A Mobile Application for Obesity Early Diagnosis Using CNN-based Thermogram Classification

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***Abstract*— Obesity is one of the major risk factors for non-communicable diseases. Developing an early obese screening method is crucial to facilitate the early treatment of obese patients. In this study, we proposed a stand-alone mobile application for early diagnosis of obesity based on Convolution Neural Network (CNN) classifier model. The proposed CNN model was developed based on MobileNetV2 by modifying the fully connected layers. We trained the proposed model with the obese thermogram dataset through the transfer learning method and compared the classification performances with pre-trained models. The testing results show that the proposed model achieved an accuracy of 87.50%, a specificity of 100 %, and a sensitivity of 75.00 %. The proposed model demonstrated an optimal fit learning with 2.5 million learning parameters, a computation cost of 0.613 GFLOPs, and a size of 9.8 MB. The proposed model has been deployed and tested into the thermal camera smartphone CAT S62 Pro to do an early diagnosis of obesity.**

***Keywords*— Obesity, Deep Learning, CNN, Thermal Imaging**

I. INTRODUCTION

According to World Health Organization (WHO), obesity and overweight are defined as abnormal or excessive accumulation of fat that may impair health [1]. Obesity is a major risk factor for many non-communicable diseases, such as diabetes, heart disease, stroke, and cancers [2]. The prevalence of obesity has been reported to be increased between 2000 to 2016 across all WHO regions [3]. The global prevalence of obese adults in 2016 is estimated at 13.1% and ranged from 4.7% in South East Asia Region, 6.4% in Western Pacific Region, 10.6% in African Region, 20.8 in Eastern Mediterranean Region, 23.3% in Europe Region, to 28.6% in American Region [3]. While in Indonesia, the prevalence of obese adults, according to WHO reports was estimated at 6.9 % in 2016 [3] and is estimated at 23.1 % in 2018, according to study of Harbuwono et al. [4].

Therefore, it is crucial to look for early prevention of obesity using early detection techniques to reduce the prevalence of obesity. There are several methods to evaluate obesity, such as: Body Mass Index (BMI) [3], [5], Bio-electrical Impedance Analyzer (BIA) [6], [7], Dual X-ray Absorptiometry (DXA) [7], [8], Computed Tomography Scan (CT-Scan) [9], and Magnetic Resonance Imaging (MRI) [10]. BMI is the most common method to evaluate obesity by calculating a patient's weight and height, but it does not linearly represent the body fat percentages and leads to inaccuracy of self-reported results [11], [12]. BIA is a fast, low-cost, and easy-to-operate technique by measuring human body compositions, but it suffers a limitation of poor accuracy in estimating individual body fat [6]–[8]. DXA, CT-Scan, and MRI methods are commonly used to visualize and quantized subcutaneous and visceral fat in the human body, but these methods require expensive equipment and trained technicians [7], [8], [10], [13].

Infrared Thermography (IRT) or Thermal Imaging method is a non-invasive, low-cost, and easy-to-use method that could be used to evaluate obesity by assessing Brown Adipose Tissue (BAT) [14], [15]. BAT is a thermogenic tissue that has a role in controlling body weight by producing energy in the form of heat [16], [17]. Several studies have reported a significant temperature difference between the BAT activation of obese and lean/ normal patients, especially in the supraclavicular and abdomen region [16], [18]–[20]. Through the thermal imaging technique, the infrared energy emitted from a human's BAT is converted into temperature numbers and visualized into thermal images or thermograms [21], [22].

The temperature features of the thermogram could be detected by an Artificial Intelligence algorithm such as machine learning to make an early diagnosis of obesity. The previous study by Rashmi et al. implemented a machine learning algorithm of Support Vector Machine (SVM), Naïve Bayes, and Random Forest classifier in classifying obese and normal thermograms [23]. However, the machine learning

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algorithm requires several steps of the feature extraction process, different from the deep learning algorithm, which is not required to do the feature extraction process manually due to its deep feature extraction process from multiple convolution layers [24]. Therefore, the study of Umapathy et al. has implemented a deep learning Convolutional Neural Network (CNN) algorithm for obesity diagnosis [25]. However, the study focused on building the CNN model for Computer Aided Diagnosis (CAD), which is more suitable for the physician's obesity diagnosis screening system.

