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Skin Disease Classification using Convolutional Neural Network via Android Smartphone Application

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Abstract: According to the global perspective of health, skin disease leads a huge major burden. Due to a lack of medical awareness among the general populace, most patients did not notice the symptoms until several months later, allowing the disease to spread. Early detection of the skin lesions is important for making treatment decisions to prevent the spread of skin disease. The main purpose of this project is to develop an Android-based mobile application using convolutional neural networks that allow the users for diagnosing the skin disease easily for defeated the limitations of the conventional method. The model was executed using the TensorFlow library, which was implemented in the mobile application. The project used the MobileNet V2 model, with 6318 photos gathered from public dermatology sources on the internet. Acne, eczema, and vitiligo were selected as the disorders for detection. The overall accuracy of the smartphone application was 91 %. The detection rate was 100 % accurate, with an inference time of 317ms. The MobileNet V2 model is more preferable for smartphone device due to excellent performance, small size and fast training.

Keywords: Classification, Convolutional Neural Network, MobileNet V2, TensorFlow

1. Introduction

In 2010, skin disorders were the fourth major source of nonfatal burden measured in years lost due to disability [1]. The genetics, hormones, medicine, and particular illnesses like diabetes are internal factors that affect skin lesions [2]. The environment also determines the external factors that impact skin health such as climate, extreme temperature, lifestyle, inappropriate skincare and chemicals [2].This skin lesion are characterized as disorders can possess an impact on the patience quality of life in a variety of aspects, including physical symptoms and emotions, social activities, and career [3, 4]. The skin disease necessitates early intervention in order for clinicians and dermatologists to detect the

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specific symptoms thus prevent the disease [5]. Initial diagnosis of several diseases, especially skin disease, can be aided by image-based computer-aided diagnostic systems [6]. Regarding to the system, the Convolutional Neural Network (CNN) is one of the machine learning algorithms that extracted the feature of the images as training input to the machine learning models [7]. The Convolutional Neural Network (CNN) model possesses an excellent performance in the classification for several objects [8].

The majority of skin diseases were diagnosed using conventional methods such as physical examinations, blood tests, and biopsy. The dermatologist employs the techniques and tools for diagnosing the skin lesion based on experience, knowledge and precision during the clinical inspection [9]. Despite the fact that medical technology based on lasers and photonics has aided to diagnose skin illness much faster and efficiently, but the expense is out of reach for most patients [10]. As a result, this project purposed to design the CNN-based model that can classify skin disease with high accuracy. After that, this model is deployed to develop an Android-based mobile application that recognize the skin diseases in real time. Table 1 shows the comparison between types of skin disease and the method use for classification from several related works.

Table 1: Comparison between types of skin disease and the method use for classification

Types of skin disease	Method	Accuracy	Limitation
Eczema	ANN	68.73%	Diagnose using only virtual context.[11]
Melanocytic nevus	GoogleNet Inception V3	86.54/3.63% 85.86/4.649%	The significant standard deviation may represent the accuracy's floating range due to the usage of small dimension of the images[12].
Seborrheic keratosis			
Basal cell carcinoma			
Psoriasis			
Melanoma	SVM	92.1 %	Using SVM algorithm for detection system[13].
Benign	CNN	70%	Using advanced computational techniques and large dataset[14].
Malignant			
Melanoma	VGG-19	87.2%	Deep learning methods have not been tested for melanoma thickness prediction[15].
Nevus	Resnet 101	91.87%	The candidate frame for the region is not very accurate, resulting in a somewhat lower segmentation accuracy[16].
Melanoma			
Psoriasis	U-Net	98.67%	The complex background and challenging surroundings[17].
Acne	MobileNet	94.4%	Used only two model different sampling techniques only[4].
Eczema			
Chicken pox			
Pityriasis rosea			
Psoriasis			
Tinea corporis			
Vitiligo			

2. Materials and Methods

2.1 Material

The data set was separated by two partitions which are train and test. The train data consists 80% of the dataset that are used to train the images for a higher accuracy, while the test data consist 20% of the dataset to provide an accurate evaluation of a final model's fit to the training data. This ratio is chosen due to the large dataset. The validated data is gathered as same number of images with the test data as show in the Table 2.

