Automatic skin disease diagnosis using deep learning from clinical image and patient information

Kedir Ali Muhaba
Dessie-Kombolcha University: Wollo University
Kokeb Dese
Jimma University Institute of Technology
Tadele Mola Aga
Jimma University College of Public Health and Medical Sciences
Feleke Tilahun Zewdu
Boru Meda Hospital
Gizeaddis Lamesgin Simegn (gizeaddis.lamesgin@ju.edu.et)
Jimma University https://orcid.org/0000-0003-1333-4555

Research

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Abstract

Background

Skin diseases are the fourth most common cause of human illness which results enormous non-fatal burden in daily life activities. They are caused by chemical, physical and biological factors. Visual assessment in combination with clinical information is the common diagnosis procedure for the diseases. However, these procedures are manual, time consuming, and require experience and excellent visual perception.

Methods

In this study, an automated system is proposed for diagnosis of five common skin diseases by using data from clinical images and patient information using deep learning pretrained mobilenet-v2 model. Clinical images were acquired using different smartphone cameras and patient's information were collected during patient registration. Different data preprocessing and augmentation techniques were applied to boost the performance of the model prior to training.

Results

A multiclass classification accuracy of 97.5%, sensitivity of 97.7% and precision of 97.7% has been achieved using the proposed technique for the common five skin disease. The results demonstrate that, the developed system provides excellent diagnosis performance for the five skin diseases.

Conclusion

The system has been designed as a smartphone application and it has a potential to be used as a decision support system in low resource settings, where both the expert dermatologist and the means is limited.

1. Introduction

Skin is the largest organ of the body which provides protection, regulates the body fluids and temperature, and enables sense of the external environment [1]. Skin diseases are the most common cause of all human illnesses which affects almost 900 million people in the world at any time [2]. According to the Global Burden of Disease project, skin disease is the fourth leading cause of non-fatal disease burden throughout the world [3]. An estimated 21–87 % of children in Africa are affected by skin diseases [4]. This is due to mechanical, physical, chemical, and biological factors. Moreover, the diseases are given less attention compared to other serious diseases because of its low mortality. However, the overall morbidity causes a financial, socio-economic, and psychological burden to the community and place a

strain on health professionals [5–12]. It affects education, relationships, self-esteem, career choices, social, sexual, and leisure activities. Beyond these, skin diseases may cause a sense of depression, frustration, isolation, and even suicidal ideation [13].

The pattern of skin diseases varies due to environmental factors, hygienic standards, social customs, and genetics. In developing countries, infection and infestation are more common [4]. There are more than 3000 known skin diseases worldwide [14]. A preliminary study conducted for this study acne vulgaris, atopic dermatitis, lichen planus, onychomycosis, and tinea capitis are among the common skin diseases in Ethiopia. A statistics show that atopic dermatitis affects 20% of children below the age of two [5]. Acne scarring is a long-term complication that can affect 95% of patients with acne vulgaris [8].The global prevalence of onychomycosis is 5.5 % and contributes 50% of all nail diseases [15]. In Ethiopia, 32.3% of school-aged children suffer from tinea capitis [16].

The common procedures for diagnosing skin diseases are patient history and symptoms analysis, skin scraping, visual inspection, dermoscopic examination, and skin biopsy. However, those diagnosis methods are tedious, time-consuming, and prone to subjective diagnosis. Most of them require experience and excellent visual perception of dermatologist. Sophisticated and robust medical imaging modalities can also be used for skin disease diagnosis [17]. However, the cost of the equipment limits the affordability in a low-resource settings.

Recently, smartphone-based imaging and sensing platforms have become an alternative means of disease diagnosis in the healthcare industry. The latest generation of a smartphone with a high-definition camera, large storage capacity, and high-performance processor enables to capture of digital images and record videos with better resolution [18]. Portability, cost-effectiveness, and connectivity make a smartphone to be applicable in many areas [19, 20]. The availability of smartphones equipped with digital cameras enables the acquisition of clinical images for investigation using computer aided diagnosis (CAD).

CAD can reduce the burden of health care professionals with the help of artificial intelligence [21]. Different literatures has proposed a means of diagnosing skin diseases using clinical images [22–29]. A support vector machine (SVM) with quadratic kernel has been proposed by Hameed et al. [24] for classification of acne, eczema, psoriasis, benign and malignant melanoma with an accuracy of 83%. Similar accuracy (about 81%) has been claimed by Nasr-Esfahani *et al.* [22] for classification of melanoma and benign lesions using convolutional neural network. Additionally, a multiclass classification system were proposed using ResNet152 for 12 skin diseases [25, 26]. Fujisawa *et al.* [23] applied a pre-trained GoogLeNet to classify 14 categories of skin tumors and an overall accuracy of 76.5% was claimed. Recently, Wu *et al.* [29] compared five pre-trained deep learning frameworks for the diagnosis of six facial skin conditions from a clinical image and using an InceptionResNet_V2 a precision of 77% was claimed. Velasco *et al.* proposed MobileNet CNN to classify seven skin diseases and claimed an overall accuracy of 94.4%.

The proposed works showed promising results for the diagnosis of different skin diseases from clinical images. However, most of the works were dependent on the availability of an online public dataset, focused on cancer and tumors and are designed to diagnose specific parts of a body. Moreover, the datasets collected and used mainly consists of white skin. Moreover, the diagnostic performance including the accuracy reported are not satisfactory.

In this study an automatic diagnosis system has been developed based on deep learning model for five most common skin diseases including acne vulgaris, atopic dermatitis, lichen planus, onychomycosis and tinea capitis by combining clinical images acquired using a smartphone camera and patient information.

2. Materials And Method

This automated diagnosis system was developed by using a pretrained mobilenet-v2 model. Both skin images and patient clinical information were preprocessed and concatenated for classification of skin diseases. Figure 1 demonstrates the general block diagram of the proposed system.