So far, we have found no study of implementing deep learning CNN on a mobile application for obese early detection yet. An early obesity diagnosis system based on a mobile application is required so it can be used by common people and not limited to health facilities or physicians. The mobile application inference model location is recommended to be designed on local mobile devices rather than designed on cloud server devices [26]. By localizing the inference tasks (i.e., prediction and classification tasks) on a mobile device, the users could use the mobile applications even in areas with poor internet connection [27].

In this study, we aim to develop a stand-alone mobile application for an early diagnosis of obesity. We developed the diagnosis algorithm based on the CNN model that can classify obese and normal thermograms through the transfer learning method. Then we embedded the proposed CNN model into the thermal camera smartphone: CAT S62 Pro in the android operating system mobile application.

Therefore, the contributions of this paper are given as follows:

1. It proposes a non-invasive and efficient method to evaluate obesity through thermal imaging and deep learning.
2. It proposes a mobile application for obese thermogram classification.
3. It proposes a high-accuracy and lightweight CNN model based on MobileNetV2.
4. It evaluated the proposed model performances with pre-trained models regarding classification performance, computation cost, and model size.

The rest of this paper is organized as follows. Section 2 describes the materials and method used to construct the proposed CNN model and compares it with other pre-trained models. This section also explained the dataset and the tuned hyper-parameters in the training and testing process. Section 3 describes the testing results and discusses the proposed model's performances. While section 4 concludes this study and provides some future works.

II. MATERIAL AND METHOD

Fig 1 shows the workflow of model development and deployment. Obese thermal images dataset from images acquisition procedures were augmented and fed into the CNN model. The CNN model was built and trained through a transfer learning procedure. Then the model is deployed and embedded into a mobile application.

A. Dataset

The obese dataset used in this study was acquired from the thermal image acquisition procedure, as explained in our previous study [28]. However, we increased the dataset quantity by capturing additional images with the thermal camera: FLIR E95. The thermograms were captured from five body regions: supraclavicular, abdomen, forearm, shank, and palm region, as shown in Fig. 2. There are 200 Thermograms labeled as the normal class (BMI lower than 25 kg/m^2) and 200 thermograms labeled as the obese class (BMI larger or equal to 25 kg/m^2). Then we started grouping the dataset into 2 groups, one for training and the other for testing. We took 180 thermograms of each class for the training dataset and took the remaining 20 of each class for the testing dataset. Thus, in total, we used 360 (90%) thermograms for the training dataset and the remaining 40 (10%) thermograms for the testing dataset.

To reduce overfitting and to optimize the CNN model in learning image modality features, augmentation is applied to the training dataset [29], [30]. Augmentation is a data-space solution to the problem of the small dataset by enhancing the size and variety of the training dataset [24]. We augmented the training dataset through the image data generator function provided by the TensorFlow Keras library. The augmentation metrics are as follows: image rotation of 10 degrees, width shifting range of 0.1, height shifting range of 0.1, shear range of 0.1, zoom range of 0.2, enable horizontal flip and batch size of 32. Meanwhile, the augmentation was not applied to the testing dataset. After the dataset is augmented, the training and testing dataset is ready to be fed as input images for CNN model training and testing in the model development step.

