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USING DEEP LEARNING FOR DERMATOLOGY DETECTION

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Abstract
Dermatoses are the fourth most common disease in humans and cause a heavy burden on daily life. They are caused by chemical, physical, and toxic substances. Visual inspection combined with medical records is a diagnostic method for the disease. However, this process is manual, time consuming, and requires expertise and approval. Purpose: This study used a technology that can diagnose five skin diseases using clinical data and patient data using deep learning before learning the mobilenet-v2 model. Medical images were acquired using a different smartphone and patient information was collected during patient registration. Use different prior data and develop pre-training methods to improve model performance.
Results: Using the proposed method, the classification accuracy reached 97.5%, sensitivity reached 9 7.7%, and accuracy reached 97.7%. There are five types of skin diseases. The results showed that the developed system had good diagnostic results for five skin diseases.

Keywords: Dermatoses, Skin Diseases, Medical Image Processing, Mobilenet-v2

1.Introduction

Skin is the largest organ of the body and provides protection, regulates body fluids and temperature, and recognizes the external environment. James WD et al. (2006) Skin diseases are the most common of all human diseases, affecting approximately 900 million people worldwide. Seth.D et al. (2018). According to the Global Burden of Disease Project, Skin diseases are the fourth leading cause of death world-wide. Kelbore AG et al. (2019) It is estimated that 2187% of children in Africa are affeceed by skin diseases. Tuchayi SM et al. (2017). Dermatological diseases create financial, economic, and psychological impacts on societyand are dependent on doctors. Silverberg Yog (2015), Drucker AM (2017). Additionally, skin diseases can cause depression, anxiety, isolation, and suicidal thoughts. Patterns of skin diseases vary depending on environmental factors, hygiene patterns, social practices, and genetics. Diseases and illnesses are more common in developing countries. There are more than 3,000 known skin diseases worldwide. Statistics show that atopic dermatitis affects 20% of children under the age of two. Acne scarring is a chronic problem that affects 95% of people with acne vulgaris. Agel M et al. (2018) Onychomycosis occurs in 5.5% worldwide and accounts for 50% of all hand infections. In Ethiopia, 32.3% of school-age children suffer from tinea capitis. 16 The most commonly used methods in the diagnosis of skin diseases are examination of patient history and symptoms, skin scraping, eye examination, dermoscopy and skin biopsy. However, these tests are cumbersome, time-consuming and often difficult to diagnose. Many of these require the experience and vision of a dermatologist. The most advanced and powerful treatment methods are available for dermatology diagnosis. Schneider SL et al. (2018). However, these technologies are complex, expensive, and limited to centralized medical facilities, making it difficult for people with limited resources to access medical care. Recently, smartphone based imaging and sensing platforms have become an alternative method of disease diagnosis in the medical industry. New generation smartphones are equipped with advanced cameras, large capacity and high-performance processors, allowing them to store digital photos and videos at higher resolutions. CAD can reduce the burden on doctors with the help of artificial intelligence. Hameed et al. (2019) proposed a support vector machine (SVM) with a quadratic kernel. Moreover, the diagnosis, including reporting of facts, is unsatisfactory. In Abbott LM (2015) study, an automatic diagnosis based on deep learning models was developed for five skin diseases, including acne vulgaris, atopic dermatitis, lichen planus and onychomycosis. Tinea capitis is treated by combining medical images with patient data obtained using a smartphone camera.

2.Materials and Methods

This automatic diagnosis is done using the pre-trained mobilenet v2 model.
Images of the skin and the patient's medical data are preprocessed

