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A Systematic Review on AI-Based Skin Disease Detection and Care Recommendation Systems

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ABSTRACT

Skin conditions are one of the most frequently happening health-related issues that occur across all age groups worldwide. Proper identification, along with consulting the doctor for treatment, is very important in preventing cost, severity, consequences. As a result of fast advancements in artificial intelligence (AI), ML, and Deep Learning (DL), automated systems for skin disease identification and care recommendation have gained immense popularity over the past few years. The objective of these systems is to analyse images of the skin and identify diseases properly, and provide personalised care recommendations accordingly. This review paper describes a detailed analysis of existing skin disease and care recommendation models designed based on conventional image analysis techniques, ML models, and Deep Learning models. The article describes the various datasets, approaches, performance analysis, advantages, and disadvantages of various models developed by others. Moreover, a general system architecture and method for developing an intelligent system for skin diseases and recommendations for care is also provided in this article. Finally, this article ends with a conclusion that recognizes some deficiencies in current-era research, which are not limited to Multimodal Learning, Real-Time Diagnostics, and Explain ability for AI and other aspects of Tele-medicine platforms.

Keywords:- Skin Disease Detection, Care Recommendation System, Machine Learning, Deep Learning, Computer Vision, Dermatology, AI in Healthcare

1. INTRODUCTION

Skin problems They're everywhere. Regardless of age or location, none of us are safe from danger. It is a constant, devious attack on all fronts at one time or another-whether the environment or what you do on a daily basis is causing the harm to your skin. Hence, the reports of troubles with acne, eczema, psoriasis, melanomas, and fungus infections are not so surprising. These aren’t just surface level problems. These aren’t just mere reactions. These are very serious conditions that are potentially fatal. They can be painful and, to be frank, they can really knock your confidence. It’s hard to feel good about yourself when your skin is angry.

Catching these issues early makes a real difference. If you spot a problem fast, doctors can get ahead of it - especially when you’re talking about something as serious as skin cancer.

Usually, dermatologists diagnose skin problems by looking - sometimes just with their eyes, sometimes with a dermo scope. That works great if you’ve got a skin expert nearby. But plenty of people don’t, especially in smaller towns or places that don’t have enough doctors. So, you end up with late diagnoses, or even the wrong ones. And that just makes things worse - health-wise and money-wise.

That’s where automated systems come in. Researchers are building tools that use machine learning and deep learning to scan digital photos of your skin. Deep learning models, especially convolutional neural networks (CNNs), are actually pretty amazing at spotting tiny changes in color, texture, or shape - stuff that can mean trouble. Some studies even say these systems can match trained dermatologists. That’s a big deal. And they won't stop at diagnosis anymore. Newer systems are beginning to offer skincare tips, suggest ways problems can be prevented, and even inform you when it's time to pay a visit to the doctor.

Nonetheless, the major part of current studies only deals with whether these tools can properly distinguish one disease from another. There isn't much emphasis on making these tools really helpful and user-friendly yet, and this issue will be dealt with in the next studies.

2. BACKGROUND AND BASICS

Skin conditions vary greatly, ranging from small to large. While some are inflammation-related issues like acnes, eczema, and psoriasis, infection sources - bacterial or fungal infection - are major players. Then you’ve got pigment issues, like vitiligo, and serious problems like melanoma. Most of the time, these diseases show up as visible changes: shifts in color, new textures, odd shapes. That’s why looking at the skin is such a useful way to spot problems, especially when you’ve got good digital images.

Earlier on, researchers leaned on classic machine learning. They’d handpick features from images - maybe it was the way texture looked, or how the color was spread out, or the shape of a spot - and plug those into algorithms like support vector machines. These old-school methods worked okay, but they depended a lot on what humans noticed and weren’t great at handling the wild variety you see in real skin images.

