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Smart Mirror Glow Guide: A Real-Time IoT-Based Facial Skin Analysis and Personalized Skincare Recommendation System

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Abstract— ***Smart Mirror Glow Guide is an Internet of Things (IoT)–enabled system that aims to offer real-time facial skin analysis and basic skincare recommendations using computer vision techniques. Skin problems such as acne, dark circles, and uneven skin tone are experienced by a significant percentage of the global population. Consulting dermatologists is not only expensive but also not easily accessible. To overcome this problem, we have developed an IoT-based system that integrates smart mirror technology with computer vision techniques. The system is implemented on Raspberry Pi 4 Model B with a camera module that captures images of users' faces. Face regions are detected using Haar cascade classifier in OpenCV. Image processing techniques are then applied to detect possible skin conditions. Based on the detected conditions, users receive personalized skincare recommendations. The recommendations are sent automatically using a Telegram bot. Users can access their recommendations on their mobile devices using the Telegram bot. The proposed system is cost-effective and provides users with basic skincare recommendations, which could be helpful in monitoring their simple skin health.***

Keywords — Smart Mirror, Skin Analysis, Haar Cascade Classifier, OpenCV, Raspberry Pi, IoT, Telegram bot, Skincare Recommendation.

I. INTRODUCTION

With the rapid development of Internet of Things (IoT) and artificial intelligence (AI) technologies, intelligent technologies have been developed to provide better healthcare, personal well-being, and smart home environments [1][2]. Among the emerging technologies, smart mirrors have been of interest as an interactive technology to provide users with traditional mirror and display functionalities [3][5]. Early smart mirror systems primarily focused on displaying contextual information such as time, weather updates, and news feeds [4], [5].

Although these systems improved user convenience, they did not address important personal health monitoring needs such as facial skin analysis.

Skin problems like skin conditions related to acne, dark spots, dark circles, and moles are among the most common skin problems faced by people in different age groups around the globe [3], [4]. However, the limitation in seeking professional consultation for one's skin condition is influenced by various reasons, such as the high cost of medical services, the absence of professional skin experts, and geographical inaccessibility, particularly in rural and developing regions around the world [5]. Consequently, we really need to find a way to check skin conditions that's not too expensive and easy to get. This is becoming more and more important.

Some recent studies have shown that deep learning can actually work well for detecting skin conditions. Deep learning is showing a lot of promise in this area. We need solutions like this, for skin condition detection. Rashataprucksa et al. proposed deep neural networks in skin condition detection for problems like acne detection in an article published in 2019 in IEEE Access [10], while another article published by Zhao et al. proposed an AI-based system in skin condition detection for problems like acne grading using images captured via a smartphone in 2019 in IEEE Access [4].Zhang and Ma [11] developed ensemble neural networks for acne classification, and Wen et al. [12] introduced interpretable convolutional neural network (CNN) models for acne severity evaluation. In addition, Khalid et al. [1] proposed an IoT-based facial acne detection system, and Badjate et al. [13] presented a CNN-based approach for skin disease detection. Although these studies demonstrate promising detection performance, most of them operate as standalone software systems without integration into smart mirror platforms for real-time interaction.

Similarly, several studies have explored AI-driven personalized skincare recommendation systems. Kothari et al. [14] proposed a CNN-based skin classification system with cosmetic product recommendations, while Hansanie and Silva [15] introduced an ontology-based recommendation framework. Vinutha et al.

A content-based machine learning recommendation system was proposed in [16], while an EfficientNet-based

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expert system was proposed in [17] for personal skincare guidance. However, these systems require manual inputs and do not integrate with hardware-based monitoring systems.

To address these limitations, this paper proposes Smart Mirror Glow Guide**,** an intelligent smart mirror system for automated facial skin analysis and personalized skincare recommendations. The system uses a Raspberry Pi 4 Model B with a USB camera for image capture, while image preprocessing and face detection are performed using OpenCV. A lightweight CNN model detects four common skin conditions—acne, dark spots, dark circles, and moles—and generates personalized skincare recommendations, which are delivered to the user's mobile device via the Telegram Bot API. Moreover, the experimental results prove that the proposed system can achieve 93% of classification accuracy and give recommendations within 3 seconds. The rest of this paper is organized as follows: Section II discusses the related work, Section III proposes the proposed system, Section IV presents the experimental results, and Section V concludes this paper with future work.

