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SkinSight: Design and Implementation of an Intelligent Skin Type Detection System

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Abstract

Identifying an individual's skin type accurately is essential for creating personalized dermatological treatments and formulating skincare products that genuinely meet user needs. In this project, a real-time skin type classification system is developed using a combination of convolutional neural networks (CNNs) and modern computer vision techniques. The system processes live video streams, isolates the facial region through Haar cascade–based detection, and applies a series of preprocessing steps to enhance clarity and highlight essential skin features. Once the facial area is prepared, the trained CNN model classifies the skin into one of three categories: dry, normal, or oily. During evaluation, the model demonstrates strong accuracy and consistent performance, making it suitable for real-time use on consumer devices or clinical tools. Beyond simple classification, this technology has the potential to support personalized skincare recommendations, assist dermatologists with initial screenings, and improve automated beauty or health applications. Future enhancements may include expanding the model to recognize additional skin concerns, improving robustness under varying lighting conditions, and integrating more advanced feature-extraction methods to further increase reliability.

Keywords: Skin type, haar cascade, CNN, dermatology, skinsight

INTRODUCTION

Understanding skin types is a key element in dermatology and skincare and forms the basis for creating personalized treatments, formulating cosmetics, and recommending the right products. Skin is generally classified as dry, normal, or oily, and accurately identifying where someone falls in that spectrum is essential for diagnosing issues and offering effective care. However, traditional methods often rely on either a dermatologist's observation or self-assessment tools such as questionnaires. These approaches can be inconsistent, biased, and difficult to scale, which highlights the need for a more objective and reliable solution.

Owing to recent advancements in artificial intelligence (AI) and computer vision, there is now a promising opportunity to improve skin type detection. Convolutional neural networks (CNNs), a type of deep learning (DL) model, are particularly suitable for analyzing images and identifying complex patterns, making them well-suited for this type of classification task. Moving to AI-based methods, we can reduce human errors and create automated solutions that are both accurate and efficient.

This study presents a real-time system that combines CNNs with computer vision to detect skin types from facial images. It uses live video input, applies face detection through Haar cascade algorithms, and analyzes the identified facial areas

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to classify the skin as dry, normal, or oily. The system provides immediate feedback and is designed to be intuitive and non-invasive, making it useful in both medical and consumer environments.

The paper walks through the design and implementation process, covering how the CNN model works, how image preprocessing is managed, and how everything connects with the live camera feed. It also evaluates the performance of the system under different lighting and skin tones, evaluates its practicality, and explores its potential applications in clinics and consumer skincare tools. Finally, the challenges encountered and suggestions for future improvements are discussed to guide the next phase of development.

By addressing the flaws in conventional methods and tapping into AI's potential, this project offers a meaningful step forward in dermatological care, bringing us closer to more accessible, accurate, and real-time skin analysis solutions.

LITERATURE REVIEW

Identifying human skin types is a crucial aspect of both dermatology and cosmetic science and plays a significant role in offering personalized skincare and accurate diagnoses. Traditionally, skin type classification has relied heavily on expert opinions, which can be time-consuming and subjective. These limitations have driven a demand for more efficient and automated solutions.

Recent progress in machine learning (ML) and DL has opened new possibilities for introducing scalable and precise methods for skin analysis. Researchers have experimented with various datasets, ranging from skin images and physiological data to user surveys, and applied enhancement techniques such as contrast-limited adaptive histogram equalization (CLAHE) and SMOTE-N to improve data balance and diversity.

Several DL models have shown strong potential for skin classification tasks. For instance, EfficientNet-V2 achieved an impressive 94.57% accuracy in distinguishing between oily, dry, and normal skin types [1]. Similarly, a CNN fine-tuned with the Adam optimizer and sigmoid activation achieved 83.3% test accuracy [2]. Another approach using a modified Inception-v3 network demonstrated over 91% accuracy in classifying the dimensions of the Baumann Skin Type, including both dry/oily and pigmented/nonpigmented categories [3]. Meanwhile, structured data analysis using XGBoost, enhanced by Bayesian optimization, reported an F1-score of 98.67% for pigmentation classification [4].

Despite these promising results, researchers have highlighted several challenges. Accurately distinguishing between similar skin types, adapting to varied lighting conditions, and dealing with small or imbalanced datasets continue to hinder the performance [5]. To address these issues, future studies should incorporate more diverse datasets, use multimodal inputs, and test newer models such as gated recurrent unit (GRU) and capsule networks [6].