Deep learning changed the game These models learn to determine on their own what’s important in the image. They require zero human intervention. That implies that these models are able to deal effectively with complicated and messy real-world data that’s not easily captured in a structured manner by humans. CNNs are the backbone here. They begin with the simplest of details: edges, tiny elevations, regions of color, and gradually work their way up to being able to spot intricate patterns of lesions. Studies keep showing that CNN-based models, especially with fancy techniques like transfer learning and model ensembles, can match or even beat human experts when it comes to classifying skin lesions. Thanks to their smarts and reliability, CNNs have become the go-to for automated skin disease diagnosis today.

3. DATASETS USED IN LITERATURE

Datasets really drive progress in automated skin disease detection. When you have high-quality, well-labeled skin images, machine learning models can actually pick up on the visual clues that separate one condition from another. Over the years, there are a few open-source collections that are standard resources in the area of dermatology. They allow everyone to test their hypothesis on the same data set, so you can effectively compare your results. For example, take the International Skin Imaging Collaboration database ISIC. It’s huge packed with dermoscopic images of both harmless and risky skin lesions. Researchers all over the world use ISIC for melanoma detection and multi-class skin lesion classification. The dataset keeps growing, and experts keep adding new labels, so it’s become a sort of gold standard.

HAM10000 is another popular one. It pulls in dermoscopic images from different places and covers several common types of pigmented skin lesions. Because it’s big and has lots of variety, people often use HAM10000 to train and test deep learning models, especially convolutional neural networks and transfer learning methods.

Of course, not everything is public. Some researchers use private or institution-specific clinical image sets. These can be messier - real-world lighting, different skin tones, images that aren’t always perfect - but that’s what makes them useful for testing if a system works outside the lab.

However, since such private data is not standard or easily accessible, drawing comparisons regarding the output of a given study versus others is rather challenging. Despite all this advancement, a couple of deep chasms exist even today. Class imbalance, not enough skin tone diversity, and inconsistent labelling. each of them contributes to holding the field back. Fixing these issues would push skin disease detection research even further.

4. REVIEW OF EXISTING TECHNOLOGIES

People have pushed automated skin disease detection through a few different phases, all chasing higher accuracy, better scaling, and practical use outside the lab. Right now, the main approaches fall into three camps: handcrafted feature-based methods, models powered by machine learning, and deep learning frameworks that do most of the heavy lifting on their own.

Handcrafted Feature - Based Approaches

At first, researchers used hand-crafted features to describe how skin lesions looked - things like colour, texture, and the shape of the edges. They pulled out these details with standard image processing tricks, then tried to sort diseases based on that. The upside? These approaches run quickly and aren’t complicated, so they are actually quite effective if you are working with a small, well-organized set of images.

However, the catch is, these approaches are not designed to deal with the messiness of the real world. Just change the lighting, the camera, or the skin tone, and the outputs can literally fall apart. Fixed features just don’t adapt, so when you take these techniques outside the lab, they end up missing a lot of what matters for clinical use [3][8].

Machine Learning - Based Approaches

Machine learning brought in classifiers like Support Vector Machines and hybrid models to help tell diseases apart by using features people pull out of skin images by hand. These methods beat old-school image processing when it comes to accuracy and dealing with complicated decision boundaries, especially for classifying lesions as one thing or another. Still, they rely on people to pick out the right features, which means you need experts and have to keep tweaking things whenever you get a new dataset or run into a different disease.

Deep Learning - Based Approaches

Deep learning, especially Convolutional Neural Networks, picks up visual features straight from raw skin images. No need to handcraft features anymore. When you train CNNs on big datasets, they can spot skin conditions about as well as a dermatologist, and they don't get tripped up easily. Throw in transfer learning or ensemble methods, and the models get even better, especially when you're dealing with lots of different classes. But there's a catch. These systems need tons of labeled data and serious computing power.

5. PERFORMANCE COMPARISON AND OBSERVED TRENDS

The efficiency of automated diagnoses of skin conditions began with traditional image processing but eventually developed along the lines of machine learning. Comparing existing studies quantitatively helps highlight strengths, limitations, and trends in the field.