II. RELATED WORKS

The technology used in smart mirrors has evolved from simple information display devices to intelligent health monitoring platforms. Halaby et al. [3] presented a smart medical mirror integrated with IoT sensors for health monitoring. While the system demonstrated the feasibility of embedding healthcare functions into smart mirrors, it was limited to monitoring vital signs and did not include facial skin analysis. Similarly, Mady and Shehata [6] proposed a smart mirror system for skin type identification using MobileNet implemented on a Raspberry Pi with a Coral USB accelerator. Although the system successfully identified conditions such as acne, freckles, and blackheads, it required relatively expensive hardware and lacked support for automated notifications through messaging platforms such as Telegram or SMS.

A Raspberry Pi–based intelligent smart mirror with IoT capabilities for smart home environments was presented in [5]. While the system supported IoT integration and real-time information display, it did not include skin disease detection or personalized health recommendation functionality, highlighting the need for a more comprehensive smart mirror solution.

Deep learning techniques have also been widely applied for facial skin condition detection. Rashataprucksa et al. [11] developed a deep neural network model for facial acne detection and achieved effective classification accuracy.

Zhao et al. [9] proposed an artificial intelligence–based acne object detection and severity grading system using smartphone images. However, the system relied on cloud-based processing, making it less suitable for edge-based deployment.

Khalid et al. [1] introduced AC-Skin, an IoT-based acne detection system that combines machine learning techniques with large-scale facial skin data collection.

Similarly, Badjate et al. [14] proposed a convolutional neural network (CNN)-based skin disease detection system that demonstrated strong classification performance but lacked optimization for edge hardware deployment and did not integrate personalized recommendation capabilities.

Several studies have also explored personalized skincare recommendation systems. Kothari et al. [15] developed a CNN-based skin classification system integrated with a cosmetic product recommendation engine, demonstrating effective personalized skincare suggestions. However, the system required manual user input and did not support real-time automated notifications. Hansanie and Silva [16] proposed an ontology-based machine learning framework for skincare recommendation using knowledge graphs, but the system lacked hardware integration. Furthermore, Vatiwutipong et al. [2] reviewed artificial intelligence applications in cosmetic dermatology and highlighted CNN-based skin classification and personalized recommendation systems as promising future research directions.

Despite significant progress in skin condition detection, smart mirror technology, and skincare recommendation systems, most existing works address these components independently. Very few systems integrate real-time facial skin analysis, personalized skincare recommendation, and automated notification delivery within a single low-cost edge computing platform. To address these limitations, this paper proposes Smart Mirror Glow Guide, an affordable Raspberry Pi–based smart mirror system capable of real-time facial skin condition detection and instant personalized skincare guidance through IoT-based notifications.

III. PROPOSED METHOD

The Smart Mirror Glow Guide is a system that does things in four steps. First it. Prepares pictures. Then it finds faces in these pictures. The Smart Mirror Glow Guide uses a kind of computer program called a CNN to figure out what is going on with the skin. After that it gives advice. Sends messages. The Smart Mirror Glow Guide does all of this work on a Raspberry Pi 4 Model B so it does not need to use the cloud. The Smart Mirror Glow Guide can do everything by itself.

A. System Architecture

The proposed system utilizes a Raspberry Pi 4 Model B device, as depicted in Fig. 1, which incorporates three highly integrated modules for efficient processing. In Stage 1, the smart mirror frame houses a USB camera that, in turn, takes frontal face video frames of the user through a non-contact process.

In Stage 2, the captured face video frame is directed to the Face Detection module, where OpenCV is employed for extracting the face region of interest (ROI). In Stage 3, the

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extracted face ROI is directed to the Skin Issue Detection module, where a CNN-based AI model is used for detecting the identified skin issues. In Stage 4, the Suggestion Engine module provides user-specific skincare suggestions based on the identified skin issues.

