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IMPLEMENTATION OF A MOBILE SKIN INFECTION DIAGNOSIS SYSTEM USING DEEP-LEARNING

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Abstract: Skin Infection is the most common type of infection. It is caused by multiple reasons, some of which includes bacteria, allergies, viruses, etc. The advancement of computer technologies in addition to improvement in the medical field makes it possible to diagnose skin infections quickly and more accurately. Due to increase in the cost of diagnosis in hospitals and the time constraints involved, image classification techniques plays a major role in skin infection diagnosis. The image classification process makes use of feature extraction technique to help in the skin infection diagnosis process. Convolutional Neural Network has played a major role in the feature extraction process. This paper contributes to the research of skin infection detection and the introduction of first-aid steps depending on what kind of infection is present. The image classification process takes the image of the infected area, and then uses image classification to classify the infection based on the infection type. The proposed approach is easy to use and does not require much equipment, other than a mobile device with a working camera and a computer. The approach works by comparing the captured image with the set of pre-trained images using Mobile-net. Finally the results are displayed to the user, including the type of infection, a step by step first aid process and more information on the type of infection. This system successfully detects 3 types of skin infections with 68% accuracy.
Keywords: Skin Infection, Deep-Learning, Convolutional Neural Network, Mobile-Net, Image Classification.

1. INTRODUCTION

Skin diseases are more common than other diseases. Skin diseases may be caused by fungal infection, bacteria, allergy, or viruses, etc. [1]. In the field of healthcare technology, an innovative approach to determine skin-related diseases is emerging. With its debut, deep learning a potent technique that emulates how human brains learn has raised the prospect of a new era in the identification of skin diseases. Skin diseases can differ greatly, making diagnosis difficult and time-consuming. Even while they work well, traditional approaches can be subjective and time-consuming. A new viewpoint is provided by deep learning, particularly when using models such as convolutional neural networks (CNNs). These models are particularly good at finding patterns in large datasets and extracting characteristics from them. This approach is easy to use and does not require much equipment, other than a mobile device with a functioning camera and a computer. Dermatology is the medical specialty that deals with diseases and conditions affecting the skin, hair, scalp. However, a larger part of dermatology focuses on skin issues and treatments. [2].

2. REVIEW OF LITERATURE

A number of researchers have suggested methods for identifying the different types of skin diseases that rely on image classification. In order to carry out this study, it is highly important to critically review all available and relevant literatures in relation to skin infection diagnosis using deep-learning so as to establish and validate the status of this research work.

In [1], a research on the realm of skin disease classification, comparing the accuracy of pre-trained CNN models was carried out. The research not only contributes insights into overcoming limited data challenges but also emphasizes the practical deployment of trained models in Android applications.

The focus of [2] was on developing an efficient skin disease classification system using MobileNet V2 with Long Short-Term Memory network (LSTM), offering a non-invasive and cost-effective diagnosis method. Evaluation metrics such as Sensitivity, Specificity, Accuracy, Jaccard Similarity Index (JSI), and Mathew Coefficient Correlation (MCC) provide a comprehensive assessment of the model's performance.

[3] sheds light on the advantages of Computer-Aided Diagnosis (CAD) in skin disease identification, emphasizing the speed and efficiency it brings to the diagnostic process. It acknowledges the system's effectiveness but suggests further research to refine the classification scheme and streamline the feature extraction process.

In [4], an automated skin disease diagnostic system is proposed, leveraging the power of a pre-trained AlexNet model. The study aims to diagnose the nine most common skin disorders in Nigeria, emphasizing the importance of expanding and improving the quality of datasets for future training sessions. [5] introduces a mobile system for skin disease diagnosis using deep learning and smartphones. Notable contributions include an affordable and noninvasive diagnostic tool, a modified ResNet-18 model, and a comprehensive dataset for seven-class skin lesion classification.

