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Android Application for Skin Cancer Prediction based on Machine Learning

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Abstract: Among the different types of skin cancer, melanoma is considered to be the deadliest and is difficult to treat at advanced stages. Detection of melanoma at earlier stages can lead to reduced mortality rates. Desktop-based computer-aided systems have been developed to assist dermatologists with early diagnosis. However, there is significant interest in developing portable, at-home melanoma diagnostic systems which can assess the risk of cancerous skin lesions. Here, we present a smartphone application that combines image capture capabilities with preprocessing and segmentation to extract the Asymmetry, Border irregularity, Color variegation, and Diameter (ABCD) features of a skin lesion. Using the feature sets, classification of malignancy is achieved through support vector machine classifiers. By using adaptive algorithms in the individual dataprocessing stages, our approach is made computationally light, user friendly, and reliable in discriminating melanoma cases from benign ones. Images of skin lesions are either captured with the smartphone camera or imported from public datasets. The entire process from image capture to classification runs on an Android smartphone equipped with a detachable 10x lens, and processes an image in less than a second. The overall performance metrics are evaluated on a public database of 200 images with Synthetic Minority Over-sampling Technique (SMOTE) (80% sensitivity, 90% specificity, 88% accuracy, and 0.85 area under curve (AUC)) and without SMOTE (55% sensitivity, 95% specificity, 90% accuracy, and 0.75 AUC). The evaluated performance metrics and computation times are comparable or better than previous methods. This all-inclusive smartphone application is designed to be easy-to-download and easy-to-navigate for the end user, which is imperative for the eventual democratization of such medical diagnostic system.

Index Terms - **Image Preprocessing**, **K-means Clustering Algorithm.**

I. Introduction

Skin is the largest organ in the human body and comprises two distinct layers: epidermis and dermis. While the epidermis protects the body from harsh exposures (such as ultraviolet radiation, infection, injuries, and water loss), the dermis provides nutrition and energy to the epidermis through a network of blood vessels. As with every organ in the body, the skin is prone to different forms of cancer. The two most common skin cancers are the basal cell carcinoma and squamous cell carcinoma, which arise from epidermal cells called keratinocytes. A third, deadlier form of skin cancer is malignant melanoma, which develops from epidermal cells called melanocytes. Today, melanoma is notoriously frequent because of increasingly high rates of incidence that lead to a majority of skin cancer deaths. To some extent, skin cancer is preventable, and regular screening of skin moles, either in the clinic or at-home, is beneficial for curtailing the progress of the disease. However, current guidelines for screening skin cancer in the United States are inconsistent across different health organizations. For instance, while the American Cancer Society recommends checking for skin cancer during periodic self-examinations by primary care physicians, the American Academy of Dermatology suggests that patients perform skin self-examination without sufficient clarity on the nature and frequency of screening. In a survey involving over 1600 physicians, it was concluded that the most effective skin cancer screening resulted when high-risk patients demanded a complete skin examination and the physicians also had sufficient medical training.
As with most cancers, early detection of melanoma can lead to reduced mortality according to several survey studies. In one study, 572 melanoma cases were detected over a 10-year timespan. In another study, 18,000 patients were checked for melanoma over a 17-year timespan. Both studies suggested that the chances of detecting melanoma early on are higher in established patients who routinely visit a skin clinic and are educated on the benefits of routine skin examinations. Besides routine physical examination by a primary care physician or dermatologist, skin self-examination in at-home settings is valuable for the early diagnosis of melanoma. A thorough skin self-examination involves a detailed diagnosis of all body parts, including the back of the body and scalp areas. In addition, imaging technologies aid in accurate diagnosis at an early stage, leading to better treatment and management strategies for melanoma. The methods to evaluate skin growth for potential prognosis of melanoma have evolved over the past few decades. Before the 1980s, melanomas were generally identified by naked-eye observation of changes in gross mole features, such as large size, bleeding, or ulceration. In the case of suspicious lesions, biopsy of the lesion was done by removing the lesion for further analysis. This invasive method is still the most accurate method for diagnosis of melanoma, but requires the use of trained personnel and expensive equipment. During that time period, early prognosis was difficult because of the lack of technological advancements in imaging hardware and software tools. As time progressed, non-invasive techniques slowly became adopted that entailed less expensive equipment with good accuracy.
Attempts to democratize skin diagnostics have been demonstrated that use cheaper alternatives to stereo microscopes as an imaging source. A method called named "mobile teledermatology" employed mobile phones to take digital images of the lesion but needed coupling with pocket dermoscopic devices to compensate for the poor-quality optics in early generation mobile devices. The acquired images were

transferred to teleconsultants via virtual private networks (VPNs) located at remote locations for analysis and evaluation. The two areas of improvement involve:

(i) better hardware to capture high-resolution images and

(ii) smarter computer-aided diagnosis (CAD) systems to accurately identify melanoma from dermoscopic images.