Table 2: Comparison between types of skin disease and the method use for classification

Types of skin disease	Number of images	Train data	Test data
Acne	3558	2846	712
Eczema	2000	1600	400
Vitiligo	760	608	152

2.2 Method

The project consists two parts which are system development and application development as shown in Figure. The system development approach the (MobileNet V2) model to classify the three types of skin diseases while the TensorFlow Lite is used in the application development to deploy the MobileNet V2 model on a smartphone to display the results.

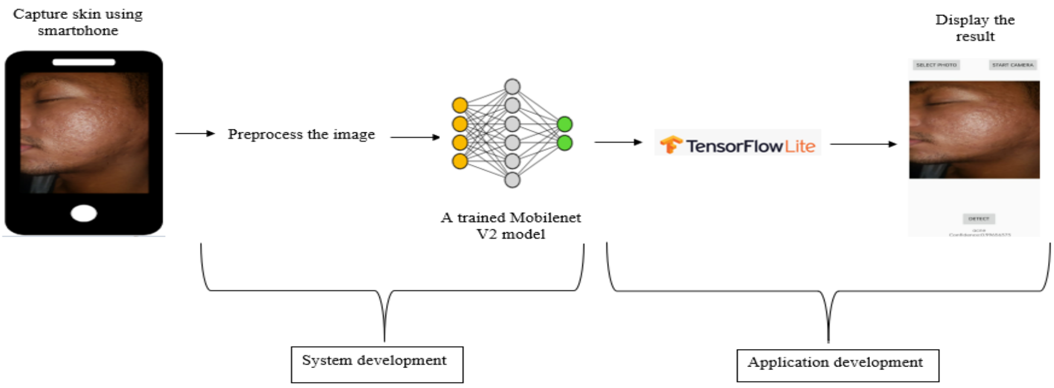


Figure 1: System overview of the project

Figure 1 shown the system overview of the project that consist of two parts which are system development and application development. The system began with a smartphone that are used to capture the patient's skin lesion. The image data is preprocessed to develop in the deep learning process. The preprocessing image includes the resizing, augmentation, data splitting, and normalization. The images are resized to 224 x 224 x 3 pixel. The data augmentation techniques such as rotate and flip, are applied to enhance the number of training images to build effective and reliable skin lesion classification systems. For feature extraction technique, the preprocessed image is used to develop the deep learning by train the images with the MobileNet V2 model. TensorFlow Lite is used to deploy a model on a smartphone in establishing an application development system.

2.3 Software development

Figure 2 shows the flowchart of the software development.

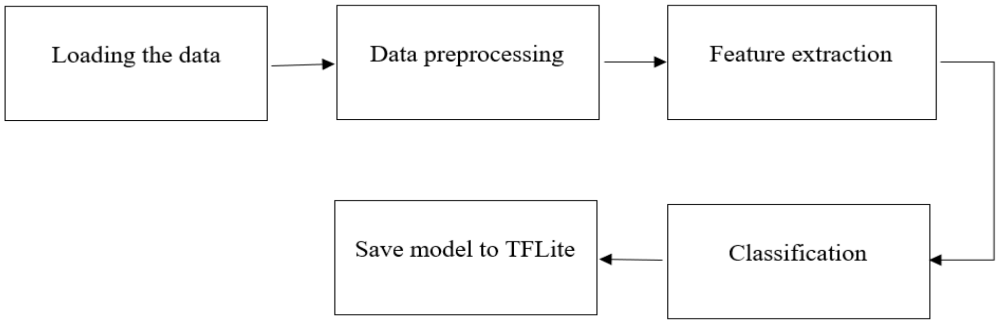


Figure 2: Flowchart of the software development

2.3.1 Loading the data

There were specified types of imported libraries that were required for training the model such as TensorFlow and Keras. Keras is a TensorFlow-based high-level neural network library. Both provide high-level APIs that may be used to develop and train models. In this project, the skin disease dataset multiclass classification is used to classify acne, eczema and vitiligo. There were 6318 images uploaded to Google Drive, including 3558 images for acne, 2000 images for eczema, and 760 images for vitiligo.

