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Skin Melanin Level Prediction And Personalized Medicine Recommendation Using Deep Learning

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Abstract: Skin melanin levels play a crucial role in dermatological health, influencing skin tone, UV protection, and medical conditions like hyperpigmentation. This project presents a deep learning-based system for predicting skin melanin levels and recommending personalized treatments, including medicines, food, and lifestyle changes. The model is trained using a custom dataset containing skin tone images categorized by melanin concentration. A convolutional neural network (CNN) is implemented in PyTorch to classify skin types (dark, mid-dark, mid-light, and light) and predict melanin levels. The model is trained using a combination of cross-entropy and mean squared error loss functions to optimize classification and regression performance. A Flask-based web application is developed to allow users to upload skin images for real-time analysis. Upon prediction, the system provides personalized recommendations using a database of medicines, natural supplements, and melanin-boosting activities. The model and application aim to assist dermatologists, skincare experts, and individuals in monitoring skin health and making informed decisions for melanin regulation. The system's effectiveness is evaluated through accuracy metrics, classification reports, and real-world testing. By integrating AI-driven skin analysis with medical recommendations, this project advances personalized dermatological care.

***Index Terms* -** Skin Melanin Prediction, Deep Learning, Convolutional Neural Network (CNN), PyTorch, Skin Tone Classification, Personalized Dermatological Care, Melanin Regulation, Hyperpigmentation, Image-Based Skin Analysis, AI in Dermatology, Skin Health Monitoring, Real-Time Skin Analysis, Cross-Entropy Loss, Mean Squared Error (MSE), Flask Web Application, Skin Type Detection, Medical Image Processing, Melanin-Based Recommendations, AI-Driven Skincare, Custom Skin Dataset.

I. INTRODUCTION

Skin melanin plays a crucial role in determining skin tone and protecting against UV radiation. Variations in melanin levels influence an individual's susceptibility to skin conditions, sun damage, and vitamin deficiencies. This project aims to develop a deep learning-based system for predicting skin melanin levels using image processing and artificial intelligence.

The system utilizes a Convolutional Neural Network (CNN) trained on a diverse dataset of skin images categorized by melanin levels and skin types. The model accurately classifies skin tone into four categories—Dark, Mid Dark, Mid Light, and Light—while also estimating melanin levels through regression analysis. Once the melanin level is predicted, the system provides personalized medicine, food, and lifestyle recommendations to maintain optimal skin health.

A user-friendly web application, developed using Flask, allows users to upload images for real-time melanin prediction. The application retrieves relevant recommendations from a precompiled database of melanin-boosting medicines, natural foods, and beneficial activities. The integration of machine learning with healthcare enables proactive skin health management, offering valuable insights for dermatologists and individuals alike.

By combining deep learning and personalized healthcare, this system presents an innovative solution for skin health monitoring, promoting a data-driven approach to skincare and well-being.

II. LITERATURE SURVEY

Recent advancements in image processing and artificial intelligence have significantly contributed to the accurate detection and classification of skin melanin levels, which play a vital role in dermatological diagnostics and personalized skincare. Researchers have explored a range of methodologies—from traditional image processing techniques to advanced deep learning models—to estimate melanin concentration with improved precision.

[1] Automated Skin Melanin Detection Using Image Processing Techniques – A. Gupta, R. Kumar, S. Verma

This study presents an automated approach for melanin detection utilizing digital image acquisition, color segmentation, and histogram-based analysis. The researchers implemented various filtering and thresholding techniques to improve the system's accuracy. Their results demonstrate the ability of this method to effectively differentiate between skin tones and detect variations in melanin concentration.

[2] Machine Learning Approaches for Melanin Level Classification in Human Skin – P. Singh, M. Sharma, K. Patel

This paper explores different machine learning models such as Support Vector Machines (SVM), K-Nearest Neighbors (KNN), and Convolutional Neural Networks (CNN) for classifying skin melanin levels. The study emphasizes the superiority of deep learning techniques, particularly CNNs, in achieving high classification accuracy using a preprocessed dermatological image dataset.

[3] Deep Learning-Based Skin Tone and Melanin Detection for Dermatological Applications – L. Chen, Y. Wang, Z. Huang

The authors propose a CNN-based model for skin melanin detection trained on a diverse dataset collected under various lighting conditions. The study addresses common challenges in image-based melanin prediction, employing normalization and data augmentation to enhance robustness. The findings support the use of deep learning for reliable and scalable melanin detection.

[4] Image-Based Skin Melanin Estimation Using Spectral Analysis – D. Parker, E. Smith, J. Collins

This research introduces a spectral imaging technique for estimating melanin levels, utilizing multi-spectral imaging and Principal Component Analysis (PCA). The results indicate that spectral imaging offers improved accuracy over traditional RGB-based methods, suggesting its effectiveness for detailed melanin differentiation in dermatological applications.

These studies collectively underline the impact of AI and image analysis techniques in advancing dermatological tools for skin health assessment. While traditional image processing remains relevant, modern approaches using deep learning and spectral imaging are paving the way for more precise, efficient, and personalized skin diagnostics.