Most of the previously reported CAD systems work on desktop personal computers (PCs) or workstations and assist the physicians to identify cancerous lesions at an early stage so that the treatment regimen can start right away. These CAD systems have generally been tested on dermoscopic or microscopic lesion images, even though they could be integrated with smartphones. Today, mobile phones are equipped with high processing power, more storage capacity, high-resolution image sensors, and larger memory. This should enable mobile phones to capture images and run large computational tasks on the image directly on the device itself.

II. LITERATURE SURVEY:

2.1 Skin Cancer Detection

Author: Sanjana M , Dr. V. Hanuman Kumar

Date added to IEEE xplore: December 2018

- This paper focuses on determining the stage of the skin cancer, based on various feature such as the area of the spread, diameter, color of the lesion, etc.
- The analysis can be made with the help of machine learning algorithm, in with we train the system based on the history of the images stored in the database, and test the current image to determine, whether the test image comes in the category of the melanoma or not, if it does, then to determine its stage.
- A comparison can be made with the existing systems, machine learning reduces the computational time. Hence, the treatment can begin faster.

2.2 Prototype of Case-based Skin Cancer Detector for Android Phones based on DePicT (Concept: CBMelanom)

Author: Sara Nasiri, Bedrettin Aslan, Simon Geller and Madjid Fathi

Date added to IEEE xplore: 2016.

- This paper presented the results of a research project that applies CBR as a methodology and utilizes DePicT concept and myCBR tool to develop CBMelanom APP.
- It makes two contributions. First, it describes the conversational cases based on DePicT concept which is patient centered and has PHR approach. Additionally, the characteristics of client server CBMelanom application are also explained.
- The unit testing and evaluation of CBMelanom functionality shows that it can be utilized in skin diseases domain and for its target group.
- Finally, for improving the retrieval phase, similarity measurement could be enhanced based on the new test results

2.3 An On-device Inference App for Skin Cancer Detection

Author: Xiangfeng Dai, Irena Spasić, Bradley Meyer, Samuel Chapman and Frederic Andres.

Date Added to IEEE Xplore: 2017.

- The combination of machine learning and mobile health technology has a great potential to transform the detection and prevention of various diseases, such as skin cancer.
- Many studies about machine learning on mobile devices have been the focus on cloud-based solutions because memory and computational power is relatively limited. However, cloud based approaches come with drawbacks such as latency and privacy, which need to be considered in the context of medical applications.
- In this study, we present an on-device inference approach, which has and number of benefits over cloud-based solutions. These include lower latency, improved privacy, lower costs and higher availability.

III. RESEARCH METHODOLOGY

3.1 Overview

This chapter presents each step of the design and implementation of the skin diseases diagnosis system and discuss the methods used in each step, and provide figures and tables from the implementation process for more explanation, the chapter is divided into three main parts the first one is discussing how the data has been gathered, the second one is discussing the classification model design and implementation and the third part is considering the system development and integration.

3.2 Dataset

Generally, collecting data that fit your application is one of the most difficult steps in developing a machine learning application, so for developing the Skin Diseases Diagnosis system based on captured images, the required data are images with a labeled classes of skin diseases, so we had two choices either to collect the images manually from hospitals, healthcare centers and individual patients or using online resources for skin diseases images database.

For the manual collection of the data, we face two major problems to apply this option, the first one is that there is lack of data collection and documentation in most of the local hospitals, neither digital data nor hard copies of the data, the second problem is that if there is a data available, it’s hardly reachable because it’s considered private for the hospitals and require permissions from the local health authorities, also the data is not sufficiently enough for the training of the model, not well prepared and require a lot of work to be ready for usage, so we choose to search for another option to collect the data.