2.1 Data collection

The dataset used for this research were collected from Dr. Gerbi medium clinic of Jimma and Boru-meda General hospital of Dessie from 286 patients (149 female and 119 male, age range 0 to 85 years). A total of 1137 images along with patient information was collected from Dr. Gerbi medium clinic and 239 images from Boru-Meda General hospital using a smartphone camera (Nokia window phone, Techno Spark4, SamsungA20, and SamsungJ6). 300 of the images were collected from healthy skin and 1376 from abnormal skin affected by acne vulgaris, atopic dermatitis, lichen planus, onychomycosis, and tinea capitis. The images were captured after the diagnosis was confirmed by expert dermato-venerologist and a tropical dermatologist. Moreover, images from other less common skin diseases were also included, labeled as an unknown class to reduce the false-positive result of the model. The unknown class includes 204 images of lichen simplex chronicus, cow pox, monkey pox, leishmania, tinea corporis, rosacea, seborrheic dermatitis, foot ulcer, papular urticaria, discoid lupus erythematosus, onchocerciasis, real world object images, and others. Table 1 shows the number of images collected for each skin diseases. Patient information including age, gender, anatomical sites and symptoms of the diseases were also collected during. The anatomical sites include; abdomen, anterior torso, armpit, chin, ear, forehead, lateral face, lower back, lower extremity, nail, neck, periorbital region, posterior torso, scalp, and upper extremity. The medical sign and symptoms of the five skin diseases were also included. A total of 41 features from patient information were extracted and used to develop the model. Figure 2 demonstrates sample of collected abnormal skin

Figures 3 and 4 demonstrates age wise and gender wise distribution of collected data for the selected five skin conditions. Table 2 shows the common symptom lists and anatomical sites of the five skin diseases.

Table 1
Data collected from Jimma and Dessie

Diseases	Number of images
Healthy	300
Acne vulgaris	307
Atopic Dermatitis	300
Lichen planus	289
Onychomycosis	211
Tinea capitis	269
Unknown	204
Total	**1880**

Table 2
Common symptoms and site invaded by the five skin diseases [30, 31]

Diseases	Acne vulgaris	Atopic dermatitis	Lichen planus	Onychomycosis	Tinea capitis
Symptoms	• Blackheads • Whiteheads • Papules • Pimples • Nodule • cysts	• Dry skin • Scale • Bumps • Thickened cracked skin	• Thickened nail • Purplish flat bumps • Lacy white on mouth lips or tongue • Painful sores in the mouth or vagina	• Nail discoloration • Nail shape distortion • Nail smell foul	• Scaly gray or reddened areas • Patches with black dots
Anatomical sites	• Lateral face • Forehead • Posterior torso • Anterior torso • Chin • Neck	• Neck • Lower extremity • Upper extremity • Anterior torso • Posterior torso • Lower back • Periorbital • Armpit • Lateral face • Forehead	• Lower extremity • Upper extremity • Lower back • Neck • Abdomen • Anterior torso • Lateral face • Nose • Ear • Scalp • Armpit • forehead	• Nail	• Scalp

Table 3
Number of clinical images present in each anatomical site

Anatomical sites	Number of clinical images collected on each site				
	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**

2.2 Preprocessing

Image resizing, color constancy, and data augmentation were performed before feeding the image to the deep learning network. All the images were resized to 224 x 224 pixels to match the input size of the pretrained mobilnet-v2 model. The shades of gray color constancy algorithm was used in the preprocessing step to remove the color bias of the clinical images. This was found to improve the classification accuracy of multisource images in literatures [31,32]. The dataset was split into training (80%), validation (10%) and, testing (10%) prior to model training. Then data augmentation was applied

to the training dataset by 90° rotation, horizontal and vertical image flipping to increase the number of datasets. The patient information was converted to a feature vector using one-hot encoding method.

2.3 Repurposing pretrained mobilenet-v2 model

MobileNet-v2 was introduced by Sandler et al. in 2019 [34], as performance improvement of mobile models. It is based on an inverted residual structure where the input and output of the residual block are thin bottle neck layers opposite to traditional residual models. The architecture of mobilenet-v2 contains fully convolutional layer with 32 filters followed by 19 residual bottlenecks. The fully convolution operation is replaced by depth-wise separable convolution that splits into two separable layers. First, depth-wise convolution performs light-weight filtering using 3 x 3 kernel per input channel. Following the depth-wise convolution, the point-wise convolution builds feature by computing linear combination of the input images. The model is suitable for mobile and resource limited environments. The feature extractor outputs 1280 image feature maps to the classifier.

In this study, we have applied transfer learning approach the pretrained mobilenet-v2 model for skin disease classification. For both binary and multi-class classification of skin diseases, using image data alone the output of the pretrained model was flattened and fed to the classifier. The classifier then uses the concatenation of both the image data and patient information to classify the skin disease. Since, the image data from pretrained mobilenet-v2 model is larger than the patient information feature, a dense layer with 128 neurons was added at the top of the pretrained model. This reduces the output image features of the model to 128 and balances the two inputs types of the classifier (a one-hot encoded patient information features and the image features). Moreover, weighted loss function based in labels frequency, which assigns more weight to less represented class, was applied to mitigate class imbalance in the dataset.

3. Results

3.1 Preprocessing

The clinical images were acquired using different smartphone camera under different illumination sources. The color variation resulting from different illumination sources were estimated and corrected by applying the shades of gray algorithm. Figure 5 depicts the effect of applying shades of gray algorithm on the clinical images.

3.2 Result of binary classification task

For the binary classification task (normal and abnormal), the model correctly predicts 59 out of 60 unseen test images. The accuracy, precision, recall, F1 score, kappa values of 98.3%, 98.5%, 98.5%, 98.0% and 0.97 respectively, were achieved for binary classification. Figure 6 below show the training and validation accuracy curve, training and validation loss curve, confusion matrix, and ROC curve of the binary classifier.

3.3 Multi-class classification

For the multi-class classification task, the model that was trained on clinical image only correctly classified 138 images out of 157 images. On the other hand, the model trained on the both combination of image and patient information correctly classified 153 images out of 157 test datasets. Figure 7 and Table 4 summarizes the result of the multiclass classification task on clinical image only. Figure 8 and Table 5 summarizes the result of multi-class classification on both clinical image and patient information.

