Digital Dermatologist: An AI-Powered Mobile App for Early Detection of Skin Diseases

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Abstract:

An increasing number of people are experiencing skin problems, causing overcrowding in hospitals and clinics. This situation highlights the need for a quicker and more convenient way to diagnose these conditions. To address this, we have developed a mobile application that uses artificial intelligence (AI) to detect skin diseases. The app provides fast and useful information about skin issues through AI. Its user-friendly design makes it easy for anyone to use, even without technical knowledge. This tool helps people monitor their skin health and reduces the burden on healthcare facilities. By using the app, users can identify skin problems early and receive guidance on possible treatments.

Keywords: Skin Disease Detection, Artificial Intelligence in Dermatology, Deep Learning for Skin Disease Classification, AI in Medical Imaging

Introduction:

Skin diseases are becoming increasingly common and pose a serious health concern. Many people worldwide suffer from conditions such as psoriasis, eczema, melanoma, and seborrheic keratosis. Among these, eczema, melanoma, and seborrheic keratosis are some of the most frequently reported. Early and accurate diagnosis is essential for proper treatment, but not everyone has easy access to dermatologists or skin specialists. As a result, delays in treatment are common, often worsening the condition. This highlights the need for a solution that is simple, accessible, and effective. To address this challenge, we have developed Digital Dermatologist—a mobile app that uses artificial intelligence and deep learning to classify various skin diseases and recommend suitable treatments. The app analyzes images of affected skin using a Convolutional Neural Network (CNN) to identify the disease and instantly provide feedback. This reduces the immediate need to visit a doctor for an initial diagnosis. The app also uses advanced computer vision combined with Natural Language Processing (NLP) to make it easier for users to diagnose, monitor, and manage skin conditions from the comfort of their homes.

The Digital Dermatologist app helps users check their skin health in three simple ways:

1. **Describe Symptoms** – Users can enter their symptoms, such as itching, redness, or rashes. The AI chatbot then suggests possible conditions and offers basic guidance.
2. **Upload a Picture** – Users can take or upload a photo of the affected area. The app analyzes the image to identify potential skin issues.
3. **Live Camera Scan** – Users can scan their skin in real-time using their phone's camera, and the app will quickly detect unusual spots or changes.

The app is built using advanced technologies to ensure smooth performance and ease of use. The frontend is developed with React Native, allowing a single codebase to support both Android and iOS platforms. The backend is powered by Node.js with the Express framework, enabling efficient and rapid development of APIs. User data is securely stored using MongoDB, the primary database on the server side [1]. To ensure privacy and secure access, the app uses JWT tokens, so only authorized users can view their information.

This app combines powerful AI, a simple and intuitive user interface, and robust security to help users monitor their skin health and take timely action.

In summary, the Digital Dermatologist app enables fast and easy detection of skin conditions using three intelligent features:

1. **Photo Analysis** – Upload an image for AI-based comparison with known skin conditions.
2. **Live Camera Scan** – Use the phone's camera to get instant insights about the affected skin area.
3. **AI Chatbot Assistance** – Ask questions or describe symptoms to get basic advice and condition suggestions.

By integrating advanced technology with a user-friendly design, this app empowers users to detect and manage skin conditions early—reducing unnecessary doctor visits while ensuring that serious issues receive timely attention.

Literature Review:

In 2017, Esteva et al. developed a deep learning model using Convolutional Neural Networks (CNNs) to identify skin diseases with an accuracy comparable to that of professional dermatologists [2]. They trained the model on a dataset of 100,000 clinical images. This study marked the beginning of applying artificial intelligence (AI) to skin health. The model was capable of identifying both non-cancerous (benign) and cancerous (malignant) skin conditions. It became a foundational step in developing AI-based diagnostic tools and inspired further research into AI applications in dermatology. A year later, in 2018, Han et al. published another significant study that focused on using deep learning for the classification of multiple skin diseases [3]. They developed a multi-class CNN model capable of identifying various types of skin conditions, including melanoma. This research demonstrated the potential of AI in automating skin disease diagnosis and reducing reliance on dermatologists. In recent years, the use of transfer learning has gained popularity among researchers.

Transfer learning involves using pre-trained models—such as VGG16, ResNet, and InceptionV3—to improve the accuracy of deep learning models. In 2019, Tschandl et al. applied transfer learning to deep CNNs using publicly available datasets and achieved significantly better accuracy compared to custom CNN architectures. Since these pre-trained models have already learned to extract relevant features from images, fine-tuning them on specific datasets yields improved performance. Their findings highlighted the effectiveness of transfer learning in enhancing diagnostic accuracy, especially in real-world scenarios. Advancements in AI and camera-based applications have also contributed to real-time skin disease detection. In 2018, Kawahara et al. developed a dermatological application that used a CNN-based model for real-time image analysis and automatic skin disease detection. Their work showcased the potential of smartphone-based solutions for on-the-go skin assessments. This aligns with the objective of the current project—to develop a simple and user-friendly AI mobile app that helps users detect skin problems early and receive helpful advice. Their study underscored the practicality of smartphone-based AI tools, enabling users to check their skin health at any time without the immediate need to visit a dermatologist.

