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Mobile Application for Skin Disease Identification

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ABSTRACT: This work describes an approach and development of an automated system for the diagnosis of skin diseases. Skin diseases are a serious concern for people all over the world. In this research, the Convolutional Neural Networks (CNN) deep learning algorithm is applied to classify skin diseases in the HAM10000 dataset. An extensive review of the skin disease classification literature was carried out and the methods were evaluated in order to find the best classification method which would suit skin disease classification. The CNN-based method was chosen as the best method for performing skin disease classification. A mobile application, on the other hand, is crafted for quick and precise operation. It assists the patient and the dermatologist in determining the nature of skin ailment that is likely to develop by examining the image of the afflicted region at the early stage of skin disease. This study found that ResNet50 with transfer learning achieving an accuracy of approximately 94% is the most suitable model for empirical skin disease detection. Based on these results, it appears that such an approach aids general practitioners in making diagnoses within minutes with precision using a smartphone. Keywords—Skin Disease, Deep Learning, Mobile App, CNN, TensorFlow Lite, Disease Classification

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I. INTRODUCTION

As the World Health Organisation stipulated, skin ailments affect people from all walks of life and strata of society. As mentioned by them, almost 30% to 70% of people are affected by skin ailments. The rise of artificial intelligence (AI) and machine learning (ML) has heralded an important opportunity for the automated diagnosis of skin disorders. Most people's understanding of skin diseases is very limited. Some of them may be harmless. They can cause severe health issues. Knowing their effects is very important. Many of these dermatological conditions, especially when neglected on a primary intervention level, borderline dangerous. It is important to control these disease early on to mitigate their subsequent spread. Skin abnormalities are often accompanied with psychological troubles leading to diminished self-esteem and self-image, thus serving as milestones on the public's health radar. Hence, these disorders need our attention at due course of time. Immediate treatment is required to prevent permanent skin damage and to preserve the skin's natural beauty and youthful glow which. . . if implemented this system will greatly help to address the dilemma. Because of the system's capability to differentiate between skin diseases, clients can convey medicines or advice to patients with the help of patients' photographs of unhealthy skin and information obtained from the patients.

II. RELATED WORK

As every part of the body, face has a skin which is the outer covering known as facial skin that has protective and visual aesthetic appearances [1]. These abnormalities or facial skin problems are disorders which are so usual among people. The modern approach is that facial skin diseases should be treated as early as possible in order to mitigate the complications associated with the disease. There are technologies in medicine that help in the diagnosis of facial skin diseases. However, they are expensive. Apart from the use of digital imaging, there is no less expensive alternative that can detect facial skin diseases [2].

Many researchers have proposed different image processing techniques based on deep learning for the diagnosis of different skin diseases. In that regard, T. Shanthi et al. [3] presents a new architecture of convolutional neural network which classifies 4 chosen classes such as acne, keratosis, Eczema herpeticum and salt urticaria from the DermNet dataset and demonstrates a skin condition recognition accuracy improvement from 98.6 Jessica S. Velasco et al. [4] described another contribution in which they examined the inclusion of transfer learning and how it affects trained models with respect to improving the classification results for different datasets. Bandyopadhyay et al. [5] introduced a model which fused deep learning (DL) and machine learning (ML). Following that, they performed an evaluation to determine the optimal prediction model. Kshirsagar et al. [6] designed a system for classifying skin diseases using MobileNetV2 and LSTM. Their emphasis was on achievement of high accuracy with respect to skin disease forecasting and ensured high efficiency in storage of complete state information for precise forecasting. They also performed evaluation against other traditional models such as CNN and ANN and found the proposed model excelled in the skin disease classification and in the assessment of tumor growth using texture-gimli tools. Kethana et al. [7] articulated a model aimed at the classification of skin disease using Convolutional Neural Network (CNN). They attained a 96% accuracy in classifying skin diseases as Melanoma, Nevus, and Seborrheic Keratosis using a dataset of 10015 images obtained from the ISIC 2019 dataset. In [8] Hao Zhang and Liang Ma discusses the advantages and concerns of employing deep learning for skin disease classification. It offers an evaluation of various skin disease datasets and the models generability.