[6] focuses on automating skin disease diagnosis, this study achieves impressive results using a pre-trained MobileNet-V2 model. Multiclass classification accuracy, sensitivity, and precision metrics demonstrate the system's excellent diagnostic performance for five common skin diseases. In [7], the research explores automated skin disease detection using transfer learning in convolutional neural networks. The study achieves a high accuracy of 94.4% by experimenting with various data sampling and preprocessing techniques, highlighting the potential for enhancing model accuracy through different approaches.

[8] demonstrates the potential of deep learning models in recognizing a wide range of skin lesions; this study sets a new state-of-the-art result for 23-class classification. It showcases the competence of Deep Neural Networks (DNNs) and the effective utilization of multi-modal input for improved classification results in dermatology. [9] evaluates the diagnostic accuracy of the Skin Image Search (SIS) AI application, comparing its performance with existing dermatological diagnostic methods. The study provides independent validation of the application's capabilities, identifying areas for further investigation.

[10] offers a comprehensive review by analyzing 45 research efforts in skin disease identification using deep learning technology. The study assesses various aspects, including disease type, dataset, data processing technology, and deep learning frameworks, providing a valuable overview of the progress in the field.

3. DESCRIPTION OF DATASET

We assembled the dataset by gathering images from Kaggle concentrating on the three specific skin conditions and dataset on healthy skin was gathered using a mobile device camera. Each disease is represented by over 1000 photos in the database with reasonable amount of images for melanoma, impetigo and eczema while the healthy skin dataset consists of over 100 images of healthy skin images. The datasets were divided using an 80:20 ratio; 80 for training data, 20 for test data.
A sampling of the images is displayed in Fig 1.

Fig 1: The first image is for eczema, the second image is for impetigo, the third image is melanoma and the last is for the healthy skin.

4. METHODOLOGY

In this section, the methodology of the system for skin infection diagnosis using deep-learning model is described. The system will assist in the detection of infections (Melanoma, Eczema and Impetigo) and also for Healthy skin. The flow diagram of the system for skin infection classification is shown in figure 2.

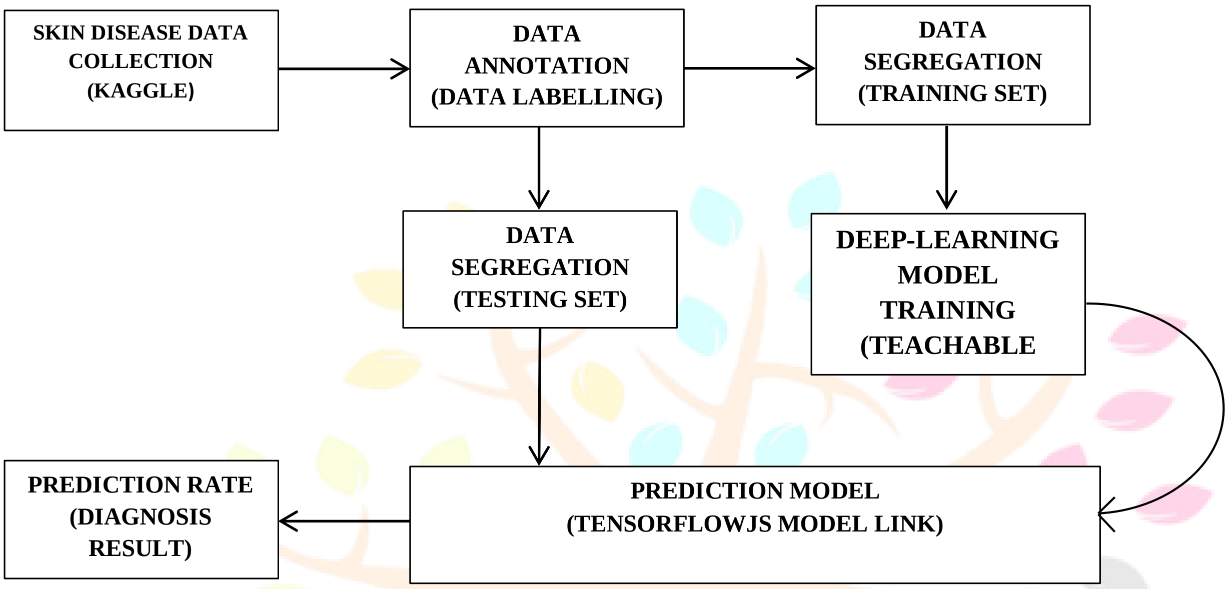


Fig 2: Flow Diagram for the skin disease identification system methodology.

