Mobile Application for Remote Monitoring of Peripheral Edema

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Abstract. The prevalence of heart disease continues to become a relevant issue globally. One of the most common symptoms in heart failure (HF) patients is peripheral edema. Peripheral edema can be caused by various underlying conditions. Thus, early detection and consistent monitoring are vital for its appropriate treatment. Several studies have explored the use of telehealth for a more accessible remote monitoring of HF patients. With the current gap in monitoring patients remotely, the proposed solution is a mobile application that detects the presence and severity of peripheral edema in HF patients. It allows patients to take a video of their extremities and a deep learning model in the application will evaluate the presence and severity of peripheral edema. The dataset collected consists of 150 photos for each edema stage. Transfer learning was utilized on a MobileNetV3 model with pre-trained weights from ImageNet. The model yielded an accuracy of 95.24% and recall of 0.96 on the test dataset, and an accuracy of 86.67% and recall of 0.95 during the field testing of the application. The high accuracy indicates that the model performs well in classifying different peripheral edema severity. Moreover, the high recall value shows that the model is able to accurately detect the presence of edema by minimizing false negatives.

Keywords: Peripheral edema · MobileNetV3 · mHealth · Convolutional neural networks · Deep learning

1 Introduction

Edema is the accumulation of fluid in the tissues [23]. Peripheral edema, more specifically, is a kind of edema that occurs in the legs, making them swollen. Due to the lack of blood circulation in arteries and veins, excess blood and fluids accumulate in the capillaries and eventually leak onto the tissues in the legs or arms, causing peripheral edema [6]. Peripheral edema is assessed by conducting a pitting test on the affected area. The pitting test is administered by applying

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pressure on the affected area, and classified into grade 1 (mild edema), grade 2, grade 3, or grade 4 (severe edema) depending on the indentation depth. A more severe peripheral edema would have a deeper indentation [20]. This type of assessment produces a burden and increased workload on physicians, requiring them to conduct the pitting test several times a day for optimal patient care. Thus, this project developed an offline mobile application for the early detection of peripheral edema and remote monitoring of patients who are prone to it. The deep learning model in the application was designed and trained using the Keras framework. The built-in libraries in Keras were used to do transfer learning and fine-tuning on a MobileNetV3-Large model with pretrained weights from ImageNet. The mobile application that hosts the deep learning model for on-device inference was developed using Android Studio.

The collection of the dataset was conducted on a Life/Form® Pitting Edema Trainer [1]. Due to the limitation of using edema simulators, nuances in actual human skin such as complexion, body hair, body marks, and other relevant variables were not taken into account during the dataset collection. The variables that were considered in the data collection were lighting, i.e., indoor or outdoor, the phone used to capture the images, and the phone operator. As for the mobile application, all features and functionalities would not require internet connection as the processing of the images will be done on the user's hardware. Thus, the user's hardware specifications can limit the application's performance.

2 Related Work

2.1 Peripheral Edema and Its Causes

Edema is the accumulation of fluid in tissues in different parts of the body. This occurs when capillary filtration exceeds its drainage limits, and fluid builds up in the tissues [23,25]. There are two types of edema: pitting (with indentation) and non-pitting edema (lack of indentation) [25]. Peripheral edema can be attributed to various medical conditions. It is crucial to determine the cause of peripheral edema, as specific therapeutic approaches are to be done based on its underlying cause [16]. Severe peripheral edema may be indicative of a severe heart condition, thus, a mild peripheral edema should be consulted to a physician for its appropriate treatment to be determined immediately.