III. SYSTEM ARCHITECTURE

The architecture includes three primary modules:

- **Dataset Collection:** Gathering a dataset of dermatoscopic images- With neural networks becoming more proficient at automated detection of pigmented skin lesions, it has become more difficult to create suitable models owing to the small-sized and homogeneous dermatoscopic datasets available. The HAM10000 (“Human Against Machine with 10000”) dataset checks this issue. We compiled images of skin conditions from people belonging to different backgrounds and captured and preserved using diverse modalities.

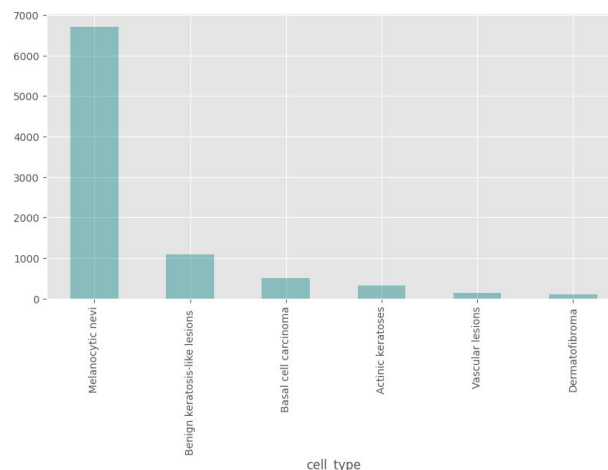


Fig. 1. The distribution of different classes of cell type

The complete dataset consists of 10,015 images which is freely accessed. The cases contain a cross-section of all important diagnostic categories in pigmented lesions. Actinic keratoses, basal cell carcinoma, benign keratosis-like lesions, dermatofibroma, melanocytic nevi and vascular lesions. More than half the lesions are confirmed histologically, the rest are corroborated by follow-up investigations, expert consensus, or via in-vivo confocal microscopy (confocal). Those diseases that have many images within the dataset can be tracked through the metadata dataset by looking at the id co. from HAM10000 dataset. The distribution of different classes of cell type have been illustrated in Fig.1, and table 1 shows the number of images available in the dataset.

TABLE I

DISTRIBUTION OF THE DATASET

Class	Number of Images
Dermatofibroma	115
Vascular lesions	142
Actinic keratoses	327
Basal cell carcinoma	514
Benign keratosis-like lesions	1099
Melanocytic nevi	6705

• **Model Training:** The purpose of the image generator is to implement various alterations to an image. There are multiple copies of images with each undergoing changes. Each duplicate is distinct image based on shifting, rota- toin, flipping etc. These changes, in some sense, affect the class of the image, but rather the view of the capture some changes to the image offers. This is precisely the reason why we make use of it for deep learning models quite often. Out of 10015 pictures, 6009 were utilized to train the CNN models while 2003 were reserved to validate model accuracy. The remaining 2003 images were set aside as baselines for comparison purposes. A 60 percent of the dataset is used for the training, 20 percent of dataset is used for both validation and testing respectively. Deep learning has revolutionized the field of computer vision and continues to do so with the advancement of Convolutional Neural Networks. The figure illustrates the most simplistic form of processing that happens in a CNN model.



Fig. 2. Basic process inside a CNN model

CNN architecture is almost related to human neurons. As illustrated in below Fig, the model's basic architecture is comprised of components and units which operate individually. CNN segments pictures with the aim of simplifying them into processes easier to work with. The filters undergoing convolution produce convolution layers. These layers with regards to the image input, filter out the basic features from the images like colors or sharp edges. A high level of detail requires significant processing power and therefore a pooling (max-pooling or pooling) layer simplifies this layer to reduce the work required. These layers can be added up to a defined number which will serve as the training model to gather the picture stage features based on its complexity. To improve the model's performance at the next stage, the output is transformed into a flat structure to use it in a traditional complete layer used for image classification. An additional, complete layer is then used to enhance the system learning the regions of interest at the image data processed nonlinearly in the previous step after the convolution layer. The output is then structured into a column vector and processed through a feedforward neural network.