In the initial phase, the data collection process involved acquiring a dataset specifically focused on impetigo, eczema, and melanoma from Kaggle and also a set of Healthy skin images. Subsequently, this dataset underwent annotation and organization into dedicated folders for each disease category. To facilitate model training, the dataset was further split into training and test sets, with an 80:20 ratio, allocating 80% for training data and 20% for testing. The training process utilized Teachable Machine, a Google AI model training engine, known for its efficiency in accelerating the image classification model training. Following the training phase, the model was hosted on the Google Cloud platform, and a unique link associated with the model was generated. This link serves as a crucial component integrated into the backend system, facilitating the image classification process. Once the link to the trained model was successfully added to the backend, a fetch function is implemented. This function enables the retrieval of the model's predictions, providing a prediction rate for the identified skin infections. The seamless integration of these steps streamlines the image classification process, ultimately enhancing the accuracy and efficiency of predicting impetigo, eczema, melanoma and healthy skin based on the trained model.

4.1 THE CLIENT-SIDE

The client-side application is developed using React Native, a hybrid mobile application development framework based on JavaScript. This framework enables the creation of a user-friendly interface with various screens to enhance the overall user experience. Key screens within the application include the camera screen, diagnosis screen, first aid screen, and an informative screen for detailed insights into specific skin infections.

The camera screen is designed to access the mobile device camera for capturing and storing images of skin. This functionality is implemented using the React Native Expo camera package, allowing users to capture, switch cameras, and store images in the device memory.

In the diagnosis screen, users can select the captured image for diagnosis. Leveraging Firebase Cloud Bucket, the local image is transformed into a remote image accessible from any location with internet

connectivity. The image classification process involves Create, Read, Update, and Delete (CRUD) operations, with POST for image submission and GET for retrieving the prediction rate.
The first aid screen provides step-by-step guidance on first aid methods tailored to the type of skin infection predicted by the system. This feature aims to offer immediate assistance and relevant information to users.
The 'read more' screen serves as an informative resource, providing additional details about the specific type of skin infection predicted. This enhances user understanding by offering in-depth insights into the nature of the identified skin condition.

4.2 THE SERVER SIDE

The backend system is implemented using Express.js, a runtime environment for JavaScript. To initiate the backend project, Express.js is installed and configured using the following commands: `npm init` for project setup and manual input for server configuration. Dependencies like Express, dotenv, CORS, and @sashido/teachablemachine-node for image classification are installed with the command: `npm install express dotenv cors @sashido/teachablemachine-node`. After installation, the server is started to listen for requests at a specified port or the default system environment port. The use of `process.environment` allows dynamic port identification during deployment. This approach accommodates the allocation of a dynamic port number by the host server network during production deployment. The project integrates the Teachable Machine library for image classification. A specific Teachable Machine model is selected, and its corresponding URL is configured in the project. The chosen model, hosted on Google Cloud at "https://teachablemachine.withgoogle.com/models/xxxxxxx/", is incorporated into the Express application. Middleware is set up, and an endpoint, '/image/classify', is defined to handle image classification requests. The server expects an image URL in the query parameters. The Teachable Machine library is utilized for image classification, and predictions are sent as a JSON response. The server listens on the specified port, with console logs indicating the listening address.