Table 4. Model performance repots of multiclass class classifier on image only

Skin Condition	Precision (%)	recall (%)	f1-score (%)	Kappa score	Accuracy (%)
Acne Vulgaris	87	90	89	**0.86**	**87.9**
Atopic Dermatitis	85	77	81		
Lichen Planus	88	79	84		
Onychomycosis	100	100	100		
Tinea capitis	100	96	98		
Unknown	69	90	78		
Average	**88.2**	**88.7**	**89.8**		

Table 5
the classification metrics of the model on both clinical image and patient information

Skin Condition	Precision (%)	recall (%)	f1-score (%)	Kappa score	Accuracy (%)
Acne Vulgaris	91	100	95	**0.976**	**97.5**
Atopic Dermatitis	100	97	98		
Lichen Planus	100	93	96		
Onychomycosis	100	100	100		
Tinea capitis	100	96	98		
Unknown	95	100	98		
Average	**97.7**	**97.7**	**97.5**		

An android application has been also developed for ease of using the proposed automatic skin diseases diagnosis system using smartphones. Through the developed application, the user can capture skin images, enter age, select anatomical sites, gender and symptoms to identify the type of skin disease. After loading the user can diagnose the skin condition by hitting detect button. The first window enables

to diagnose the skin condition as healthy or abnormal. Next, if the result is abnormal hitting the continue button pops up another window to diagnose the five-skin condition. If the disease was out of the five classes the model returns Unknown. Figure 9 demonstrates the developed android application.

4. Discussion

Skin diseases are any condition that affects human skin. According to the global burden of diseases project, skin diseases are the fourth leading cause of non-fatal disease burden [3] which can affect almost 900 million people worldwide [2]. Skin diseases injure physical health and cause serious psychological problem: depression, frustration and even suicidal ideation [13].

Visual inspection, laboratory test, imaging, and biopsy tests are the common skin disease diagnosis techniques. However, the limited number of sophisticated diagnostic devices and dermatologist and even general practitioners, especially in developing countries hurdle the service delivery. Moreover, the common diagnostic techniques are tedious and require experience and excellent visual perception. Computer-aided diagnosis systems has a potential to revolutionize the current disease diagnosis techniques enabling optimal treatment planning.

The aim of this study was to design and develop a smartphone based automatic skin disease diagnosis method using skin images and patient information including age, gender, anatomical site of the disease and symptom list. A total of 1880 skin images of top 5 disease were collected from the population of southwest Ethiopia (Dr. Gerbi Medium clinic, Jimma), Eastern Amhara, and Afar region (Boru-Meda General Hospital), using different smartphone cameras with the corresponding patient information. The type of skin diseases was different from place to place, but the selected five disease were common, in average, in these places.

From the collected data, tinea capitis was common in children with the age range of 0–9 years, rare on 10–19 years and absent above the age of 20 years. On the other hand, atopic dermatitis was found in all age ranges, but it was found to be common within the age range of 0–39 years. Moreover, acne vulgaris was common in the age range of 10–49 years, especially teens and adults were found to be more vulnerable in the age range of 10–29 years. Even though, onychomycosis was found to occur in evenly people with the age of 0–59 years. In addition, lichen planus was also common between the age of 20–49 and rarely found in teens adults and elderly people. This is demonstrated in Fig. 3. Figure 4 demonstrates gender wise distribution of the skin disease from the collected data. Acne vulgaris and onychomycosis were more common on females than males, and tinea capitis was more common on males than females.

A mobilenet-v2 model was trained using the collected data, first to identify normal skin from abnormal using images only and then uses a combinations of skin images and patient information to identify the type of skin disease.

All images and patient information were pre-processed prior to model training. The color cast resulted from illumination variation was removed and the actual color of the images were restored by applying shades of gray color constancy algorithm [35]. After data pre-processing, the clinical images along with the corresponding patient data were split to 80%, 10% and 10% for training, validation and testing, respectively. Data augmentation was applied by using image transformation technique to increase the number of training data. The weighted loss function based on labels frequency was applied to tackle class imbalance issue. A pre trained Mobilent-v2 model was selected and fine-tuned for binary and multiclass classification for training, since it is the best model for mobile devices and resource limited environment.

For binary classification, best result was achieved by applying a learning rate of 0.0001, sigmoid activation function as classifier, and cross entropy loss as a loss function. The average accuracy, precision, recall, F1-score, and kappa score achieved were 98.3%, 98.5%, 98.5, 98.5, and 0.97% respectively. The multiclass classifier classifies the input clinical image in to six different skin conditions. The unknown class was added as a sixth class to reduce false-positive result. As a result, image lesions out of the five classes were classified as unknown. The best result was achieved by applying learning rate of 0.00001, SoftMax activation function as a classifier and weighted cross-entropy loss as a loss function. The model was tested using unseen datasets and evaluated using a variety of performance metrices. The average accuracy, precision, recall, F1-score, and kappa score were 87.9%, 88.2%, 88.7%, 89.8%, and 0.86, respectively, using images only (Table 4). An improved performance was achieved using a combination of images and patient information and an average accuracy, precision, recall, F1-score, and kappa score of 97.5%, 97.7%, 97.7%, 97.5% and 0.976, respectively were acquired after testing the model on unseen dataset (Table 5). Using the combined image and patient information increase the classification accuracy of the model by 9.6%.

Since there are about 3000 and more skin diseases [14], different researchers proposed machine learning and deep learning based diagnosis systems for specific types of diseases [22–29]. Our study focused on top 5 disease that are common in Ethiopia. Even though, the dataset used and the types of diseases considered were slightly different, the current work, achieved significantly improved overall accuracy compared to [22–29] by incorporating patient and clinical information. A user-friendly android application will also enable non-expert users to identify the skin diseases using their smartphones. The developed system has a potential to be used as a decision support system for physicians, general practitioners, and patients.

5. Conclusion

In this study, a smartphone based automatic diagnosis of five common skin diseases, is proposed based on a deep learning technique using clinical image and patient clinical information, and an average accuracy, precision, recall, F1-score, and kappa score of 97.5%, 97.7%, 97.7%, 97.5% and 0.976, respectively, were achieved. The results demonstrate that, the developed system provides excellent diagnosis performance for the five skin diseases. The developed diagnostic system has a potential to be

used as a decision support system for dermatologists, general practitioners, health practitioners in rural areas and patients in the diagnosis of skin disease.

