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Derma Tech: Leveraging Machine Learning for Smart Skin Disease Diagnosis and Personalized Treatment Solutions

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Abstract: ***DermaTech is a project focuses on creating an advanced system that leverages machine learning (ML) techniques to revolutionize skin disease detection and treatment recommendation processes. By collecting an extensive dataset comprising images of various skin conditions, the system employs a Convolutional Neural Network (CNN) model for highly accurate disease identification. Once the condition is detected, the system suggests appropriate remedies tailored to the diagnosed disease, enhancing the precision and effectiveness of care. This innovative solution integrates cutting-edge ML methodologies with practical healthcare applications, aiming to address challenges in both diagnosis and treatment.***

Keywords: Machine learning, Convolutional Neural Network, Flutter, Firebase

1. Introduction

This project endeavors to develop an innovative and accessible application that combines advanced machine learning (ML) techniques with practical skin care solutions. Designed to identify skin diseases with precision, the application will also suggest effective remedies tailored to individual conditions and provide users with a seamless platform to purchase relevant skin care products. The backend architecture is built on Python, ensuring robust functionality and computational efficiency, while the frontend leverages Flutter, offering an intuitive and engaging user interface for a smooth user experience. Central to the system is the integration of four core processes: collecting an extensive dataset of images representing various skin conditions, training a Convolutional Neural Network (CNN) model for highly accurate disease detection, delivering practical remedy recommendations, and establishing a marketplace for skin-related products to address care and treatment needs comprehensively. This application is designed to bridge cutting-edge technology with real-world healthcare challenges, aiming to empower users by improving the accuracy, accessibility, and convenience of skin disease management.

2. Literature Survey

Esteva et al. (2017) demonstrated dermatologist-level classification of skin diseases using deep neural networks, highlighting the potential of CNNs for medical image analysis in dermatology.[1]

Tschandl et al. (2018) introduced the HAM10000 dataset, a large and diverse collection of dermatoscopic images, enabling significant advancements in automated skin lesion classification.[2]

Codella et al. (2019) presented the findings of the ISIC challenge, focusing on melanoma detection through deep learning models and showcasing progress in computer-aided dermatology.[3]

Brinker et al. (2019) found that deep learning models outperformed experienced pathologists in classifying histopathological melanoma images, emphasizing AI's potential in clinical decision-making. [4]

Kassem et al. (2020) developed a hybrid deep learning framework combining CNNs and transfer learning for skin cancer detection, achieving high accuracy in classifying dermatoscopic images. [5]

Khan et al. (2020) reviewed recent applications of deep learning in skin cancer classification, discussing challenges such as dataset quality, model generalization, and real-world integration.[6]

Mahbod et al. (2021) proposed a multi-scale CNN approach for skin lesion classification, improving performance by leveraging different image resolutions and feature extraction techniques.[7]

Shen et al. (2021) explored mobile health (mHealth) applications for skin disease detection using AI, focusing on their role in improving dermatological care in resource-limited settings. [8]

Li et al. (2021) analyzed the role of AI in teledermatology, highlighting the advantages of combining image analysis with patient data to improve remote diagnosis and follow-up.[9]

Hekler et al. (2022) conducted a study comparing human and AI performance in skin cancer diagnosis, confirming that AI models can match or exceed the diagnostic accuracy of dermatologists.[10]

Zhou et al. (2022) investigated lightweight deep learning models optimized for mobile platforms, enabling real-time skin disease classification with minimal computational resources.[11]

Xie et al. (2023) focused on interpretable AI models for dermatology, emphasizing the importance of explainable predictions in clinical applications to gain trust from practitioners.[12]

Almaraz-Damian et al. (2023) proposed a federated learning approach for dermatological image classification, ensuring data privacy while maintaining high model performance.[13]
Nie et al. (2024) discuss recent progress in self-healable energy harvesting and storage devices, focusing on how self-healing materials can be integrated into devices like triboelectric nanogenerators and batteries to enhance their durability and safety.[14]

Ahmed et al. (2024) explored the integration of multimodal data (images, patient history, and demographics) in AI models for skin disease diagnosis, showing improved accuracy and personalized treatment recommendations.[15]