2.3.2 Data preprocessing

Since all values of the pixel are in [0, 255] range, the images are preprocessed by converting the pixel values in the range [0, 1]. For a better result, the input data are scaled to 22 x 224 pixels as an input, as specified by the networks. During the augmentation process, the images were rotated, flipped, translated, sheared, and split until each of the images was normalized. After that, the images were split into training and testing data sets. The train data are split into 80 % of the dataset (5055 images) that are used to train the images for higher accuracy, and the test data is split into 20 % of the dataset (1263 images) that are used to provide an accurate evaluation of a final model's fit to the training data.

2.3.3 Feature extraction

The Hub module is used as layer a linear classifier on top of the feature extractor. A non-trainable feature extractor is employed for speed, but it also allows fine tuning for greater accuracy and training the model takes a long time.

2.3.4 Classification

A pretrained model for transfer learning is applied in this project, hence the Mobile Net V2 model was imported. The model achieved 91 % with 15 epochs after training has been completed. Several parameters have been used to fit the model, including the learning rate of 0.0001, softmax activation, categorical crossentropy loss, and Adam as the optimizer. After training the model, the performance of the test data is evaluated. After the performance test data is evaluated by confusion matrix, the model weight and architecture are saved. The model is converted into a "FlatBuffer" (. tflite) that provided by the TensorFlow Lite to be deployed in smartphone device.

2.4 Convolutional Neural Network

A Convolutional Neural Network (ConvNet/CNN) is a Deep Learning algorithm that can receive an input image and apply (weights and biases) to diverse aspects of the image [18]. Figure 3 shows the CNN architecture. There were four main operations in the Convolutional Neural Networks such as convolution, non-linearity, pooling and fully connected layer. The major purpose of the convolution operation is to find appropriate features of the image that is used as an input to the first layer. Convolution preserves the pixels' spatial information. The Rectified Linear Unit, or ReLU, is a non-linear operation that is executed per pixel and substitutes all non-positive values in the feature map by zero. The Pooling layer functioned to reduce the Convolved Feature's spatial size. Through dimensionality reduction, the processing power is required to minimize the process data. Lastly, Fully Connected layer employs these features to classify the input image based on the training dataset.

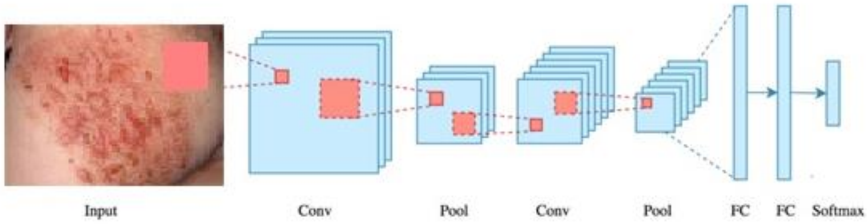


Figure 3: The CNN architecture

2.5 MobileNetV2

MobileNet V2 is a deep neural network architecture that uses depthwise separable convolutions to generate light-weight deep neural networks[19]. There were three main basic blocks in the Mobile Net v2 architecture such as depths separable convolution, linear bottlenecks, and inverted residuals[20]. In this block, 3 x 3 depthwise separable convolutions are employed to reduce the computational cost by 8 to 9 times when compared to regular convolutions. Furthermore, the inverted residual mechanism establishes a direct connection between bottleneck layers. In the architecture of this 53-layer MobilenetV2, there is an initial full convolutional layer backed by 19 residual bottleneck layers.