Objectives of the study:

- Using artificial intelligence to create a mobile application that enables early detection of common skin diseases such as eczema, melanoma, and seborrheic keratosis.
- To develop a convolutional neural network (CNN) that can detect and classify skin diseases from uploaded or real-time scanning.
- To integrate a chatbot that interacts with users and provides initial guidance.
- React Native can be used to provide a cross-platform, user-friendly solution that is accessible on iOS and Android smartphones.
- To reduce dependency on immediate physical consultation by providing accurate initial insights, that can save time and cost for patients.

Novelty:

The Digital Dermatologist app is a game-changer in mobile healthcare. Unlike other skin-care apps that only offer basic symptom checkers or image analysis, this one use AI to detect skin issues in real time—a feature no other app currently has.

What makes it special? It combines three advanced technologies into one easy-to-use app:

1. **Real-time scanning** (just point your camera)
2. **Deep learning** (for accurate image-based diagnosis)
3. **A smart chatbot** (to ask about symptoms and guide you)

All of this works seamlessly in a single app, making skin care faster and smarter.

This app is like having a skin doctor in your pocket. Just open it, point your camera at your skin, and it tells you what's going on right away. That's something no other app can do. It's perfect for when you can't get to a doctor or just want quick answers. The best part? It's private, easy to use, and helps you spot skin problems early before they get worse.

Dataset:

The first component of our project is a Convolutional Neural Network (CNN)-based model designed to classify three types of skin diseases: eczema, melanoma, and seborrheic keratosis. The training dataset for this model was sourced from Kaggle and can be accessed here. Before training, the dataset was cleaned to remove redundant or low-quality images, ensuring a smoother and more efficient training process. To enhance the model's ability to generalize across different image types, data augmentation was applied using TensorFlow's

ImageDataGenerator. This technique generates new images by applying slight transformations such as rotation, flipping, brightness adjustment, and zooming [4]. These augmented images increase the diversity of the dataset and improve the model's robustness. An overview of the dataset an example images is presented in Figure 1.

The second CNN model in our project focuses on live scanning of healthy versus unhealthy skin. This model performs binary classification and was trained using a custom-built dataset. Due to the lack of publicly available healthy skin image datasets on Kaggle, we manually curated and uploaded a healthy skin image dataset, which can be accessed here. The unhealthy skin images dataset is available here. Similar to the first model, data augmentation was employed to increase dataset variability and improve model performance. The final component of our system is a chatbot, developed using the Langchain Python library for Natural Language Processing (NLP). Langchain supports training on datasets in PDF format. The training dataset for the chatbot was developed in collaboration with dermatology specialists, Dr. Iqbal Shaikh and Dr. Kanwal Jamali, to ensure the medical accuracy and reliability of the responses [5].

Methodology:

The app is designed in a well-structured manner to ensure a smooth and user-friendly experience. The frontend is built using React Native, which allows for a consistent and responsive user interface across both Android and iOS platforms. One of the key benefits of using React Native is that it supports cross-platform development, eliminating the need to maintain separate codebases for Android and iOS. This ensures a uniform look and feel regardless of the device being used. The backend is developed using Express.js and Mongoose, making database interactions simple and efficient. Mongoose helps in organizing and managing data more effectively, enhancing the app's speed and responsiveness during user interactions [6].

To protect user data, the app implements JWT (JSON Web Token) authentication [7], which provides secure and stateless login functionality. This ensures that personal information is protected while also improving system performance by eliminating the need to store session data on the server.