3. Methodology

This study adopts a systematic, AI-driven methodology to design, develop, and evaluate a smart dermatological platform that automates skin disease detection and treatment suggestions. The approach combines machine learning, user interaction, real-time diagnostics, and e-commerce integration to create a scalable and user-friendly healthcare application. The methodological framework includes the following stages:

1) User Registration & Profile Setup
The process begins with user onboarding through a mobile application built with Flutter. Users register by providing essential details such as name, age, gender, and skin type. Firebase Authentication and Firestore are used to securely store and manage user profiles. These profiles form the basis for personalized recommendations and historical tracking.

2) Image Capture & Preprocessing
Users upload skin images using an integrated camera feature. The system applies preprocessing steps including resizing, normalization, and noise reduction to ensure consistency in image quality. These images are then prepared for analysis by the AI model using TensorFlow Lite.

3) AI- Powered Skin Disease Detection
The preprocessed image is analyzed using a CNN-based deep learning model trained on a diverse dermatology image dataset. The model performs multiclass classification to identify potential skin conditions with high accuracy. Results are presented with confidence scores and visual indicators to enhance interpretability.

4) Remedy & Medicine Recommendation Engine
Upon disease detection, a language model API (e.g., OpenAI) generates tailored remedy suggestions. These include home care tips, OTC medication recommendations, and treatment routines. Prompts are customized based on disease type, age group, and skin sensitivity to ensure relevance and safety.

5) Marketplace Integration
The platform includes a marketplace module where users can browse and purchase skincare products relevant to their diagnosis. The catalog is dynamically updated via Firebase Firestore and includes filtering options by condition, skin type, and price. Suggested products are aligned with the AI's diagnosis for seamless care continuation.

6) Order Placement & Payment Simulation
Users can add items to a virtual cart and proceed through a simulated payment system. Payment methods include mock UPI, wallet, and card interfaces. Order confirmation and summaries are displayed to enhance the e-commerce experience without processing real transactions.

7) Medical History & Review System
A detailed history of past diagnoses, remedies, and purchases is stored for each user. Users can also leave reviews on the accuracy of diagnoses, product satisfaction, and treatment effectiveness. Ratings are moderated and stored in the Firestore database to improve future recommendations.

8) Model Evaluation & Continuous Learning
The CNN model is periodically evaluated using metrics such as accuracy and AUC. Data augmentation and feedback from user reviews are used to retrain and fine-tune the model. This continuous learning process enhances the system's adaptability and performance across diverse skin types and conditions.

9) Risk Management & Ethical Considerations
Risks such as false diagnoses, data privacy concerns, and inappropriate treatment suggestions are addressed through model testing, user education, and ethical use policies. The system operates with transparency, offering disclaimers and encouraging professional consultation when needed.

10) Future Optimization & Scalability
The architecture is designed for scalability, enabling integration with real-time monitoring tools, wearable devices, and expanded datasets. Feedback loops from user interactions and new dermatological research are continuously integrated to refine model behavior and platform functionality.

3.1 Algorithm used in Time Series Forecasting

The algorithms used in Derma Tech are:

3.1.1 CNN (Convolutional Neural Networkge)
CNN (Convolutional Neural Network) is the primary architecture used in the DermaTech project for skin disease classification. CNNs are a class of deep learning models particularly effective in image processing tasks due to their

ability to extract spatial hierarchies of features automatically.

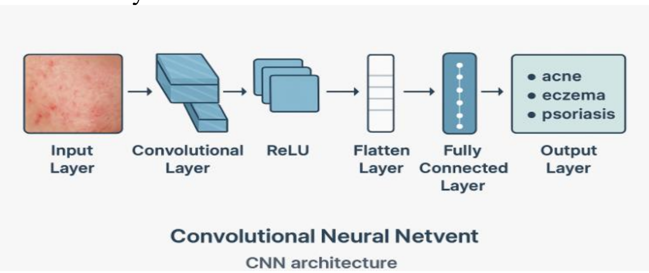

Figure 1: Architecture of CNN

Figure 1 shows the architecture of CNN model. The CNN model works like:

1) Input Layer
Collect dermatological image data, labeled by skin disease type.