• **Mobile Application Development:** Android Studio is a popular mobile development platform that assists in the creation of friendly and reliable mobile applications. With Android Studio, the implementation of machine learning models using TensorFlow Lite becomes more stream- lined. Models that have been trained can be converted to lightweight versions suitable for mobile applications. The system's overall architecture integrates the CNN model with an Android smartphone application. In the diagram, you can see an overview of the processes concerning the design of the system. The mobile application func- tionality enables clients to capture images in real time using their phone cameras or select images stored in their phone gallery as app system inputs. The interface is also designed in such a way that enables users to analyze the results remotely and see the type of diseases displayed on the screen of their Android devices.

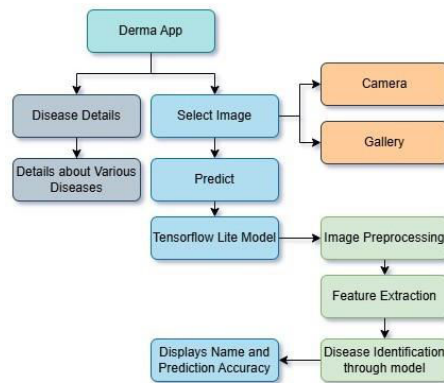


Fig. 3. Design of the Skin disease Identification Mobile Application

To implement on mobile android devices, the Keras model has to be converted into a tflite model. Keras models were saved .h5 from the Keras training process. This model can't be used for Android development as the only accepts .tflite. TensorflowLite is a lightweight package that enables access to the Android Neural Networks API. The conversion was carried out in python. The model is now able to work with android and so the This model is for use in android studio. The mobile application development model will assist with the understanding from figure 3 which Details of the Skin disease Identification Mobile Application Design Overview are provided as explanations to the diagram. The mobile app has feature like details about some common skin diseases.

IV. RESULTS

Every image belonging to the validation dataset has been processed in order to compute the validation accuracy. This iterative procedure will continue until the training and validation datasets have traversed the layers of the model a set number of times, known as epochs. After each epoch, the model assesses the images within the validation dataset to gauge the accuracy of the model's weights for that epoch. The model has been trained in 2 Phases: Phase 1: Only the newly added dense layers on top of the base model are trained The rest of the layers in the base model remains frozen. This allows the output of CNN convolution captures to be stable, permitting the dense layers to learn to assign For Figure 4, I show training loss and accuracy of phase 1. Phase 2: Here we further increase the predictive accuracy of the network by applying a more careful model-wide fine tuning. A slower learning rate is applied to restrain overly aggressive feature extracters run of adjustments. Training loss and accuracy metrics for phase 2 are presented in Figure 5. Skipping phase 1 and training the full CNN at once would cause dense layers to emit high-loss random predictions causing severe overfitting to erroneous features.

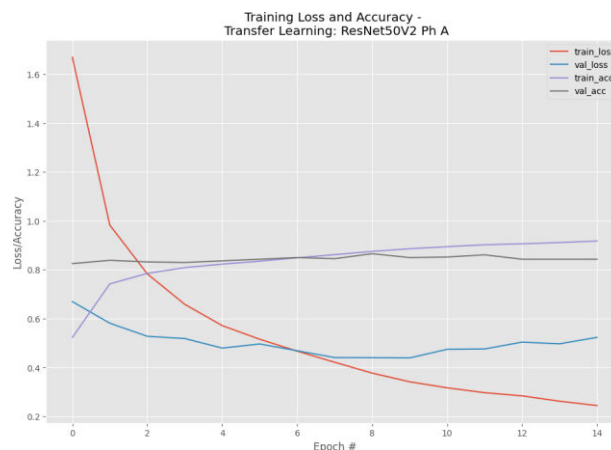


Fig. 4. Training Loss and Accuracy Phase 1

The untrained layers would have used highly volatile dynamics and destroy the careful balance feature detectors had already learned. The dataset had an imbalance problem, which is why the data was upsampled. The model was kept for 15 epochs which is the duration for both phases while maintaining a batch size of 128. 105 mb in size and achieving 98% accuracy on the test dataset was what the Original model delivered. To enable application placement on mobile, the model had to be quantized to shrink the size. The formed tflite model is 26.6 mb. with accuracy fell in to 94%. Fig 6. shows the Skin disease recognition mobile application user interface. A key aspect of the user interface is that the user is able to choose the image using the select image option. When we select the image, the image classification is done by pressing the prediction button. In this case, the model has determined that the lesion is a Melanocytic nevi with a confidence level of 99.31% accuracy. This information is provided underneath the interactive controls for the user interface. Clicking the disease details button will direct the user to a new interface which gives useful details about various types of a diseases.