Declarations

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Ethics approval and consent to participate

This research has been approved by Jimma University's research ethics institutional review board (IRB). This research has been performed in accordance with the ethical standards as laid down in the 1964\Declaration of Helsinki and its later amendments or comparable ethical standards.

Consent for publication

An informed written consent form was obtained from all participants prior to data collection

Availability of data and Materials

The datasets used and/or analyzed during the current study are available from the corresponding author on reasonable request.

Competing interests

The authors declare that they have no competing interests

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Not Applicable

Authors' contributions

KA and GL conceptualized, designed, and improved the study in collaboration with KD, TM, and FT. All authors contributed to the preliminary study, the design, prototyping and testing. The article was drafted by KA and GL, taking into account the comments and suggestions of the coauthors. All coauthors had the opportunity to comment on the manuscript and approved the final version for publication.

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Figures

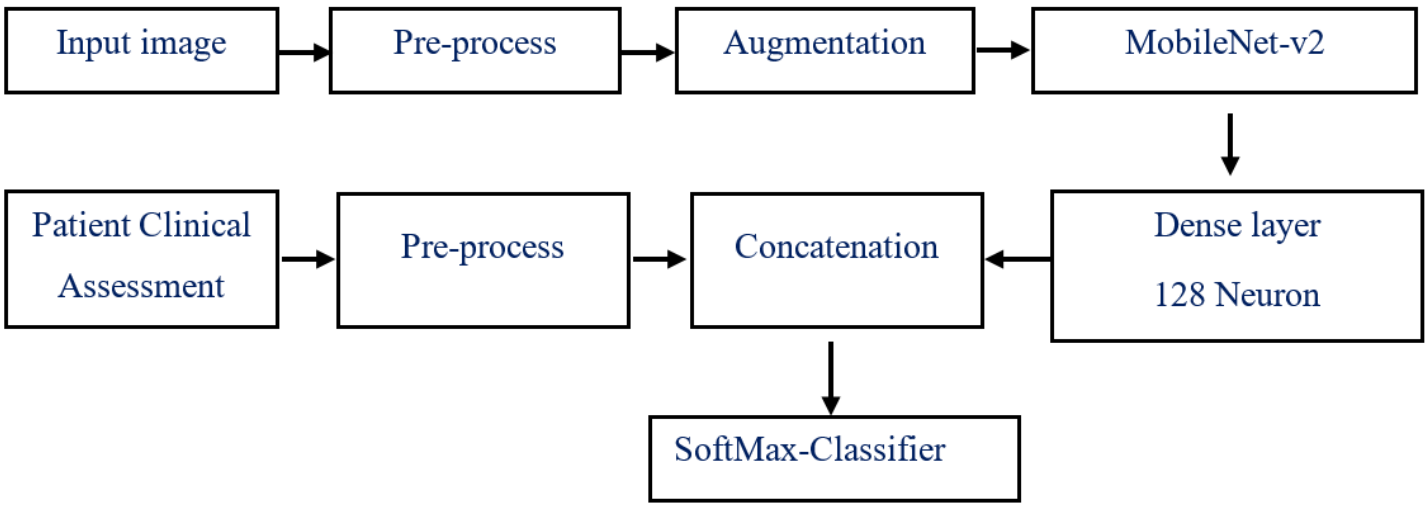

Figure 1

block diagram of the skin disease multi-class classification system

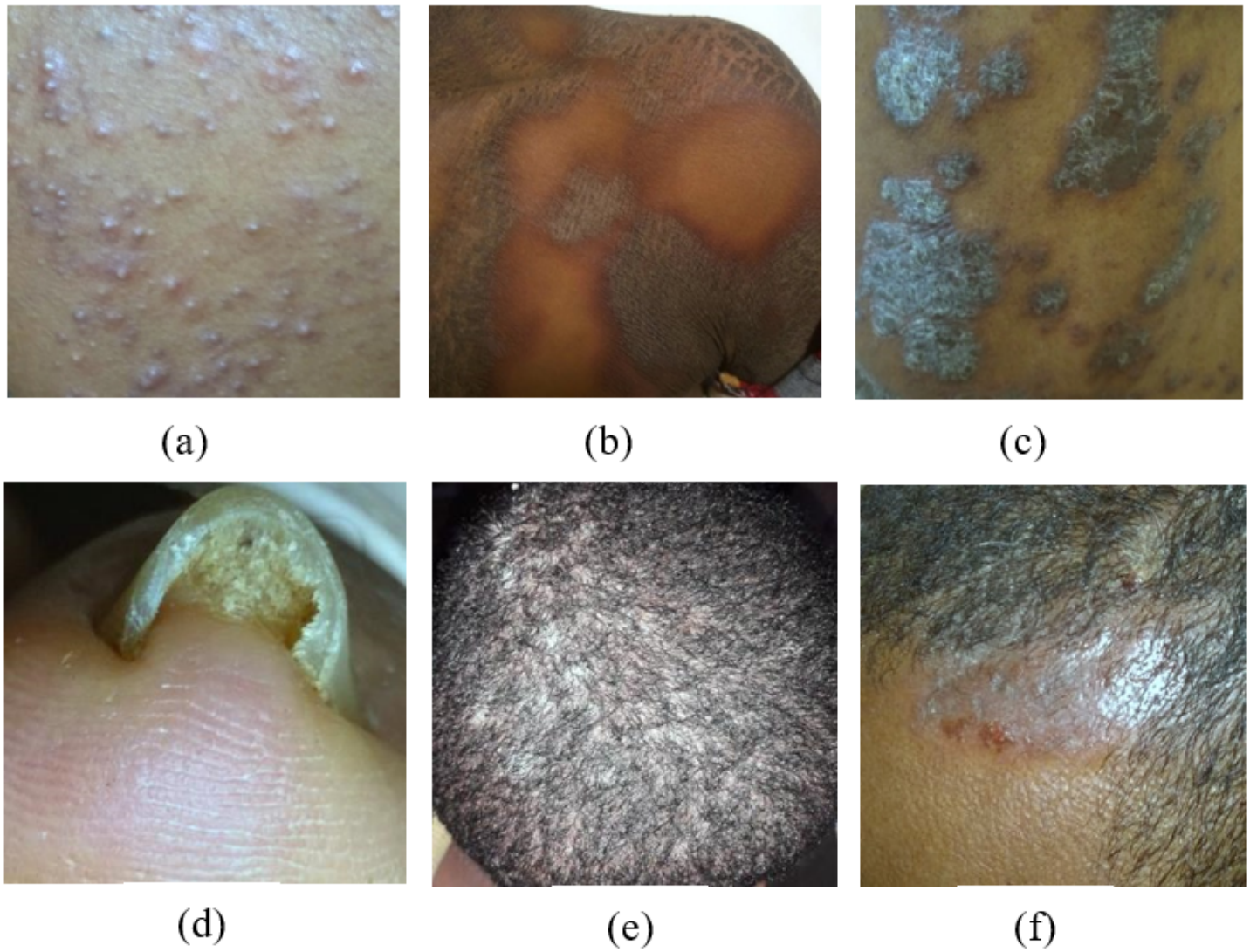

Figure 2

sample image from five skin diseases (a) Acne vulgaris (b) atopic dermatitis (c) Lichen planus (d) Onychomycosis (e) Tinea capitis (f) seborrheic dermatitis (labeled as unknown class).