2.2 Assessment of Edema and Current Challenges

The traditional way of differential diagnosis of peripheral pitting edema is through physical examination [21]. A pitting test is done, where the severity of pitting edema will be classified according to the indentation depth and/or rebound time of the skin [3]. While the pitting test is a widely used technique, this method of assessing the severity of peripheral edema is primarily qualitative due to the highly variable technique of applying the pressure [3,20]. The most widely known quantitative assessment in edema testing is water displacement volumetry [18]. The results of the study by Petersen et al. show that water displacement volumetry is a reliable way of measurement specifically in lower-extremity swelling. However, this method is considered time-consuming and inapplicable to postoperative conditions [8]. Another proposed quantitative way of detecting peripheral edema is through bioelectrical impedance vector analysis (BIVA), where the conductivity of electrical current in the body is normalized by the subject's height and plotted in a nomogram [15]. This study shows that BIVA is a semi-quantitative volume assessment method which produces highly accurate results. However, this process was proven to be inconvenient for immediate testing of patients and requires equipment that is expensive and not easily accessible. Finally, the assessment of peripheral edema puts extra workload on the medical staff who are already burdened due to inadequate staffing and poor workforce planning [10]. Thus, this issue has to be emphasized as this burden on hospital staff affects many aspects, including quality of care and patient outcomes [14].

2.3 Telehealth Monitoring

Implementing a system that allows patients to monitor their condition remotely will help promote active patient participation in taking care of their health and reduce the workload of hospital staff onsite. Such systems can be described as telehealth or telemedicine which are means of providing healthcare services remotely with the use of technology [11]. Monitoring the condition of heart failure (HF) patients remotely via telehealth will be highly beneficial since the majority of their treatment costs are allotted to hospitalizations. Moreover, the treatment of chronic HF patients also consists of frequent outpatient visits to monitor their current health status. Thus, several advanced monitoring means and devices are being introduced to lessen both the patients' mortality rate and financial burden [2]. Information and Communication Technology (ICT) has potential in improving the healthcare system, specifically in monitoring at-risk patients without requiring any in-person health consultations [22]. Due to the increased risk of HF patients to develop peripheral edema [17], the challenge is to utilize existing technologies that will aid in monitoring the presence and severity of peripheral edema remotely with telehealth.

2.4 Deployment of Telehealth Services via Mobile Applications

Global mobile technology usage has significantly increased in the past decade. With this trend, the use of mobile phones in healthcare, also known as Mobile Health (mHealth), has proven to be beneficial for patients and healthcare providers. Mobile health assists patients through various means, such as follow-up appointments and adherence to treatments [4]. Studies have shown the effectiveness and acceptability of patients on the usage of mobile applications for their health-related treatments [7]. Thus, mobile applications have the potential to be an ideal medium to deliver telehealth services that will remotely monitor the presence and severity of peripheral edema.

2.5 Potential Application of Deep Learning in the Assessment of Peripheral Edema

Due to the qualitative nature of peripheral edema assessment through the pitting test and low accessibility to other methodologies, there is a need for a more quantitative and accessible approach. The application of machine learning and deep learning in monitoring the presence of peripheral edema has already been explored in previous studies. Chen et al. evaluated the accuracy of machine learning using linear support vector machine (SVM) trained on histogram of oriented gradients (HOG) to classify the severity of edema (no edema, grade 1, grade 2, grade 3, grade 4+) based on images and videos taken right after a pitting test [5]. The performance of AlexNet with pretrained weights from ImageNet was compared to the performance of the HOG+SVM method. The dataset used in their model training consisted of two sets: single-frame images showing the indentation depth of the skin and three-frame stacked images which include temporal information on the skin's rebound time. Their dataset was obtained from pitting edema simulators which are tissue pads used to emulate the tissues of humans with different edema grades. Their results showed that the HOG+SVM approach has an accuracy of 87.33% when trained on single-frame images and 94.22% when trained on three-framed stacked images. The deep learning model proved to be a more accurate model regardless of the dataset used with 97.33% accuracy on single-frame images and 98.77% accuracy on three-frame stacked images. However, the paper lacked testing on actual human skin so there is uncertainty on whether the accuracy of the model will hold when it is used with inputs from actual human skin.

