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Mobile-based Intelligent Skin Diseases Diagnosis System

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Abstract— **Skin diseases are the most common diseases in humans. The inherent variability in the appearance of skin diseases makes it hard even for medical experts to detect disease type from dermoscopic images. Recent advances in image processing using the Convolution Neural Networks have led to better results in diagnosing systems. We aim to develop an advanced diagnostic system in a manner that meets the requirements of real-time and extensibility of medical services for skin disease detection. The proposed system provides offline diagnosis for the users who have not Internet connection or online diagnosing uses on-cloud service. The user captures the affected area and get the offline immediate report. The schema offers the users a communication window with dermatologists to get medical recommendations in addition to an online accurate diagnosis service. The new images that are labeled by dermatologists are used to retrain the model to enhance model accuracy. To maximize the number of users, the system is implemented in a mobile-based environment. With the growing numbers of portable apps, it becomes easy for people to obtain up-to-date data. Users are familiar with looking for answers from the virtual globe including health issues. The following experimental results demonstrate the feasibility of the proposed method. The average obtained accuracy is 83% in testing cases.**

Keywords— Convolution Neural Networks, Virtual globe, dermoscopic, dermatologists.

I. Introduction

Skin disease is the most common disease in the globe. It is known as a pathological condition on the body's surface [1]. Skin diseases have different appearances and various degrees of effects, from the slightest effects such as changing body characteristics to impact effects like death. Diagnosing skin diseases in early stages is very important due to a high survival possibility especially for skin cancer. That accounts for around 80% of all newly diagnosed cancers. Early diagnosis of melanoma has an elevated cure rate and a relative survival rate of 99% for 5 years. This rate falls to 20% [1] or 18% with late diagnosis [2]. Skin diseases spread widely. According to the American Cancer Society report [3], an estimated 96,480 new cases of melanoma will be diagnosed in 2019. On the other side, skin disease deaths in Yemen reached 166 or 0.11% of the total deaths [4].

The arrival of smartphones into many fields especially the medical field has resulted in the development of new technology to help individuals identify and diagnose illness precisely. So For maximizing the number of users of the proposed system, it is implemented as a mobile-based application. In the report [5], the number of users of smartphones is expected to reach 7.2 billion in 2024. General diagnostic services can be provided at low costs [6]. The paper [7] stated `that mobile devices with a deep neural network could extend the variety of dermatologists outside the outpatient department. The traditional systems for detecting skin disease complete the classification production by extracting picture information as input features while current researches adopt the deeper framework for automating learning feature with the priority of automatic classification accuracy [8–10].

In recent years, image processing has performed an important part in this study field and has commonly used to detect skin diseases. These illnesses can be recognized accurately with combined techniques like image processing, data mining, and machine learning algorithms, etc.

Skin disease is a global problem and many studies in this field have been conducted so far. Studies start from developing an online diagnostic system for children's skin diseases [11] to the use of machine learning approaches such as Artificial Neural Networks [12, 13, 14] or Convolution Neural Networks [15]. Kabari et al. in the research [12] developed a system with an ANN to predict the diagnosis of skin diseases with a 90% accuracy rate. Rathod et al. [15] discussed an automated system for recognition of skin diseases using the CNN algorithm for feature extraction. The image of the affected area is classified using CNN and softmax classifier. Five diseases were initially tested with an accuracy of 70%.

In May 2019, Akar et al. introduced the skin lesion diagnosis system based on the cloud using CNN [2]. The user takes a photo using the android-based application and uploads the image to the cloud. Then, a deep learning-based classifier hosted in a server to filter and classify uploaded lesion images. Furthermore, in the paper [16], Hameed et al. presented skin disease detection with an android platform, offering true and helpful dermatologic data regarding four skin diseases like Acne, Heat Rash, and Melanoma. It is stepping towards making mobile application help in the diagnosis and cure of their users without visiting dermatologists. The accuracy of this system reaches 82.5% for melanoma and 90.09% for Psoriasis. Recently, Ahmed et al. introduced an intelligent system for detecting skin diseases using machine-learning algorithms [17]. To provide communicating services with the doctor, the system is linked with Raspberry Pi that is hosted in Tensorflow to identify four types of skin diseases.