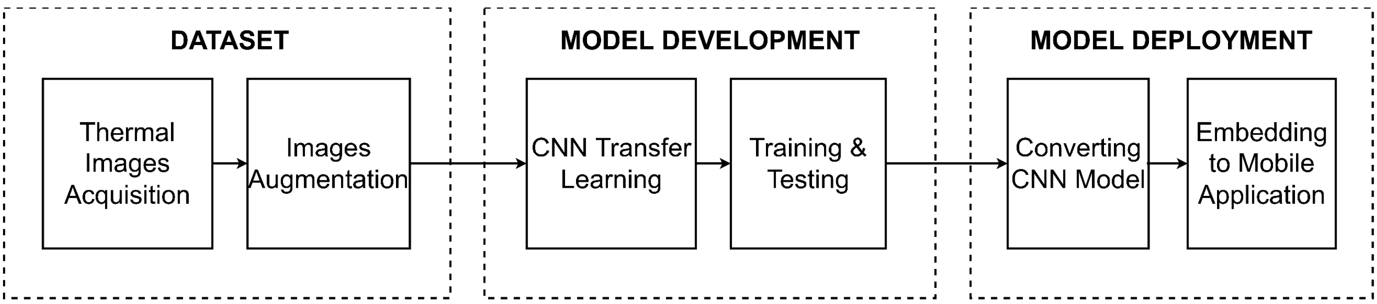
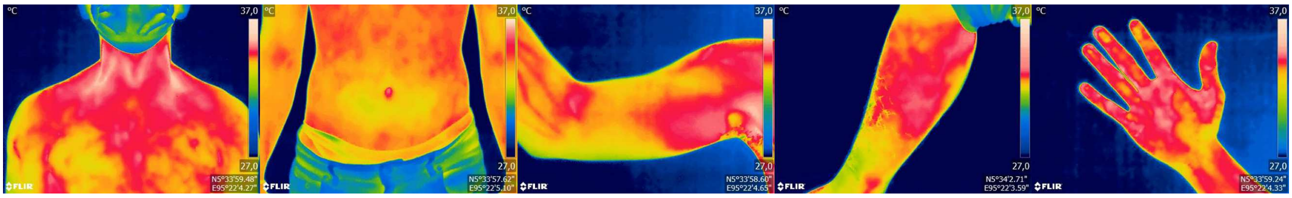
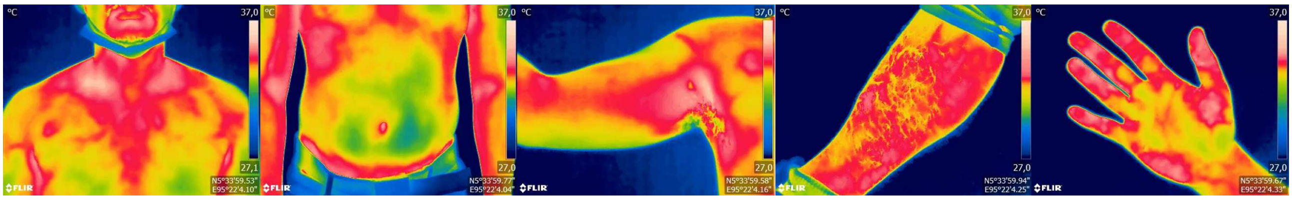


Fig.1 The Workflow of Model Development and Deployment



(a)



(b)

Fig.2 Thermograms of Supraclavicular, Abdomen, Forearm, Shank, and Palm regions (a) Normal Thermogram (b) Obese Thermogram

TABLE I. The Proposed CNN Architectures

CNN Architectures	Input Size	Output Size	Architecture Layers
Input Layer	464 × 368 × 3	224 × 224 × 3	Thermal Images
Bottom Layer	224 × 224 × 3	7 × 7 × 1280	MobileNetV2 baseline
Pool Layer	7 × 7 × 1280	1280	Global Average Pooling Layer
Top Layer	1280	256	Fully Connected Layer [256, ReLU]
	256	2	Fully Connected Layer [2, Softmax]

B. Model Development

In this study, the CNN model is developed by applying the transfer learning method. The transfer learning method was used to apply the knowledge gained from solving the classification task of the larger general dataset to solving a different classification task of a smaller dataset [30]. Since the obese thermograms used in this study were limited, we applied transfer learning on the pre-trained model and trained it with an obese thermogram dataset. We modified the pre-trained architectures to achieve the highest performance by adding additional fully connected layers. Then we fine-tuned the developed CNN model to achieve the best performances in training and testing.