2.6 Android application development

Figure 4 shows the process flow of Android application development. The trained model is saved and converted into TensorFlow Lite FlatBuffer format file (. tflite) from the previous goggle colab. FlatBuffer is a cross-platform, open-source serialization toolkit that serializes data speedily. The (.tflite) model is loaded and the interpreter is executed in Kotlin and C++.After that, the interpreter module is operated with the operation kernels. For hardware acceleration, the interpreter will use the Android Neural Networks API (NNAPI). The Android Neural Networks API (NNAPI) can surmise for image classification, behavior prediction, and the selection of a suitable feedback to a search query. This API can distribute computation workload across on-device processors, graphics processing units, and specialized neural network hardware (GPUs).

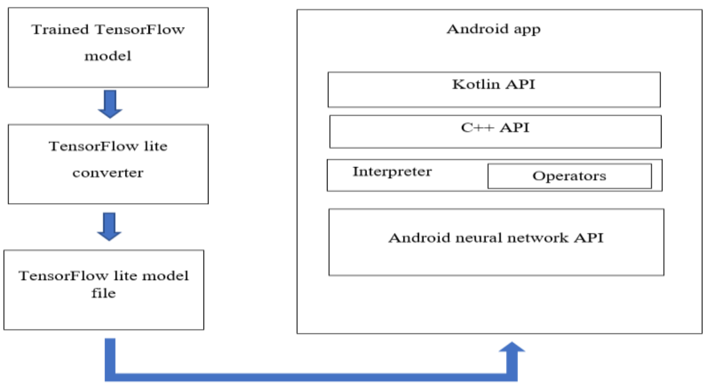


Figure 4: The process flow of Android application development

2.7 Performance evaluation

The performance of the model was evaluated to determine the efficient it is and to analyze the problem in the proposed method. The parameter that were used TP, FN, TN and FP. True positives (TP) refer to the number of positive cases that are classified correctly, whereas false negatives (FN) refer to the number of positive cases that are incorrectly classified as negative. Furthermore, (TN) represents the number of true negatives, or negative cases that are negative and defined as negative, whereas (FP) represents the number of false positives, or negative cases that are wrongly classified as positive cases.

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \qquad Eq.\ 1$$

$$Precision = \frac{TP}{TP+FP} \qquad Eq.\ 2$$

$$F - score = 2 * Precision * Recall\ Precision + Recall \qquad Eq.\ 3$$

3. Results and Discussion

The results and discussion section present data and analysis of the study. This section can be organized based on learning curve of the model, confusion matrix and performance evaluation. Besides that, application result, detection rate and confidence of images also were analyzed is this section.

3.1 Learning curves of MobileNet V2 model

Since the learning rate is 0.0001, 15 epochs were chosen, providing results of 0.94, 0.91, 0.15, and 0.32 for training accuracy, validation accuracy, training loss, and validation loss, respectively. Considering that the accuracy was steadily increasing and the loss was steadily decreasing, the Mobile Net V2 model proved that this process performed extremely well. Figure 5 show (a) accuracy and (b) loss curve of MobileNet V2 model. Despite the fact that the process worked effectively, there was overfitting behavior at the loss Figure 5 (b) curve. The training loss plot remains to decrease, while the validation loss plot decreases to a point before increasing again.