5. RESULT

This system implementation was done using React-native, ExpressJs and @sashido/teachablemachine-node. An AMD Ryzen 3 2200U with Radeon Vega Mobile Gfx 2.50 GHz with a 8Gb RAM and a Samsung A03 core mobile device was used. Figure 3, 4, 5, 6, 7 and 8 shows the results of the implementation. The result is a hybrid mobile application that is simple to use and easy to navigate. Upon opening the app, users are greeted with onboarding screens to familiarize them with the application's features. Following this, users input their details before proceeding to the image capture screen.
Here, users effortlessly capture and store images of infected areas directly to their device memory. Moving forward, users access the 'diagnosis' screen to select the saved image for analysis. Utilizing Firebase, the app converts the selected image into a remote URL for diagnosis.
Results are promptly displayed, providing users with valuable insights. They then have the option to switch between a 'first-aid' screen for immediate assistance and a 'read-more' screen for additional information. This seamless process empowers users to efficiently navigate through the app, making health management accessible and straightforward.

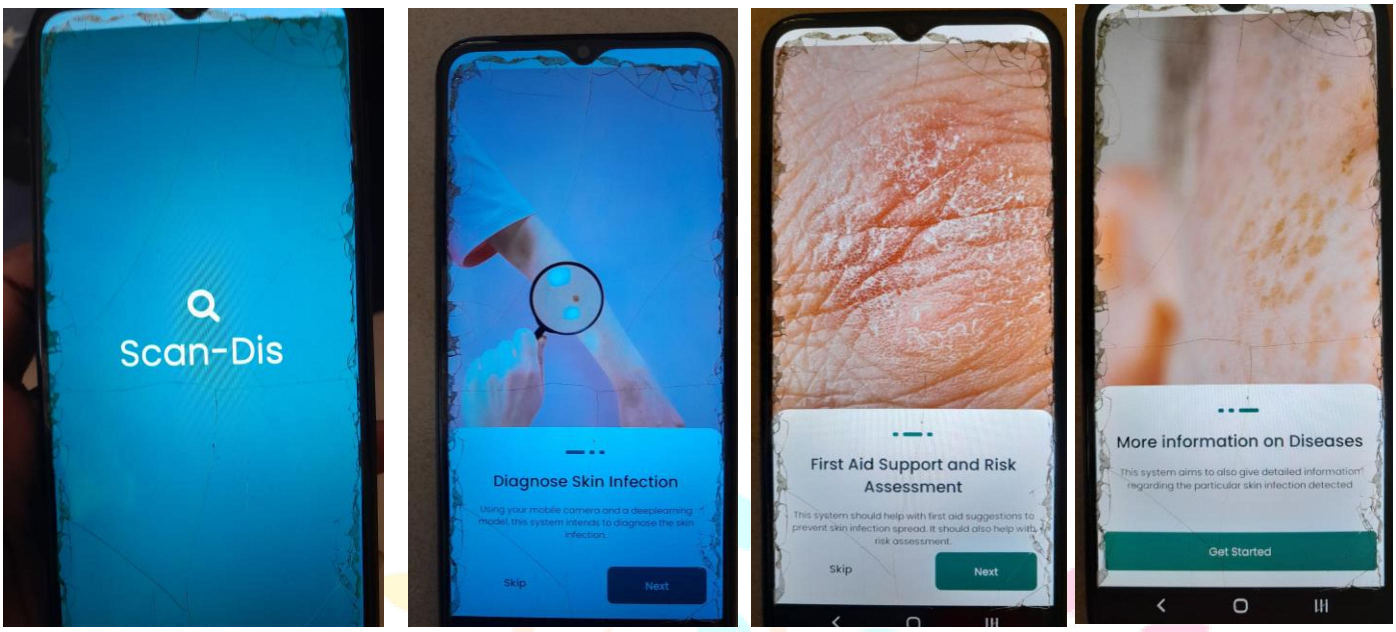


Fig 3: Onboarding Screens.