1) Pre-Trained CNN Model

In the image classification domain, Convolutional Neural Network (CNN) models were recently shown significant classification performances through the transfer learning method on pre-trained CNN models [31], [32]. These pre-trained models were trained on million images of the ImageNet dataset to classify common image classification problems and then could be fine-tuned to a specific classification task. Applying transfer learning on pre-trained models could shorten and optimize the time required for training the model to achieve better learning performances.

In this study, pre-trained CNN models MobileNetV1 [33] and MobileNetV2 [34] were trained with an obese thermograms dataset through the transfer learning method by modifying its last fully connected output from 1000 class into 2 class outputs. We chose MobileNetV1 and MobileNetV2 models due to their depthwise separated filters, which drastically reduced computation and model size [33]. Those models were designed to match the design requirements for mobile and embedded vision applications with limited computation resources and memory.

2) Proposed Modified CNN Model

As the fine tuning of pre-trained model had not yet achieved the optimum performances, then the pre-trained architecture was modified by adding several additional layers. The increased layers were added to improve the model's performance in generalized features better. The procedure was performed for both pre-trained models: MobileNetV1 and MobileNetV2. However, the modified MobileNetV2 was achieved better performances than modified MobileNetV1, which is will explained later at next section. Therefore, the modified MobileNetV2 is considered as the proposed modified CNN.

The proposed CNN architecture was shown in Table 1. The input images from thermal camera were resized first into size of 224 × 224 × 3 (RGB) at the input layer. The bottom layers of the pre-trained MobileNetV2 were imported, as well with its filter's weight. Then the input images were convoluted in the bottom layers into size of 7 × 7 × 1280 and pooled by global average pooling layer into one dimension matrix size of 1. Then followed with fully connected layers with 256 nodes followed with Rectifier Linear Units (ReLU) activation function. The last fully connected was added with size of 2 nodes followed with softmax activation function to classifying the output into 2 classes of normal or obese.

3) *Training and Testing*

All the models were trained and tested on Google Cloud Engine Virtual Machine (GCE VM) with GPU: Tesla P-100 and RAM of 16 GB. The models were constructed and developed on an open-source framework: TensorFlow 2.0 and Keras library. The training and testing procedures were executed in 100 epochs and a batch size of 32. The prediction loss was calculated with a categorical cross-entropy loss function. Adam optimizer was used to optimize the learning performances to optimal accuracy with a constant initial learning rate of 0.0001.

To evaluate the model performances in classifying obese and normal thermograms, we measure the training and testing metrics of accuracy, specificity, and sensitivity shown in mathematical equations (1)-(3). In this study, the positive value is described as obese class images, while the negative value is described as normal class images. True Positive (TP) is defined as correctly predicted images of an obese class. While True Negative (TN) is defined as correctly predicted images as a normal class. False Positive (FP) is defined as wrongly predicted images as an obese class, and False Negative (FP) is defined as wrongly predicted images as a normal class.

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \quad (1)$$

$$Specificity = \frac{TN}{FP + TN} \quad (2)$$

$$Sensitivity = \frac{TP}{TP + FN} \quad (3)$$

C. *Model Deployment*

After developing a high performances model, we implement the proposed CNN model into mobile devices. The model was deployed as a stand-alone mobile application which is not required an internet connection to perform obese diagnose. The proposed model was first converted into a TensorFlow lite format extension and then embedded into a mobile application. In this study, we implement the CNN model into a thermal camera smartphone CAT S62 Pro with an android operating system. The mobile application user interface (UI) was designed with android studio IDE in dart programming language and flutter framework.

