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MOBILE-BASED DEEP LEARNING FRAMEWORK FOR CLASSIFYING COMMON SKIN DISEASES IN THAILAND

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Abstract. *Skin diseases have an impact on several aspects of a patient's life. Statistic records of outpatients who received treatments at the Institute of Dermatology, Thailand show a continuously increasing number of patients. Skin disease classification is an important step leading to an appropriate treatment of the disease. It is necessary to bring in technologies to support the work of dermatologists. The goal of this study is to propose a framework for skin disease classification using mobile-based deep learning in consideration of model size and computational resources. For conducting experiments, deep learning AI-based models using different skin disease image sizes were created and their effects on the model's performance were observed. In data preprocessing, five classes of original skin disease images from a standard public dataset, Dermnet, were employed and segmented into different sizes. Results of five deep learning-based models show that reducing image size decreases model-training time while the models retain a certain level of accuracy. The results also shed light on using a smaller size of input images for training deep learning-based models that can be used for further development of mobile applications for skin disease classification.*
Keywords: Skin disease classification, Deep learning-based model, Pre-trained weight, Medical image segmentation

1. **Introduction.** Skin diseases affect patients' life and their family in many ways, including psychological and social consequences, treatment costs, relationships, and occupations [1,2]. Statistic records of outpatients who received treatment at the Institute of Dermatology, Thailand show an increasing number of patients [3]. There is a report ranking top five skin diseases between 2016 to 2019 by Ministry of Public Health, Thailand; the diseases include 1) Acne, 2) Dermatitis, 3) Psoriasis, 4) Disorders of pigmentation, and 5) Seborrheic dermatitis [3]. The process to diagnose and classify skin diseases is an important step leading to the right and proper treatments. Meanwhile, the average number of medical doctors specializing in dermatology in Thailand is 22 who receive certificates every year reported by the Medical Council of Thailand [4]. This shows a limited number of dermatologists specializing in skin diseases in Thailand.

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With the problem of the shortage of dermatologists mentioned earlier, advanced technologies can be one of potential solutions to support the work of dermatologists. Artificial Intelligence (AI) technology has made a lot of changes and impacts on the development of healthcare systems [5-8]. Several approaches were developed to support and improve treatment processes such as skin disease classification using deep learning, Convolutional Neural Network (CNN) [9], and a detection of skin disease at an early stage using CNN [10]. Due to the advancement of mobile devices, mobile applications for skin disease classification can provide more accurate and timely treatment [11,12]. Zhu et al. [13] applied Google's EfficientNetB4 on the ImageNet dataset for constructing AI-based skin disease classification under real clinical settings and their framework achieved high classification performance. Some studies used trained models on mobile applications. Velasco et al. [14] created a skin disease classification system using the MobileNet model trained with preprocessed images of seven skin diseases, on Android application. Typically, the AI mobile-based approaches concern limited processing capability, device storage, response time, and communication bandwidth [15]. Recent studies [16-18] on mobile-based applications of AI in healthcare investigate several sub-topics including the utilization of wireless network connectivity, sensors for health monitoring system, and data compression techniques for data transfer.

As mentioned about research studies on skin disease classification on mobile devices, image size for training CNN models needs to be considered in order to develop small-size models. This study proposes a mobile-based deep learning framework for classifying common skin diseases in Thailand. Skin disease images were collected from the standard public dataset, Dermnet, and used in the model training process. Images were segmented into different sizes, rotated, zoomed, and flipped before entering into the training process. Experiments were conducted to observe the effects of different image sizes to train deep learning models for skin disease classification on mobile devices. The results show that a MobileNetV3, trained with image size 64×64 pixels reduced training costs and time compared to DenseNet201, EfficientNetB4, and ResNet50. While the MobileNetV3 model accuracy is comparable to the models trained with intensive training resources.

The remaining parts of this paper are organized into 4 sections. Section 2 presents a framework of a mobile-based deep learning model for classifying common skin diseases. This section briefly reviews four state-of-the-art deep learning models. Section 3 describes data collection and preparation process. Section 4 shows experimental settings and results. Section 5 provides conclusions.

2. Mobile-Based Deep Learning Framework for Skin Disease Classification.

A component of the proposed mobile-based deep learning framework for skin disease classification is shown in Figure 1. The framework consists of three important components: image segmentation, image augmentation, and image classification. The target application of the framework is on mobile devices which have limited computational resources. Dermatologists take skin disease photos from the patients, and then input them into the application which generates classified results of skin disease. The classified results can potentially support for decision-making of dermatologists to diagnose skin diseases.