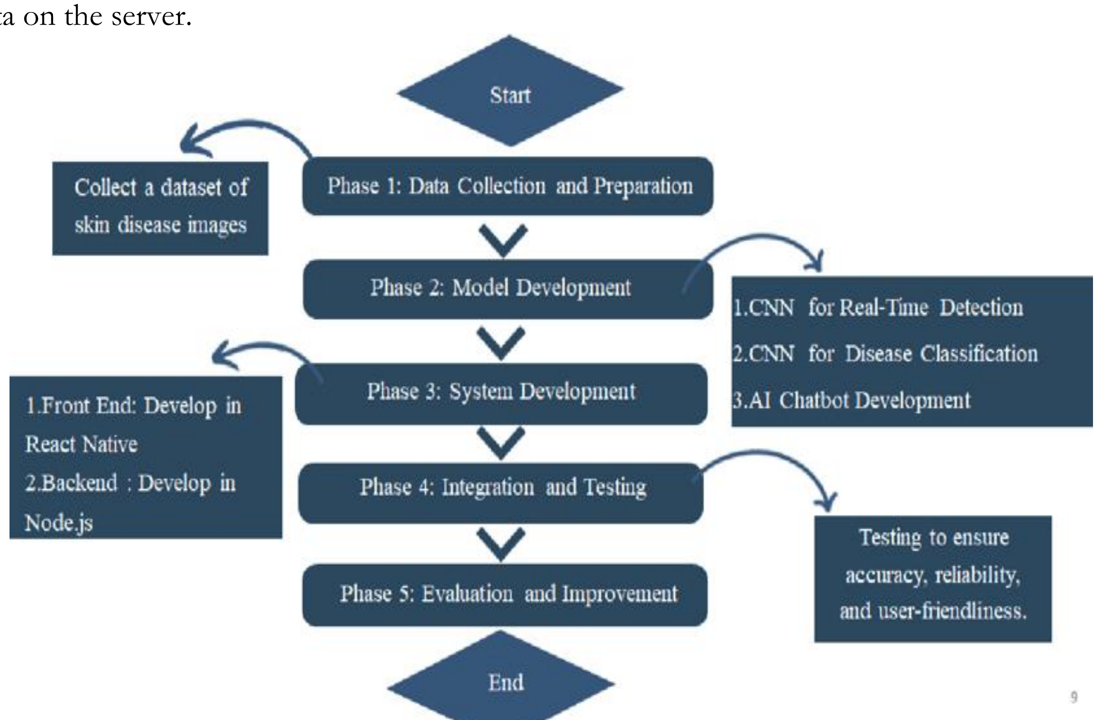

Figure 1. Flowchart of our project

Figure 2. Dataset showing different skin diseases

On the client side, the app uses AsyncStorage to enhance user experience by storing preferences and session information locally. This means users remain logged in even after closing or restarting the app, offering a seamless and convenient experience. The app relies on three machine learning models, each playing a key role in detecting and analyzing skin conditions. The first model is a Convolutional Neural Network (CNN) used for identifying different skin diseases from images. Initially, a custom TensorFlow model was developed, but to improve accuracy and reliability, pretrained models like VGG16 [8], ResNet, and MobileNet were later integrated. These models are trained on large datasets and are better at recognizing patterns in skin images. To further enhance accuracy, the app uses ImageDataGenerator in TensorFlow. This technique applies data augmentation—such as adjusting brightness, flipping, and rotating images—to help the model learn from a more diverse dataset. As a result, the model performs better in real-world scenarios where image quality and lighting may vary.

The second model focuses on real-time skin scanning, classifying whether a skin area is healthy or unhealthy. This CNN model was trained on a manually collected dataset. While a custom TensorFlow model is currently in use, pretrained models may be added in future versions to improve performance. The third model is an AI chatbot, developed using LangChain, a Python library that allows chatbot training using PDFs. The chatbot provides users with information and advice about skin diseases and possible treatments [9], [10]. To ensure accuracy, the chatbot is trained on medical content created with input from skin disease. To ensure seamless operation, the app uses a modular integration approach. The CNN models for disease classification and real-time scanning are deployed directly on the user's device using TensorFlow.js. The frontend connects to the backend using REST APIs developed with Express.