The mobile application's workflow is shown in Fig 3. The application starts with displaying a home page with 2 buttons: Capture and Gallery. When the user presses the capture button, the application will open "My FLIR Pro" application and let the user captures thermograms with the thermal camera. When the gallery button is pressed, the application will let the user choose which photos to be fed into the CNN model to classify obese and normal thermograms. When an image is chosen, the application will load the CNN model and show the prediction value in probability values from 0 to 1. If the obese value is higher than the normal value, the application will show the results to the user and vice versa.

III. RESULTS AND DISCUSSION

A. *Training and Testing Results*

The testing results are recorded and summarized in Table. 2. We comparing the performances of the pre-trained CNN models, the modified CNN models and snekhalatha et al. [25] CNN models from previous study. In classification performances, the results showed that the proposed model

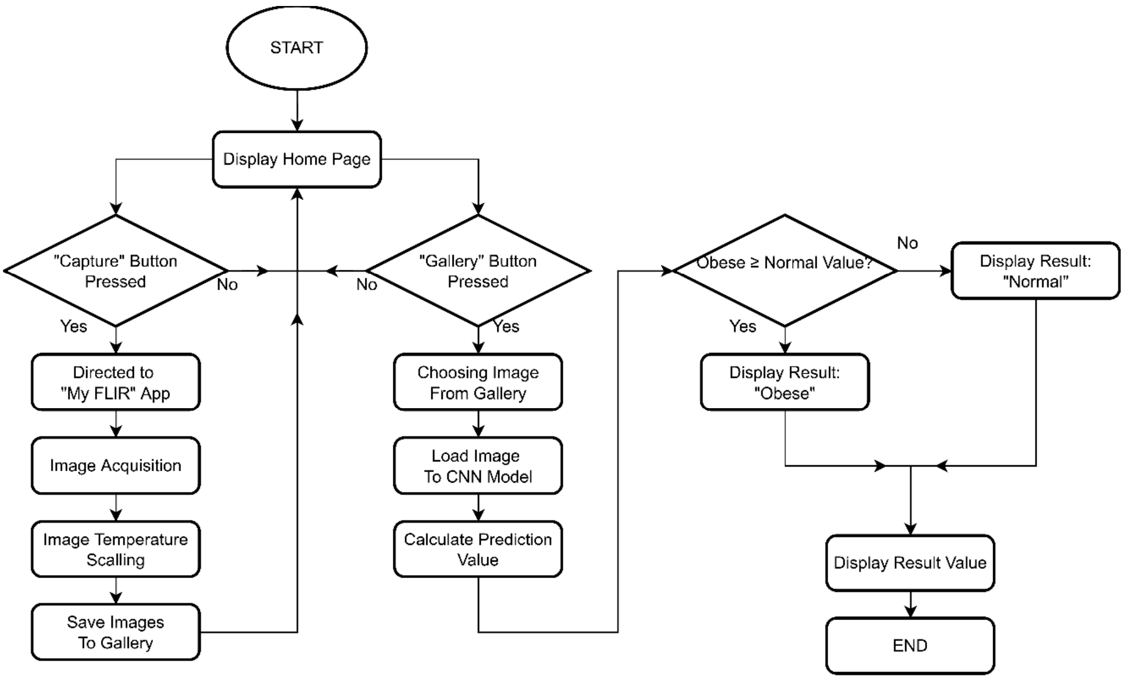
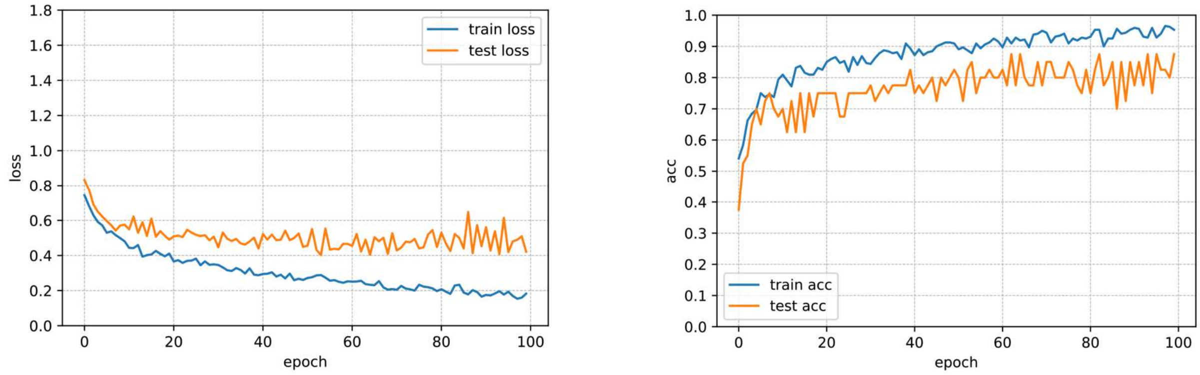