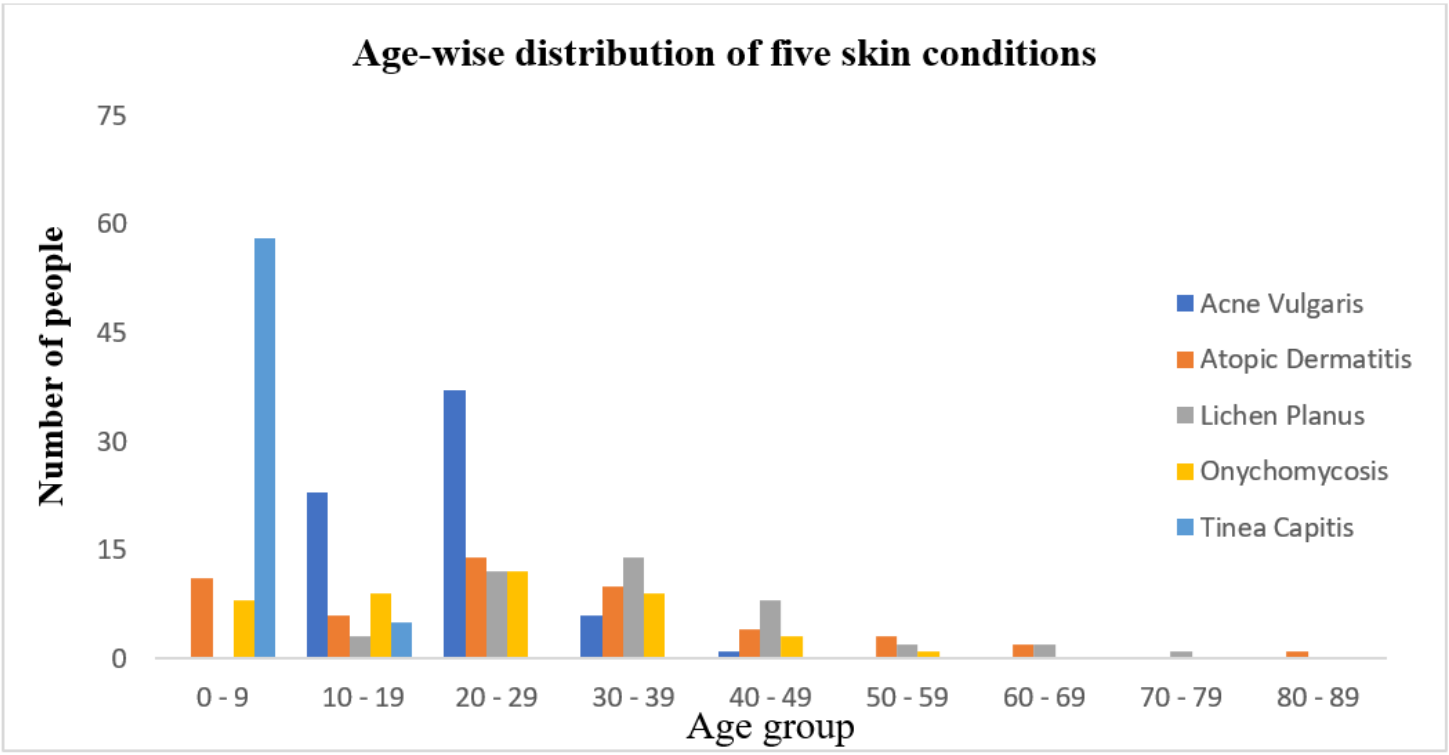

Figure 3

Age-wise distribution of five skin diseases

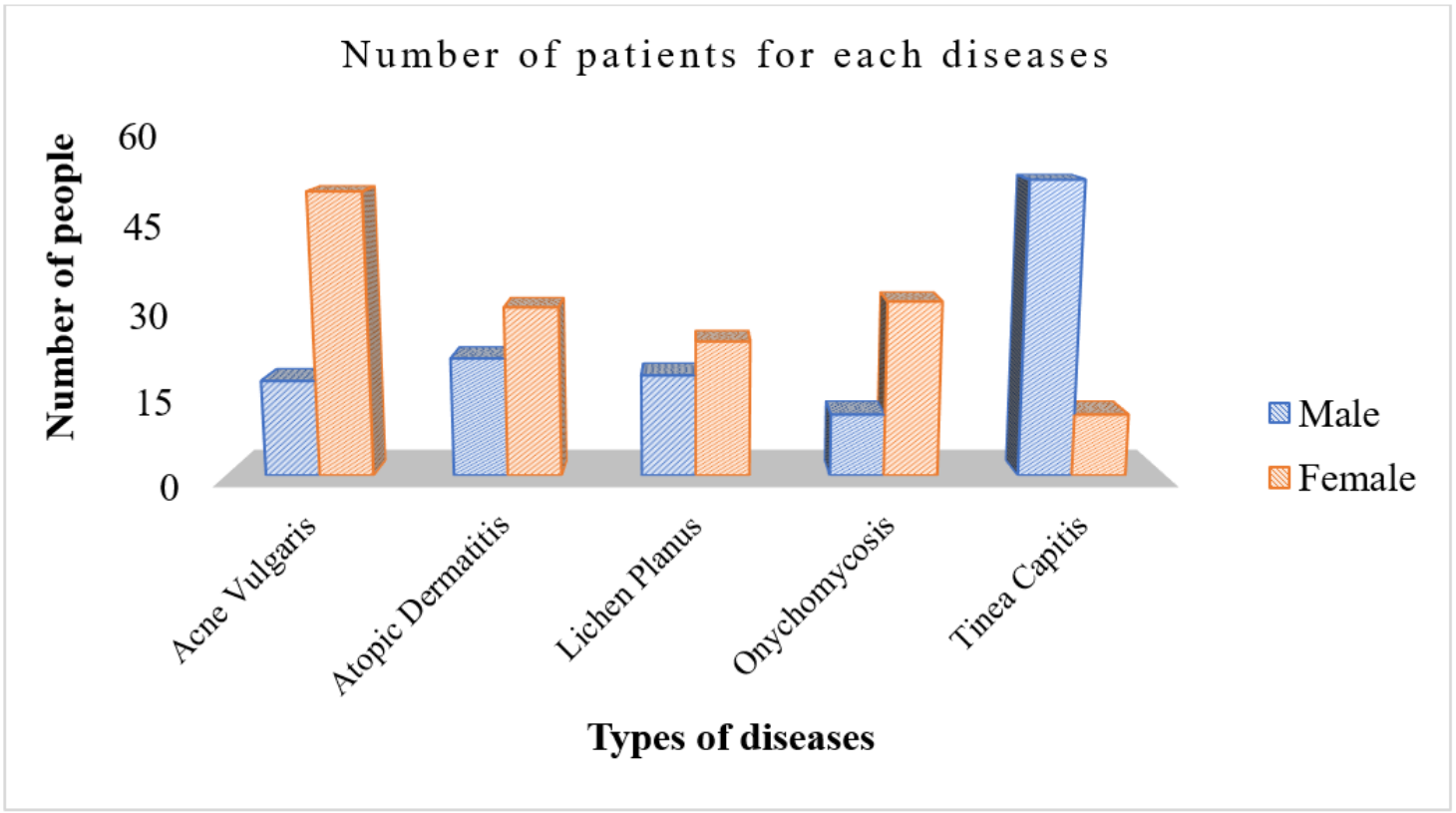

Figure 4

gender-wise distribution of the five skin diseases

Figure 5