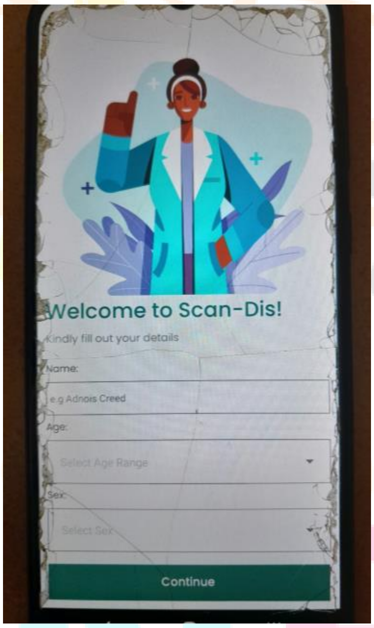
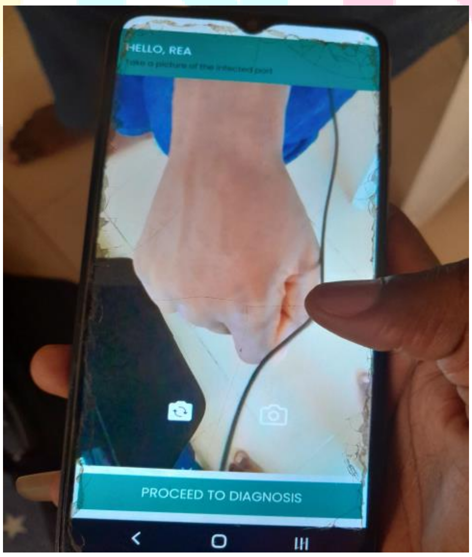


Fig 4: User Input Form Screen.