For the online resources option, there are a lot of researches are done to obtain resources for skin diseases diagnosis images. DERMNET.COM was the dominant resource for the system data, it is one of the largest dermatology photos resource that are available publicly. Although it has more than 23,000 skin disease images on a wide variety of skin conditions, but there was not direct way to download a whole class of diseases at once, so we were forced to download each single image every time. in contrast this data couldn’t be downloaded at once, we were forced to download each image individually.

To increase the reliability and generalization of our model, it must be trained on different images with different characteristic such as background color of different resources, to achieve this more images were downloaded from other multiple resources such as medicine.uiowa.edu, dermnetnz.org, dermquest.com, dermquest.com along with other websites available at dermweb.com. Most of those images were normally captured by camera with acceptable resolution that more probably will match the type of photos that will be captured by the users.

Our system has been designed to detect 3 types of skin diseases namely, Eczema, Melanoma and Acne. These classes were chosen because Acne and Eczema are of the most common skin diseases that have multiple effects on the patients on different aspects, they are painful in addition they have psychological effect caused by the changes that happen in skin specially for teenagers. Melanoma is the most dangerous form of skin cancer, most often caused by ultraviolet radiation from sunshine or tanning beds [21], If melanoma is recognized and treated early, it is almost always curable, but if it is not, the cancer can advance and spread to other parts of the body, where it becomes hard to treat and can be fatal.

For the training of our system, 200 images for each of Acne, Eczema and Melanoma were collected, although most of the images were downloaded from Dermnet about 140 of each, but they were signed with watermark in the middle of the image, shown in the Figure 3.3.1.1-1, which restrict us in applying different preprocessing techniques, that will be explained later, this is another reason why we download more data from other sites.

Figure: Dernmet image sample

3.3 Learning Model

3.3.1 Images Preprocessing

Before using the images to train our model, series of preprocessing have been applied to our data to enhance the images also to increase our data for better generalization. All these processes were implemented using MATLAB image processing toolbox.

3.3.1.1 Resizing the image

At first all images were resized to be 293*192, resizing the image is important 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 list of preprocessing are applied to the image.

3.3.1.2 Gray images

Images were converted from RGB – red, green and blue- type to gay scale images. Sample is shown in Figure below.

Figure : Grayscale image sample

3.3.1.3 Powered images

Since Negative images are useful for enhancing white or grey detail embedded in dark regions of an image, then we convert these gray images to their negative, then power of two is applied to the negative image to darken the image. Sample is illustrated in Figure 3.3.1.3-1, notice that the injected area here is more visually appealing, but also the water mark become more clearly.

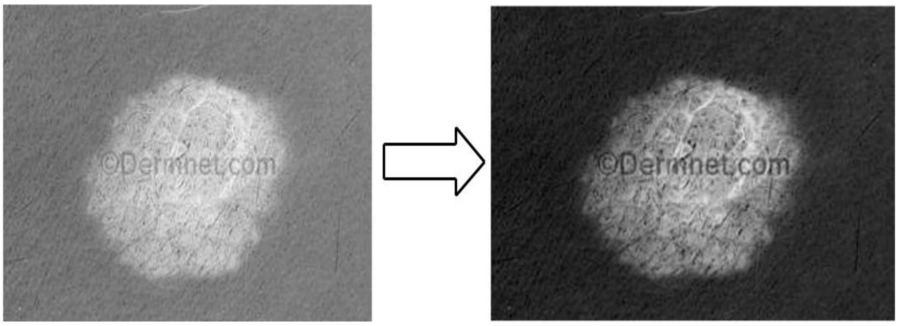


Figure : From Negative Image to Power of two Image

3.3.2 Learning Model Selection

Before using Bag-of-Features as basis for training the data, list of techniques for classification was used, *Table 3.3-1* shows the results of these models using jkkjk200 images as input for training and evaluation, only Cross-Validation is applied.

Convolutional Neural Networks in addition to its low accuracy, it requires very high computational resources (when using GPU, it requires GPU computational capabilities greater than 3.0 which was not available for us), or then when using CPUs, it will take very long time for training our data.

Then we attempt to extract HOG features of each image and classify these features using SVM classifier, the result was insufficient because HOG features are not suitable to present our data.

3.3.3 Bag of Features Model

Bag of Features approach in computer vision in the past few decades has been used a lot in many applications. Bag of Features (BoF) methods have been applied to image classification, object detection, image retrieval, and even visual localization for robots.