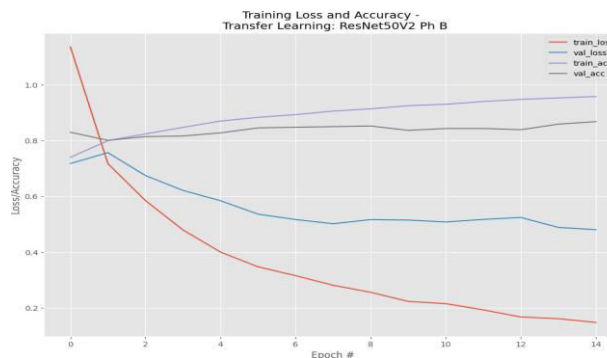


Fig. 5. Training Loss and Accuracy Phase 2

The Original model gave an accuracy of 98% in the test dataset and was of the size 105 mb. The model have to be quantized to minimize the size in order to deploy it in the mobile app. The tflite model formed is 26.6 mb. The accuracy dropped to 94%, which is still a good enough accuracy.

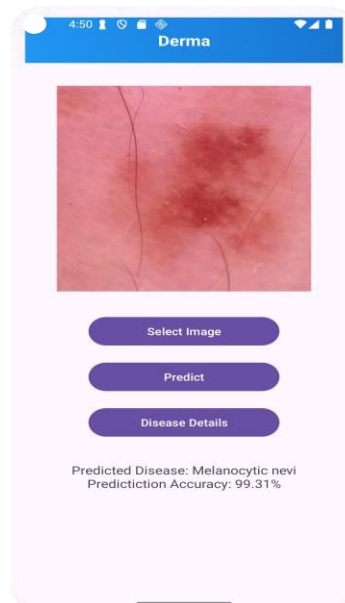


Fig. 6. Mobile application for Skin disease identification

Fig.6. depicts the user interface of Skin disease identification mobile application. The main feature of the interface is that user can select the image via select image button. Upon image selection, the prediction button initiates the disease classification process. In this instance, the model has identified the lesion as Melanocytic nevi with a prediction accuracy of 99.31%. This output is displayed below the interactive controls for user awareness. Upon clicking the disease details button it will take it to the new interface where it provide necessary information about different type of a disease.

V. CONCLUSION

Combining features and improving an image's quality increases accuracy within the result. For this research study, we looked at two different features to identify the ailment. Even though skin diseases are the fourth most prevalent health concern, a lot of people choose to postpone medical assistance. Automated and accurate diagnosis systems were designed for dermatological disorders. Addressing skin disorders at an earlier stage is more efficient and less disfiguring. In this document, the skin disease prediction model is created based on deep learning algorithms. The Convolutional Neural Network algorithms are capable of diagnosing real-life skin diseases with astonishing precision. Accuracy can be immensely improved with a vast dataset and advanced technology and software. Also, due to the non-invasive nature of the model, clinical tests can be conducted effortlessly.

VI. FUTURE SCOPE

Going forward, researchers can test image classification algorithms with different sets and types of images to improve the accuracy of disease identification. Proposed future research could assist in formulating this model into proxy standards for skin disease preliminary diagnosis. With this approach, both the time and costs associated with diagnosis and treatment can be reduced. This work can assist the healthcare sector by helping the dermatologists to identify vitiligo, a skin disease, much earlier than before. This will improve the estimation accuracy which will refine the outcomes. Future studies could be more successful because these factors were not altered during the investigation. The future study aims to implement a system designed in this paper to a Big Data environment. Furthermore, the study seeks to improve the model's efficacy by strategically applying TensorFlow on Spark and other platforms. The model can be improved by equipping it with the ability to be self-taught and autonomously retrieve information and experience-based knowledge. The effort needed to adjust the model will be considerable less.

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