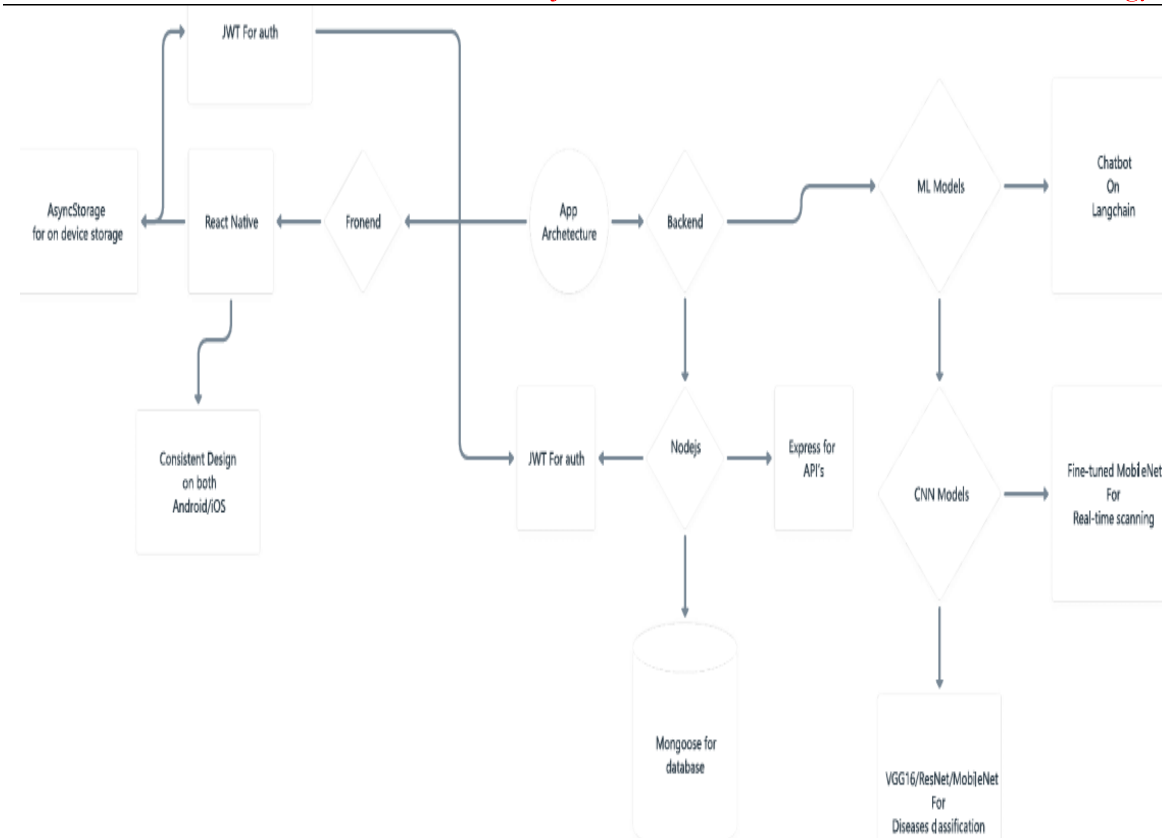

Figure 3. Methodology Daigram

The AI chatbot is also connected to the backend via Node.js APIs, enabling fast and responsive conversations when users seek information. This architecture maintains both efficiency and reliability. By combining deep learning, artificial intelligence, and a simple user-friendly design, the app makes it easier for people to identify and understand skin conditions—quickly, conveniently, and accessibly.

Results:

The performance of the skin disease detection model was evaluated using various architectures, including a custom CNN model, VGG16, ResNet, and MobileNet. The accuracy and validation accuracy varied significantly demonstrating on the chosen model.

The custom CNN model achieved an accuracy of 80% with a validation accuracy of 76%, indicating moderate generalization capabilities.