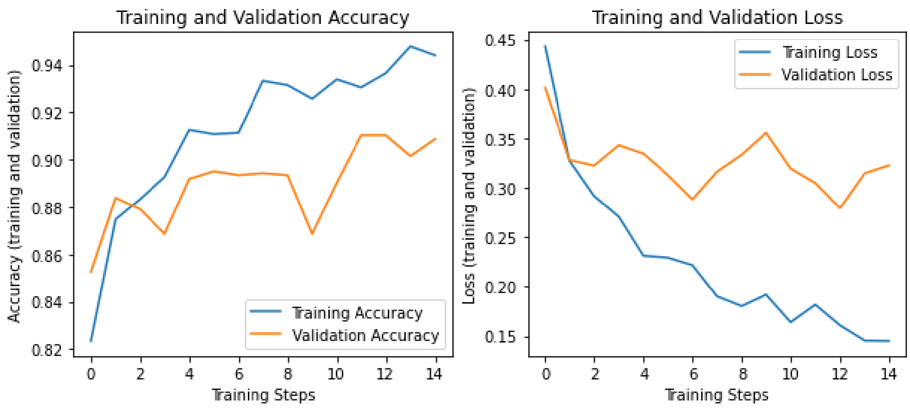


Figure 5: (a) Accuracy and (b) loss curve of MobileNet V2 model

3.2 Confusion Matrix

The predicted and actual labels are shown in the appropriate columns and rows. The confusion matrix is 3 x 3 as there are three different types of the skin disease which were acne, eczema and vitiligo. This depicts how the system consistently misclassify the three types of the skin disorders. As illustrated in Figure 6, the accuracy for acne is 96 %, 83 % of eczema, and 92 % for vitiligo. 16 % of the eczema have been misclassified as acne. Furthermore, the overall accuracy of this model is 91%, whereas the misclassification rate is 0.8%.

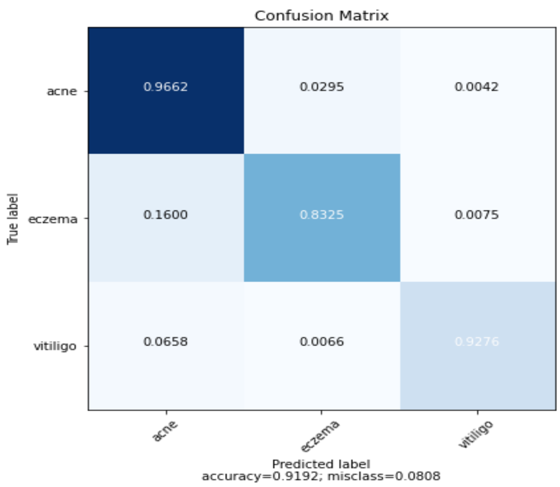


Figure 6: Confusion matrix of MobileNet V2 model

3.3 Performance evaluation

Figure 7 shows the Classification report of MobileNet V2 model. According to the classification report, the Mobile Net V2 model predicted 91% of the classes accurately. The vitiligo disease performed better than other diseases in terms of precision. Whereas the acne predicted 96% of the positive classes than eczema and vitiligo diseases which were obtained only 82% and 93% in recall. Furthermore, vitiligo has a better F1-score of 94 % than acne and eczema, which have F1-scores of 87% and 94%, respectively.

```
Classification Report
              precision    recall  f1-score   support

        Acne       0.90      0.96      0.93       711
      Eczema       0.93      0.82      0.87       400
    Vitiligo       0.96      0.93      0.94       152

    accuracy                           0.91      1263
   macro avg       0.93      0.90      0.92      1263
weighted avg       0.92      0.91      0.91      1263

79/79 [==============================] - 25s 317ms/step - loss: 0.2942 - accuracy: 0.9192
[0.2941876947879791, 0.91923987865448]
```

Figure 7: Classification report of MobileNet V2 model

3.4 Application result

Figure 8 shows the result of three skin disease using a Realme 8 Pro smartphone. The image is rescaled into the exact input shape (224 x 224 pixels) when the user captures or takes it from the gallery. The image is then classified using the proposed MobileNet V2 model. Figure 3.4 displays a preview of an image of acne, a skin disease with a confidence of 0.99%. Vitiligo has the same confidence as acne, at 0.99%, whereas eczema has only 0.81%. Furthermore, the inference time to display the image did not exceed 317ms with size of application size 18MB.