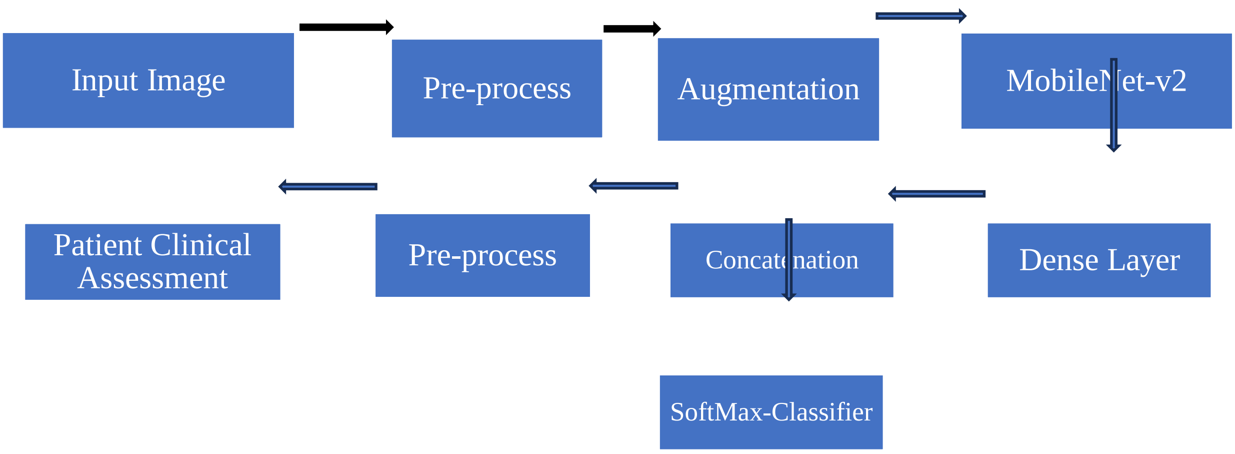

Fig.

2.1 skin disease multi-class classification system

Fig 2.1 shows the images collected for each skin disease. Patient information such as age, gender, anatomical location and symptoms of the disease was also collected at this time. Anatomical divisions include: abdomen, anterior hip, armpits, chin, ears, forehead, flanks, back, lower extremities, nails, neck, periorbital region, posterior ear, scalp cap, and upper extremities. Clinical signs and symptoms of five skin conditions are also included. A total of 41 features of the patient's data were extracted and used to build the model.

2.2 Pre-processing:

Image resizing, color correction, and data augmentation are performed before the images are fed into deep learning. All images were converted to 224* 224 pixels to fit the size of the premobilenetv2 learning model. Gray scale color constancy algorithm is used in the preprocessing step to eliminate different colors in medical images. This has been shown in the literature to increase the classification accuracy of many image sources. 32,33 Before model training, the data is divided into training (80%), validation (10%) and testing (10%). Then, data enlargement is applied to the data.

Table 2.1 Data

Diseases	Number of Images
Healthy	300
Acne Vulgaris	307
Atopic Dermatitis	289
Lichen planus	201

Tinea capitis	211

by 90° rotation, horizontal and vertical image flipping to increase the dataset.use a single-bit encoding method to transform patient data into feature vectors.

2.3 Repurposing pre-trained mobilenet-v2 model

MobileNetv2 was proposed by Sandler et al. In 2019, the 34 comes with improved functions for mobile models. Unlike the traditional residual model, it is based on the inverse residual model, where the inputs and outputs of the residual block are separate bottleneck layers.