For the first component in Figure 1, image segmentation, original skin disease images from the standard public dataset were cut into different sizes 64×64, 128×128, 224×224, and 448×448 pixels, focusing on image areas with skin disease lesions. The original images were cropped into different smaller sizes while maintaining the same sharpness. Cropped images are from different positions having skin disease lesion on the original images. All segmented images were input to the image augmentation. Second, image augmentation manipulates segmented images by applying rotation, zoom, and random flip techniques. All preprocessed images were input to the image classification. Mobile-based deep learning models were next trained and evaluated using preprocessed images. Finally,

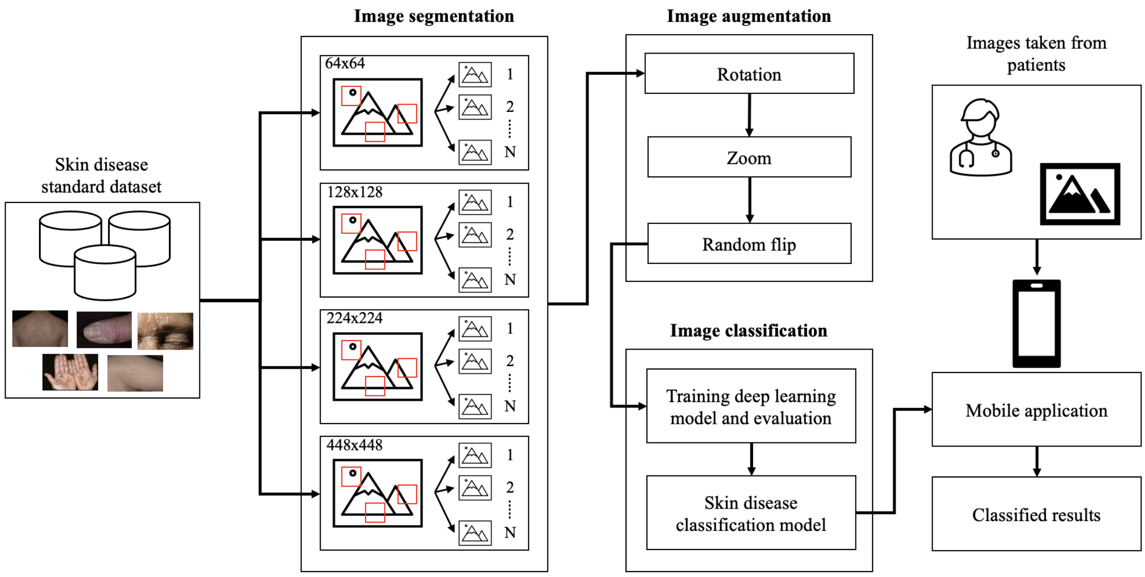


FIGURE 1. A mobile-based deep learning framework for skin disease classification

the obtained model is used for skin disease classification targeted on mobile application. Due to the limitation of computing resources of mobile devices, in this study, experiments on various state-of-the-art deep learning models considering with different image sizes were compared to find the suitable model for further development of skin disease classification on mobile application. Among the chosen architectures, MobileNetV3 represented architectures that produce small-size models, while EfficientNet, RestNet, and DenseNet represented architectures that produce larger models with higher accuracy. A brief detail of the model architectures used in this study is described below.

MobileNetV3 Model Architecture

The advancement of mobile devices has potential for development of deep learning-based applications. There is a trade-off between accuracy and latency when using deep learning models on resource-constrained devices [19,20]. Howard et al. [21] explained the development of MobileNetV3 architecture to address this issue. MobileNetV3-Large and -Small are Convolution Neural Network (CNN) models aimed at implementing on mobile devices for computer visions, e.g., object classification and object identification.

EfficientNet Model Architecture

An EfficientNet model was introduced in 2019 as a CNN model for image classification. Tan and Le [22] presented the EfficientNet models, including EfficientNet-B0 until EfficientNet-B7, the complexity of each model increases with the increasing numbers. It is possible to improve the accuracy of the CNN models, if more resources are available. The EfficientNet model proposes a new scaling method that scales depths, widths, and resolutions uniformly based on a highly-effective-compound coefficient. The EfficientNet architectures were developed by leveraging a search technique based on multi-objective neural architectures.