Together, these findings underscore how ML and DL transform the landscape of skin type detection [7]. With models achieving over 90% accuracy in many cases, there is a clear opportunity to shift toward more efficient, personalized, and data-driven dermatological practices [8].

METHODOLOGY

System Overview

This project addresses the challenge of automatic skin type detection by combining ML with real-time image processing. Its core is a CNN that is trained to accurately classify skin types. The system connects this model to a live webcam feed, enabling real-time predictions as users interact with it [9].

The process flows through several key stages: capturing the image, preprocessing it, extracting relevant features, making a prediction using the model, and displaying the result. The CNN model was trained on labeled facial images that were grouped into three categories: dry, normal, and oily skin. It processes grayscale images resized to 48 × 48 pixels, which is the optimal size for recognizing subtle texture patterns [10].

The system uses the Haar cascade algorithm to detect faces in the video feed. Once a face is found, that portion of the image is cropped, resized, and preprocessed before being fed into the model. Based on this prediction, the skin type was displayed in real time on a screen [11].

Designed to be both scalable and user-friendly, the setup works with basic hardware—standard webcams—and uses tools, such as OpenCV and TensorFlow. The result is a smooth, responsive, and accessible system for classifying skin types [12].

Hardware Design

To ensure reliable and accurate real-time detection, the system integrated a carefully chosen set of hardware components.

High-Resolution Camera

The Logitech C920 webcam captures detailed, high-quality images of the user's face, which is crucial for an accurate analysis. It connects to the Raspberry Pi via a USB and is positioned to provide a clear view of the face [13].

Processing Unit

A Raspberry Pi 5 with 8GB RAM served as the brain of the system. It manages all the processing tasks, runs the ML model, manages the image input, and delivers predictions [14].

LED Ring Light

An adjustable LED ring light was mounted around the camera to ensure consistent and even lighting on the user's face. This helps to reduce shadows and lighting inconsistencies that could affect the accuracy of the model [15].

One-Way Mirror

A one-way mirror is installed in front of the camera setup, allowing users to see themselves while the camera captures their image from behind the reflective surface. This enhances both comfort and usability [16].

LED Monitor

A compact HDMI-compatible monitor was used to display live predictions and camera feed. It connects to the Raspberry Pi and serves as the user interface [17].

Wi-Fi Module

The built-in Wi-Fi of Raspberry Pi enables wireless connectivity for updates, data syncing, or cloud integration for advanced features such as remote access or storage [18].

System Setup

All components, camera, lighting, and monitor, are connected and powered by stable power sources. The ring light surrounds the camera, and a one-way mirror is carefully positioned to maintain clear facial capture [19].

Software Architecture

The software backbone of the system combines ML, image processing, and user interface components to deliver accurate predictions with real-time performance [20].

Machine Learning Model
A custom CNN was built using TensorFlow/Keras and trained on a dataset of grayscale images labeled according to skin type. The images were resized to 48 × 48 pixels and augmented to improve model generalization. The final model is saved in.json and.h5 formats and loaded during real-time execution [21].

Real-Time Processing
Using OpenCV, the system captures videos from the Logitech C920 webcam and applies the Haar cascade classifier to detect faces. The detected region is then preprocessed, converted to grayscale, resized, normalized, and passed to the CNN for classification [22].

User Interface
The LED monitor displays a live video feed with the predicted overlaid skin type. The LED ring light ensures optimal image quality by maintaining steady lighting. Optionally, predictions can be transmitted via Wi-Fi to external devices or cloud storage for analysis [23].

Model Design
The system uses a dual-model approach: a custom-built CNN and a fine-tuned version of the ResNet-50 architecture, both capable of classifying images into dry, normal, or oily skin types [24]

Model Architecture
The custom CNN starts with convolutional layers (with 32 and 64 filters), followed by pooling layers, a flattening layer, and dense layers that extract and classify skin features. The final layer uses SoftMax to output one of the three skin types [25].

ResNet-50, pre-trained on ImageNet, was fine-tuned by replacing its output layer to match the skin type categories. Most of the early layers are frozen, and only the last few are retrained on the skin dataset [26].

Preprocessing
All the input images were resized to 48 × 48 pixels and converted to grayscale. Pixel values were normalized, and data augmentation (such as flips and rotations) was used to reduce overfitting and enhance model robustness [27].