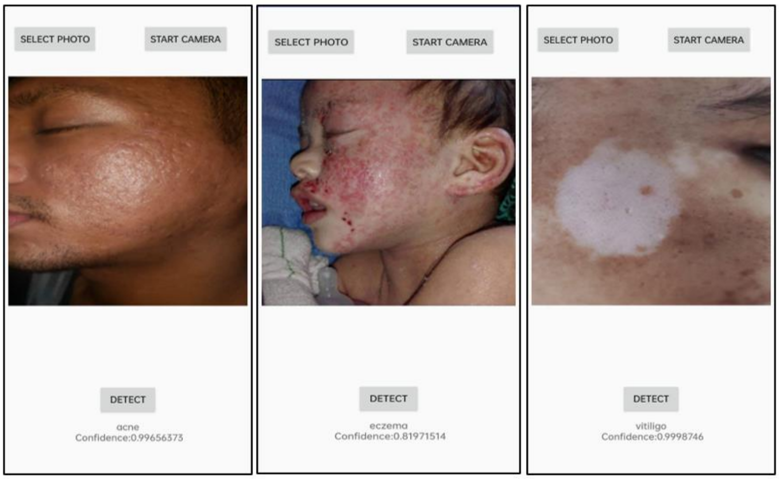


Figure 8: The result of three skin disease using Realme 8 Pro smartphone

3.5 Confident percentages with different optical zoom

In this analysis, the confidence result is determined using the distance between the camera (optical zoom) and the skin. There were three different optical zooms considered which were 1x (35mm), 2x(70mm), and 5x (105mm). The outcome of confidence percentages with varied optical zoom is shown in Table 3. From three of optical zoom, acne has outstanding percentages with 0.99 %. Besides, the eczema scored 0.98% for 1x zoom, 0.80% for 2x zoom and 0.98% for 5x zoom. There was a significant decrease in the 2x zoom, with the percentages scoring only 80 %. This could be because eczema and acne had remarkably similar symptoms, with acne causing pimples and eczema causing bumpy rashes similar to pimples. The vitiligo scored 0.99% and 0.94% for 1x zoom and 2x. When 5x zoom in vitiligo image, the percentages scored 0.80 % of acne. This is because the user's skin experienced a variety of skin disease problems. As a result, the confident percentages scored acne disease a higher grade.

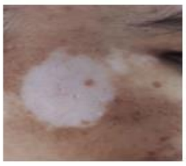
Table 3: Confident percentages with different scale ratio

	Confident percentages (%)		
Optimal zoom	Acne	Eczema	Vitiligo
1x	0.99	0.98	0.99
2x	0.99	0.80	0.94
5x	0.99	0.98	0.80 (acne)

3.6 Average confidence rate

In further analysis, three sample images from each type of skin disease were captured and loaded to the smartphone device. The image is considered by the condition of light. There are two types of light conditions which were high light intensity and low light intensity. The sample of three image is acquired from the user that willing to share their skin problem. Based on Table 4, the image for the acne sample image was acquired with high light intensity while eczema with high light intensity. Besides, the vitiligo is captured with the low light intensity. This result shows that the importance between pixel value and amount of light for detection the images. The pixel density and dynamic range affect the camera's capability to accurately record the fluorescent light coming from the sample image. For conclude, this proposed system is capable of detecting three different skin diseases with a 100% average confidence rate.

Table 4: Average confidence rate

Disease name	Sample image	Condition of light		Average confidence rate (%)
		High intensity	Low intensity	
Acne		/	/	100
Eczema		/	/	100
Vitiligo		/	/	100

3.7 Confidence percentages

This analysis was conducted by five males and four females. For the acne skin, the test images were diagnosed on face area. Figure 9 shows the confidence level of 9 test images of skin disease. The confidence percentage for the first image, which was acne, was 0.99 %, followed by the second and third images. For eczema, the test images were diagnosed on face and arm area. The fourth images scored only 0.81% of confidence score. Furthermore, the confidence percentage has risen rapidly to 0.90% in fifth test images followed by sixth image with confidence percentages 0.99%. This is due to the fact that the images are in better pixel dimension than the fourth image. The seventh images which were vitiligo images, the confidence percentages are 0.78 %. Whereas the eighth and ninth images scored 0.99% of confidence percentages. In addition, the test images of vitiligo were diagnosed on arm and face area.