Sample result of applying shades of gray color constancy algorithm

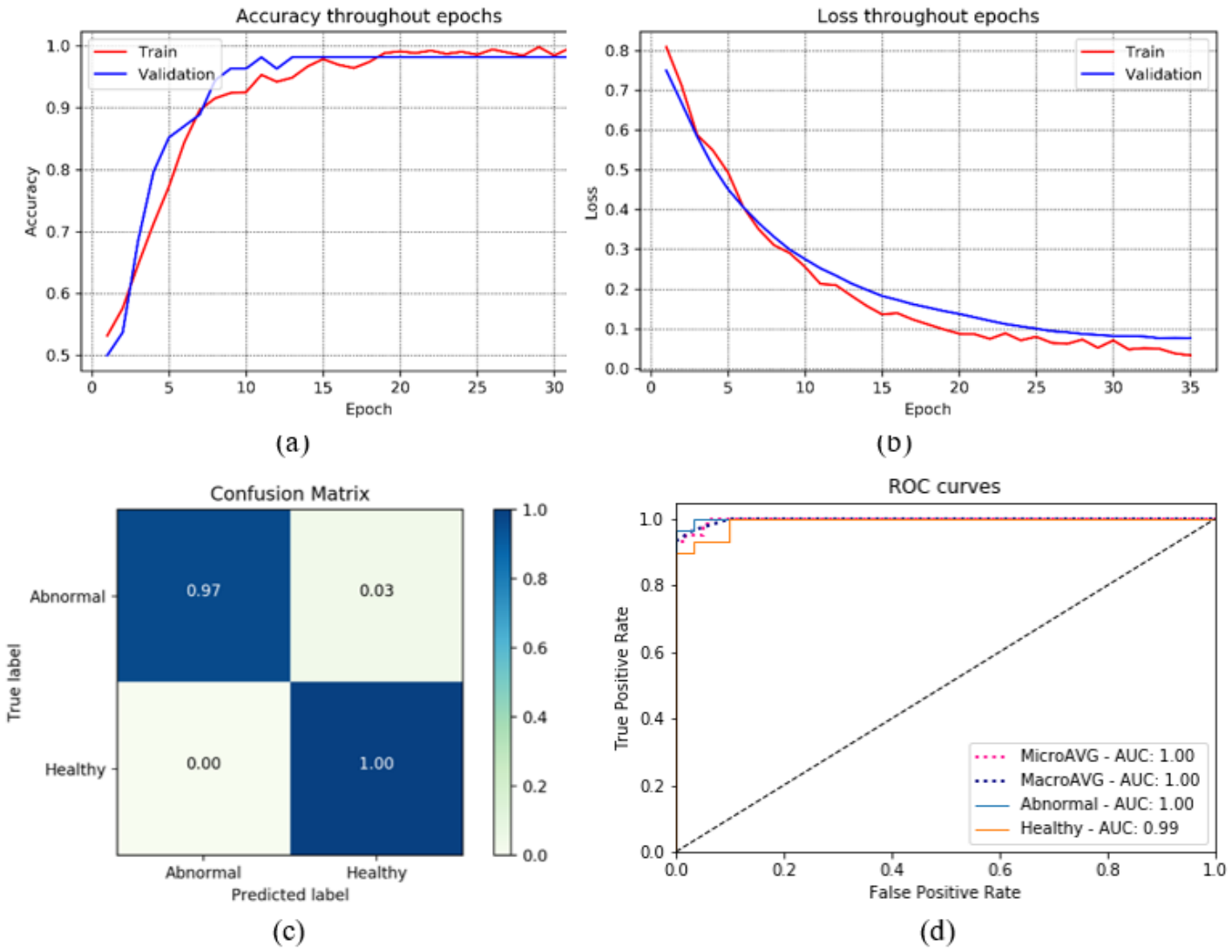

Figure 6

Detail of binary classifier (a) training and validation accuracy (b) training and validation loss (c) confusion matrix (d) ROC curve