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In [1], Chen et al. introduced an intelligent system called AI-Skin that recognizes skin diseases using an AI framework. The system is based on self-learning through a closed-loop framework, that uses accumulated database to store historical uploaded images from user to enhance detection accuracy of various groups. The accuracy when they used five classes of skin diseases is 0.79 for Skin acnes, 0.80 for Skin spots, 0.91 for Skin blackheads, 0.78 for dark circles, and 0.95 for a clean face. This means that the average accuracy of the system for the five skin diseases is ((0.79+0.80+0.91+0.78+0.95)/5 = 0.846).

Existed skin disease diagnosis systems have few solutions available, which are still under research developments. Therefore, we suggested a method of using mobile vision techniques to detect different types of skin diseases. This work tries to overcome the existing problems by proposing an intelligent system for diagnosing skin diseases and providing accurate medical recommendations. The system will help users diagnosing their skin disorders easily use their smartphones regardless of their place or time.

II. System Architecture

A. *System phases*

This intelligent skin disease system can be categorized into five phases as illustrated in Figure 1.

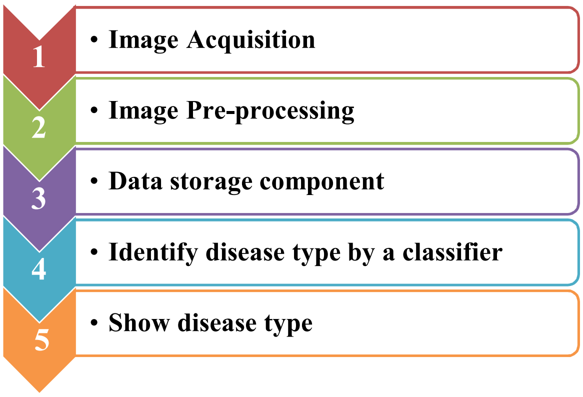

Fig. 1. System's phases

i. Image Acquisition

This phase is done on the client-side. The user takes an image for the affected area of his skin through a smartphone or any other terminal device. Whatever the source, the input image must be clear and precise. For this, a high-quality image is required to get precise results.

ii. Image Preprocessing

This stage aims to extract and strengthen the characteristic features of the image by increasing the recognition efficiency for the image. We used a cropping feature to emphasis the defected area and ease the uploading process.

- Resizing the image to 224*224 is required to have a uniform size for all images because the number of features that will be extracted from each image must be unified. We choose this size to reduce the computational efficiency after resizing, then the list of preprocessing is applied to the image.
- Removing Noise: Image processing unit will enhance the image by removing noise and unwanted parts of the skin then the image will be segmented into different segments to differentiate from normal skin. After that, the features of the image will be extracted to find out whether the skin is infected or not.

iii. ***Data Storage Components to maintain the system***

In this stage, we use Google Firebase Storage. This storage provides establishing a connection between the server (where classification and training are done) and clients [18]. Then, the user uploads the taken image to the Cloud Storage and the Server can download the image and classify it accurately. We should notice that the application itself is provided by on-device service to classify images and recognize skin diseases, but not in high accuracy.

iv. ***Identify the type of skin disease with a classifier***

The softmax classifier used here is the last layer of the network that yields the actual probability of each label. The architecture contains two major parts Image processing unit and classification unit.

v. ***Show disease type***

This phase gives a user a report of whether the image includes skin disease or not. If there is a disease in the skin, the user will receive a report about the type of disease and medical advice in emergency cases.