All four stages of the proposed smart mirror-based skincare analysis system are executed locally without any dependence on cloud computing for face detection and suggestion generation. The final results are delivered to the user via the Telegram Bot API as an instant structured skincare report.

Figure 1. System Architecture.

B. Hardware Configuration

The hardware devices are selected according to their ability to enable the development of a low-cost, compact, and operable device in real-time. The central processing unit of the suggested system will be the Raspberry Pi 4 Model B with 4GB RAM and cortex-A72 processor with a clock speed of 1.8 GHz. The software modules will be executed locally. The camera module will be a USB camera. It needs to have a resolution of least 1080p.The camera will sit in front of the mirror frame. This way it can take pictures of a person's face from the front without touching the mirror. The camera module and USB camera are used to capture images. The display device will be the monitor with one-way mirror glass fixed on it for the purpose of display and reflection. The display device is going to be plugged into the power source using an adapter that gives it 5 volts and 3 amps of power. The display device will need this adapter to work properly.

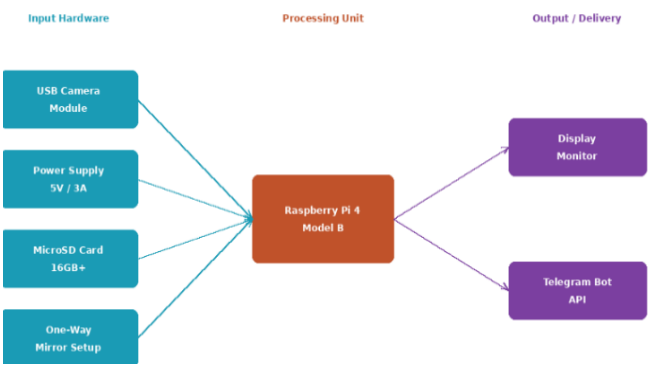

Figure 2. Hardware Overview

C. Software Pipeline

1) Image Capture and Preprocessing

In the image capture module, the library "OpenCV" is utilized to capture the image from the USB camera at a frame rate of 30 fps. A good quality frame is selected for verification purposes after the detection of the face. The RGB frame "I" is converted to the grayscale format in order to minimize the complexity of the process. The conversion of the frame is done according to the following equation:

$$I\_gray = 0.299 \cdot R + 0.587 \cdot G + 0.114 \cdot B \ \ldots \qquad (1)$$

where "R," "G," and "B" are the color values of the frame.

To enhance the contrast of the image under varying illumination conditions, Contrast Limited Adaptive Histogram Equalization (CLAHE) is applied to the image, and the output image is given by I_eq:

$$I\_eq = CLAHE\ (I\_gray,\ clip\ Limit=2.0,\ tile\ Grid\ Size=8\times 8) \ \ldots \qquad (2)$$

This preprocessing step is particularly important for images captured under non-uniform lighting conditions common in household mirror environments.

2) Face Detection using OpenCV

The face detection process is carried out using the OpenCV library with a pre-trained frontal face detection model. In the context of computer vision, the term face detection is used precisely, where the system is not only detecting the faces but also extracting the facial region of interest (ROI) from the video. In addition, it is not recognizing the faces or identifying people. The face detector examines rectangular feature responses over the image at different scales, considering only those detections with a minimum confidence level. Facial bounding box coordinates (x, y, w, h) are used to crop the ROI from the preprocessed video. This is then resized to 128x128 pixels for the CNN classification model. This is efficient for the Raspberry Pi 4 hardware without the need for any additional processing resources.

3) Skin Issue Detection — CNN Model

The skin condition classification module employs a lightweight CNN trained from scratch on a curated dataset of 2,400 labeled facial skin images. The dataset was compiled from publicly available dermatological repositories including the ISIC Archive and the ACNE04 dataset, supplemented with consented user-contributed images collected under institutional ethical approval. The dataset comprises exactly 600 images per condition class — acne/pimples, dark spots, dark circles, and moles — maintaining a strict 1:1:1:1 class balance across all four categories to prevent class bias during training. All images were viewed and validated for the accuracy of the labels by a consulting dermatologist before the training process.