2.6 Limitations in the Integration of Deep Learning and Mobile Application Development

Deploying a deep learning model on mobile applications that will assess peripheral edema will be advantageous in telehealth monitoring because the patients will be able to do it with just their handheld devices. However, there are issues that need to be addressed regardless of the infrastructure being used. Web-hosted deep learning models are vulnerable to adversarial attacks and data privacy issues such as reverse engineering of the model and recovery of sensitive user data used for training [13]. Deploying the model on the client's device is one solution to address these issues since no data has to be transmitted over the internet. However, with the increasing complexity of deep learning models, there is also an increase in the demand of hardware resources that are needed to run the model. Since mobile phones are resource-constrained in terms of computing power, memory, and storage due to its form factor, the complexity of the model poses a challenge in its deployment [24]. Therefore, there is a need for the use of deep learning models that are mobile friendly in terms of efficiency while also maintaining good accuracy.

2.7 Use of the MobileNetV3 CNN Model for Image Classification in Mobile Devices

MobileNetV3 was developed in a bid to optimize the deployment of deep learning models in mobile and embedded devices. Qian et al. compared the performance of MobileNetV3-small and MobileNetV3-large to AlexNet, InceptionV3, ShuffleNetV2 and concluded that MobileNetV3 uses less floating point operations than other models. The training and validation accuracy of MobileNetV3 was also comparable to the accuracy of the other models that are more complex and designed for more powerful devices [19]. Hussain et al. also evaluated the performance of MobileNetV3 on image classification of plants through handheld devices. Their results showed that the accuracy of MobileNetV3 is comparable to existing leaf recognition CNN algorithms with the training time being significantly lower while also keeping the model size as small as less than 5 megabytes [12].

3 Methodology

3.1 Dataset Collection

The Life/Form® Pitting Edema Trainer was used in collecting the dataset for the deep learning model. The pitting edema trainer simulates human tissue to demonstrate edema from grades 1 to 4. It is a medical grade equipment that adheres to a standardized criteria specific to its use, and is often used for training clinicians in assessing pitting edema. Upon conducting a pitting test on the Life/Form® Pitting Edema Trainer, the grades 1 and 2 edema simulator pads did not show distinguishable indentations because of their toughness. Due to these issues, only grades 3 and 4 were used to represent mild and severe edema, respectively. Furthermore, the edema trainer pad for grade 1 edema was used to represent grade 0 (no edema), as it more closely resembles the effect of pitting test on a normal skin. For each edema grade, 150 closeup images of the trainer pad were collected right after the finger was lifted from the pitting test (see Fig. 1). This amount of data collected was based on the experiment of Chen et al. where they used 150 single-frame images per peripheral edema grade as their dataset for training an AlexNet model [5]. Moreover, the temporal information in the edema pads' rebound time was omitted since the results of Chen et al. showed only a 1.44% increase in Alexnet's accuracy in three-framed stacked images compared to single-framed images. This was also done to reduce the computational size and resources needed to train the model. The mobile phones used had a resolution of at least 1080p, and the images were captured under unregulated environmental conditions, i.e., varying lighting conditions.

3.2 Deep Learning Model Design

To determine the severity of peripheral edema (normal, grade 3, or grade 4), the convolutional neural network (CNN) must be suited for multiclass classification.

Fig. 1. Sample images of grade 3 (left), grade 4 (middle), and no edema (right) from the dataset

Given the small dataset for this application, training a CNN model from scratch to evaluate the presence and severity of edema will likely yield poor accuracy due to overfitting [27]. Thus, transfer learning was utilized to reduce the effects of overfitting from small datasets since the ability of the model to distinguish features has already been pretrained on a larger dataset [28]. A MobileNetV3-Large model with pretrained weights from ImageNet was used for this application.