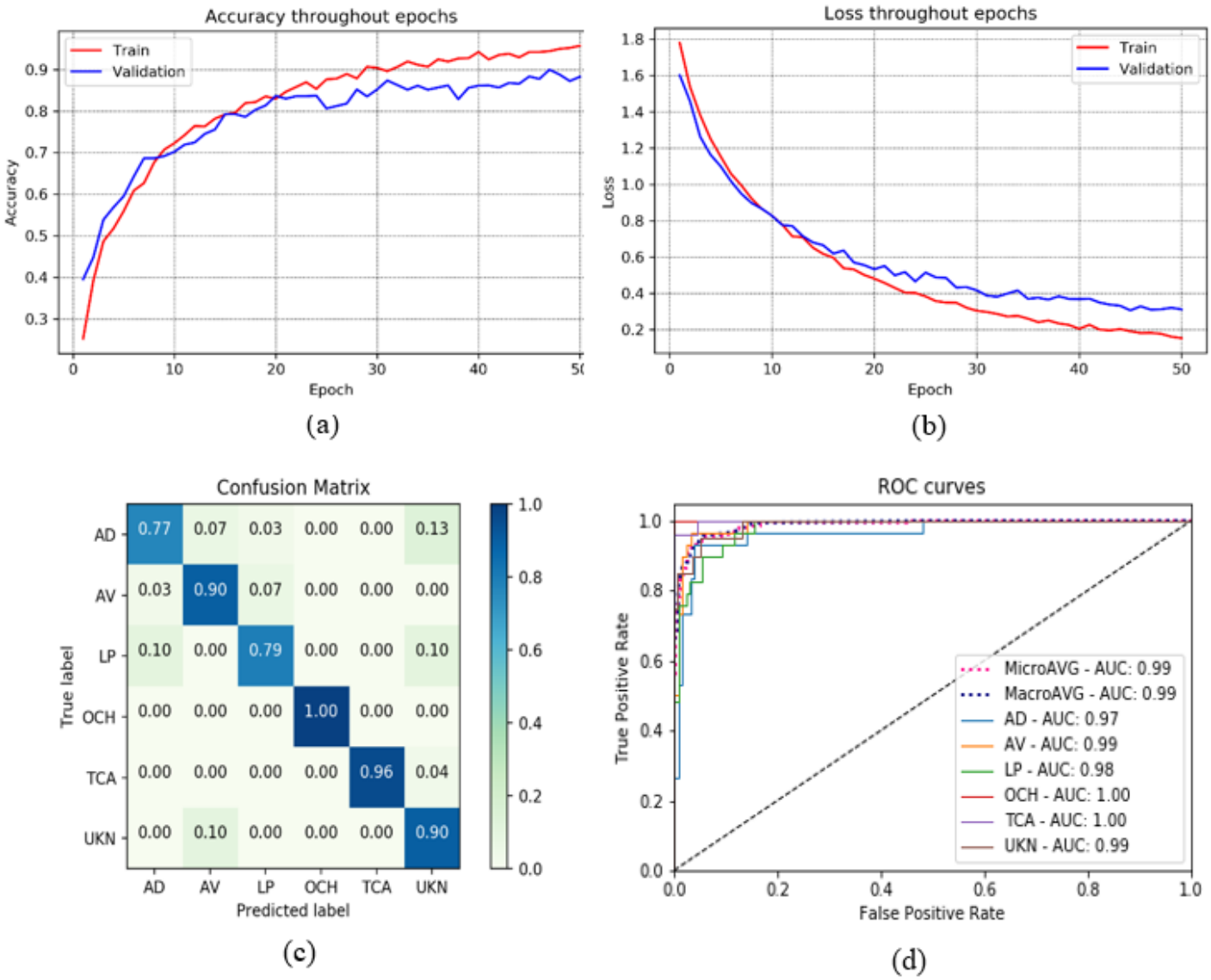

Figure 7

Summary of a multi-class classifier using image only (a) training and validation accuracy (b) training and validation loss (c) confusion matrix (d) ROC curve