In our System BoF approach is implemented to train our data, since it is used to classify images based on its texture. BoF approaches are characterized by the use of an order less collection of image features. Lacking any structure or spatial information this eliminates the effect of the water mark in our images which increase the accuracy compared with other learning models such as Convolutional Neural Networks and manually HOG features extraction along with SVM classification, as will be discussed in **Error! Reference source n ot found.**.

All preprocessed images are combined together along with their labels (Acne, Eczema and Melanoma) to form the input data to lean the BoF model, to implement BoF model approach, three steps must be followed. The first step is to extract features from the images, interest point must be detected and described in this step, step two is Quantization, finally the last step is the Classification of the quantized vectors.

3.3.3.1 Step One: Feature Extraction

This step is the base for the coming steps, the features that will be used to train the classifier will be extracted at this step, to achieve this the interest points must both be detected and described.

Interest points detection can be achieved in several ways. Dense feature could be used, also one of the feature extraction techniques such as Harris Corner Detection, FAST, SURF and SUFT that described in 2.4 .

At first we attempt to use SURF features to detect interest points but it was not sufficient, because the result list of the interest points was crossed and concentrated together ignoring large part of the image that considered as important points also. The next figure shows the strongest 10 points extracted using SURF detector.

Figure : Strongest 10 points extracted using SURF

For better results we choose dense features, every part in the image contributes and effects on the features selected to describe the image, the image is simply divided in regular grid, when the interest points are detected then features are extracted based on these points.

In our model we select SURF algorithm to extract features from each block of each interest point. These features represent what is called visual words describing the image.

3.3.3.2 Step Two: Quantization

All feature of all images (visual of words) are quantized, i.e. using clustering technique to cluster these visual words to specific number of clusters (visual vocabulary), the image is represented as distribution of these words. This is done by k-means clustering to represent group of similar visual words as single cluster (visual vocabulary). The number of desired clusters is selected manually, optimal selection of the number of visual words vocabulary depends on two factors, the first one if it's too long then the computational cost will increase, the second one is that when number of visual words vocabulary is too short then no proper discrimination between features will be obtained. In our model number of 2000 visual words is selected to be the number of visual words.

K-means Clustering Algorithm

K-means is a method of clustering observations into a specific number of disjoint clusters. The "K" refers to the number of clusters specified. Various distance measures exist to determine which observation is to be appended to which cluster. The algorithm aims to minimize the measure between the centroid of the cluster and the given observation by iteratively appending an observation to any cluster and terminate when the lowest distance measure is achieved [22]. K-means clustering is one of the simplest clustering techniques, typical steps of the algorithm are:

The sample space is initially partitioned into K clusters and the observations are randomly assigned to the clusters.

For each sample Calculate the distance from the observation to the centroid of the cluster. IF the sample is closest to its own cluster THEN leave it ELSE select the closest cluster.

Repeat steps 1 and 2 until no observations are moved from one cluster to another.

Common distance measures include the Euclidean distance, the Euclidean squared distance, The Euclidean measure corresponds to the shortest geometric distance between two points, a faster way of determining the distance is by use of the squared Euclidean distance. Euclidian distance d between n points is determined by:

$$= \sqrt{\sum_{=1} (\quad - \quad)^2} \qquad . \ 3.4\ 1$$

Sample of Visual Vocabularies Histograms for the model classes

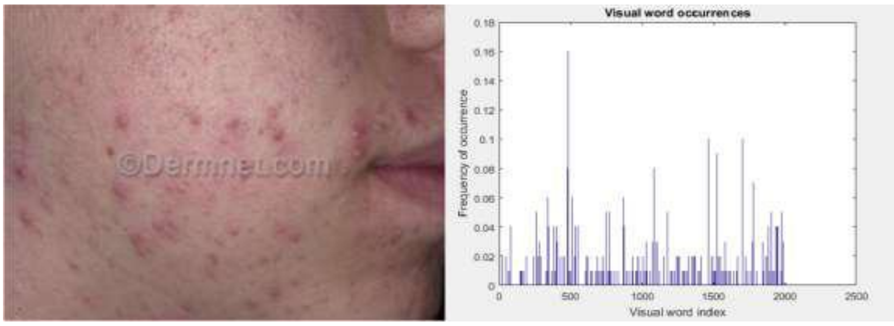


Figure : Sample Image for class 1 Acne & Its Histogram of Visual vocabularies

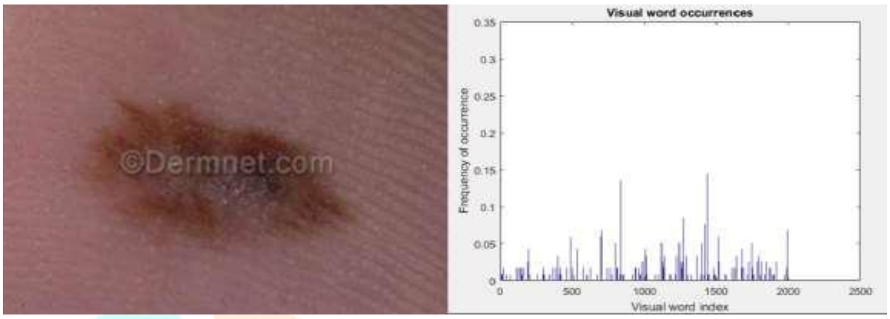


Figure : Sample Image for class 2 Melanoma & Its Histogram of Visual vocabularies

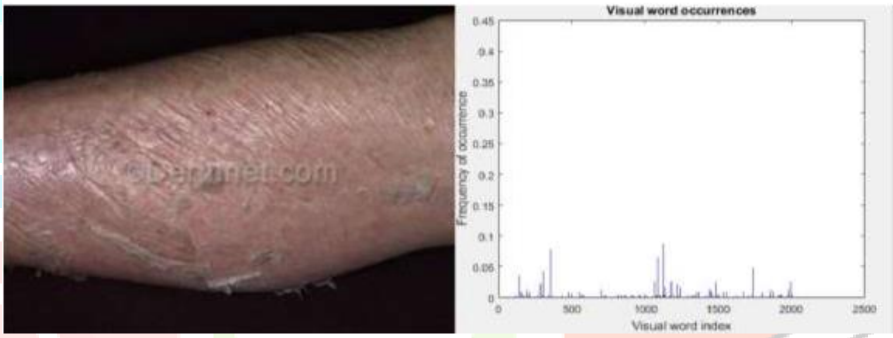


Figure: Sample Image for class 3 Eczema & Its Histogram of Visual vocabularies

3.3.3.3 Step Three: Classification

When different visual vocabularies are obtained then each image is described using these vocabularies, the histogram of each visual vocabulary is determined and stored in what is called feature vector, all vectors of all images represent the input to the classifier. There are many classification techniques as mentioned in 2.5.

Here Support Vector Machine -SVM- classifier is used, since the input data is complicated and nonlinearly separable then SVM with Radial Basis Function kernel is used.

There are many types of radial basis functions such as Gaussian radial basis function, Multi-Quadric Functions and Thin Plate Spline Function, Gaussian function is the most commonly used.

Gaussian Function:

$(\ ) = \ (^{-}\ {}^{2}\!/_{2}\ {}_{2})$ 3.3-1

For further information about SVM see Appendix A.

An overall view of Bag-of-Features model is illustrated in the Figure below.

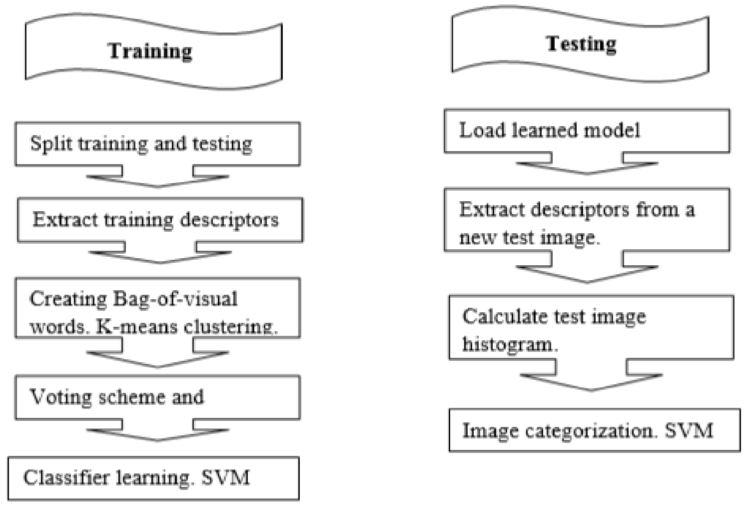


Figure: Bag-of-Features Model

3.3.4 Model Training and Evaluation

In the training, we use 400 images of each class, 200 of them were colored images, 200 were gray images, so we get overall 1200 images, the dataset was separated that 60 percent of the images were used for training and 40 percent used for the evaluation.