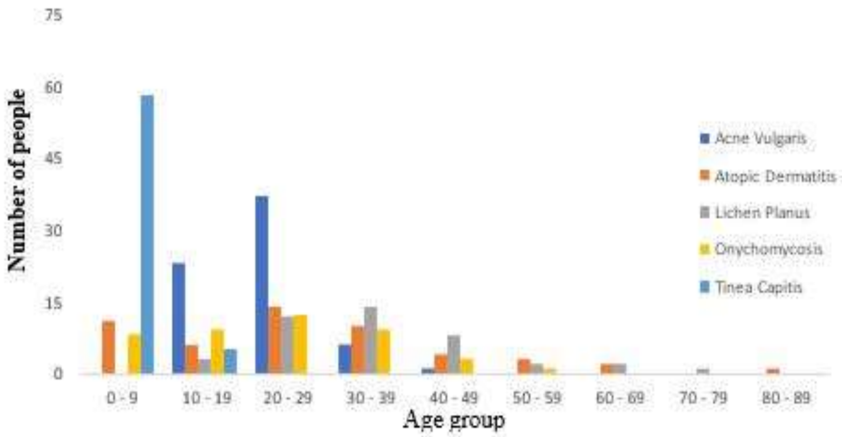

Fig 2.2 Age-wise Distribution

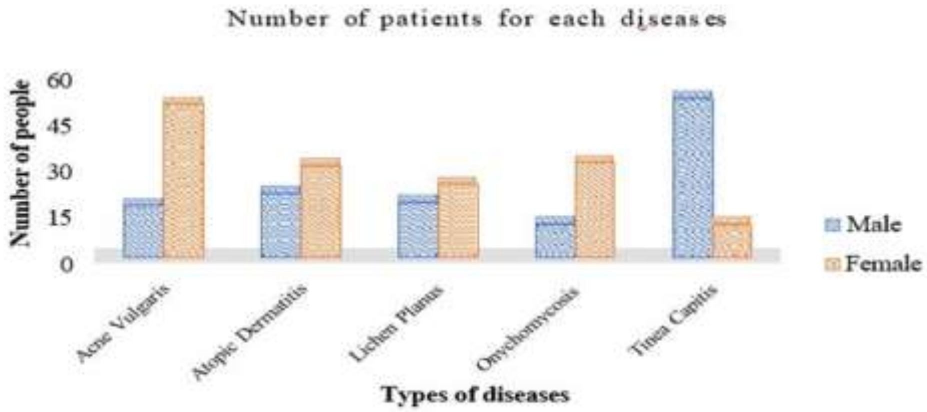

Fig 2.3 Gender-wise Distribution

3.Results

The advanced convolution process is replaced by a separate process split into to separate layers. First, deep convolutions perform lightweight filtering using 3 3kernels on each input channel. After depth convolution, point convolution creates features by calculating the corresponding lines of the input image. The feature extractor extracts 1280 image feature maps for the classifier. This model is suitable for environments where resources are limited, including smartphones. In this study, we use a transfer learning method using the mobilenetv2 pre-learning model to classify skin diseases. Both binary classes and multiple representations should be used to reduce the number of classes in the database. The best results were found using Adam optimization, cross entropy loss function and 0.0001 learning rate for binary and multiclass. Performance of the model using accuracy, precision, recall, F1 score and kappa score. Additionally, the receiver operating characteristic (ROC) curve (a graph that provides information about how well the model classifies positive and negative examples) and the kappa value, a measurement used to compare observed accuracy with expected accuracy or random chance, were used .

3.1 Pre-processing
Medical images are obtained using different smartphone cameras in different lighting conditions. Predict and correct color variations from different lighting sources using grayscale algorithms. Figure shows the results of using the grayscale algorithm on medical images.

3.2 Result of binary classification task
For the binary distribution tasks (normal and abnormal), the model correctly predicted 59 of 60 unknown test images. The accuracy, precision, recall, F1 score, and kappa values for binary classification are 98.3%, 98.5%, 98.5%, 98.0%, and 0.97, respectively. The training and validation curve, training and validation curve, confusion matrix, and ROC curve of the binary classifier.

3.3 Multi-class classification
The training model using medical images achieved only 94.2% training accuracy and 88.3% validation accuracy on the 45th run, with the lowest validation loss of 0.306. The model was split into 138 of 157 test images. Accuracy was 87.9% and kappa score was 0.86 .On the other hand, the training model using medical images and patient data achieved 99.5% training and 97.9% validation accuracy in epoch 214 with the lowest validation loss of 0.084. The model is divided into 153 images. The accuracy rate of 157 test files was 97.5% and the kappa score was 0.97 . An Android application was also developed to facilitate the use of dermatology diagnostic procedures using smartphones. Thanks to the app design, users can capture skin images, enter age, and select anatomical location, gender, and symptoms to determine the type of skin disease. Users can click the Check button to check the skin during installation. The first window detects whether the skin is healthy or abnormal. Then, if the results are abnormal, click the continue button; Another window will appear to check the five skin conditions.