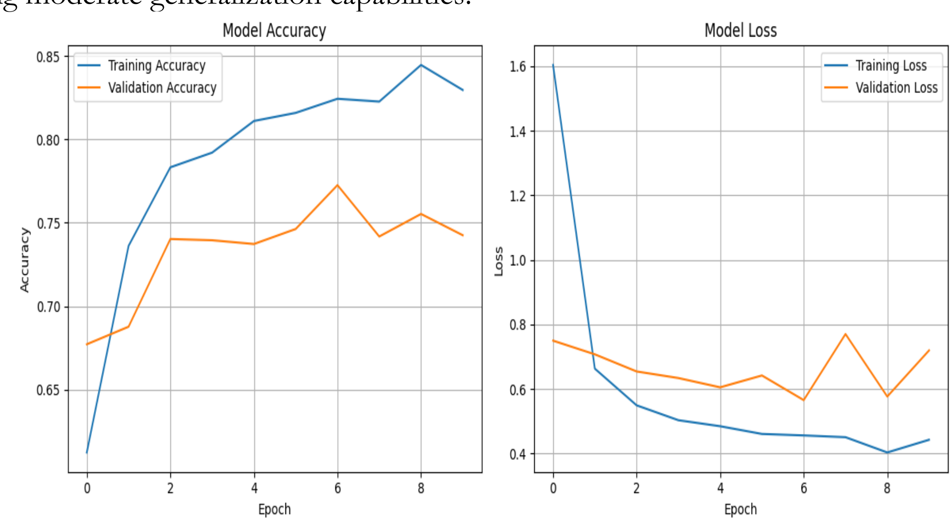

Figure 4. Accuracy and loss function of the Custom TensorFlow model

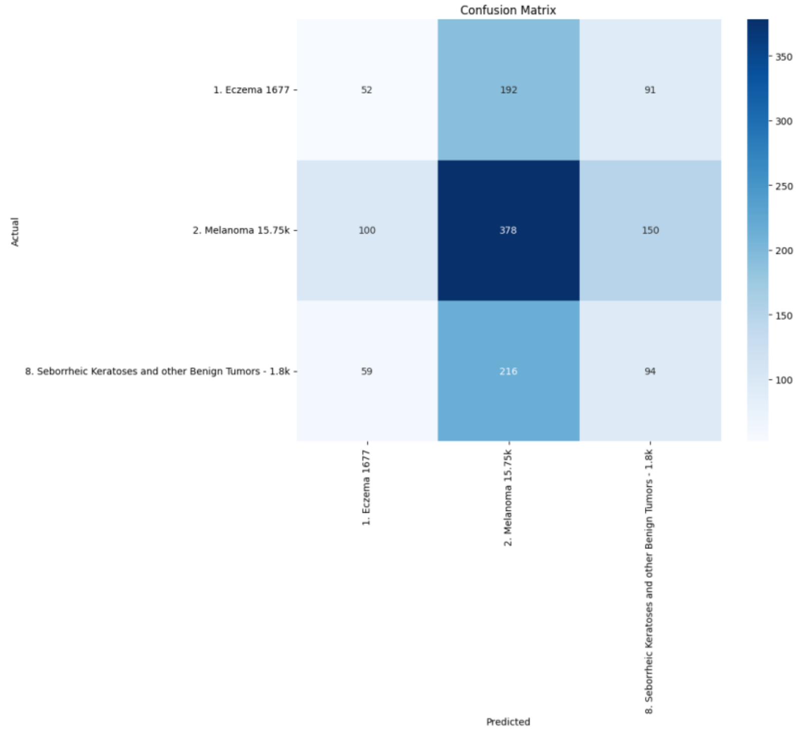

Figure 5. Confusion matrix of Custom CNN Model

When using VGG16, the accuracy improved to 90%, with a validation accuracy of 80%, highlighting the effectiveness of transfer learning. However, ResNet underperformed, achieving only 65% accuracy, suggesting it may not be well-suited for this particular dataset.