Fig.3 The Overall Application Flow

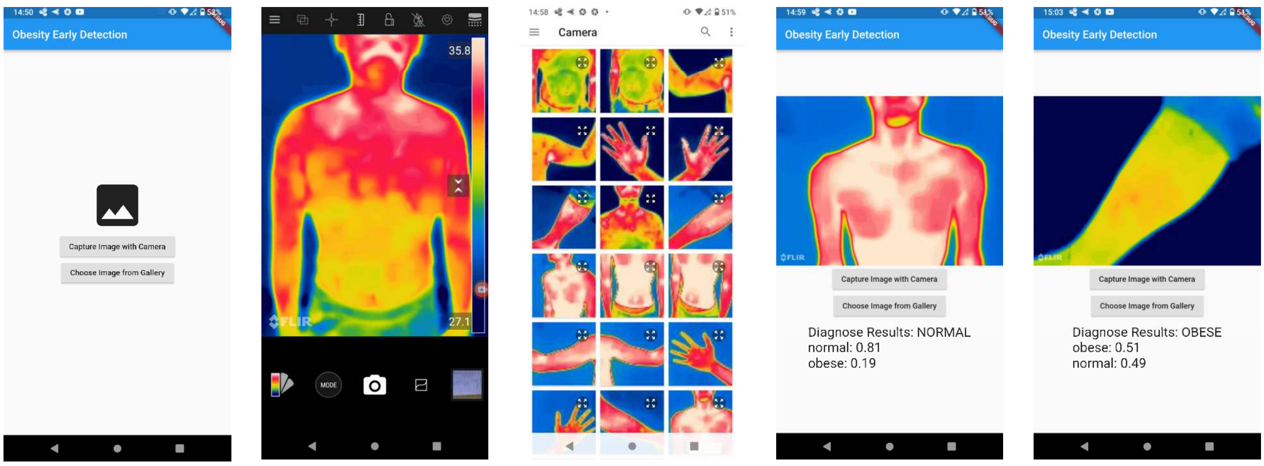
TABLE II. Testing Results

Model	Accuracy	Specificity	Sensitivity	Learning Parameter	GFLOPs	Model Size (MB)
MobileNetV1	0.850	0.950	0.750	3,230,914	1.15	12.325
Modified MobileNetV1	0.875	1.000	0.750	3,491,778	1.15	13.320
MobileNetV2	0.725	0.900	0.550	**2,260,546**	**0.613**	**8.623**
Proposed Modified MobileNetV2	**0.875**	**1.000**	0.750	2,586,434	0.613	9.866
Snekhalatha et al. [25]	0.825	0.850	**0.800**	36,327,690	3.03	138.58



(a) (b)

Fig.4 Proposed Model Learning Performances Between Training and Testing (a) Loss (b) Accuracy



(a) (b) (c) (d) (e)