Observed Trends and Insights

Skin detection technology has evolved significantly, moving from early methods that struggled with lighting to deep learning models that now hit over 90% accuracy. Thanks to transfer learning, these tools can even run on smartphones, though quality still varies. However, major gaps remain: datasets often lack diverse skin tones, and the high computing power required limits accessibility. Crucially, for doctors to fully adopt these systems, the AI needs to be 'explainable' so the reasoning behind a diagnosis is clear.

Table 1: Quantitative Comparison of Existing Studies

Reference	Year	Dataset	Method	Accuracy / Performance	Key Limitation
Esteva et al. [1]	2017	Thermoscopic images	CNN (Deep Neural Network)	91%	Large dataset, high computational cost
Kawahara et al. [2]	2018	ISBI	Deep features + ML	85%	Requires manual feature extraction
Abbas et al. [3]	2019	Clinical images	Texture + SVM	78%	Sensitive to lighting and skin tone variations
Han et al. [4]	2020	Clinical images	CNN	87%	Limited real-world evaluation
Ali et al. [5]	2021	Smartphone images	CNN	88%	Mobile device variability affects performance
Liu & Wang [16]	2019	HAM10000	CNN (multi-class)	90%	Needs large labeled data
Harangi [17]	2018	HAM10000	Ensemble CNN	92%	Computationally intensive
Khan & Riaz [22]	2022	Multiple datasets	Transfer learning + CNN	93%	Dataset imbalance issues
Tan & Zhou [20]	2021	Acne dataset	CNN mobile application	89%	Focused only on acne

6. SKINCARE RECOMMENDATION SYSTEM

Modern research on automated skin health has shifted beyond detection toward personalized skincare guidance, integrating actionable recommendations with AI-driven diagnosis [6][12][21][23]. These systems aim to assist users in managing skin conditions, preventing complications, and promoting overall skin health.

Table 2: Functional Overview

Feature	Description	References
Personalization	Tailor recommendations based on skin type, history, and real-time environmental factors	[6][12]
AI Integration	Links disease detection (CNN/transfer learning) with recommendation engines for end-to-end guidance	[5][21]
Mobile Accessibility	Delivers advice through smartphone apps, increasing accessibility and adherence	[5][20]

Strengths, Limitations, and Observations

Skincare apps are changing the game by letting people treat minor issues early without a doctor, which helps prevent bigger problems later. However, there are still cracks in the system: limited datasets mean they don't work for everyone, and a lack of clinical validation makes the advice hard to trust completely. To become truly reliable, the next generation of tools needs rigorous real-world testing, diverse data, and AI that clearly explains its reasoning.

7. CHALLENGES AND RESEARCH GAPS

Despite progress in automated skin care, big hurdles remain. Most datasets lack diversity in skin tones and real-world conditions, so models struggle outside the lab. While deep learning is accurate, it's resource-heavy and acts like a 'black box,' making it hard for doctors to trust. Connecting detection to advice is also tricky without proper validation or lifestyle context. For real progress, we need diverse data, efficient tech, and AI that explains its reasoning - so patients and clinicians can actually trust the results.

8. FUTURE RESEARCH DIRECTIONS

To make skin analysis tools truly viable, research must move beyond the lab. We need diverse datasets covering all skin tones and lightweight models that run smoothly on smartphones. Detection should also trigger personalized advice rooted in a user's daily habits. Above all, the AI must be transparent; if clinicians can't understand the reasoning behind a diagnosis, they won't trust it. Real success lies in balancing better data, efficiency, and explainability.

9. CONCLUSION

Automated systems for spotting skin diseases and giving skincare advice have come a long way. They started off using basic image processing, but now they rely on deep learning, which has pushed accuracy way up. Still, there are some real hurdles - like limited datasets, the need for lots of computing power, confusing black-box models, and the fact that recommendation features don't always fit in smoothly.

A better approach brings everything together: accurate detection, advice that actually fits each person, and results you can understand - not just numbers. When researchers focus on building more diverse datasets, tougher models, explainable AI, and real clinical testing, these skin health tools get a lot more useful and easier for real people to use. This review looks at where the field is right now, what's working, and what needs fixing, and lays out a path for researchers and developers moving forward.

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