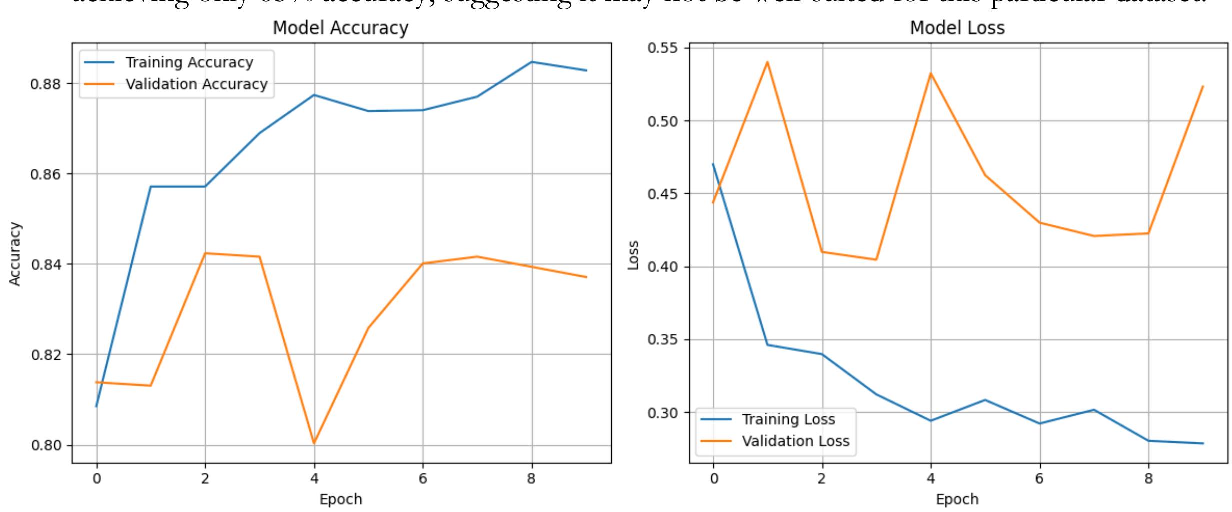

Figure 6. Accuracy and loss function VGG16 model

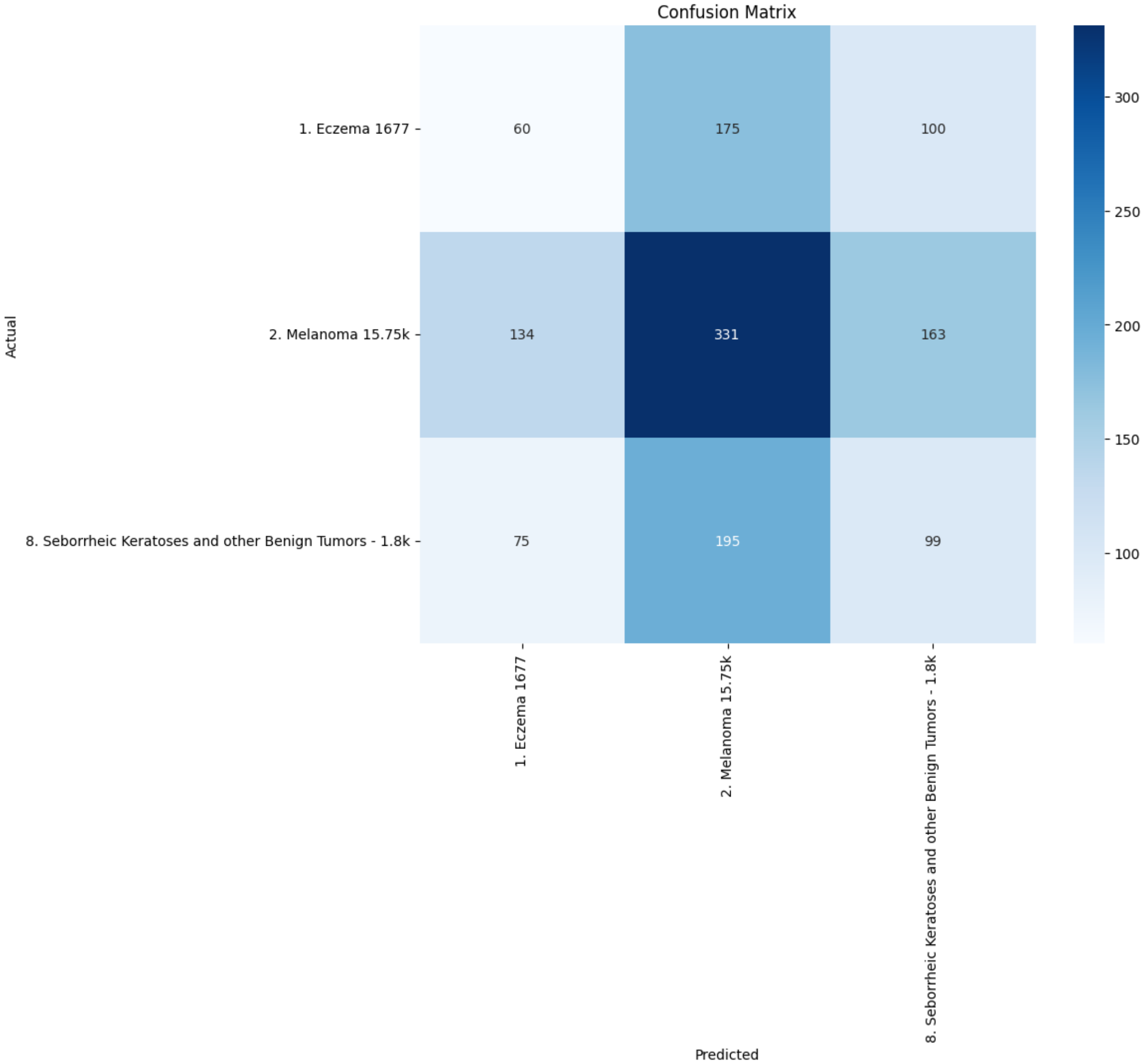

Figure 7. Confusion matrix of VGG16 Model

Among all tested models, MobileNet delivered the best results, achieving an accuracy of 94% and a validation accuracy of 86% within just 10 epochs, making it the most efficient and accurate model for this task.