Fig.5 Mobile Application User Interface (a) Home page (b) Thermal Camera Application (c) Choosing Image in Gallery (d) Detection Result of Normal Thermogram (e) Detection Result of Obese Thermogram

achieved the best accuracy of 87.5 %, specificity of 100 %, and sensitivity of 75.00 %. The modified MobileNetV1 model also achieved the same classification performance as the proposed model. However, the proposed model has a smaller complexity than the modified MobileNetV1 model. The proposed model has 2.5 million learning parameters, a computation cost of 0.613 GFLOPs, and a model size of 9.8 MB. The proposed model has a bigger complexity size than its baseline MobileNetV2 model due to additional layers at the fully connected layers, resulting in a comparable trade-off between classification performances and complexity size.

Compared with the previous CNN model of Snekhalatha et al. [25] study, the proposed model shows better accuracy and specificity but poorer sensitivity. However, the proposed model achieved a significantly smaller complexity in total parameters, FLOPs, and model size than the snekhalatha [25] model. The previous study [25] proposed customized CNN architectures consisting of four conventional convolution layers followed by multiple dense layers, which increase the model's complexity and are more suitable for embedded Computer-Aided Diagnosis (CAD) systems rather than smartphone devices.

The proposed model's learning performances of loss and accuracy are shown in Fig 4. As shown in Fig. 4 (a), there is a gap between the train and test loss. It's indicated that the model achieved a smaller loss in classifying training images than testing images. However, the gap started to bigger after the 75th epoch, and we stopped the training at the 100th epoch to prevent overfitting. Then the current fine-tuning attempt is considered in the good fitting, which is tuned between underfitting and overfitting conditions. While on Fig. 4 (b) also shows the gap between the training and testing accuracy of the proposed model. However, the learning performances show acceptable performance in the final accuracy results in the 100th epoch, which achieved the best accuracy than other models.

As a summary of the testing results, the proposed model has achieved a balanced trade-off between its classification performance (accuracy, specificity, sensitivity) and complexity (computation cost, learning parameters, model size). Even though the proposed model did not outperform the modified MobileNetV1 in classifying performance and the complexity model was not smaller than the modified MobileNetV2 model. The proposed considered has comparable performances and is suitable to be implemented into mobile applications due to its latency and accuracy in classifying obese thermograms.

B. Mobile Application Deployment Results

The mobile application for obesity early diagnosis was constructed by embedding the proposed CNN model into the thermal camera smartphone: CAT S62 Pro. The mobile application user interface is shown in Fig. 5. The application started with a home page with 2 main buttons, as shown in Fig. 5 (a). The user could press the capture button to redirect the user to the thermal camera provided by the mobile devices, as shown in Fig. 5 (b), or could press the gallery button to choose the thermograms that need to be diagnosed, as shown in Fig. 5 (c). The detection results are shown in Fig. 5 (d) and Fig. 5 (e). The results did not only display the detection conclusion between "obese" and "normal". Therefore, the application also showed the obese and normal prediction values from embedded CNN models.

IV. CONCLUSION

In this study, we built a classifier model by modifying the pre-trained CNN model through transfer learning to classify obese thermograms into obese and normal binary classes. We built the proposed CNN model based on the MobileNetV2 model by adding additional fully connected layers on the top layer architecture. The proposed model achieved the highest classification performance accuracy of 87.50%, specificity of 100 %, and sensitivity of 75 %. The proposed model demonstrated an optimal fit learning with 2.5 million parameters, a computation cost of 0.613 GFLOPs, and a size of 9.8 MB. Then we considered the proposed model a lightweight CNN model, which has a balanced and comparable tradeoff between classification performances and complexity size. Then we embedded the proposed CNN Model as a mobile application for the thermal camera smartphone: CAT S62 Pro. By implementing it on stand-alone mobile devices, the benefits of the applications can be more easily used by common people to make early obesity diagnoses. In future works, the mobile application accuracy could be improved by adding segmentation procedures and increasing the output classes into 3 classes: normal, overweight, and obese.

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