The convolutional layers of the model were frozen to retain their weights during the training of the model on the edema dataset. This allowed the model to keep the general feature extraction and recognition capabilities that it has already learned from training on millions of images on ImageNet. To use the pretrained model for the specific purpose of classifying the severity of peripheral edema, the fully connected layers were designed accordingly and appended to the frozen convolutional layers (see Fig. 2). First, an average pooling layer was added to help the model accurately predict the classification of an object regardless of the positioning of its features in the input while also cutting the computation cost by reducing the number of parameters and weights [9]. Three dense layers with rectified linear units (ReLU) as their activation function and 512, 256, and 128 neurons at their outputs, respectively, were then appended. These layers are responsible for the prediction of the edema classification. Finally, the output layer is a softmax layer with three neurons to represent the three edema stages and their probability distribution. The neural network hyperparameters that helped improve the accuracy of the model were also specified. A dropout of 0.5 was used. Dropout is a form of regularization that reduces overfitting by dropping random neurons in the fully connected layers. The optimizer used was the Adam optimizer with a learning rate of 0.001. Moreover, categorical cross entropy loss was used as the loss function for the training. During training, the dataset was also augmented to further improve the generalization of the model. Particularly, the brightness of the images was randomly varied from 20% to 100%. The images were also rotated within the range of -90∘ to 90∘. These hyperparameter configurations that yielded the best-performing model were determined empirically.

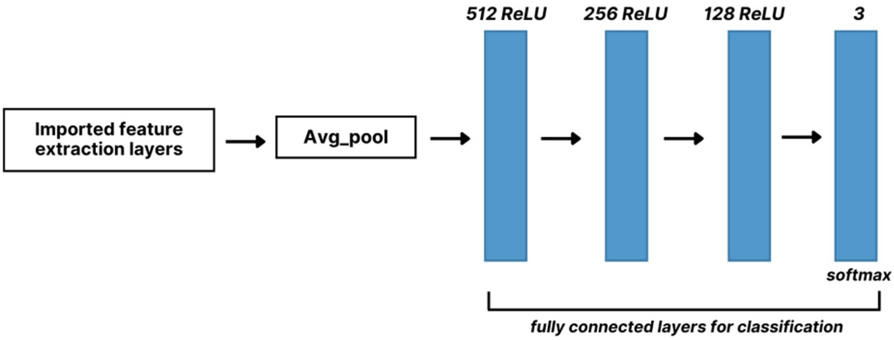

Fig. 2. MobileNetV3-Large model for peripheral edema classification

3.3 Deep Learning Model Validation Strategy

Due to the small dataset that was used for this project, it was not ideal to split the dataset into training and validation sets because there are some useful information that might be excluded from the model training. To address this limitation, the K-Fold Cross Validation technique was used [26]. This technique splits the dataset equally into an arbitrary value of k partitions or folds, each with equal class distribution. In particular, the proponents set the number of folds to five. The training was done five times where for each iteration, one fold was used as the validation set while the others were used for training. This technique allows every fold to be used as the validation set, thus, leaving no data unused for training. Moreover, 42 test images were collected which consist of seven images for each edema grade in certain lighting environments, i.e., indoor or outdoor. The accuracy of the model on images outside the dataset was evaluated in these test images.

3.4 Mobile Application Development

The mobile application developed aims to provide a medium for peripheral edema assessment which would allow patients to monitor their condition remotely without the supervision of medical practitioners. This would effectively reduce the workload of medical practitioners as they will only need to attend to their patients if the application detects the presence of peripheral edema. Since the application is targeted for the use of patients using their own mobile phones, it is ideal for the design of the application to be clear and straightforward. The application's main feature is a camera to capture a close-up video of the pitting test. The user will be instructed to capture the moment the finger is lifted during the pitting test (see Fig. 3). After the video is taken, the application will divide it into frames. The user must then select the first frame without a visible finger or shadow. A cropping feature will then allow the user to crop the frame such that only the indentation occupies the whole image (see Fig. 1). This cropped image will be used as the input to the deep learning model hosted inside the application. Finally, the application will display the results of the model evaluation indicating the predicted edema grade along with the model's prediction confidence, which will then be saved to the phone's gallery.