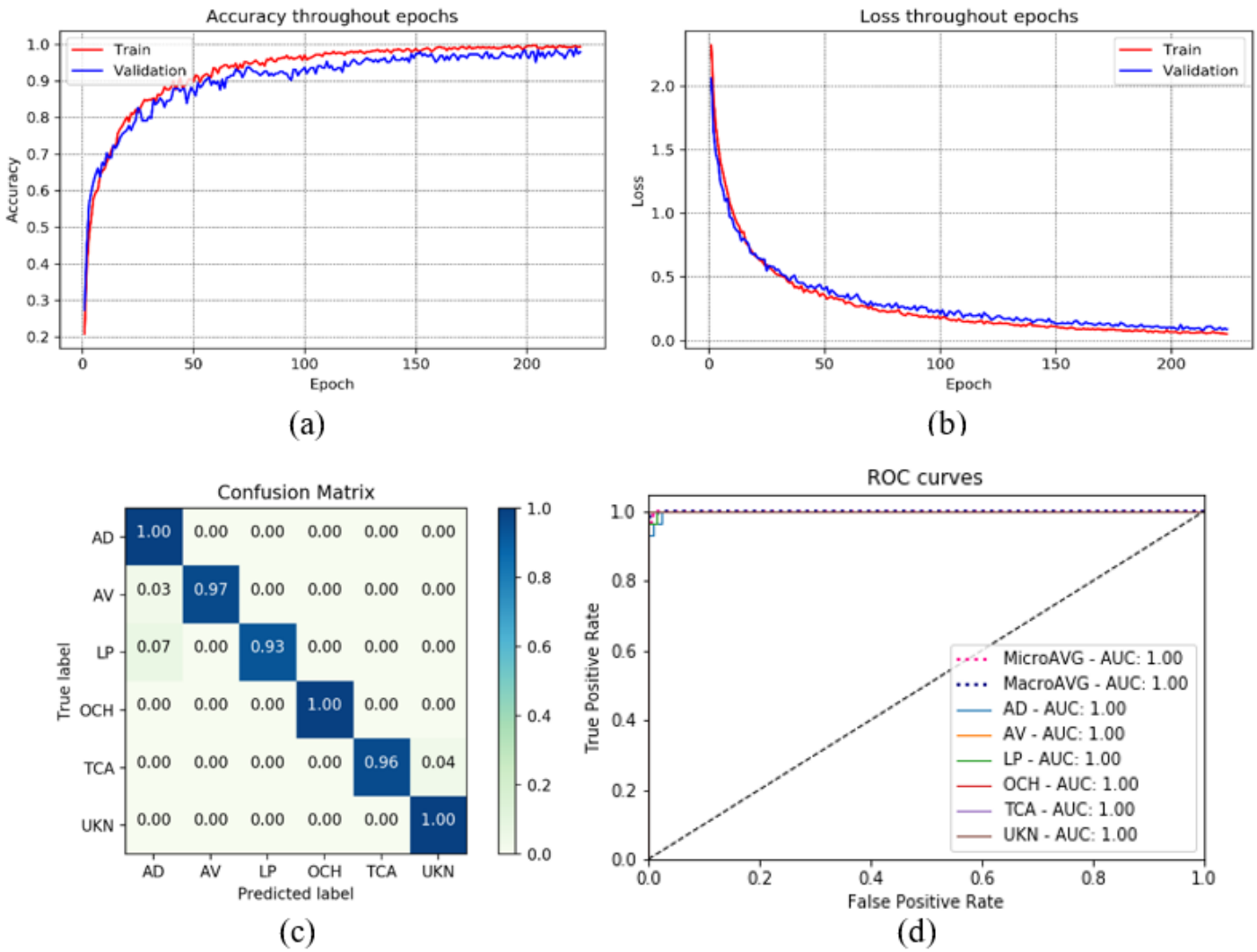

Figure 8

Summary of multiclass classifier using both image and patient information. (a) training and validation accuracy (b) training and validation loss (c) confusion matrix (d) ROC curve

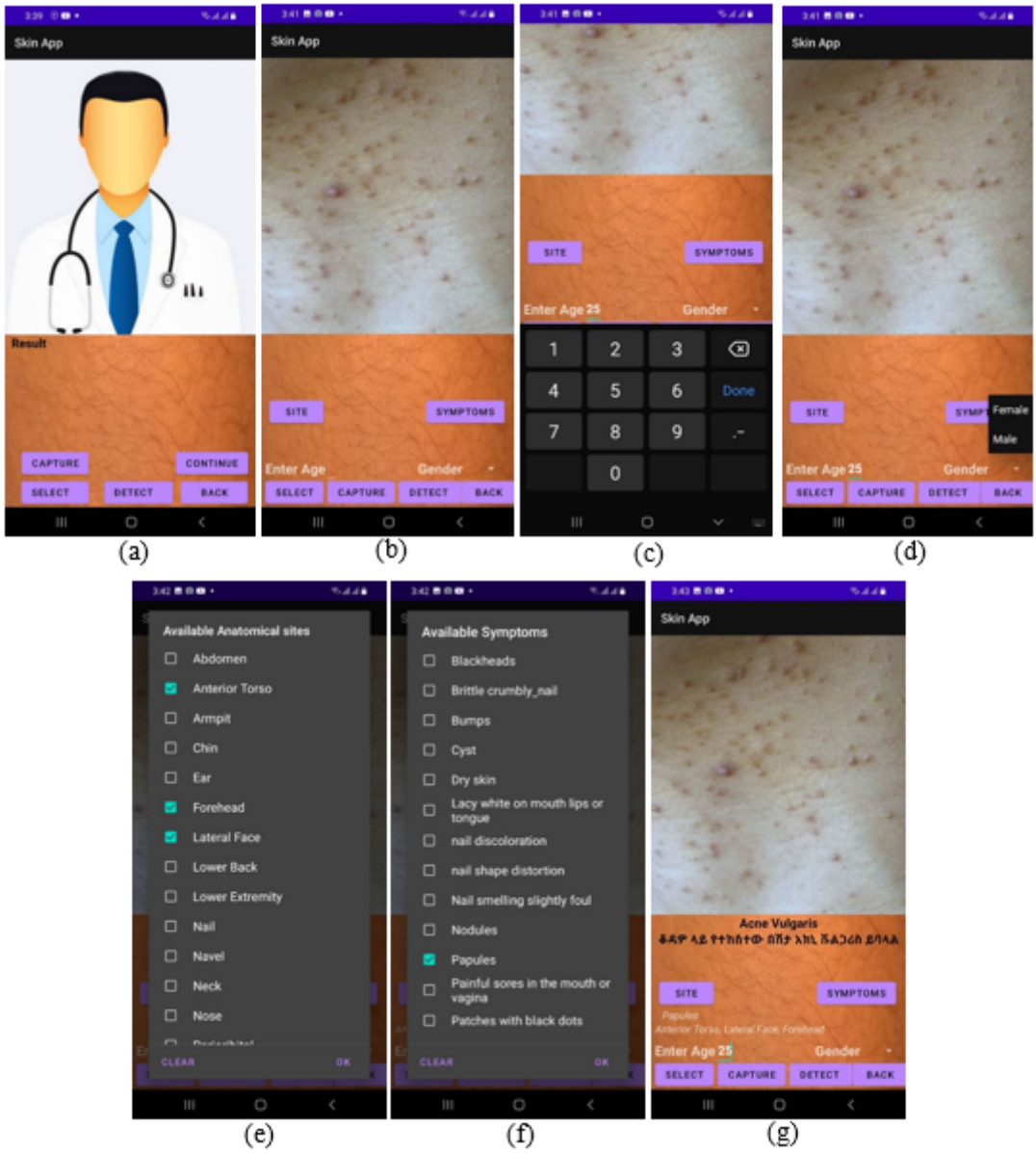

Figure 9

An android application used for diagnosing skin diseases using clinical image and patient information. (a) Home page of the App. (b) Image Capturing. (c) Age information. (d) Gender selection. (e) Anatomical site selection. (f) symptom list selection. (e) Predicted skin disease