B. *System Services*

An intelligent skin disease diagnosis system provides three independent services. The first is a primary diagnosing service called on-device. It does not need an Internet connection. Therefore, it is important for users who are out of internet coverage area. The second is on-cloud services, which are provided with a machine learning technique and algorithms. A self-learning environment enhances the accuracy of the system by training with labeled data. The third service is medical reviewing and recommendation services where a medical staff review uploaded images and provide users with medical advice or recommendation in emergency cases. The above is illustrated in Figure 2 below.

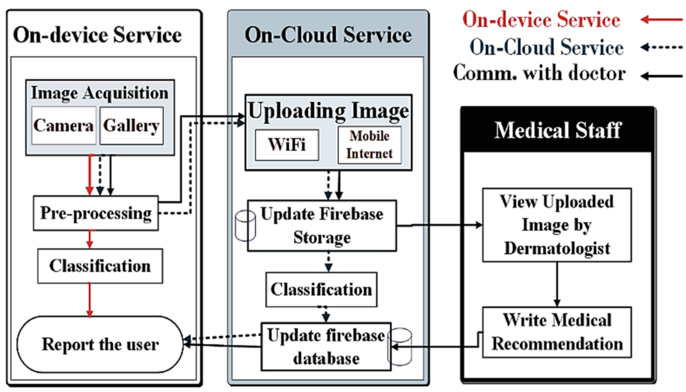

Fig. 2. System Services

i. ***On-device Service***

The user takes an image of the skin. Then, the image pre-processed and classified in the device without a need for the Internet connection. The user gets a report that includes the predicted type of skin disease.

ii. ***On-Cloud Service***

The user takes an image of the skin and uploads it to Cloud Storage. Therefore, either a server or a dermatologist from the medical center can download it. The server classifies the diseases and updates the cloud firebase database, then the user can get immediate feedback. Dermatologists can review the medical report and provide medical recommendations in emergency cases.

iii. ***Medical Staff***

The user can communicate with the medical staff and get medical recommendations.

III. METHODOLOGY

A. ***Training Dataset***

In general, the collection of data that is suitable for your application is one of the hardest steps in the development of a skin-learning application. For the development of a diagnostic system based on captured images, the data are images with a class of skin disease products labels.

We face two major challenges for collecting data in a manual fashion: first, the majority of local clinics do not have data or documentation; second, if there is data, it is difficult to reach because it is considered the privacy of clinics and requires the permission of clinical officer to obtain this information. There are many investigations to gain funds to diagnose pictures of skin diseases for online resource choice. DermNet dataset [19] is one of the biggest dermatological images accessible to the public and the dominant website for different skin diseases' images. Moreover, a comprehensive ISIC 2019 dataset [20-22] that includes 25,332 images of skin lesions in a broad range of skin circumstances have been downloaded, but all those images are archived in a Zip file in one folder. Therefore, every class of skin diseases must have a particular folder includes the images that are related to it. Furthermore, we were compelled to download every single image of Eczema and Acne individually because we could not download this information in one attempt and ISIC dataset includes only skin lesions' images.

To enhance the accuracy and generalization of our system, different pictures with distinct features like the background color of various materials have been trained, and more pictures from various other sources like medicine.uiowa.edu, dermnetnz.org, dermquest.com, dermque.com and other databases on dermweb.com have to be accessed. Our system can successfully recognize six types of skin disorders, which are Eczema, Melanoma, Acne, Basal Cell Carcinoma, Dermatofibroma, and Actinic keratosis. These classes have been selected because Acne and Eczema are the most prevalent skin illnesses with various patient impacts on various dimensions. They have a psychological impact due to modifications in the body, particularly on youths. It is usually curable if it is identified at its early stages, but if it is not, it will be difficult to control especially skin cancer. It can develop and extend to other areas of the skin where it is difficult to handle and control. The total images are 6099 images belong to six classes. For the training phase, we have used 80% of the total images that are 4879 images. The rest 20% of the total images have been used for the validation phase. Table I. shows the numbers of images used for each disease type.