In the training process, bag of features model is used, implemented in Machine Learning, many parameters were tuned such as the size of visual vocabulary, grid step, box constraint (A parameter that controls the maximum penalty imposed on margin-violating observations, and aids in preventing overfitting) and the percentage of total extracted features, to determine the optimal or close to optimal of values of these parameters.

To evaluate the model, the accuracy has been used, the accuracy of the model is the number of positive predictions divided by the total number of positive class values predicted.

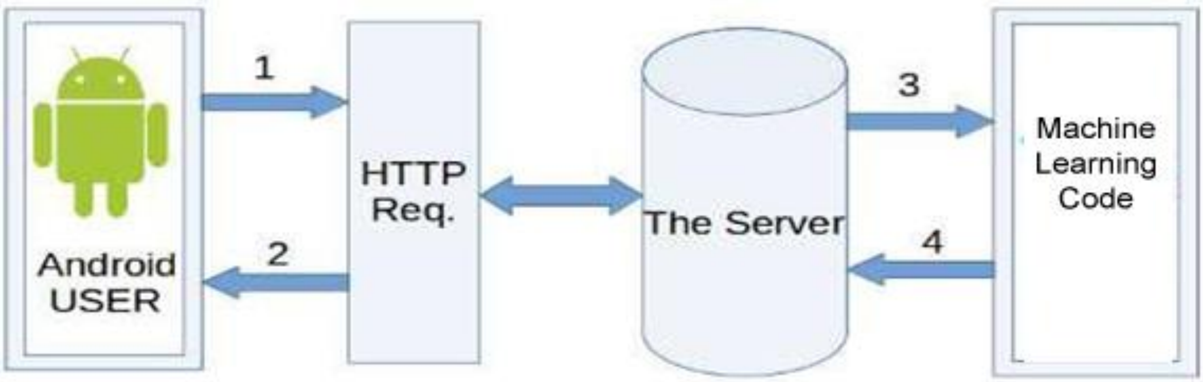
We use Cross-Validation method, that is randomly dividing the data set to training and testing datasets based on percentage, our data was divided to 60% images for training, and

40% images for testing and evaluation. Also additional data is obtained to test our model that's called Holdout evaluation method.

3.4 System Design

In this part, we discuss the overall system architecture, and explain in details the design and development process of each part of the system, and the tools and methods used to do that.

The skin diseases diagnosis system mainly consists of two parts that represents the server side and the client side each one contains a separate application and linked together over a shared network. The server side is a MATLAB application that contains the main machine learning model which implement the training and classification task. The client side is an Android application that acts as an interface to the MATLAP application, its main task is to receive the input from the user and pass it to the server and return the output of the server. The two sides are connected together through apache server and SQL database server using HTTP protocol.



3.4.1.2 Development Tools and Libraries

The tools used in the development process of the android application.

Android Software Development Kit (ADK)

It provides the developers the API libraries and developer tools necessary to build, test, and debug applications for Android, enabling them to create android virtual devices (AVD) for testing, helping the developers to monitor and control AVDs and physical devices connected to the computer.

Android Studio

Android Studio is the official Integrated Development Environment (IDE) for Android app development, based on IntelliJ IDEA. On top of IntelliJ's powerful code editor and developer tools, Android Studio offers even more features that enhance your productivity when building Android apps, such as:

A flexible Gradle-based build system A fast and feature-rich emulator

A unified environment where you can develop for all Android devices

Instant Run to push changes to your running app without building a new APK
Code templates and GitHub integration to help you build common app features and import sample code
Extensive testing tools and frameworks
Lint tools to catch performance, usability, version compatibility, and other problems C++ and NDK support
Built-in support for Google Cloud Platform, making it easy to integrate Google Cloud Messaging and App Engine
All these features make android studio the best development tools for developing android applications, the version used to develop skin diseases diagnosis system is android studio 2.3.

VOLLEY LIBRARY
Volley is an HTTP library that makes networking for Android apps easier and faster, it provides many benefits such as [23]:
Automatic scheduling of network requests. Multiple concurrent network connections.
Transparent disk and memory response caching with standard HTTP cache coherence.
Support for request prioritization.
Cancellation request API. You can cancel a single request, or you can set blocks or scopes of requests to cancel.
Ease of customization, for example, for retry and back off.
Strong ordering that makes it easy to correctly populate your UI with data fetched asynchronously from the network.
Debugging and tracing tools.