Table 3. Number of clinical images collected from each anatomical site for the five skin disease

	Number of clinical images collected on each site				
Anatomical sites	Acne vulgaris	Atopic dermatitis	Lichen planus	Onychomycosis	Tinea capitis
Upper extremity	-	107	77	-	-
Lower extremity	-	63	99	-	-
Periorbital	-	6	2	-	-
Armpit	-	11	7	-	-
Navel	-	2	-	-	-
Lower back	-	4	9	-	-
Scalp	-	-	1	-	269
Nail	-	-	-	211	-
Abdomen	-	-	4	-	-
Nose	-	-	3	-	-
Ear	-	-	1	-	-
Lateral face	183	45	26	-	-
Forehead	61	4	13	-	-
Anterior torso	23	23	26	-	-
Posterior torso	31	11	4	-	-
Chin	5	-	-	-	-
Neck	4	24	17	-	-
Total	307	300	289	211	269

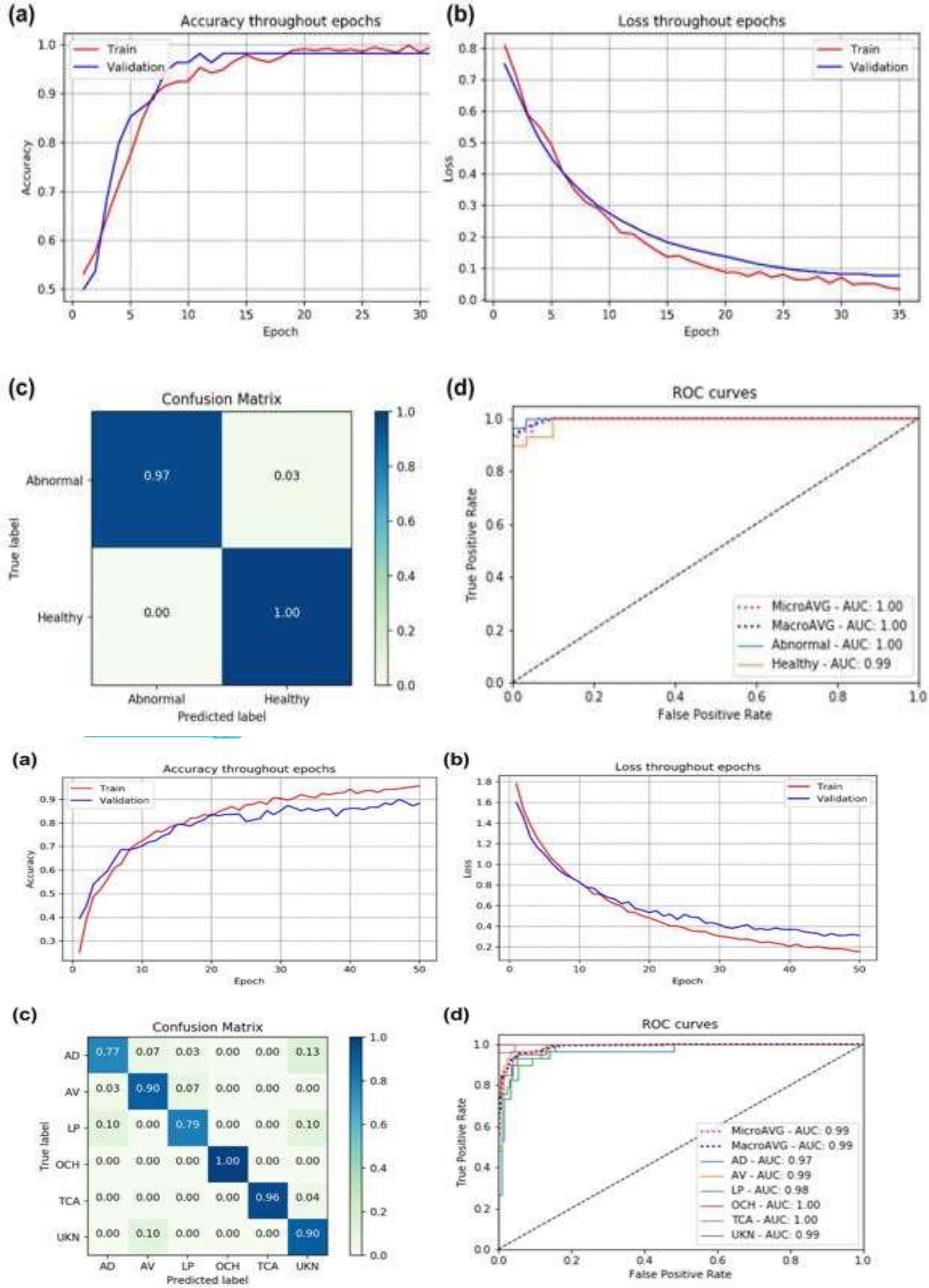

Fig3.1 Comparison

However, for our purposes, we choose the MobileNetv2 model due to its small number of parameters and high accuracy. All images and patient data were pre-processed before model training. Remove colours created by lighting changes and use the grayscale chromaticity constant algorithm to adjust the true colour of the image. After preliminary data, medical images and patient data are divided into 80%, 10% and 10%. 10% is used for training, certification, and compliance testing. Increase information using data augmentation using image transformation techniques. A weight loss function based on the frequency label was used to solve the uncertainty class problem. Since there are approximately more than 3,000 skin diseases, Different researchers Gupta AK et al. (2018). Tizek L (2019) et al. have applied machine learning and deep learning to diagnose specific diseases. 22 - 29 Our study focused on five common diseases in Ethiopia. Although the data used and the type of disease considered were slightly different, the current study improved overall accuracy compared to studies by combining patients and data treatment.

Final Output:
Visual Integration and Deployment:

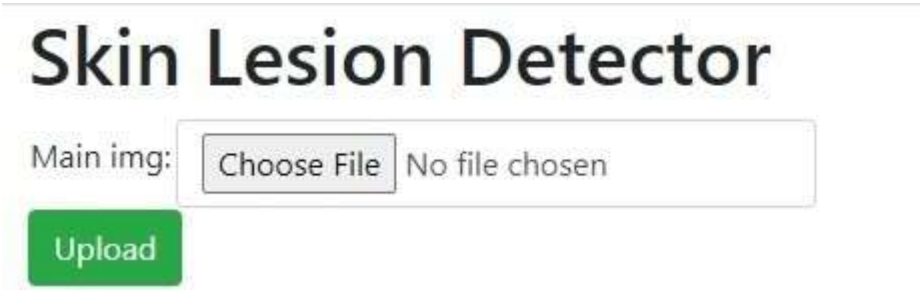

Fig:3.2 Visual Integration

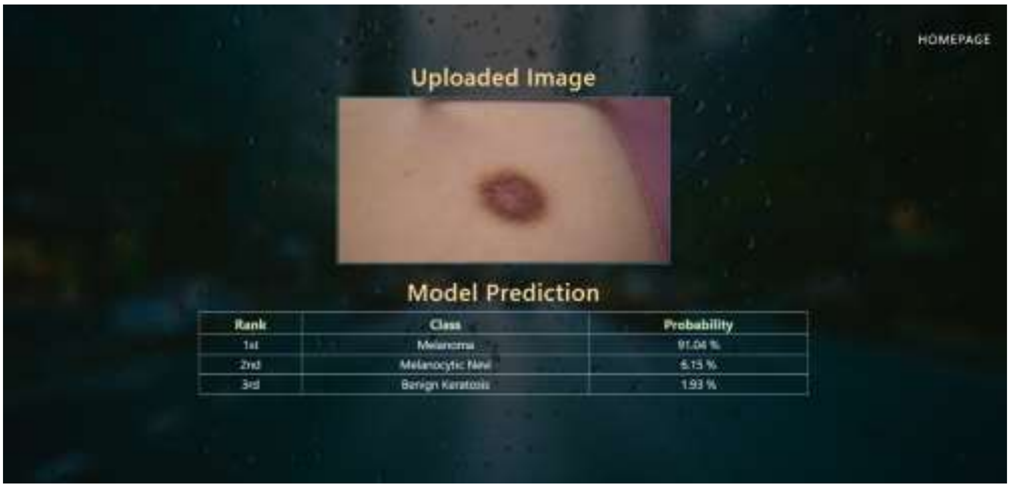

Fig 3.3 Final Output after Classification

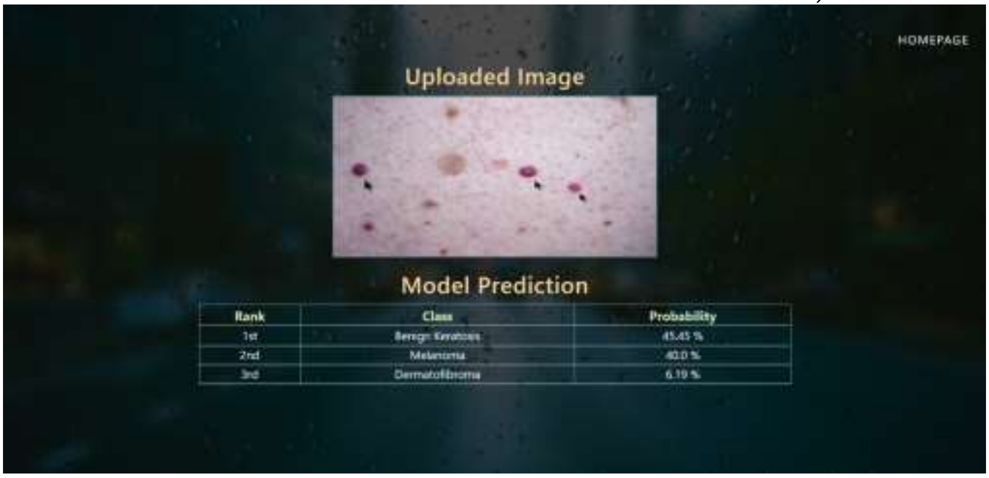

Fig 3.4 Model Prediction and Probability

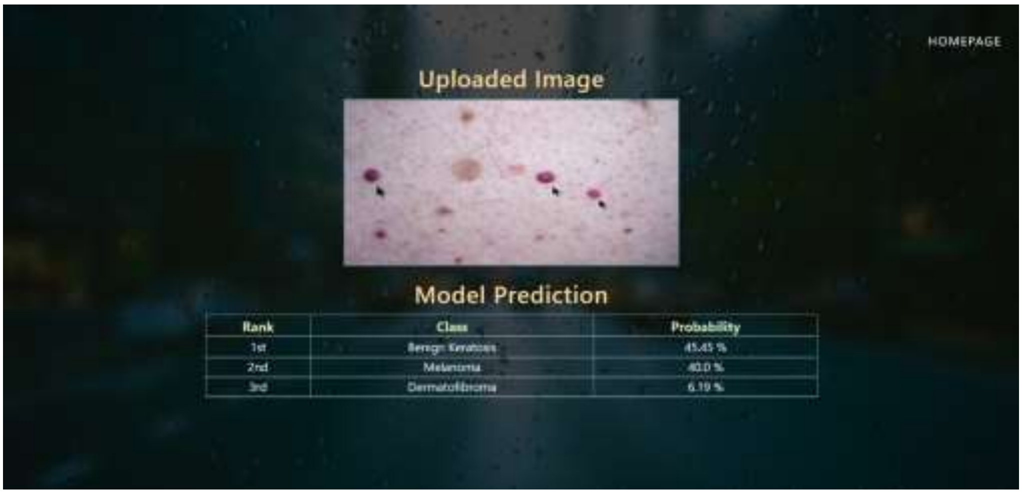

Fig 3.5 Different outputs after classification

4.Conclusion

In this paper, based on an in-depth study, automatic diagnosis of five skin diseases based on smartphones using patient's medical images and medical records achieved 97.5% with average accuracy, accuracy, recall, F1 score and kappa Score , 97.7%, 97.7%, 97.5% and 0.976, respectively. The results showed that the developed system had good diagnostic results for five skin diseases. The developed diagnostic criteria can be used by dermatologists, doctors, rural doctors, and patients to make skin diagnosis decisions.

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