Because the images of some kinds of skin diseases has not enough images, we used the data augmentation process for generating more images. Data augmentation is a process of generating more images from the limited ones. The new images are generated by mirroring, scaling, rotating, and cropping existed ones. Data augmentation is so useful for classification task especially mirroring images because the mirrored image of a person is still an image for the person.

TABLE I. THE USED IMAGES TO TRAIN THE MODEL

Disease's type	Total Images	Training 80%	Validation 20%
Acne	48	38	10
Eczema	149	119	30
Actinic Keratosis	1117	894	223
Melanoma	2084	1667	417
Basel Cell Carcinoma	1767	1414	353
Dermatofibroma	934	747	187
The total	6099	4879	1220

B. ***Firebase Database***

Firebase is a platform for developing mobile and web apps. It provides various tools and services that help programmers develop high-quality apps [23]. Firebase has more than one component used. A real-time database is used as a cloud-hosting database in real-time. Data is stored as JSON and linked to each related customer in real-time [24]. All customers use one real-time data server. Then, data is shared in real-time between all clients and remains available on the offline basis for your app. Firebase sends you new data as soon as it is updated. When your client makes a change to firebase the database, all connected clients receive the updated data almost instantly. This component is used for storing the personal information of both users and doctors in addition to storing communication scripts and messages. Furthermore, Firebase storage is used as storage that supports uploading and downloading large objects to Google Cloud Storage [25]. One of its biggest advantages is the reliability and saving users' minutes. So, Firebase restarts the uploading process immediately if an uploaded document fails due to the slow Internet connection. Moreover, Firebase Cloud has great features and performance from a security point of view [26].

ML Kit is a mobile SDK that offers Google's machine learning expertise in a powerful user-friendly package for Android and iOS apps. You can execute the functions you need in just a few lines of code, whether you're a beginner or advanced in machine learning. The main reason for using this tool is that provides simple APIs for using your version of the Tensorflow Lite for your mobile applications, if you are an advanced ML programming [25,26].

C. ***Proposed Algorithms and Techniques***

i. ***Convolution neural network (CNN)***

Deep learning relates to the bright part of machine learning focused on representational level training. CNN is one of the most common algorithms in a deep learning approach. Convolutional neural networks algorithm is commonly used in image classification. In CNN, neurons weight exchange reduces the general amount of trainable weights and leads to sparsity [27, 28], as shown in figure 3.

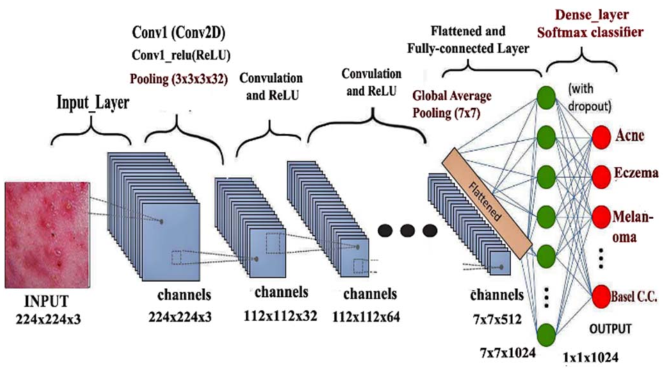

Fig. 3. Convolutional neural network.

The MobileNet train model is used where the input is 224x244x3 and the output is 1x1x1024. Through the layers of CNN, the input image is filtered to obtain a 7x7x1024 feature map. A convolution layer is commonly followed by the batch normalization layer and activation layer. In this model, the activation layer uses ReLU as an activation function. Global average pooling layers are placed at the very end layer of CNN with a 7x7 filter to pool the feature map from 7x7x1024 to 1x1x1024 followed by flattened and fully-connected layers; the softmax classifier.

ii. Transfer Learning

Transfer Training or transfer learning is a master technique in which a model developed for a task is replicated as the basis of a second task model. It's a popular approach in deep learning in which prepared models are used as a starting point for computer vision, provided that neural network models develop comprehensive calculations and time resources and skills in these fields [29] that is used as a feature extractor. In this system, MobileNet is used for transfer learning. The input images were resized to 224*224 to fit the size of the first convolution neural network layer of MobileNet [30]. Fig. 4 shows the difference between Transfer Learning and learning from scratch.