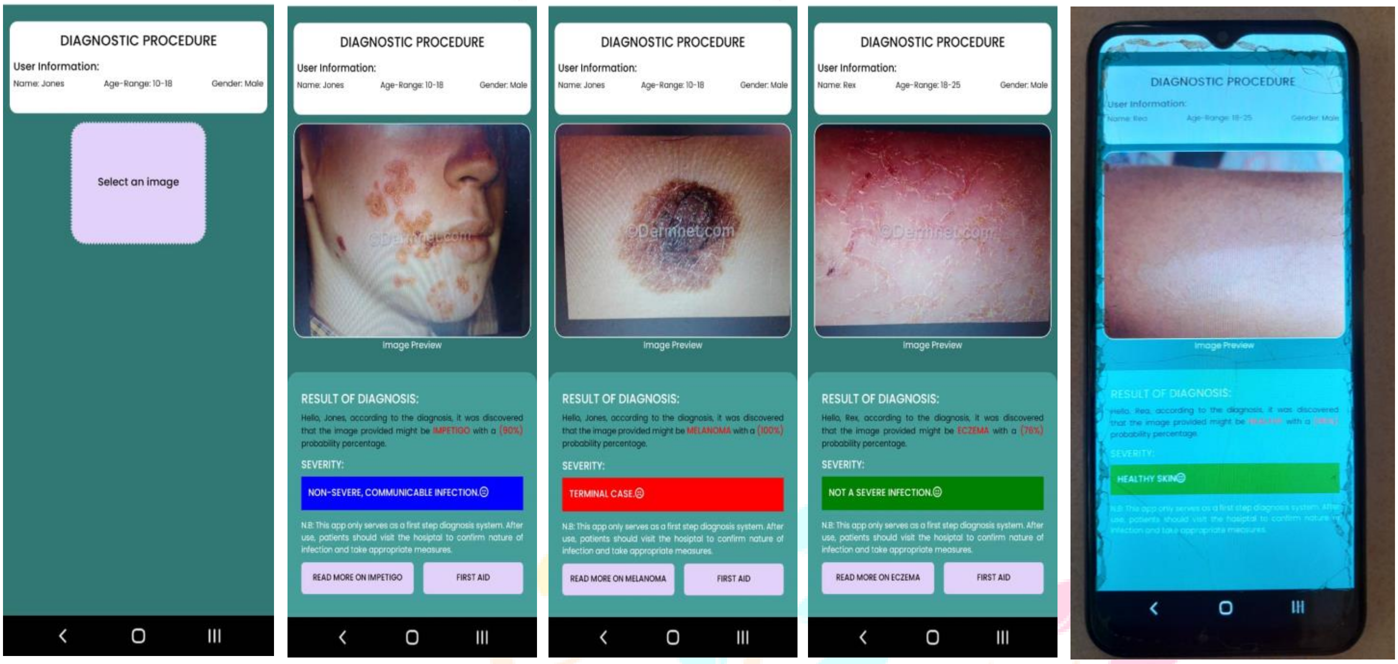


Fig 5: Camera Screen.

Fig 6: Diagnosis Screens

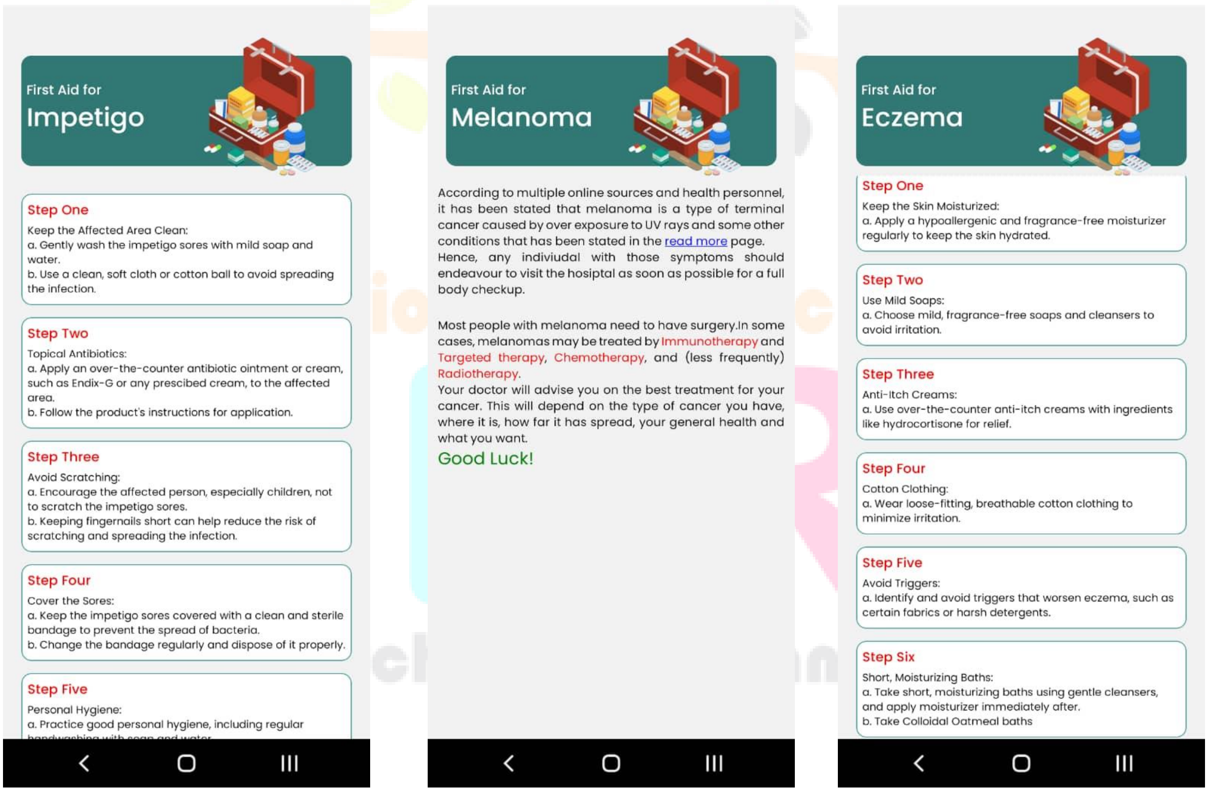


Fig 7: First aid Screens.