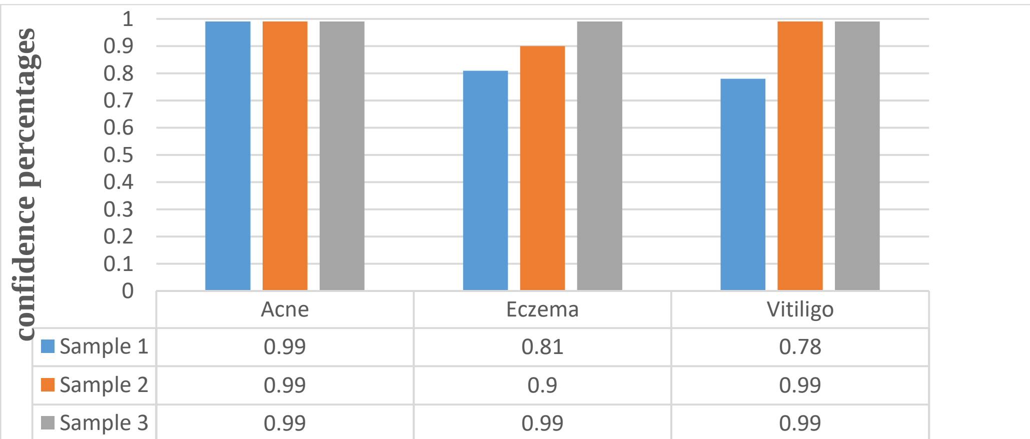


Figure 9: The confidence level of 9 test images of skin disease

4. Conclusion

This project shows the effectiveness of smartphone application for diagnosing the three types of skin disease which were acne, eczema and vitiligo. Based on Convolutional Neural Network (CNN) image processing, the detection and classification of skin disease are presented. To diagnose the types of skin disease, the data set images must go through preprocessing, feature extraction, and classification process. For trained the images, the MobileNet V2 model is preferred over other models due to its excellent performance, small size and fast training since the accuracy is 91%. Furthermore, the performance evaluation also applied in this project such as precision, recall and F1-Score. The result of performance evaluation is quite good since it is above than 90%. Using a TensorFlow Lite converter, the trained model is deployed on a smartphone application, and the result of skin disease is successfully displayed. In short, the objectives in this project is achieved. This smartphone device is compatible with a wide range of Android smartphones and may not require up much space on the device's internal storage due to this application size is only 18MB.The effectiveness of smartphone application has achieved the inference time in only 317ms when diagnosing the image of skin disease.

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References

[1] R. J. Hay *et al.*, “The global burden of skin disease in 2010: An analysis of the prevalence and impact of skin conditions,” *Journal of Investigative Dermatology*, vol. 134, no. 6, pp. 1527–1534, 2014, doi: 10.1038/jid.2013.446.

[2] “Understanding skin – Factors that influence skin,” *Eucerin*. https://www.eucerin.my/about-skin/basic-skin-knowledge/factors-that-influence-skin (accessed Dec. 07, 2021).

[3] K. YW, “The impact of skin disorders on patients’ quality of life in Malaysia,” *Journal of Clinical Intensive Care and Medicine*, vol. 4, no. 1, pp. 001–009, Jan. 2019, doi: 10.29328/journal.jcicm.1001018.

[4] J. Velasco *et al.*, “A smartphone-based skin disease classification using mobilenet CNN,” *International Journal of Advanced Trends in Computer Science and Engineering*, vol. 8, no. 5, pp. 2632–2637, Sep. 2019, doi: 10.30534/ijatcse/2019/116852019.

[5] O. Abuzaghleh, B. D. Barkana, and M. Faezipour, “Noninvasive real-time automated skin lesion analysis system for melanoma early detection and prevention,” *IEEE Journal of Translational Engineering in Health and Medicine*, vol. 3, 2015, doi: 10.1109/JTEHM.2015.2419612.

[6] A. Masood and A. A. Al-Jumaily, “Computer aided diagnostic support system for skin cancer: A review of techniques and algorithms,” *International Journal of Biomedical Imaging*, vol. 2013. Hindawi Publishing Corporation, 2013. doi: 10.1155/2013/323268.

[7] L. C. de Guzman, R. P. C. Maglaque, V. M. B. Torres, S. P. A. Zapido, and M. O. Cordel, “Design and evaluation of a multi-model, multi-level artificial neural network for eczema skin lesion detection,” in *Proceedings - AIMS 2015, 3rd International Conference on Artificial Intelligence, Modelling and Simulation*, Oct. 2016, pp. 42–47. doi: 10.1109/AIMS.2015.17.