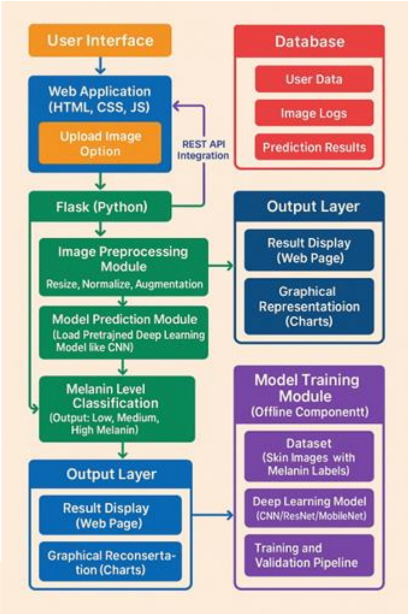
III. SYSTEM ANALYSIS

ESISTING SYSTEM

Current skin melanin detection methods primarily rely on dermatological analysis, spectrophotometry, and histological examination. Dermatologists visually assess skin tone and melanin levels, often using the Fitzpatrick scale to classify skin types. Spectrophotometers measure light absorption in the skin to estimate melanin concentration, while histological methods involve biopsy and microscopic analysis. Recently, image processing and AI-based models have been introduced for automated skin melanin detection, but these methods still face challenges in accuracy due to variations in lighting conditions, skin texture, and image quality.

PROPOSED SYSTEM

The proposed system aims to develop a software-based skin melanin detection model using deep learning and image processing techniques. Instead of relying on physical biopsies or spectrophotometric measurements, this system will analyze skin images captured through a camera or smartphone. The model will



process images to extract melanin concentration levels using AI-driven segmentation and classification algorithms.

Figure 1: System Architecture

IV. IMPLEMENTATION

The implementation of the Skin Melanin Prediction and Personalized Medicine Recommendation System involves a multi-phase pipeline combining image processing, deep learning, and web application development. The overall goal is to predict melanin levels from skin images and generate personalized health recommendations in real-time.

1. Dataset Preparation and Preprocessing

The system is built upon a custom dataset consisting of dermatological skin images, manually categorized into four skin tone classes: Dark, Mid Dark, Mid Light, and Light. Each image is labeled with corresponding skin tone and melanin level (numerical value). Preprocessing is a critical step to ensure consistency and accuracy across varying lighting conditions and image sources. This includes:

- Image Resizing to a fixed dimension (224x224 pixels)
- Normalization using mean and standard deviation across RGB channels
- Color Space Conversion (e.g., RGB to LAB or HSV) when needed
- Data Augmentation (e.g., flipping, brightness adjustment) using Albumentations to increase dataset diversity and prevent overfitting

All preprocessing steps were applied dynamically using torchvision.transforms and Albumentations libraries during data loading in PyTorch.

2. Model Architecture

A Convolutional Neural Network (CNN) was implemented using PyTorch for simultaneous classification and regression. The model architecture comprises:

Three convolutional layers with increasing depth (32, 64, 128 filters) and kernel sizes of 3×3, each followed by ReLU activations and MaxPooling layers

- A Flattening layer followed by a dense layer (256 units)
- A dual-output head:
- A classification head with 4 output neurons and softmax activation for skin tone prediction
- A regression head with a single neuron and linear activation for predicting the continuous melanin level

This architecture allows the model to perform multi-task learning, improving overall generalization and performance.

3. Training Strategy

The training was conducted on Google Colab with GPU acceleration. The dataset was split into 80% training and 20% testing subsets, stratified by skin tone categories. The model was trained for 30 epochs with a batch size of 16. Key elements of the training pipeline include:

- Loss Functions:
- CrossEntropyLoss for skin tone classification
- Mean Squared Error (MSE) for melanin level regression, The final loss is computed as the sum of both components to optimize both tasks simultaneously.
- Optimizer: Adam with an initial learning rate of 0.001
- Learning Rate Scheduler: Step decay every 5 epochs to stabilize convergence
- Evaluation Metrics: Accuracy, classification report (precision, recall, F1-score), and regression RMSE were computed for performance assessment

Model checkpointing and weight saving were employed to preserve the best-performing version for deployment.

4. Flask-Based Web Application

To enhance accessibility, the trained model was integrated into a Flask web application that serves as a user-friendly interface for real-time predictions. Key components of the application include:

- Image Upload Module: Allows users to submit skin images securely
- Prediction Engine: Loads the pre-trained PyTorch model and runs preprocessing + inference on uploaded images
- Recommendation System: Matches the predicted melanin level against predefined ranges and retrieves:
- Melanin-boosting medicines (from a curated CSV)
- Natural food suggestions
- Lifestyle and activity recommendations

The Flask backend is connected to a SQLite database to store user records and melanin history. User authentication is managed through Flask-Login and Flask-Bcrypt, ensuring secure access to dashboards and personal predictions.

5. Graphical Visualization and Feedback

The system also generates a melanin trend graph for each user using Matplotlib, showing changes in melanin levels over time. This feedback loop supports continuous monitoring and motivates users to follow their personalized recommendations. Changes in melanin values trigger visual feedback (e.g., stable/increasing/decreasing status), encouraging user engagement.