Testing Device
In the android development there are two options generally for building and running your project, the first one is using AVD to create a virtual device within your PC and run the application into it, or you can use an external physical device that using Android OS to run your application into using physical connection, this option is a very efficient compare to the first one, even though it requires providing an external device but it give a better performance than the first option, the external device must be configured first to be able to run the application into it. For that the second option is selected and a SAMSUNG device has been used for the testing and debugging operations of the android development.

3.4.1.3 Android Application Development
The development of the android application of the skin diseases diagnosis system is done using android studio IDE installed on Ubuntu operating system, generally in the android applications there are basic functions that must be in each application, and each one of them is called at specific time these functions are explained in the reference [23], also there are some specific function for this application each one is developed for specific task, which is called along the application running to do the certain task and get the result then the application continue through the lifecycle of the basic functions, these specific functions are:
getStringImage:
this function take the image captured by the user and convert it to array of bytes stream class and encode the image using base64 encoder to make it suitable to be send to the server.
uploadImage:
this function is to take the image capture by the user and make string request to the server to send the image to the server using the PHP code saved in the server side.
getResult – Android side:
this function is called after the response of the upload image is received, it creates another string request to the server, and execute the getResult PHP script in the server, then it get the result from the server and write it down to a text view field to print it to the user.

Android Device Permissions Policy
The new android versions from android 6.0 or higher, has a new permissions policy for granting the access to the device resources, simply they don't accept the general access permission from the android manifest file, as applied for the older versions, they require to grant a permission whenever you need to access a device resource, so an online permission algorithm has been implemented to check the permission grants whenever there's a need.

3.4.1.4 Application Functionality

Capture an Image
This function is used to capture an image using the mobile camera and feed it as input to the android application, which contains the skin disease image to be classified.

Load image from storage
This function holds the other option instead of capturing the image, which is loading an image stored in the device storage or any associated SD card.

Send the image to the server
This function is used to send the input image to the server using HTTP request.

Receive the results from the server
This function receives the result data from the server and store it in the android application.

Show the results
This function is used to view the result data that has been received from the server to the user which contains the classification output class.

IV. RESULTS AND TESTING

4.1 Results of Unit Test Modules of Study Variables

Table 4.1: Unit Test Modules

Test Units	Expected Output	Test Results
Fragment Activity	Screen should be divided into 2 fragments	Passed
Camera Activity	Camera should get the surface view	Passed
ML Interaction	Communicated with the ML Code Stored in Firebase	Passed
Colour Change on Camera	Colour should and per the prediction	Passed
Prediction in Percentage	Percentage should be displayed based on the result	Passed
Skin Cancer Result	Display predicted result	Passed

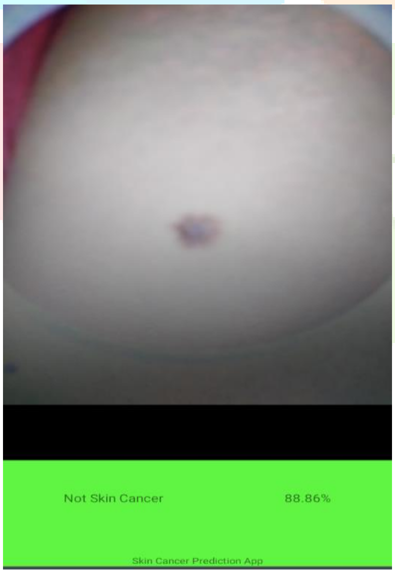
4.2 Integration testing:

Data can be tested across a device interface. One module can have an involuntary, adverse effect on the other. **Integration testing** is a systematic technique for constructing a program structure while conducting tests to uncover errors related with integrating.
This integration testing involves the integration of all the units together and testing it. The following units are integrated and tested as one.

4.3 Integrated System Results

The skin diseases diagnosis system is successfully built with all the specified functionalities, giving the expected outcome at each step, the data successfully flow between client and server without problems.
The image is captured using a mobile camera and is sent to the server successfully, the image information is recorded in the database, then the ML script read the data immediately and load the image and perform the classification with the pre-trained model, then writing the result back to the database, then the mobile application read the result directly from the database and print it to the user.
The system also performs the task with a good performance, an addition its easily used requiring uncomplicated configurations to be used, so it's a user-friendly application.

SNAPSHOTS



Normal Mole

Infected Skin

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