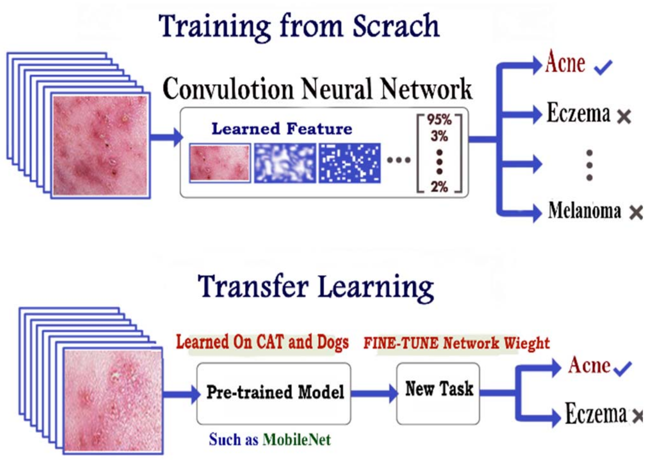

Fig. 4. Transfer Learning.

During transfer learning, first, we train a base network on a large dataset. Then, we update or pass the learned features to a second destination network to be trained in a target dataset with different tasks.

IV. Implementation and System Design

After preparing your dataset, a model that will detect skin diseases should be constructed and trained.

The steps of creating TensorFlow model

Tensorflow model is a data structure that is representing the logic and expertise of a training machine network to solve a given problem. There are numerous ways to get a Tensorflow model, from a pre-trained model to train a particular model from scratch [31].

i. Prepare database then choose a pre-trained model

Constructing your system database is a very important stage in building a successful system but none denies the time and computing resources that are needed during training. Therefore, transfer learning makes it possible to train your model with another model to increase accuracy and minimize training time and resources.

ii. Re-train a model

One of the most common method in image classification tasks is a transfer learning to retrain a new model from pre-trained one. Transfer Training helps you to adapt and re-train a qualified model to execute another function from existed pre-trained ones. For instance, a model may be retrained to understand new image classes. Here, we have retrained our model using the MobileNet. The retraining phase takes less time and needs fewer data than scratch learning.

iii. Convert the model to TensorFlow Lite

This step is done by the TensorFlow Lite converter is a Python API method that converts TensorFlow model into TensorFlow Lite format [32]. To make the model compatible with smart devices apps, conversion to Tensorflow lite is required. To obtain the TensorFlow lite format that can be embed in mobile or IoT applications, a proper Tensorflow model must be converted to the TensorFlow Lite format. it impossible task to train a TensorFlow lite model directly. Therefore, you must start by using a standard Tensorflow model for training. Then, you can convert a saved Tensorflow model to the TensorFlow Lite format using a code such as the following:

```
import TensorFlow as TF
converter =
TF.lite.TFLiteConverter.from_saved_model(saved_model dir)
tflite_model = converter.convert()
open("converted_model.tflite", "wb").write(tflite_model)
```

iv. Put the trained model on-cloud or on-device

After training a model, you can host it on a cloud or on your device. The difference is that on the cloud it needs an Internet connection, whereas on-device it does not need the Internet. After hosting the Tensorflow lite model in Apps assets, the application will support artificial intelligence features. As known, model precision is based on the data size that it has been trained on. We surfed the Internet to get a new image for testing, as shown in Fig. 5.

Fig. 5. Image for skin disease.

From the above figure (Fig.5), the image shows the type of skin disease called Basel Cell Carcinoma.

Fig. 6. Skin disease sample

The test process: the image as shown in Figure 6. cropped from the original image that has been taken from the Internet.