ResNet Model Architecture

He et al. [23] introduced the ResNet model in 2016 as a specific type of CNN. The model employed a deep residual learning framework to improve its performance. Plain and residual networks are the two architectures of ResNet. The plain network has fewer filters and complexity compared to VGG networks [24]. The residual network is based on the plain network with additional shortcut connections. Recently, Gao et al. [25] improved the ResNet50 model and then found an outstanding performance for astronomical object classification. For skin disease classification, Anand et al. [26] proposed an automated deep learning model based on the ResNet architecture for an early stage of skin diseases.

DenseNet Model Architecture

Huang et al. [27] introduced DenseNet to cope with deeper networks to be more accurate and efficient to train. DenseNet alters a standard CNN architecture, and each layer is directly connected to all other layers in a feed-forward fashion to address problems of information lost once the layers get deeper. In recent study, a developed DenseNet architecture, which is DenseNet201, for a skin lesion image classification framework with augmentation techniques was adopted by Zhao et al. [28].

3. **Data Collection and Preparation.** This section describes the data preprocessing and experimental settings. Skin disease images were obtained from a standard public dataset, Dermnet. The Dermnet dataset contains more than 2300 images of skin diseases categorized into 23 classes [29]. In this study, the images of five skin diseases, which are common skin diseases in Thailand, were selected from Dermnet. Each image was partitioned into different image sizes. Five subclasses Acne-cystic, Eczema-chronic, Lentigo-adults, Psoriasis-chronic-plaque, and Hives-urticaria-acute from classes Acne and rosacea, Eczema, Light diseases and disorders of pigmentation, Psoriasis lichen planus and related diseases, and Urticaria hives were selected respectively to conduct experiments as shown in Table 1.

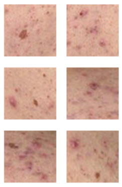
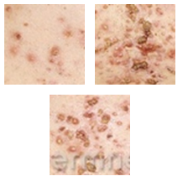
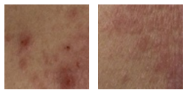
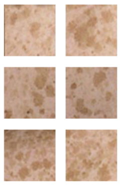
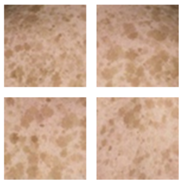
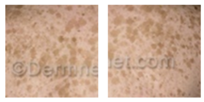
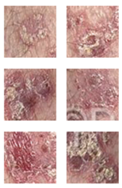
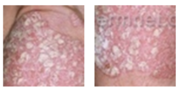
Table 1. Distribution of skin disease images in the dataset

Subclasses (Classes)		**Number of skin disease images**				
		64 × 64 pixels	**128 × 128 pixels**	**224 × 224 pixels**	**448 × 448 pixels**	**Total**
Acne-cystic (Acne and rosacea)	Train	954	483	345	142	1924
	Test	230	194	88	48	560
	Total	1184	677	433	190	2484
Eczema-chronic (Eczema)	Train	212	150	94	52	508
	Test	100	71	32	16	219
	Total	312	221	126	68	727
Lentigo-adults (Light diseases and disorders of pigmentation)	Train	269	182	123	80	654
	Test	64	50	22	16	152
	Total	333	232	145	96	806
Psoriasis-chronic-plaque (Psoriasis lichen planus and related diseases)	Train	613	459	283	135	1490
	Test	161	110	56	33	360
	Total	774	569	339	168	1850
Hives-urticaria-acute (Urticaria hives)	Train	617	378	221	124	1340
	Test	191	99	50	21	361
	Total	808	477	271	145	1701

For data preparation, images of five sub-class skin diseases were segmented, in order to partition an image into multiple image segments [30]. First, an original image was selected and manually segmented to cover areas having skin disease lesions. For each segmentation, the original image can produce multiple image portions. In addition, some portions from the same original images have overlap areas. Four different sizes of image portions were recorded in a JPG file format. Each image size was used in different experiments of training CNN models. The preprocessed images were split into train and test datasets for training CNN models. Numbers of images of different sizes for each class and example images are shown in Table 1 and Table 2, respectively.