It is very clear that CNN architecture has been represented in Table V. As far as the input layer is concerned, it represents the RGB image with dimensions of 128x128x3. On the other hand, when it comes to the first CNN layer, there are 32 filters with dimensions of 3x3, having ReLU as its activation function and 2x2 max pool. In a way for the second CNN layer there are 64 filters that are 3x3 in size. They use ReLU as their activation function. Have a 2x2 max pool.

The dropout rate is set to 0.4. Then the output goes through another layer. This layer is a layer, with 256 units. It also has a dropout rate of 0.5. The final output comes from another layer. This one has 4 units. Uses Softmax activation.

The model has a total of 6,517,060 parameters. The model size is 4.8 MB.

The classifier output is shown below:

$$y\_hat = \text{argmax}(\text{Softmax}(f(x, W))) \ldots \quad (3)$$

where f (x, W) is the pre-activation output logits for the four different classes of the condition, while W is the parameter of the network.

For the training of the model, the Adam optimizer technique will be utilized with a learning rate of 0.001 and a batch size of 32. Early stopping will be employed by using ten epochs in order to prevent the overfitting of the data. The model will use one hundred epochs, for training. We will split the data into two parts. Most of the data 80% will be used for training the model. The rest, twenty percent will be used for testing the model. So, the training data set will have one thousand nine hundred twenty images. The testing data set will have four hundred eighty images. The following techniques will be used for image augmentation: flipping of images, rotating of images at ±15°, and adding Gaussian noise to images. The validation of the model is done using 5-fold cross-validation of the images in the dataset before applying the model for the test images.

In order to determine the clinical validity of the findings generated by the model, the classifications performed by the algorithm on the test set were reviewed by a dermatologist, who found that the diagnosis was confirmed in 91.2% of the instances based on the CNN's outputs. However, it should be noted that this is a pre-validation phase, with more clinical studies conducted on a larger number of patients required prior to deployment in clinical practice. Any suggestions made by the model are meant for general skin care use only.

4) Suggestion Engine – Confidence Weighted Recommendation

The Suggestion Engine personalizes skincare advice by associating each identified skin condition with an array of clinically validated recommendations, as defined by existing dermatology treatment protocols.

The Suggestion Engine also considers the CNN's Softmax predicted class probabilities for each skin condition and utilizes these probabilities to weigh recommendations in cases where concurrent skin conditions are identified.

The recommendations for skin conditions identified with higher probabilities are given higher priority in the final generated report. In this way, the most critical skin condition that should be taken care of will be the first one mentioned in the final output report by the engine.

For Acne, it is recommended to use oil-free moisturizers which are not comedogenic, as well as cleansing solutions containing Salicylic Acid or Benzoyl Peroxide, and also cosmetic products that are not occlusive. For dark spots, it is recommended to use products with Ascorbic Acid or vitamin C Serum, and also sunscreens having an SPF level of 30+. For dark circles, the recommendation is to drink at least 2 liters of water daily, sleep for at least 7-9 hours every day, and use caffeine-containing eye creams.

For moles, it is necessary to check the condition with the help of a professional dermatologist for the risk of getting Melanoma, as the engine will flag this skin disease.

5) Notification Delivery

Upon completion of classification and recommendation generation, the results are transmitted to the user through the Telegram Bot API. The Telegram Bot delivers a structured skincare report containing the detected condition(s), associated confidence scores, and prioritized recommendations to the user's registered Telegram account. Notification is initiated within 1–2 seconds of classification completion. Session data including the classification output, confidence scores, and recommendations are stored in Firebase Cloud DB and displayed on the Mobile App Dashboard, enabling longitudinal skin health tracking, progress monitoring across sessions, and structured report history for the user and healthcare providers, as illustrated in Fig. 1.