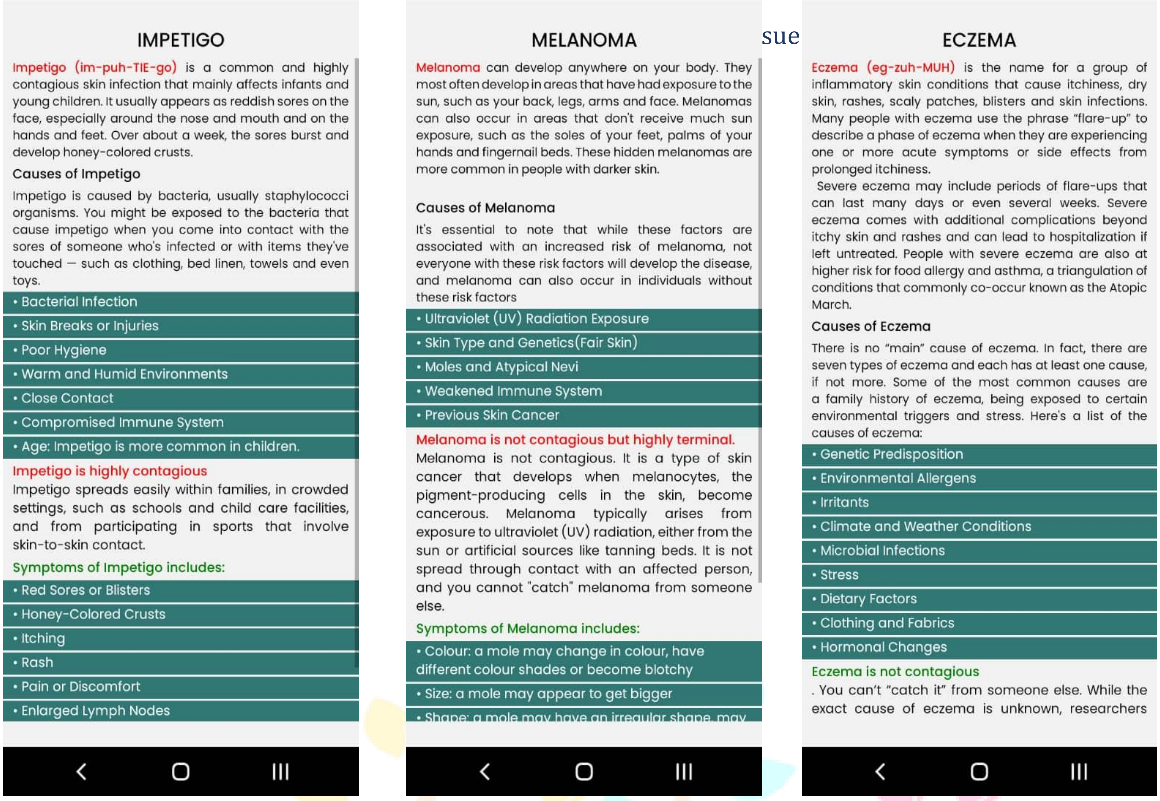


Fig 8: 'read more' Screens.

6. FUTURE WORKS

Future developments call for a number of improvements and extensions. Initially, skin lesions in the dermis layer of the skin must be identified. New approaches must be developed for detection of all skin diseases worldwide, along with their respective degrees of severity. New technology can be worked on for identification of skin diseases and remedies for a better life.