Training and Validation
The dataset was split into training, validation, and test sets. The model uses categorical cross-entropy as the loss function and the Adam optimizer (learning rate = 0.001).

Training was monitored by early stopping to prevent overfitting. Key metrics—accuracy, precision, recall, and F1-score—were tracked to evaluate the performance [28].

Model Evaluation
Accuracy measures the overall success of the predictions. Precision, recall, and F1-score provide class-specific insights, whereas a confusion matrix offers a breakdown of how well each skin type is identified [29].

Optimization
To ensure fast performance on the Raspberry Pi, the model was optimized using techniques such as pruning (removing redundant layers) and quantization (reducing model size), allowing it to make predictions quickly without losing much accuracy, as shown in Figures 1 and 2.

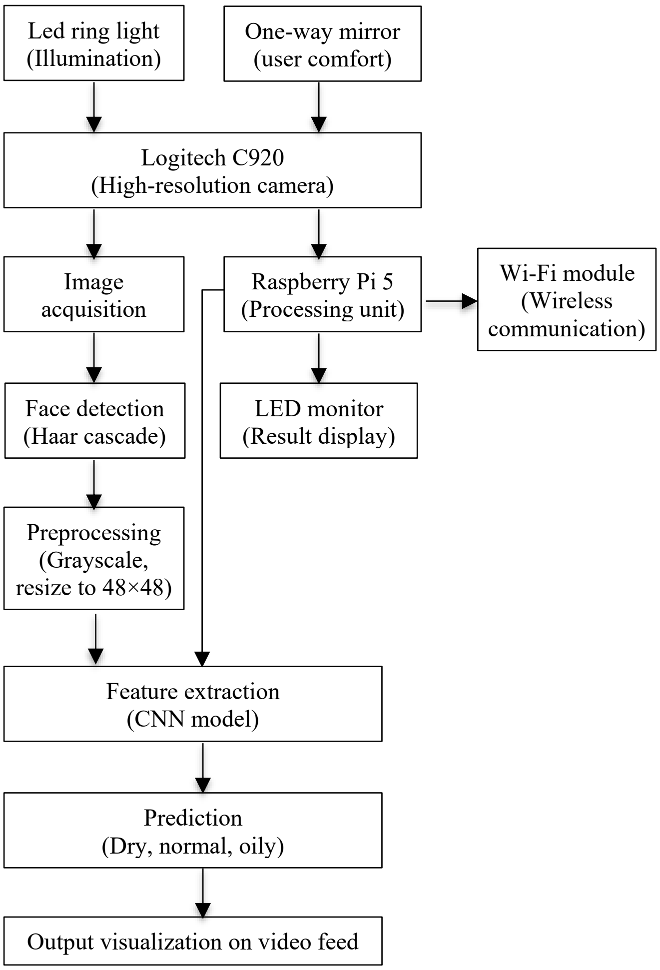

Figure 1. Workflow of the entire device.

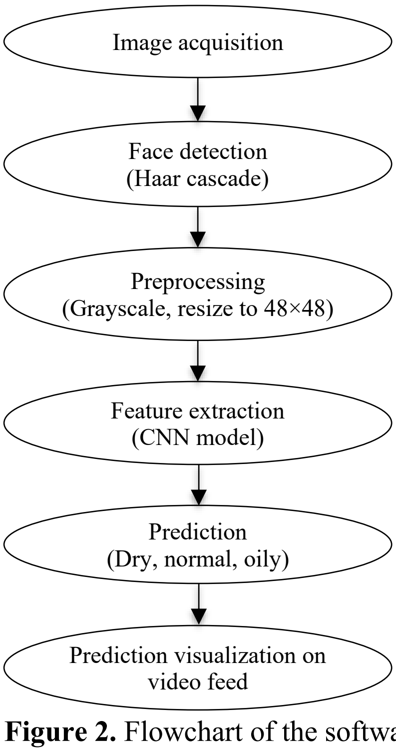

Figure 2. Flowchart of the software implementation of the model.

RESULTS

The performance of the skin type detection model was evaluated using several key metrics to assess its ability to classify skin as dry, normal, or oily. On the test dataset, the model achieved an overall accuracy of 80.38%, indicating that it can reliably distinguish between the three skin types [29].

To understand how well the model performed across each category, we also examined the precision, recall, and F1-score. These metrics help gauge not only how many predictions were correct but also how consistent and reliable the model was for each specific class. The weighted average across all three skin types showed a precision of 0.81, recall of 0.80, and F1-score of 0.80, indicating balanced performance across the board (Figure 3).