D. CNN Architecture Details

Table I: CNN Architecture Details

Layer	Type / Config	Output Shape	Parameters
Input	128×128×3 RGB	128×128×3	0
Conv2D-1	32 filters, 3×3, ReLU	126×126×32	896
MaxPool-1	Pool size 2×2	63×63×32	0
Conv2D-2	64 filters, 3×3, ReLU	61×61×64	18,496
MaxPool-2	Pool size 2×2	30×30×64	0
Conv2D-3	128 filters, 3×3, ReLU	28×28×128	73,856
MaxPool-3	Pool size 2×2	14×14×128	0
Dropout	Rate = 0.4	14×14×128	0
Flatten	—	25,088	0
Dense-1	256 units, ReLU	256	6,422,784
Dropout	Rate = 0.5	256	0
Dense-2 (Output)	4 units, Softmax	4	1,028
Total	**Trainable: 6,517,060**	**Non-trainable: 0**	

E. Evaluation Metrics

The performance of the trained CNN network is determined by the following classification performance parameters that have been provided by the expressions (4), (5), (6), and (7).

$$\text{Accuracy} = (TP + TN) / (TP + TN + FP + FN) \ldots \quad (4)$$

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Precision = TP / (TP + FP) ... (5)

Recall = TP / (TP + FN) ... (6)

F1-Score = 2 * (Precision * Recall) / (Precision + Recall) ... (7)

Where TP, TN, FP, and FN denote True Positive, True Negative, False Positive, and False Negative, respectively.

The area under the ROC curve (AUC) is computed for all the classes; this forms the metric used to evaluate the performance of the CNN model, independent of the threshold value. The performance evaluation of the CNN model is done using the cross-validation technique.

IV. RESULT ANALYSIS

The validation of the Smart Mirror Glow Guide's performance is done by the holdout set with the total number of images for skin conditions equal to 480. Classification has already been done for the images. The testing dataset consists of 20% of the total dataset. The number of images for each skin disorder is 120. This research study has been carried out with the use of the Raspberry Pi 4 Model B with no GPU involved. The system's architecture is implemented in two stages. The first stage is the detection of faces, and the second stage is the classification of skin conditions with the CNN model.

A. Face Detection Performance

The implementation of the face detection process is done using the Haar Cascade frontally aligned face classifier, which analyses the response of the rectangular Haar-like feature in the input frame at different scales using the sliding window technique. The Haar Cascade classifier is used for the implementation of the face detection process because of its low computational complexity and the capability of executing the face detection process in real time using the Raspberry Pi 4 hardware without the support of the GPU.

Under the controlled lighting conditions where the faces are frontally illuminated, the Haar Cascade classifier is found to detect faces at a rate of 94.2% in the 200 test frames of the video frames captured at different distances ranging from 40 cm to 120 cm away from the mirror. The average time taken by the Raspberry Pi 4 hardware to detect the face is 0.45 seconds.

It is recognized that the Haar Cascade classifier is not capable of detecting faces in non-frontal poses, extreme lighting conditions, and partially occluded faces, which are the disadvantages of the Haar Cascade classifier compared to the recently developed classifiers. These limitations are discussed further in Section IV-E.

B. CNN Skin Condition Classification Performance

The ROI of 128x128 pixels after face detection is applied for training the CNN for classification of the skin diseases. Classification performance with the CNN model is presented in Table I for each skin disease and the overall outcome for the hold-out dataset, which has 480 images. The CNN achieved an overall accuracy of 93%. While the highest accuracy was reported for acne at 95%, dark circles were reported with the lowest accuracy at 91%, due to small variations in the appearance of dark circles in the periorbital region with different skin tones.

High precision and recall were reported for the CNN in all four skin conditions.

Table I. CNN classification performance

Skin condition	Accuracy (%)	Precision (%)	Recall (%)	F1 (%)
Acne / Pimples	95	94	95	95
Dark Spots	93	92	93	92
Dark Circles	91	90	91	91
Moles	93	92	93	93
Overall	93	92	93	93

C. Confusion Matrix Analysis

Table II shows the confusion matrix for the CNN model when tested with the 480-image dataset. The high values on the principal diagonal indicate strong multi-class discrimination. The most confusion was between dark spots and dark circles, with five samples incorrectly classified. This was due to similar pigmentation features in the periorbital and malar facial areas. Acne and moles showed the least confusion with each other.