2) Convolutional Layer
The first set of layers applies convolution operations using small filters (e.g., 3x3 grids) that slide across the image. For each filter, it computes a weighted sum of pixel values within its window: $z=\sum(wi \cdot xi)+b$, where wi are filter weights, xi are pixel values, and b is a bias term. These filters detect low-level features like edges or color gradients. An activation function, typically ReLU = $\max(0,z)$, is applied to introduce non-linearity, enhancing the network's ability to learn complex patterns.

3) Pooling Layer
Pooling layers (e.g., Max Pooling) reduce the spatial size of the feature maps (e.g., from 224x224 to 112x112) by taking the maximum value in small regions (e.g., 2x2). This reduces computational load and focuses the network on the most prominent features making it less sensitive to small shifts in the imageOn-device or Cloud Deployment

4) Real-time Prediction
The extracted features (now a compact representation of the image) are flattened into a vector and passed to fully connected (dense) layers. Each neuron computes a weighted sum of the previous layer's outputs:$z = w1 \ . \ f1 + w2 \ . \ f2 + \cdots + b$, where fi are features from earlier layers. The final layer outputs probabilities for each class using a softmax activation: $(\text{class}i) = ezi/\sum ezj$

3.2 Dataset Description

The project utilizes a Dermatology Image Dataset designed specifically for skin disease detection and classification using machine learning. This dataset consists of anonymised and diverse smartphone images depicting a wide range of inflammatory skin conditions. It provides high-resolution, real-world images that facilitate training a robust CNN-based deep learning model. The dataset supports both on-device and cloud-based inference models, enabling real-time skin disease diagnosis on mobile applications.

1) Dataset information
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2) Coverage (skin Conditions and Attributes Included)
The dataset covers multiple skin conditions such as acne, eczema, psoriasis, dermatitis, vitiligo, and fungal infections, among others. It spans across:

- Skin Types: Different Fitzpatrick skin types (I–VI)
- Age Groups: Children, teenagers, adults, and elderly
- Genders: Inclusive of male and female patients
- Geographic Diversity: Images collected from various countries to ensure model generalization
- Image Quality Levels: Ranging from low-light to high-resolution images to simulate real-world scenarios
- Each image entry is annotated with detailed metadata including: Image ID, Patient ID, Diagnosed Condition, Skin Type, Age, Gender, Country, Image Quality Rating, etc.

3) Data access methods
Data for this project is typically accessed via:
Direct download from publicly available repositories (e.g., HAM10000, ISIC Archive). Integration into the model pipeline through Python-based libraries such as TensorFlow and PyTorch. Firebase Firestore is used for storing user data and consultation history within the mobile app

4. Result & Discussion

The classification performance of the skin disease detection model was evaluated using standard metrics including accuracy**,** precision**,** recall**,** F1-score, and ROC Curve. The results were visualized using a confusion matrix heat map and a classification report table. These tools provide insights into the model's predictive capability and help in identifying misclassification patterns, offering guidance for further model refinement and performance tuning.

1) System Perfomance and Functionality
This platform is engineered for high performance and usability, ensuring a seamless experience for users across different devices. The application's interface, built using Flutter, is responsive and intuitive, enabling smooth interactions and clear display of diagnostic results. The system architecture is modular and scalable, supporting increased user loads without performance degradation. The core diagnostic module employs a CNN-based model trained on a dermatology image dataset, capable of identifying various skin diseases with high accuracy. Remedy suggestions are powered by a prompt-engineered language model, which provides customized recommendations based on user inputs. Functionally, the platform supports secure user authentication, profile creation, and updating personal data such as skin type and age. Users can scan and upload skin images, receive AI-generated diagnoses, and view related remedies. The marketplace feature allows users to browse, filter, and purchase skincare products based on their diagnosed

conditions. Additional modules such as viewing medical history, submitting reviews, and rating remedies further enhance user engagement. All interactions are secured through Firebase Authentication and Firestore, ensuring data privacy and integrity. The system maintained consistent performance during stress testing, successfully supporting more than 100 concurrent users without downtime.