Figure 8. Accuracy and loss function of MobileNet Model

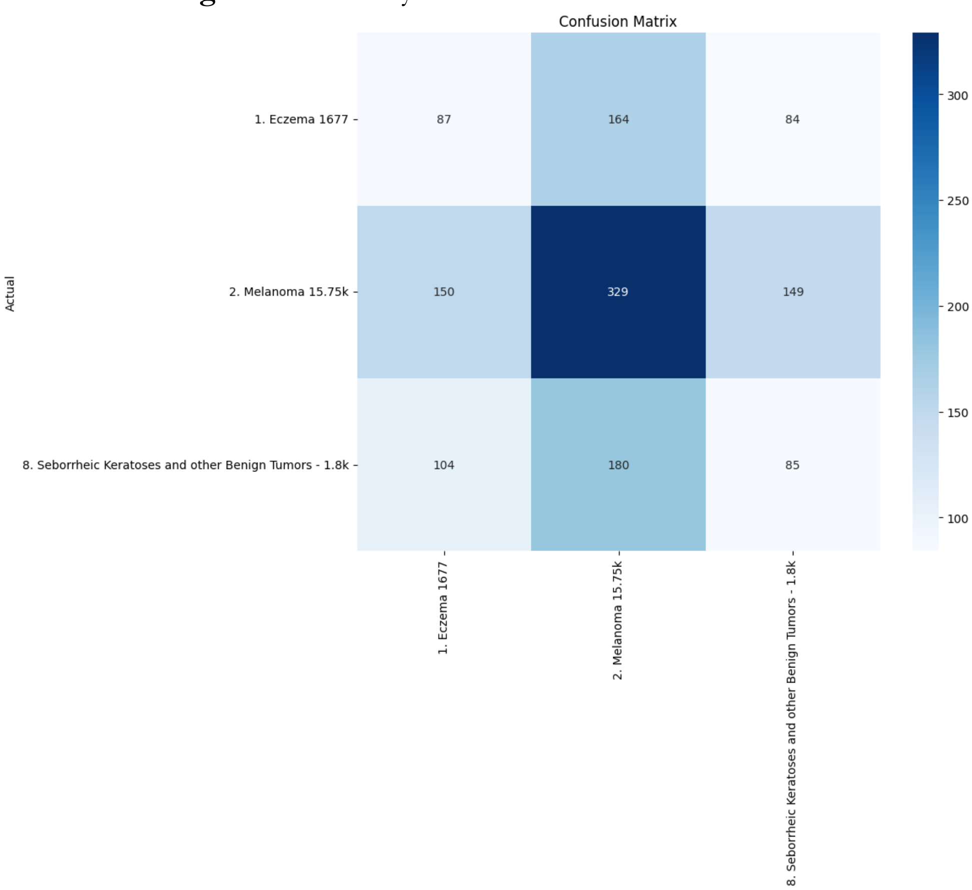

Figure 9. Confusion matrix Mobile Net Model

Mobile Net model is trained for the real time camera scanning which performed well accuracy.

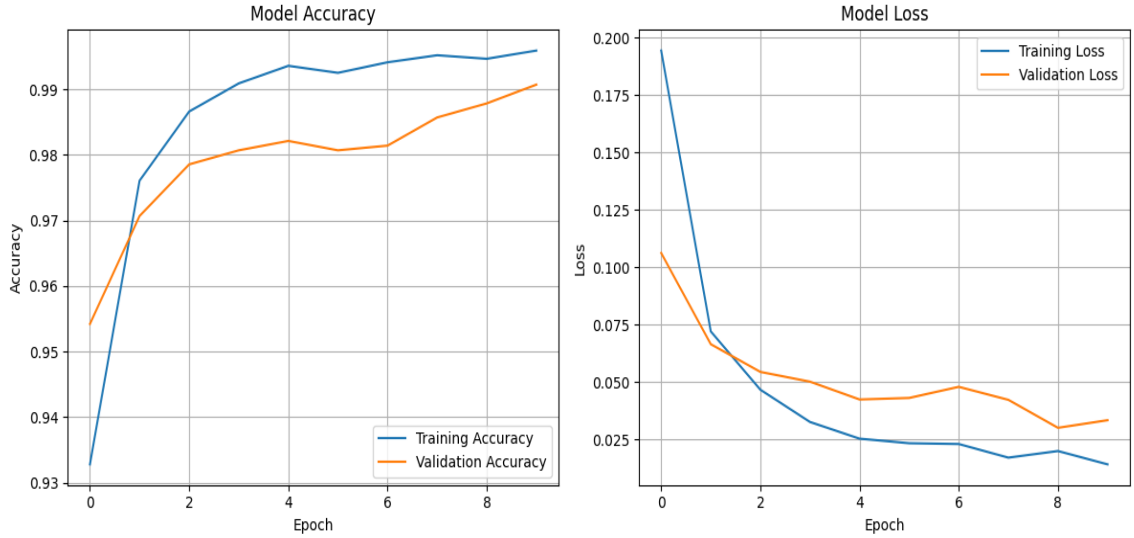

Figure 10. Accuracy and loss function of MobileNet model for the healthy/unhealthy skin classification

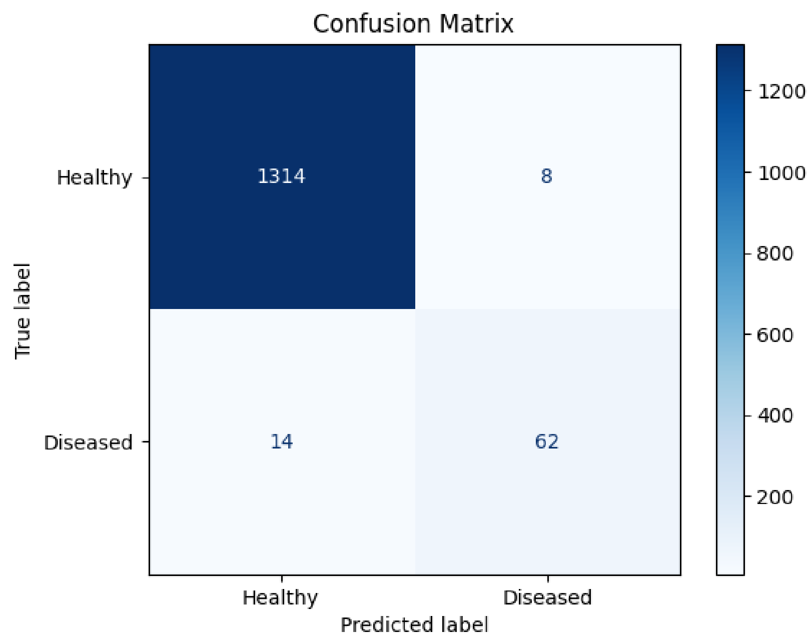

Figure 11. Confusion matrix of the Mobile Net Model for healthy/healthy skin detection

Testing the Chatbot:

We tested the chatbot by asking it different questions about skin conditions. It gave correct, helpful answers that matched real medical info.