4. **Experiments and Results.** To conduct experiments, five state-of-the-art CNN models were applied. The models were developed on the computer system using CPU M1 Pro 10-core and RAM of 16 GB. We selected five common skin diseases in Thailand, and they

TABLE 2. Segmentation of skin disease images

Subclasses (Classes)	Image sizes 64 × 64 pixels	128 × 128 pixels	224 × 224 pixels	448 × 448 pixels
Acne-cystic (Acne and rosacea)				
Eczema-chronic (Eczema)				
Lentigo-adults (Light diseases and disorders of pigmentation)				
Psoriasis-chronic-plaque (Psoriasis lichen planus and related diseases)				
Hives-urticaria-acute (Urticaria hives)				

are available in Dermnet dataset. The original images were segmented into smaller sizes 64 × 64, 128 × 128, 224 × 224, and 448 × 448 pixels. As a result, there are four sets of input, each of them contains images for testing and training models. The segmentation process was done manually by a researcher. Each segmented image covered disease lesions in different areas of original images where partial overlap between segments is possible. For the training process, four sets of training data were used to construct each classification model. The obtained models were then evaluated with test datasets. The details of skin disease images in the train and test datasets are shown in Table 1.

Five CNN models, i.e., MobileNetV3-Small, MobileNetV3-Large, EfficientNetB4, ResNet50, and DenseNet201, which have model sizes 2 MB, 5 MB, 75 MB, 98 MB, and 80 MB, respectively reported by Hussain et al. [31] and Nguyen et al. [32], were used in this study. Images of skin diseases, i.e., Acne-cystic, Eczema-chronic, Lentigo-adults, Psoriasis-chronic-plaque, and Hives-urticaria-acute, selected from the Dermnet dataset, were employed. In this study, the models were trained with images at different resolutions as shown in Table 1. The pretrained model "ImageNet" was also applied for training models. We used hyperparameters in model training process, e.g., learning rate = 0.0001, batch size = 32, and early stopping parameters with patience = 10 and min_delta = 0.001.

The model performance metrics (accuracy, sensitivity, and specificity) presented in Tanantong et al. [33] were employed for measuring the model performance. The accuracy shows number of correct predictions over number of total predictions. In this study, accuracy is determined by the result of testing each model using a test dataset. The sensitivity shows how well the model detects positive results, while the specificity shows how well the model predicts true negative results. Sensitivity and specificity are calculated by the average values of five classes. F1-score, mentioned by Srijiranon et al. [34] and Tanantong and Yongwattana [35], are determined from various different image sizes in the test dataset. Four evaluation measures, i.e., accuracy (Acc), sensitivity (Sen), specificity ($Spec$), and F1-score ($F1$), are shown in equations below.

$$Acc = (TP + TN)/(TP + TN + FP + FN) \tag{1}$$

$$Sen = TP/(TP + FN) \tag{2}$$

$$Spec = TN/(TN + FP) \tag{3}$$

$$F1 = TP/(TP + 1/2 * (FP + FN)) \tag{4}$$

where TP, TN, FP, and FN are the number of true positives, true negatives, false positives, and false negatives, respectively.

The experimental results for skin disease classification are presented in Table 3 and Table 4. It is observed that the accuracy of MobileNetV3-Small and -Large varies more than the accuracy of DenseNet201, EfficientNetB4, and ResNet50 when trained using different input image sizes. Although the accuracy of MobileNetV3-Small and -Large seem to be impacted by input image sizes, both models retain an accuracy between 77% to 88%. This accuracy is comparable to DenseNet201, EfficientNetB4, and ResNet50 which require intensive training resources and larger output model sizes. Related works on skin disease classification using deep learning models and our proposed framework are summarized in Table 5.

Table 3. Accuracy and sensitivity of CNN models in each image size

Models	**Accuracy**				**Sensitivity**			
	64 × 64	**128 × 128**	**224 × 224**	**448 × 448**	**64 × 64**	**128 × 128**	**224 × 224**	**448 × 448**
MobileNetV3-Small	77%	82%	83%	83%	72%	75%	80%	83%
MobileNetV3-Large	82%	85%	88%	85%	78%	76%	75%	83%
EfficientNetB4	81%	84%	85%	86%	77%	80%	83%	84%
ResNet50	77%	79%	85%	84%	79%	74%	82%	79%
DenseNet201	79%	82%	80%	80%	74%	77%	74%	76%