7. CONCLUSION

One of the most crucial steps in reducing the rate of disease, its spread, and its growth is the early detection of skin disorders. Clinical tests to identify skin conditions are costly and time-consuming. Early on in the development of a mobile skin infection diagnosis system, image classification technique was helpful to classify a skin infection. One important factor in the classification of skin diseases is the feature extraction process, during the classification process, the images are checked thoroughly and the distinct feature related to the set of data is selected and is used for individual classification of images.
In this paper, a pre-trained convolutional neural network (Mobile-Net) was used to build the detecting algorithm for skin infection image classification. This research can help identify three skin conditions: eczema, impetigo, and melanoma. The table 1 below shows the confusion matrix after testing the system. After running 80 test cases, 20 each for the three skin infections and 20 for healthy skin, the confusion matrix provided detailed insights into the model's performance across different skin infections:

a) For Melanoma, out of 20 tests, the model predicted 14 correctly as melanoma, 2 as impetigo, and 4 as eczema.
b) For Eczema, out of 20 tests, the model predicted 15 correctly as eczema, 4 as impetigo, and 1 as melanoma.
c) For Impetigo, out of 20 tests, the model predicted 12 correctly as impetigo, 5 as melanoma, and 3 as eczema.
d) For Healthy skin, out of 20 tests, the model predicted 20 correctly.

Table 1: Confusion matrix for the mobile skin infection diagnosis system.

	Predicted Melanoma	Predicted Impetigo	Predicted Eczema	Predicted Healthy
Actual Melanoma	14	2	4	0
Actual Impetigo	5	12	3	0
Actual Eczema	1	4	15	0
Actual Healthy	0	0	0	20

References

[1] ALKolifi ALEnezi, N. S. (2019). A Method Of Skin Disease Detection Using Image Processing And Machine Learning. Procedia Computer Science, 163, 85-92.
[2] Omotosho, L., sotonwa, K., Adegoke, B., Oyeniran, O., & Oyeniyi, J. (2022). An Automated Skin Disease Diagnostic System Based on Deep Learning Model. Journal of Engineering Studies and Research, 27(3), 43-50.
[3] Srinivasu, P. N., SivaSai, J. G., Ijaz, M. F., Bhoi, A. K., Kim, W., & Kang, J. J. (2021). Classification of Skin Disease Using Deep Learning Neural Networks with MobileNet V2 and LSTM. Sensors (Basel, Switzerland), 21(8), 2852.
[4] Sonawane, M. M., Gore, R. D., Gawali, B. W., & Medhekar, S. (2021, January 20). Computed Aided Diagnosis System for Skin Disease Identification.
[5] Oztel, I., Yolcu Oztel, G. and Sahin, V.H. (2023), Deep Learning-Based Skin Diseases Classification using Smartphones. Adv. Intell. Syst., 5: 2300211.
[6] Muhaba, K. A., Dese, K., Aga, T. M., Zewdu, F. T., & Simegn, G. L. (2021). Automatic skin disease diagnosis using deep learning from clinical image and patient information. Skin health and disease, 2(1), e81.
[7] Velasco, J. S., Jomer, V. C., Edmund, G. M., Villamor, M. A., Glenn, C. V., & Lean, K. S. (2023). Classification of Skin Disease Using Transfer Learning in Convolutional Neural Networks. International Journal of Emerging Technology and Advanced Engineering, 13(4).
[8] Bajwa, M. N., Muta, K., Malik, M. I., Siddiqui, S. A., Braun, S. A., Homey, B., Dengel, A., & Ahmed, S. (2020). Computer-Aided Diagnosis of Skin Diseases Using Deep Neural Networks. Applied Sciences, 10(7).
[9] Zaar, O., Larson, A., Polesie, S., Saleh, K., Tarstedt, M., Olives, A., Suarez, A., Gillstedt, M., & Neittaanmäki, N. (2020). Evaluation of the Diagnostic Accuracy of an Online Artificial Intelligence Application for Skin Disease Diagnosis. Acta Derm Venereol, 100(adv00260).
[10] Li, H., Pan, Y., Zhao, J., & Zhang, L. (2021). Skin disease diagnosis with deep learning: A review. Neurocomputing, 464, 364-393.