Among the individual classes, the model was the most precise when identifying oily skin (Class 2), meaning it rarely mis-classified other types as oily. In contrast, normal skin (Class 1) achieved the highest recall, suggesting that the model was particularly good at correctly identifying most of the normal skin samples (Figures 4 and 5). The F1-scores for each class reflected a strong balance between precision and recall, thereby reinforcing the overall reliability of the model [30].

A closer look at the confusion matrix provides a clearer picture of how each class was classified. For instance, while dry skin (Class 0) was identified correctly in many cases, there were some misclassifications in which it was mistaken for normal or oily skin. Normal skin (Class 1) showed a solid performance with very few errors, and oily skin (Class 2) had the best overall classification accuracy, with minimal confusion with the other two categories (Figure 6).

In terms of the model's behavior during training, the loss curve steadily decreased, suggesting that the model learned effectively from the training data. However, the validation loss showed some fluctuations, suggesting possible overfitting or inconsistencies in the validation set. Although the model nearly reached 100% accuracy on the training set, the validation accuracy stabilized at approximately 80%, highlighting the gap between training and generalization.

Overall, the model demonstrated strong performance, especially for a real-time classification task. That said, there is room for improvement, particularly in making the model more robust and better generalized to new, unseen data in Tables 1 and 2.

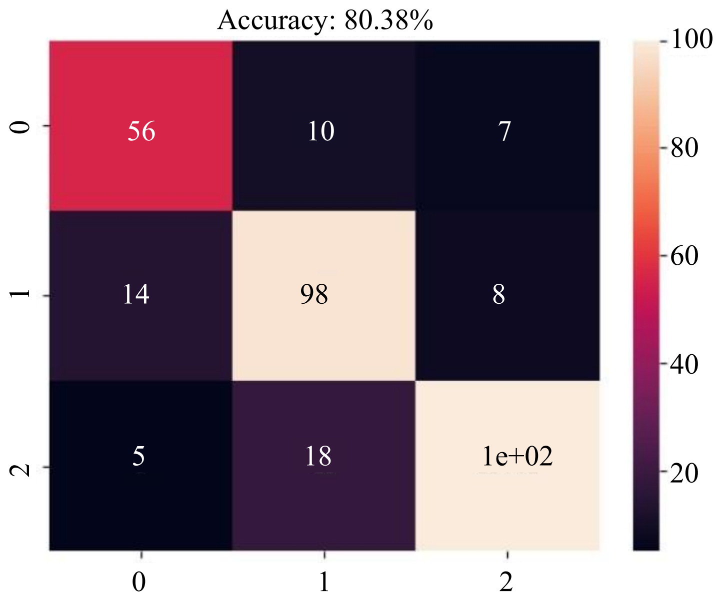

Figure 3. Confusion matrix of the model.

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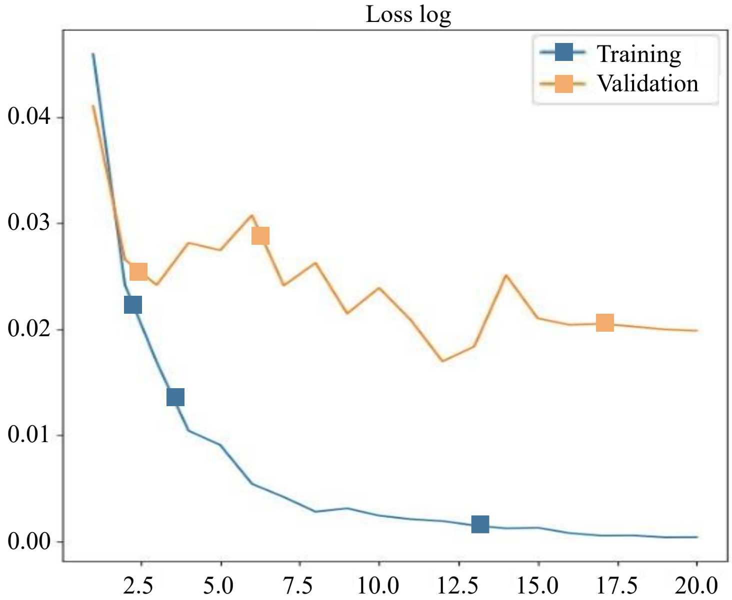

Figure 4. Loss log of the model.