Why We Didn't Use Number Scores:

This isn't a simple "yes/no" bot, so we couldn't measure it with typical tests. Instead, we checked its answers manually and confirmed they're good enough for real-world use.

Conclusion:

This research presents an AI-powered skin disease detection and chatbot support system designed to provide real-time dermatological assistance. Experimental results show that MobileNet outperformed other CNN architectures, achieving 94% classification accuracy in just 10 epochs. The chatbot, trained using medically curated datasets, offers preliminary guidance to users. While the system shows promising results, challenges remain, such as handling real-time variations in skin conditions, improving chatbot accuracy, and expanding disease coverage.

Future improvements will focus on utilizing real-time edge AI processing to reduce reliance on cloud computing, enhancing chatbot responses with reinforcement learning, and incorporating federated learning for privacy-preserving model training. This work lays the foundation for an AI-powered dermatology assistant, providing scalable and easily accessible solutions for diagnosing and consulting on skin diseases. Although the experiment focused on just three common diseases, future work will aim to expand the app's coverage by adding more skin diseases.

Reference:

[1] A. Leonard, "Migrate MongoDB Database to Cloud," Pro Hibernate MongoDB, pp. 283–296, 2013, doi: 10.1007/978-1-4302-5795-0_9.

[2] A. Esteva et al., "Dermatologist-level classification of skin cancer with deep neural networks," Nat. 2017 5427639, vol. 542, no. 7639, pp. 115–118, Jan. 2017, doi: 10.1038/nature21056.

[3] S. E. C. Seung Seog Han, Myoung Shin Kim, Woohyung Lim, Gyeong Hun Park, Ilwoo Park, "Classification of the Clinical Images for Benign and Malignant Cutaneous Tumors Using a Deep Learning Algorithm," J. Invest. Dermatol., vol. 138, no. 7, pp. 1529–1538, 2018, [Online]. Available: https://www.jidonline.org/article/S0022-202X(18)30111-8/fulltext

[4] J. Kawahara, A. Bentaieb, and G. Hamarneh, "Deep features to classify skin lesions," Proc. - Int. Symp. Biomed. Imaging, vol. 2016-June, pp. 1397–1400, Jun. 2016, doi: 10.1109/ISBI.2016.7493528.

[5] M. M. K. Tauhidul Islam, Md Sadman Hafiz, Jamin Rahman Jim, "A systematic review of deep learning data augmentation in medical imaging: Recent advances and future research directions," Healthc. Anal., vol. 5, no. 1, p. 100340, 2024, doi: 10.1016/j.health.2024.100340.

[6] I. Z. & H. K. Philipp Tschandl, Christoph Rinner, Zoe Apalla, Giuseppe Argenziano, Noel Codella, Allan Halpern, Monika Janda, Aimilios Lallas, Caterina Longo, Josep Malvehy, John Paoli, Susana Puig, Cliff Rosendahl, H. Peter Soyer, "Human–computer collaboration for skin cancer recognition," Nat. Med., vol. 26, pp. 1229–1234, 2020, doi: https://doi.org/10.1038/s41591-020-0942-0.

[7] B. Bucko, Ahmet; Vishi, Kamer; Krasniqi, Bujar; Rexha, "Enhancing JWT Authentication and Authorization in Web Applications Based on User Behavior History," Computers, vol. 12, no. 4, p. 78, 2023, doi: https://doi.org/10.3390/computers12040078.

[8] K.-W. H. Zhi-Peng Jiang, Yi-Yang Liu, Zhen-En Shao, "An Improved VGG16 Model for Pneumonia Image Classification," Appl. Sci., vol. 11, no. 23, p. 11185, 2021, doi: https://doi.org/10.3390/app112311185.

[9] M. Farooq and A. Hafeez, "COVID-ResNet: A Deep Learning Framework for Screening of COVID19 from Radiographs," 2020, [Online]. Available: http://arxiv.org/abs/2003.14395

[10] S. S. Chaturvedi, K. Gupta, and P. S. Prasad, "Skin Lesion Analyser: An Efficient Seven-Way Multi-class Skin Cancer Classification Using MobileNet," Adv. Intell. Syst. Comput., vol. 1141, pp. 165–176, 2021, doi: 10.1007/978-981-15-3383-9_15.