Table II. Confusion matrix — CNN model (480 test samples)

Actual ↓ Predicted →	Acne	Dark spots	Dark circles	Moles
Acne	114	3	2	1
Dark spots	2	111	5	2
Dark circles	2	6	109	3
Moles	1	2	2	115

Correct (diagonal) Main misclassification

D. System Latency

The end-to-end processing latency was also evaluated for 50 consecutive test runs on Raspberry Pi 4 hardware. Table III provides the maximum values for all the steps in the processing chain.

The average time it takes for something to go from start to finish is 2.82 seconds. This is really good because it is, below the maximum time we allow which is 5 seconds. When we use Telegram to send a notification it takes an average of 0.82 seconds to send it after we have finished classifying something.

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Table III. System latency — 50 runs, Raspberry Pi 4 Model B

Processing stage	Mean (s)	Max (s)
Image capture and preprocessing	0.32	0.41
Face detection (Haar Cascade)	0.45	0.58
Skin classification (CNN)	1.12	1.38
Recommendation generation	0.11	0.14
Notification delivery (Telegram)	0.82	1.10
Total end-to-end	2.82	3.61

E. Comparison with Existing Systems

Table IV presents a feature-level comparison of the proposed Smart Mirror Glow Guide against representative existing systems from the literature. The proposed system is the only system to simultaneously provide a smart mirror interface, edge processing without cloud dependency, multi-condition detection across four skin conditions, and IoT-based Telegram notification delivery. Existing systems with comparable classification accuracy either depend on cloud infrastructure [4], require specialized hardware [9], or lack any notification mechanism [13].

Table IV. Feature comparison with existing systems

System	Mirror interface	Edge processing	Multi-cond. detection	IoT notify	Acc. (%)	Latency (s)	Cloud dependency
Halaby et al. [6]	Yes	Yes	No	No	N/A	>5	No
Mady [9]	Yes	Yes	Partial	No	~87	>5	No
Zhao et al. [4]	No	No	No	No	~91	>5	Yes
Badjate [13]	No	No	Yes	No	~91	>5	Yes
Proposed	Yes	Yes	Yes	Yes	93	2.82	No

F. Limitations

Despite the good performance results, some limitations of the current implementation should be noted.

Firstly, it should be noted that the accuracy of the Haar Cascade face detector could be affected by large pose variation, extreme lighting, and/or occlusion.

Secondly, it should be noted that the classification accuracy could be affected by low ambient lighting due to the lack of control of the lighting in the current implementation.

Lastly, it should be noted that the current dataset does not cover all the global skin tone ranges, which could affect the accuracy of the system for darker Fitzpatrick skin tone ranges.

Lastly, it should be noted that the current recommendation engine only relies on the rules-based mapping of the conditions to the skincare advice. Future work should include the development of the recommendation mechanisms.

It should also be noted that the system was not clinically validated, and the recommendation should only be used as general skincare advice.

V. CONCLUSION

This study introduced the Smart Mirror Glow Guide, an IoT-based intelligent system designed to perform facial skin analysis and provide automated skincare recommendations. The system utilizes real-time face detection through the use of the Haar Cascade classifier and also utilizes a lightweight Convolutional Neural Network (CNN) model in the identification of common skin problems such as acne, dark spots, dark circles, and moles present in the faces of the users. Once the face condition is detected, the system utilizes the recommendation module in providing the user with appropriate skincare suggestions through the Telegram Bot API.

All the computations are done locally using the Raspberry Pi 4 hardware, which ensures the privacy of the user and the system's ability to perform well in environments with limited internet access. From the experiments, the system was able to attain an accuracy of 93% in classifying the skin conditions while ensuring that the average processing time was less than three seconds. Therefore, the system has the potential to be used in homes, beauty centers, and community health facilities due to its low hardware cost.

The future plans involve making the system more robust. This includes the integration of more complex algorithms in the face detection module, the addition of more skin conditions and tones, and the creation of a mobile dashboard for the skin health monitoring system.

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