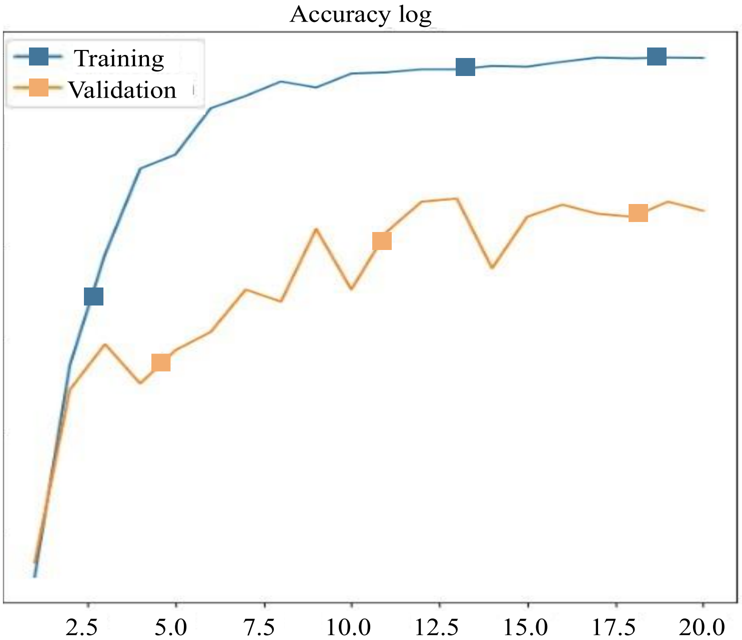

Figure 5. Accuracy log of the model.

Table 1. Classification report on the model.

Class	Precision	Recall	F1-score	Support
Class 0 (dry)	0.75	0.77	0.76	73
Class 1 (normal)	0.78	0.82	0.80	120
Class 2 (oily)	0.87	0.81	0.84	123

Table 2. Accuracy report on the model.

Class	Predicted class 0	Predicted class 1	Predicted class 2
Actual class 0	56	10	7
Actual class 1	10	98	12
Actual class 2	6	17	100

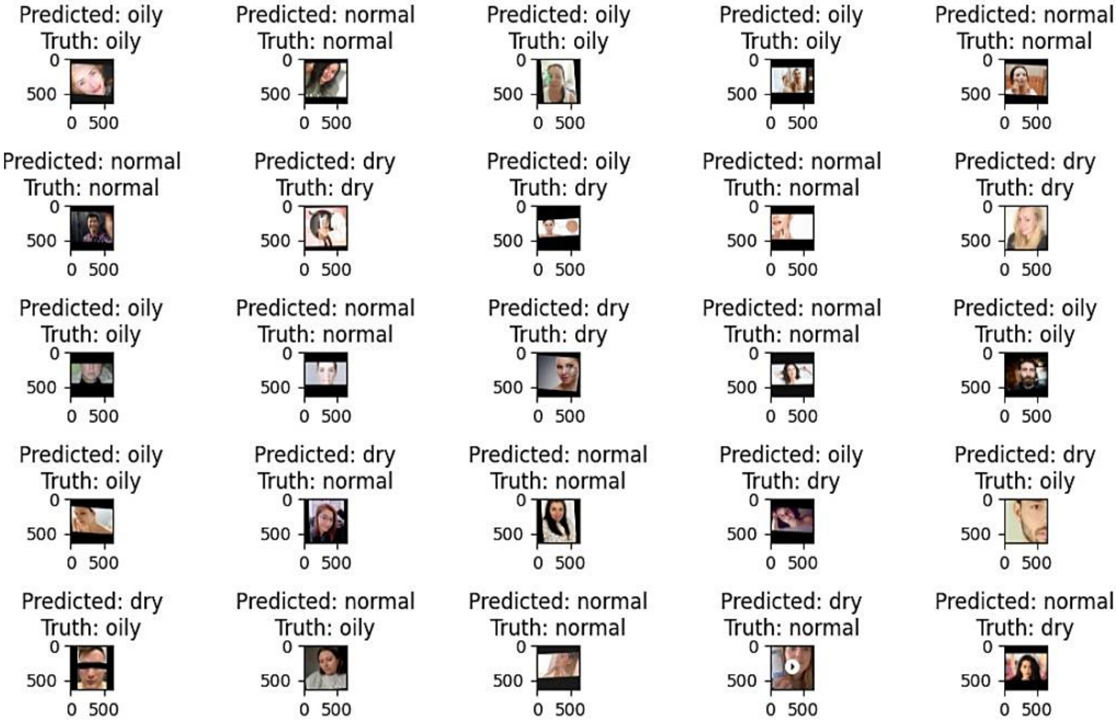

Figure 6. Predictions made by the model.