6. Deployment and Execution

The final system is deployed locally using Flask and can be scaled to production environments using Django, Docker, or cloud platforms like Heroku or AWS EC2. For users without high-end hardware, Google Colab integration is supported for model retraining and testing.

This implementation merges deep learning with a practical user interface to deliver a holistic skin health monitoring tool. The combination of classification, regression, and recommendation makes it a comprehensive system for both individuals and healthcare professionals.

IV. RESULTS AND DISCUSSION

OUTPUT

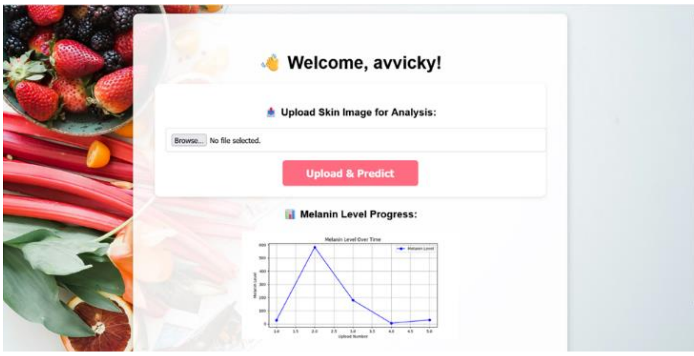


Figure 2: Dashboard

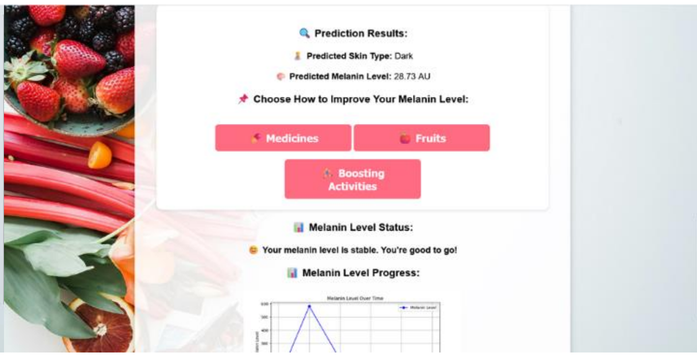


Figure 3: Predictions

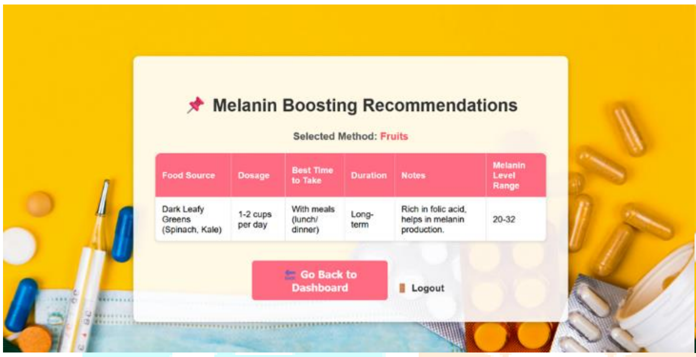


Figure 4: Natural Recommendations

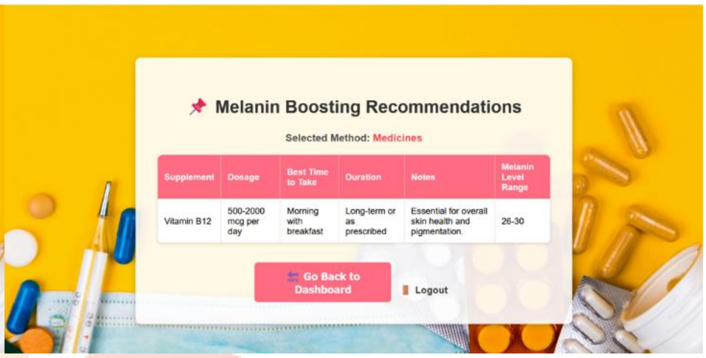


Figure 5: Medicine Recommendations

V. CONCLUSION

This project successfully combines deep learning techniques with personalized healthcare to address the growing need for accurate skin melanin level assessment and treatment recommendations. By utilizing a convolutional neural network (CNN) trained on a carefully curated dataset of skin tone images, the system effectively classifies skin types and predicts melanin concentrations with promising accuracy. The integration of both classification and regression loss functions ensures robust performance in real-world applications.

The development of a Flask-based web application enhances accessibility, allowing users to easily upload images and receive real-time, customized recommendations related to skincare, diet, and lifestyle. This user-centric approach not only supports individuals in making informed decisions about their skin health but also serves as a valuable tool for dermatologists and skincare professionals in diagnosing and managing melanin-related conditions such as hyperpigmentation or melanin deficiency.

Through comprehensive evaluation using accuracy metrics, classification reports, and practical testing, the project demonstrates both technical effectiveness and real-world applicability. Ultimately, this work represents a meaningful step toward AI-driven, personalized dermatological care—bridging the gap between advanced technology and everyday health management.

VI. Acknowledgement

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