Fig. 3. Sample frames from a captured video

3.5 Integrated Testing of Mobile Application

The performance of the integrated mobile application and deep learning model was tested on images not included in the dataset. The proponents used the application to take 10 images of each peripheral edema stage from the edema simulator for a total of 30 images. The real-life accuracy of the model was then computed.

$$\%Accuracy = \frac{Number\,of\,Correct\,Predictions}{Total\,Number\,of\,Tests} \times 100\% \tag{1}$$

Moreover, it was determined if the model can accurately assess the presence of peripheral edema, i.e., if it can distinguish no-edema class from the other two classes using a metric called recall. Recall is the measurement used to compute the fraction of actual positives that were correctly classified. This metric needs to be maximized because it is important to avoid false negatives, i.e., images with peripheral edema being classified as normal. Regardless of the model's accuracy in distinguishing grade 3 from grade 4 edema, having a high accuracy on the detection of presence of edema will provide useful information for medical intervention since the patients would need to be treated regardless of severity.

$$Recall = \frac{TruePositive}{True\,Positive + False\,Negative} \tag{2}$$

3.6 User Satisfaction Survey

After the completion of the mobile application, a user testing was held to evaluate the functionality and user interface of the application. The mobile application was used and evaluated by five users who were selected through convenience sampling. The selected users are aged 22–23 years old students at the University of the Philippines Diliman. They had no prior knowledge on the purpose of the mobile application and edema classification. Thus, the users were given a brief background of the study and its objectives. The pitting test was demonstrated using the Life/Form® Pitting Edema Trainer pads, in order to show the users how to properly use the tool. A single Android phone was used by all the test users to explore the functions and flow of the application on their own without any external help.

A survey questionnaire on Google Forms was given to the users in order to understand their perspective and consider their suggestions to improve the mobile application. Criteria such as ease of use, mobile application design and user experience were asked in the survey, asking the respondents to provide their thoughts on the specific criteria. Lastly, the respondents were asked for any improvements and feedback on the application.

4 Results

4.1 Deep Learning Model

The training and validation accuracy and loss of the model during the k-fold cross validation were collected (see Fig. 4). This shows the performance of the best model derived after hyperparameter tweaking and data augmentations. It can be seen that the accuracy and loss of both training and validation sets flatten out at around the 10th epoch.

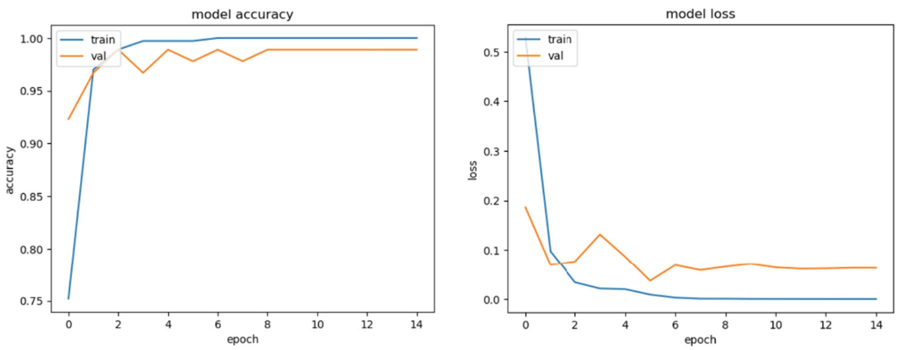

Fig. 4. Training and validation accuracy and loss

From the test dataset, a confusion matrix was generated to see how the model misclassifies each edema grade (see Fig. 5). From this, the recall can be calculated. Both grades 3 and 4 served as the positive variables, whereas the normal class served as the negative variable. This means that even if a grade 3 was misclassified as grade 4, it was still counted as a true positive as long as they were not misclassified as normal. This essentially measures the performance of the model in predicting the presence of peripheral edema regardless of its accuracy in detecting the specific severity. It can be seen that there are 27 true positives and one false negative. Therefore, the recall is 0.96. Moreover, the total accuracy of the model is computed to be 95.24%.