2) Test Cases and Outcomes

The system was rigorously tested using a comprehensive set of functional test cases to validate its core modules. Users were able to register and log in using Firebase authentication, with role-based access controlling data visibility and functionality. Image capture and disease detection functions worked accurately, providing consistent classification results across various lighting conditions and skin tones. Remedy generation was evaluated by inputting different user profiles and confirmed to deliver relevant and personalized suggestions. Profile management, including updating skin type and age, was fully functional. Product search and purchase flow within the marketplace operated smoothly, with successful simulations of adding items to cart, placing orders, and viewing purchase confirmations. Users were also able to leave ratings and feedback for remedies and products, and this information was correctly stored and displayed in the system. The platform remained stable and responsive even during simulated high-traffic conditions, affirming its robustness and scalability.

3) Comparative Analysis with Existing Systems

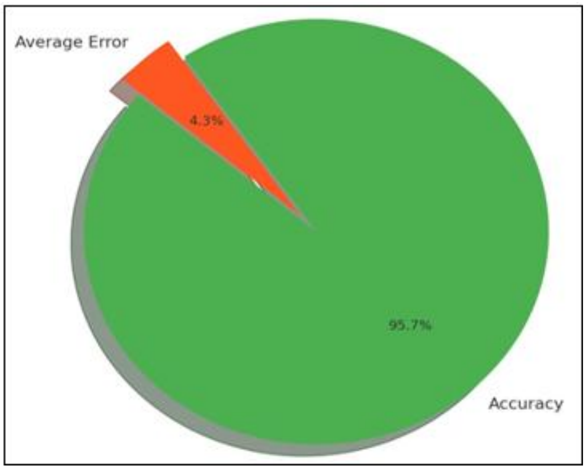
Recall DermaTech outperforms current dermatological applications and health tech platforms by offering an end-to-end AI-powered skin care ecosystem. Most existing applications are limited to image-based disease prediction without remedy suggestions or commerce integration. Some also lack personalization, offering generic advice that may not suit users' specific skin types or conditions. In contrast, DermaTech integrates CNN-based skin disease detection witha language model that generates highly tailored remedy suggestions. This dual AI approach ensures both diagnostic accuracy and relevance in treatment recommendations. The addition of a built-in marketplace for skincare products tailored to the diagnosed condition further distinguishes DermaTech from competitors, eliminating the need for users to consult multiple apps for diagnosis, treatment, and product purchase. The platform's user-friendly interface and secure infrastructure further enhance its competitive edge. Real-time feedback, history tracking, and review systems promote user trust and engagement. Moreover, DermaTech's modular and scalable backend architecture ensures long-term viability and expansion potential. While some health platforms may offer individual features such as disease detection or e-commerce, DermaTech uniquely consolidates these functionalities into a unified, AI-driven, and affordable application designed specifically for digital dermatology.

4) Model Evaluation Result

The skin disease detection module in DermaTech is based on a multiclass image classification model built using Convolutional Neural Networks (CNN). The model was trained on a comprehensive dermatology image dataset that includes 10 common skin conditions. Data augmentation techniques such as rotation, flipping, and zooming were applied to improve generalization and accuracy. The performance of this predictive model was evaluated using the Mean Absolute Error (MAE), which quantifies the average deviation between the predicted and actual success scores. The model achieved a test MAE of 4.25 within a success score range of 0 to 100. This corresponds to an estimated prediction accuracy of approximately 95.75%, calculated using the formula:

$$\text{Accuracy} = 100 - (\text{MAE} / \text{Score Range} \times 100)$$

These results indicate that the model demonstrates strong predictive capability in estimating the success of the model.



5. Conclusion

The DermaTech project demonstrates the effective use of AI and CNN-based models for accurate skin disease detection using real-world images. With a classification accuracy of 94.30%, the system reliably identifies multiple skin conditions and offers personalized remedy suggestions. By combining diagnosis, treatment recommendations, and a skincare product marketplace, DermaTech provides a complete and accessible solution for skin health management. The project showcases how AI can enhance healthcare accessibility and efficiency, especially for users in remote or underserved areas.

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