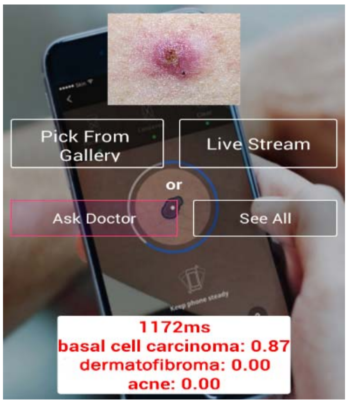

Fig. 7. Testing results

In Fig. 7. It can be noticed that the tested image's type was classified as Basel Cell Carcinoma disease. The number 1172ms stands for the time that the program takes from choosing the image until the system shows the result. Furthermore, this system provides Live Stream diagnosis like a real-time skin scan service.

Fig. 8. Live stream diagnosis for a leg.

The image in Fig. 8. Shows the output results of a live stream diagnosing for an image of Eczema disease. The image was downloaded from DermNet website [19]. Then, it was displayed on the laptop's display to be tested using the proposed App. The number 1237ms stands for the time from choosing/taking the image until showing the result.

A. Major libraries and platforms used for Implementation

In addition to what has been mentioned in the Methodology Section, the following platforms or libraries are used:

i. TensorFlow

Tensorflow is an open-source software library launched by Google in 2015, which makes designing, creating and training deep learning models simpler for developers. Although TensorFlow is only one of many choices for developers, due to its thoughtful design and ease of use; we choose to use it to implement this system. Tensorflow is an extremely high-level library in Python allowing users to dynamically simulate information as a diagram or a graph of data flows [32].

TensorFlow Lite

Tensorflow Lite provides all the tools that are needed to convert and run Tensorflow models on mobile, embedded system and IoT devices [31].

ii. Keras

Keras is a python library that is commonly used to build machine-learning models. It is a high-level API, written in Python and is able to work on Tensorflow, CNTK or Theano. It has been designed to enable rapid experimentation [33].

iii. Google Colab

Google Colaboratory is known as Colab that uses Jupyter Notebooks with Python. It is commonly used as free cloud services for programming and developing deep learning applications. Therefore, it uses common libraries such as Keras, TensorFlow, Pytorch, and OpenCV. The most important feature of Google Colab is supporting free GPU in addition to TPU.

V. RESULTS AND OBSERVATION

Initially, we used 6 classes of diseases. Then the observed average accuracy reaches 83%. The following table. 2 shows the differences between this work and the current researches.

TABLE II. COMPARISON BETWEEN THE PRESENT AND CURRENT RESEARCHES

The Researcher	Publishing Year	On Device	On Cloud	Comm. with Doctor	No. Diseases	Average Accuracy
Rathod et al. [15]	2018	√	X	X	5	70%
Ech-Cherif et al. [34]	2019	√	X	X	2	91.3%
Chen et al. [1]	2019	X	√	√	5	84.6%
This work	-	√	√	√	**6**	**83%**

The main differences between this research and the previous ones are the number of diseases and their types in addition to the number of services that are provided by the system. We have used Google Colab for implementing this model. Moreover, we have implemented it with Pycharm using Keras. The results are encouraging. The observed results in the initial training give an output accuracy of 83%.

We can easily enhance the accuracy by training the model with a large dataset.

VI. CONCLUSION AND FUTURE WORK

The main concept of this project is to design and implement a mobile-based diagnosis for skin diseases. The developed system performs encouraging results. The proposed modifications of the skin disease diagnosis system are generally to increase the performance of the system, resolve the system limitations, or to increase its capability. Therefore, there are several suggested modifications to both the system core model and the system mobile interface:

- The use of a comprehensive dataset to increase the accuracy.
- The use of other processing techniques. That means the use of other AI algorithms.
- To retrain a deep neural network using the uploaded images which are collected from the users to enhance the accuracy of the system.
- To develop the application using a cross-platform development environment.

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