4.2 Integrated Testing of Mobile Application

The performance of the deep learning model was also evaluated once it was hosted in the mobile application. A confusion matrix was generated to summarize the model's performance in the integrated testing (see Fig. 5). Similar to the test dataset, the integrated testing yielded a high recall measurement of 0.95 with only one out of 20 positives being classified as a false negative. The total accuracy of the mobile application is 86.67%. It is also notable that all misclassifications in both test dataset and integrated testing involve grade 4 edema and normal classes being misclassified as grade 3 edema, and vice versa.

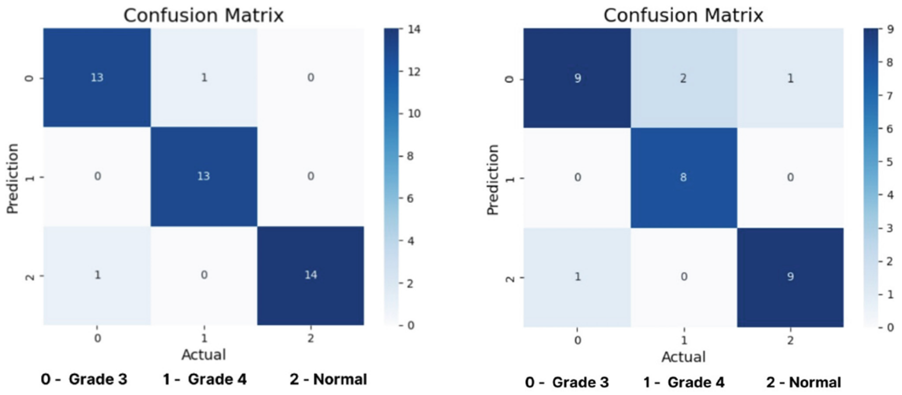

Fig. 5. Confusion matrix from the test set (left) and integrated test (right)

4.3 User Satisfaction Survey

Opinions of test users on some aspects of the user interface and experience of the mobile application were obtained (see Fig. 6). The users were also asked for suggestions on the improvement of the application, specifically regarding its functionality and design. Some users mentioned additional functions in the application that could aid them in the video recording and frame selection to maximize their chances of getting accurate results. First, a function that would detect the angle of the video recording, which would also state if the current angle is optimal or needs to be adjusted. Another functional improvement would be an automatic selection and cropping of a frame from the recorded video. Having these additional features would improve the ease of use of the application.

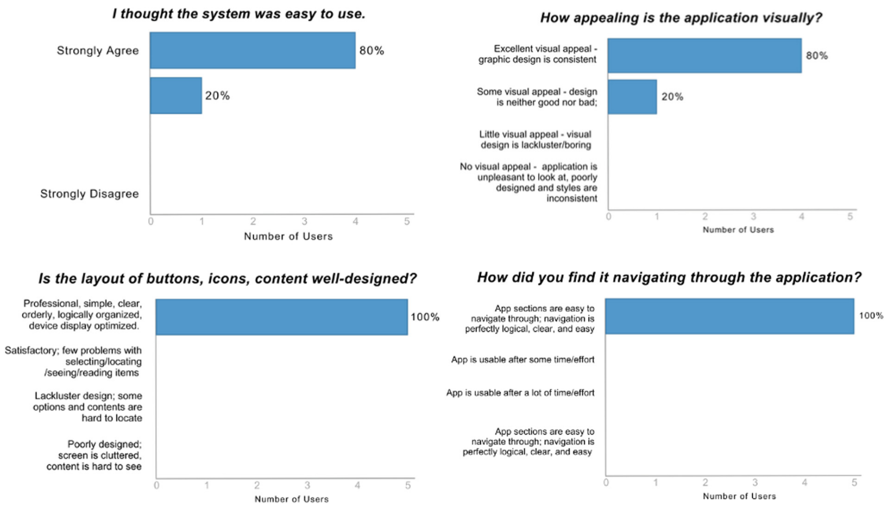

Fig. 6. Survey response summary

5 Discussion

It was shown that there was a quick stabilization of the deep learning model's accuracy to its maximum performance and a steep decline of the loss after just a few epochs. These results can be attributed to the nature of the dataset used. Since the dataset is small and the images generally have the same image composition with just the lighting and angle of capture varying (see Fig. 7), the model was able to easily distinguish the feature, i.e., the indentation depth, that defines the different edema grades. The high validation accuracy and low validation loss even at the earlier epochs can be explained by the fact that even the validation set had similar image composition as the training set. These results may be indicative of model overfitting as the model only performs well on new images outside the training and validation set that have the same image composition as the dataset.