APPLICATIONS

Dermatology

In clinical settings, this system can help dermatologists to quickly determine a patient's skin type, which is essential for creating effective treatment plans and skincare routines. It also serves as a helpful tool for diagnosing conditions linked to certain skin types, such as dryness, oiliness, and sensitivity. This system allows for early intervention and preventive care by tracking changes in skin conditions over time. Additionally, it fits well into telemedicine platforms, giving patients the ability to share real-time skin analysis remotely with their doctors and improving access to dermatological advice and care.

Cosmetics

Cosmetic brands can use this system in stores or mobile apps to suggest products tailored to each customer's skin type, such as moisturizers, cleansers, and foundation shades. This not only enhances the shopping experience but also reduces the chances of negative skin reactions from unsuitable products. The system can be paired with virtual makeup tools to recommend options that suit specific skin types, ensuring better results. Brands could also use it at events or pop-ups to engage in demonstrations, showing how their products work for different skin types in real time.

Skincare

For individuals, this system offers a practical way to better understand and manage their skin. It helps users build and maintain skincare routines suited to their unique skin type and provides real-time feedback that supports smarter decisions about which products to use and how to adjust habits. Over time, it can track changes and help users measure how well products work, enabling more informed, data-driven choices.

This technology makes advanced skin analysis more accessible, even in areas where dermatology services are limited. This provides a cost-effective way to monitor skin health without requiring specialized equipment or frequent clinic visits. As more people adopt the system, it could also help skincare companies analyze broad trends in skin type data, fueling the development of smarter, more targeted products and reducing waste from mismatched purchases.

FUTURE WORK

Although the current system shows strong promise, there is still plenty of room for growth, especially in terms of accuracy, functionality, and accessibility. Future improvements could begin by expanding the training dataset to include a wider variety of skin tones, textures, and lighting conditions. This would help the model perform more consistently across diverse populations and real-world environments. Incorporating high-quality labeled datasets for specific skin concerns could also allow the system to go beyond basic classification and support condition detection.

From a technical standpoint, exploring more advanced model architectures, such as Vision Transformers or the latest versions of EfficientNet, could boost the performance. Enhancements such as fine-tuned hyperparameters, transfer learning, and ensemble methods may also make the model smarter and more reliable. Improving real-time performance by reducing latency and increasing frame rates is another key area, particularly for users on mobile devices or in low-power settings.

Upgrading the hardware can play a significant role in pushing the system forward. Using high-resolution cameras or multispectral imaging could give the model better input data to work with, whereas devices such as the NVIDIA Jetson Nano could provide more processing power without sacrificing portability.

Expanding the capabilities of a system is a major goal. In the future, it could be trained to detect specific skin conditions, such as acne or eczema, monitor long-term skin health, or assess sensitivity levels. Bringing the system into a mobile app or turning it into a standalone device with options for cloud storage or wearable tech integration would make it even more accessible and versatile.

With continued innovation, AI-driven tools such as this could become powerful personal skincare assistants, blending convenience with deep, real-time insights to support both everyday users and professionals.

CONCLUSION

This project presents meaningful advancements in the use of ML and computer vision for skincare analysis. By integrating high-quality hardware such as the Logitech C920 webcam and Raspberry Pi with powerful DL models, including a custom CNN and a fine-tuned ResNet-50, the system successfully classified skin types into oily, normal, and dry with an accuracy of 80.38%.

A major highlight of this study is the seamless fusion of hardware and software for real-time analysis. The system captures facial input, detects regions of interest, and instantly outputs skin type predictions, making it practical for both clinical environments and everyday use. Its non-invasive nature and accessibility make it a promising tool for modern dermatology and personalized skincare.

Although the current system performs well, there is clear potential for further development, such as improving classification accuracy, broadening functionality, and deploying it in mobile or standalone formats. These future directions can make the system even more versatile and impactful, bridging the gap between AI innovation and real-world skincare.

Overall, this work demonstrates how AI-driven solutions can make skin health analysis more accurate, accessible, and user-friendly, pointing toward a future in which smart dermatology tools are within reach for everyone.

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