[8] D. Choe, E. Choi, and D. K. Kim, “The Real-Time Mobile Application for Classifying of Endangered Parrot Species Using the CNN Models Based on Transfer Learning,” *Mobile Information Systems*, vol. 2020, 2020, doi: 10.1155/2020/1475164.

[9] C. Quintero, F. Merchán, A. Cornejo, and J. S. Galán, “Uso de Redes Neuronales Convolucionales para el Reconocimiento Automático de Imágenes de Macroinvertebrados para el Biomonitoreo Participativo,” *KnE Engineering*, vol. 3, no. 1, p. 585, Feb. 2018, doi: 10.18502/keg.v3i1.1462.

[10] N. S. Alkolifi Alenezi, “A Method of Skin Disease Detection Using Image Processing and Machine Learning,” in *Procedia Computer Science*, 2019, vol. 163, pp. 85–92. doi: 10.1016/j.procs.2019.12.090.

[11] R. v. Golhar, P. A. Vyawahare, P. H. Borghare, and A. Manusmare, “Design and implementation of android base mobile app for an institute,” in *International Conference on Electrical, Electronics, and Optimization Techniques, ICEEOT 2016*, Nov. 2016, pp. 3660–3663. doi: 10.1109/ICEEOT.2016.7755391.

[12] IEEE Staff, *2017 IEEE International Conference on Bioinformatics and Biomedicine (BIBM).* IEEE, 2017.

[13] H. Alquran *et al.*, “The Melanoma Skin Cancer Detection and Classification using Support Vector Machine.”

[14] J. Rathod, V. Wazhmode, A. Sodha, and P. Bhavathankar, “Diagnosis of skin diseases using Convolutional Neural Networks,” in *Proceedings of the 2nd International Conference on Electronics, Communication and Aerospace Technology, ICECA 2018*, Sep. 2018, pp. 1048–1051. doi: 10.1109/ICECA.2018.8474593.

[15] J. Jaworek-Korjakowska, P. Kleczek, and M. Gorgon, “Melanoma thickness prediction based on convolutional neural network with VGG-19 model transfer learning,” in *IEEE Computer Society Conference on Computer Vision and Pattern Recognition Workshops*, Jun. 2019, vol. 2019-June, pp. 2748–2756. doi: 10.1109/CVPRW.2019.00333.

[16] C. Huang, Y. Yu, and M. Qi, “Skin Lesion Segmentation Based on Deep Learning,” in *International Conference on Communication Technology Proceedings, ICCT*, Oct. 2020, vol. 2020-October, pp. 1360–1364. doi: 10.1109/ICCT50939.2020.9295941.

[17] R. Raj, N. D. Londhe, and R. S. Sonawane, “Automatic Psoriasis Lesion Segmentation from Raw Color Images using Deep Learning,” in *Proceedings - 2020 IEEE International Conference on Bioinformatics and Biomedicine, BIBM 2020*, Dec. 2020, pp. 723–728. doi: 10.1109/BIBM49941.2020.9313356.

[18] Sumit Saha, “A Comprehensive Guide to Convolutional Neural Networks — the ELI5 way,” Dec. 2018, Accessed: Jan. 11, 2022. [Online]. Available: https://towardsdatascience.com/a-comprehensive-guide-to-convolutional-neural-networks-the-eli5-way-3bd2b1164a53

[19] A. G. Howard *et al.*, “MobileNets: Efficient Convolutional Neural Networks for Mobile Vision Applications,” Apr. 2017, [Online]. Available: http://arxiv.org/abs/1704.04861

[20] A. J. Deo, S. K. Behera, and D. P. Das, “Detection of Material Build-Up during Online Size Distribution Analysis of Iron Ore Green Pellets using MobilenetV2,” in *2021 International Symposium of Asian Control Association on Intelligent Robotics and Industrial Automation, IRIA 2021*, Sep. 2021, pp. 426–431. doi: 10.1109/IRIA53009.2021.9588756.