To address the problem of overfitting, more images must be added to the dataset for training. Moreover, the composition of the new images should deviate from those that are already in the existing dataset. Having new images with more noise, i.e., background objects, shadows, etc., will negatively affect the training and validation accuracy and loss due to the model having to deal with random features and objects aside from the indentation. However, this will improve the model's generalization.

It was also shown in the confusion matrices that grade 3 edema was always involved in the model's incorrect predictions. These misclassifications are due to the fact that grade 3 edema may look similar to both normal and grade 4 edema depending on the lighting of the image. In the integrated testing, more factors involving human error could explain the lower accuracy compared to the

Fig. 7. Sample grade 4 edema images from the dataset

model's evaluation on the test dataset. This involves the angle at which a user took the video, the force they applied on the edema simulator pads, and the distance between the camera and the pad.

As for the mobile application, the users mostly found the application to be easy to navigate and understand, despite it being their first time using the application. The aesthetic design of the application was well received and the logical flow of the application was found to be cohesive. Some improvements need to be implemented to improve the application's ease of use to allow patients to capture the optimal image for edema prediction.

The results obtained in this study show that the performance of MobileNetV3-Large, a lightweight deep learning model specifically designed for mobile and embedded devices, is comparable to those of more complex and computational resource-heavy models such as AlexNet and SVM+HOG model [5]. The model's accuracy of 95.24% on the test dataset and 86.67% during the field testing of the application comes close to the 87.33% accuracy of HOG+SVM approach and 97.33% accuracy of AlexNet. This further enables the use of mobile devices in remote assessment of peripheral edema as there would be less reliance on expensive and inaccessible equipment used in water displacement volumetry and BIVA assessment [15,18]. Moreover, this will lessen the burden on clinicians as the application can be used by patients to monitor their condition remotely without their supervision.

6 Conclusion and Recommendations For Future Work

6.1 Conclusion

It was demonstrated in this paper the development of a deep learning model, particularly the MobileNetV3-Large, using transfer learning to predict the presence and severity of peripheral edema. A dataset which contains images of different edema severities was collected from an edema simulator due to the lack of publicly available dataset and the difficulty of obtaining images from actual patients with peripheral edema. The resulting model accuracy is comparable with the performance of SVM+HOG and Alexnet models, trained on both single-frame and three-frame images [5]. Moreover, both tests yielded a recall value of at least 0.95 which indicates that the model performs well in detecting the presence of peripheral edema. However, it was also observed that the model experiences overfitting on the dataset. This entails that new images to be fed to the model for prediction must also have the same image composition as the images in the dataset to get an accurate result. Thus, the mobile application was specifically designed to guide users on how to take images that will closely resemble how the images in the dataset look to aid the model in making correct predictions.

6.2 Recommendations

For the application to be viable for use in the medical field, a larger dataset with thousands of images of peripheral edema in actual human skin has to be collected. This dataset should take into account factors such as skin complexion, body hair, body marks, different lighting environments, and others that might be relevant to further improve the generalization of the model. Subject to ethical and technical review of concerned institutions, this would require a pilot study to assess the feasibility of obtaining the dataset from actual patients and testing of the application in hospital setting. To ensure correct labeling of the dataset and fair evaluation of the application's performance in assessing peripheral edema, a medical practitioner must verify the severity of the patients' peripheral edema using conventional methods of assessment such as the pitting test. Several improvements in the mobile application can also be done in terms of functionality and design. An automatic selection of the most optimal frame for use in edema prediction may be implemented to lift the burden of choosing from the users. The application may also employ an online infrastructure to allow real-time updates and communication between patients and medical staff.

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