Table 4. Specificity and F1-score of CNN models in each image size

Models	**Specificity**				**F1-score**			
	64 × 64	**128 × 128**	**224 × 224**	**448 × 448**	**64 × 64**	**128 × 128**	**224 × 224**	**448 × 448**
MobileNetV3-Small	94%	95%	96%	96%	74%	77%	82%	84%
MobileNetV3-Large	95%	95%	96%	97%	80%	78%	78%	83%
EfficientNetB4	96%	96%	97%	96%	79%	82%	85%	85%
ResNet50	96%	95%	96%	96%	81%	75%	82%	80%
DenseNet201	95%	95%	95%	95%	75%	79%	77%	76%

As shown in Table 6, reducing image size also reduces model training time. In contrast, sizes of trained models remain the same although image sizes are changed. Training models using different image sizes does not impact the size of trained models. MobileNetV3-Large retains accuracy at 88% when trained using an image size of 224 × 224 pixels. The image size and an area of skin disease lesions within the image may affect the model accuracy. A larger image size could cover more areas of disease lesions. At the same time,

Table 5. Comparison of recent studies of skin disease classification using deep learning

Author	Objectives	Diseases	CNN architectures	Number of images in dataset	Accuracy
Velasco et al. [14]	To design a skin disease classification application based on Android phones	1. Acne 2. Eczema 3. Chickenpox 4. Pityriasis rosea 5. Psoriasis 6. Tinea Corporis 7. Vitiligo	MobileNet	3,406	94.40%
Goceri [11]	To construct novel model using MobileNet and implement a mobile phone application for skin disease diagnosis	1. Seborrheic dermatitis 2. Rosacea 3. Hemangioma 4. Psoriasis 5. Acne vulgaris	Modified-MobileNet	725	94.76%
Muhaba et al. [36]	To propose an automated system for five common skin diseases diagnosis using deep learning pre-trained MobileNet-v2 model	1. Healthy 2. Acne vulgaris 3. Atopic dermatitis 4. Lichen planus 5. Onychomycosis 6. Tinea capitis 7. Unknown	MobileNet-v2	1,137	97.50%
Karthik et al. [37]	To develop a system for skin disease detection based on EfficientNetV2	1. Acne 2. Actinic keratosis 3. Melanoma 4. Psoriasis	EfficientNetV2	4,930	84.70%
Our proposed framework	To develop a mobile-based deep learning framework for classifying common skin diseases	1. Acne and rosacea 2. Eczema 3. Light diseases and disorders of pigmentation 4. Psoriasis lichen planus and related diseases 5. Urticaria hives	- MobileNetV3-Small - MobileNetV3-Large - EfficientNetB4 - ResNet50 - DenseNet201	3,411	88.00% (MobileNetV3 -Large with small size images, 224 × 224 pixels)

Table 6. Training and testing time of CNN models in each image size

Models	Training time/testing time (hour:minute:second)			
	64 × 64 pixels	**128 × 128 pixels**	**224 × 224 pixels**	**448 × 448 pixels**
MobileNetV3-Small	0:02:23.32/0:00:00.38	0:03:09.17/0:00:00.61	0:04:52.89/0:00:00.59	0:16:34.34/0:00:02.14
MobileNetV3-Large	0:03:50.26/0:00:00.59	0:05:48.56/0:00:01.13	0:16:21.07/0:00:01.36	0:29:20.99/0:00:03.72
EfficientNetB4	0:15:05.43/0:00:02.57	0:44:26.48/0:00:06.17	1:39:35.10/0:00:09.39	4:51:25.34/0:00:26.80
ResNet50	0:30:03.45/0:00:03.49	0:49:23.49/0:00:08.20	0:53:18.42/0:00:08.86	3:12:04.04/0:00:20.28
DenseNet201	0:25:14.26/0:00:04.59	1:01:23.77/0:00:09.91	2:28:28.69/0:00:11.43	4:17:56.76/0:00:49.19

the characteristics of the disease itself may also impact models' accuracy such as disease with scattered spots and disease with a single area of lesion.

5. **Conclusions.** We proposed a mobile-based deep learning framework for skin disease classification that consists of three components: image segmentation, image augmentation, and image classification. The objective of the framework is to support the development of skin disease classification in mobile applications. The experimental results suggested that a small size CNN model, MobileNetV3, trained with small size images reduced training costs and time. While the model accuracy is comparable to the models trained with intensive resources. The proposed framework demonstrates that smaller sizes of input images can be used for the development of skin disease classification models which can be applied to mobile applications. Further study investigates on an implementation of skin disease classification on mobile devices and an evaluation of mobile applications tested by dermatologists.

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