Limitations**: Many datasets lack diversity in terms of patient demographics and lesion types.

**Generalization**: Models often struggle to perform well on unseen data due to overfitting or underfitting.

**Clinical Integration**: Bridging the gap between research and real-world applications requires rigorous validation and explainability.

Future research should focus on developing more diverse datasets, improving model interpretability, and integrating AI systems into clinical workflows. The use of hybrid approaches that combine traditional ML and DL techniques could also enhance performance.

## **Conclusion**

Automated skin cancer detection systems have made significant progress but face ongoing challenges. By leveraging advanced architectures, ensemble techniques, and diverse datasets, this project aims to overcome these barriers and provide an accessible, high-performance diagnostic tool.

## **Competitors**

There are a few direct competitors in the skin cancer detection space, such as SkinVision, MoleMapper. However, SkinVision stands out as the most direct competitor to my project, given its similar use of AI and image-based risk assessment for skin cancer detection. Here's a breakdown of how it compares to my project:

**SkinVision**

SkinVision allows users to take photos of moles and other skin lesions and assesses their risk of skin cancer using AI and machine learning algorithms. The app provides users with risk assessments to guide whether they should seek medical advice. Key Differences:

* **Paid Service vs. Free**: SkinVision is a premium, paid service, whereas my project will be completely free for all users. The only "cost" will be related to user images potentially being anonymized and stored for research purposes.
* **Advanced AI Models**: SkinVision utilizes transfer learning on pre-trained models (e.g., ResNet, VGG16). In contrast, my project will implement more advanced architectures, such as EfficientNet or Vision Transformers, known for their higher performance in image recognition tasks.
* **Ensemble Approach**: My project will also combine CNNs with Support Vector Machine (SVM) classifiers as part of an ensemble method. This hybrid approach aims to increase classification accuracy and outperform standalone models.

While SkinVision is a direct competitor, several research-focused projects exist that apply similar technologies for skin cancer detection, but they often lack the user-centric focus that my project aims to provide.

**MoleMapper**

MoleMapper is a tool that utilizes photography to monitor changes in moles over time. It helps track variations in size, shape, and color, which may indicate a mole’s progression toward malignancy. While this approach does not prevent skin cancer, it facilitates early detection of melanoma and other skin cancers, allowing for timely treatment and improved patient outcomes. Keys are Differences:

* **long-Term Tracking vs. Instant Results**: MoleMapper focuses on tracking moles over time, requiring users to periodically submit images to monitor changes. In contrast, my project provides **instant results** by analyzing a single image, offering users an immediate assessment of melanoma risk.
* **Physician-Recommended vs. Direct Access**: MoleMapper is typically recommended by physicians or specialist nurses and often used under medical guidance. My project is designed for **direct access by users**, making it simple and accessible without needing prior medical consultations.
* **Monitoring vs. Diagnosis Support**: MoleMapper excels in long-term **monitoring** of multiple moles to detect changes over time. My project aims to provide a **diagnostic aid** for a specific mole or lesion in one session, catering to users who need quick insights.

**Research-Based Competitors**

**[7]Skin-Cancer-Detection-using-Transfer-Learning-with-PyTorch**

This GitHub repository demonstrates a model that uses transfer learning with PyTorch for skin cancer detection. It employs pre-trained models (such as ResNet and VGG16) and fine-tunes them for classification tasks. Key Differences:

* **Model Architecture**: While the repository primarily focuses on using transfer learning with CNNs, my project will take it a step further by integrating more cutting-edge models like EfficientNet and Vision Transformers, which have demonstrated superior performance for image recognition.
* **Ensemble Methods**: The repository doesn't mention the use of ensemble methods (combining multiple models for higher accuracy). My project will explore combining CNNs with SVM classifiers to improve performance.

**[9]Skin Cancer Classification using Deep Learning**

This repository uses deep learning, specifically CNNs, to classify skin lesions based on publicly available datasets (e.g., ISIC, HAM10000). Key Differences:

* **Model Variety**: While CNNs are effective, my project will explore the use of more advanced architectures like Vision Transformers and EfficientNet, which may be more effective at handling complex skin lesion images.
* **Ensemble Techniques**: Unlike this repository, my project will implement ensemble methods, combining the strengths of different classifiers like CNNs and SVMs to improve classification accuracy and robustness.

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