RitaWiryasaputra
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COMMITTEES REGISTRATION VENUE AND ACCOMMODATION HELP DESK

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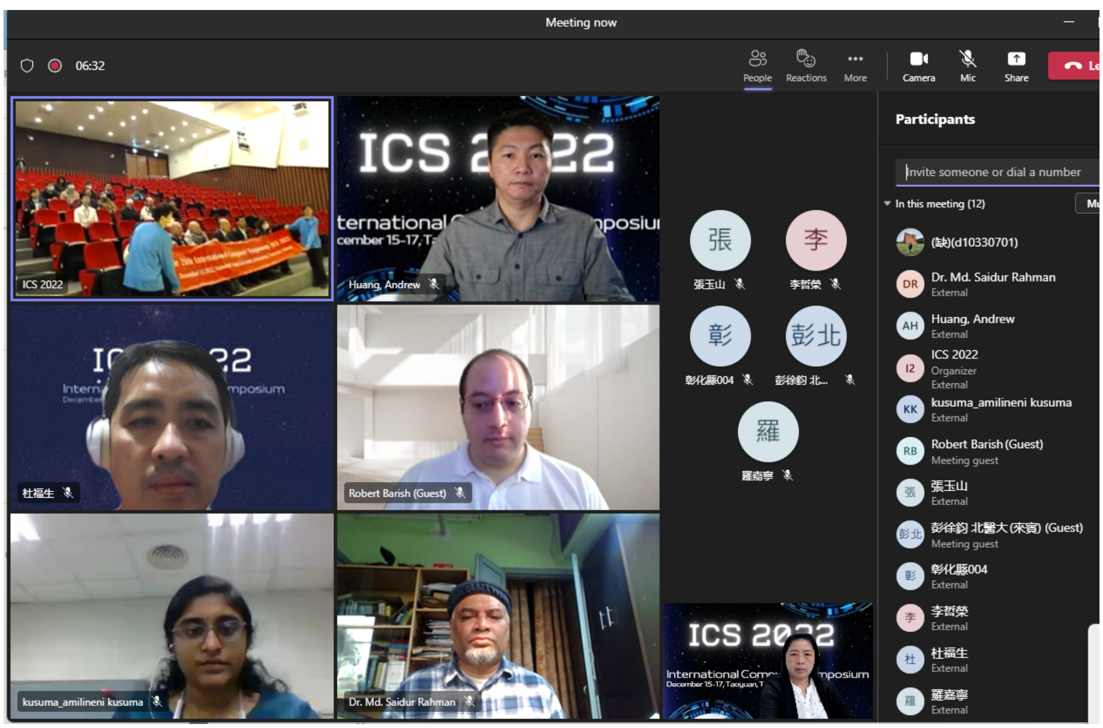
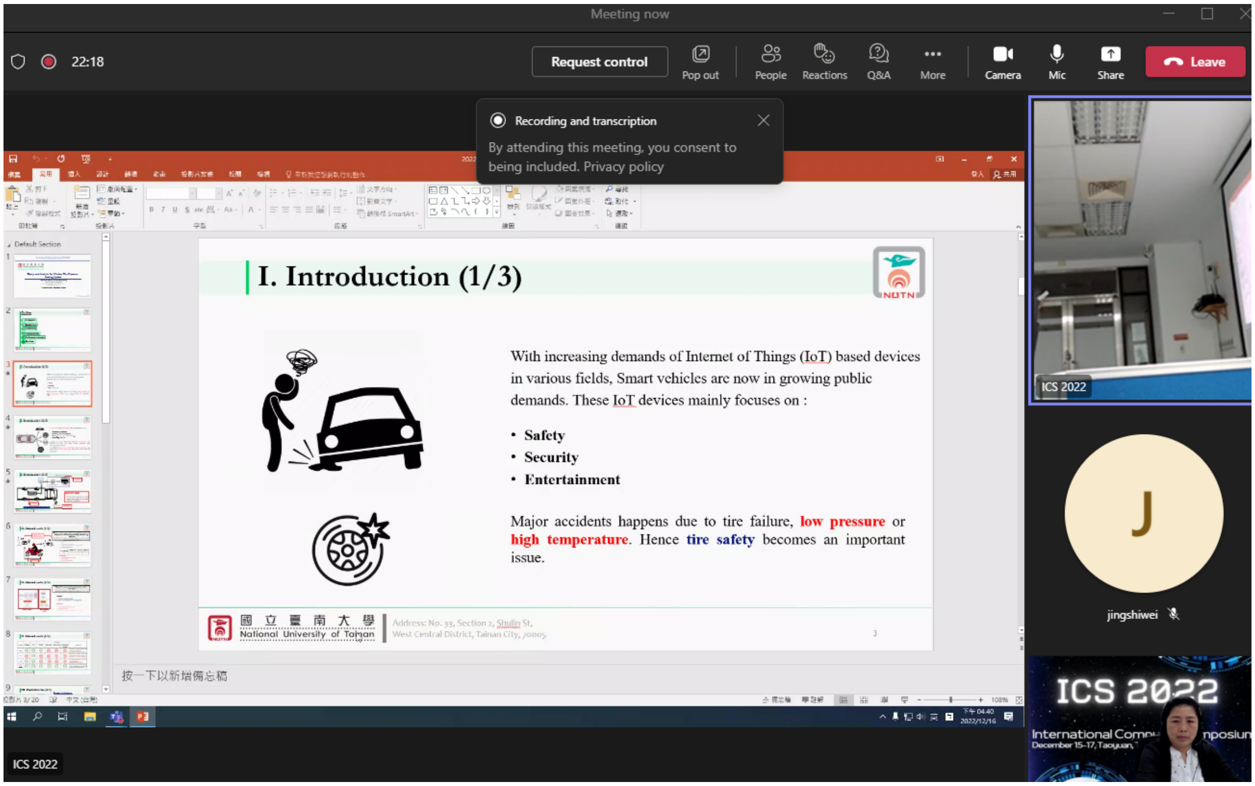
97. Shih-Wen Jiang, Syuan-You Chen, Whai-En Chen and Hsin-Te Wu. Development of Personnel Epidemic Prevention Monitoring Access Control System

120. Rita Wiryasaputra, Chin-Yin Huang, Rio Willyanto and Chao-Tung Yang. Prediction of Middle-Aged Unhealthy Facial Skin using VGG19 and Support Vector Machine Models

133. Sheng-Kai Wang, Wan-Lin You and Shang-Pin Ma. Semi-Automatic Chatbot Generation for Web APIs

142. Che-Wei Chang, Xinyu Zhang and Hung-Chang Hsiao. Query Regrouping Problem on Tree Structure for GPUs Accelerated Platform

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I. Introduction (1/3)
NUTN
With increasing demands of Internet of Things (IoT) based devices in various fields, Smart vehicles are now in growing public demands. These IoT devices mainly focuses on :
• Safety
• Security
• Entertainment
Major accidents happens due to tire failure, low pressure or high temperature. Hence tire safety becomes an important issue.
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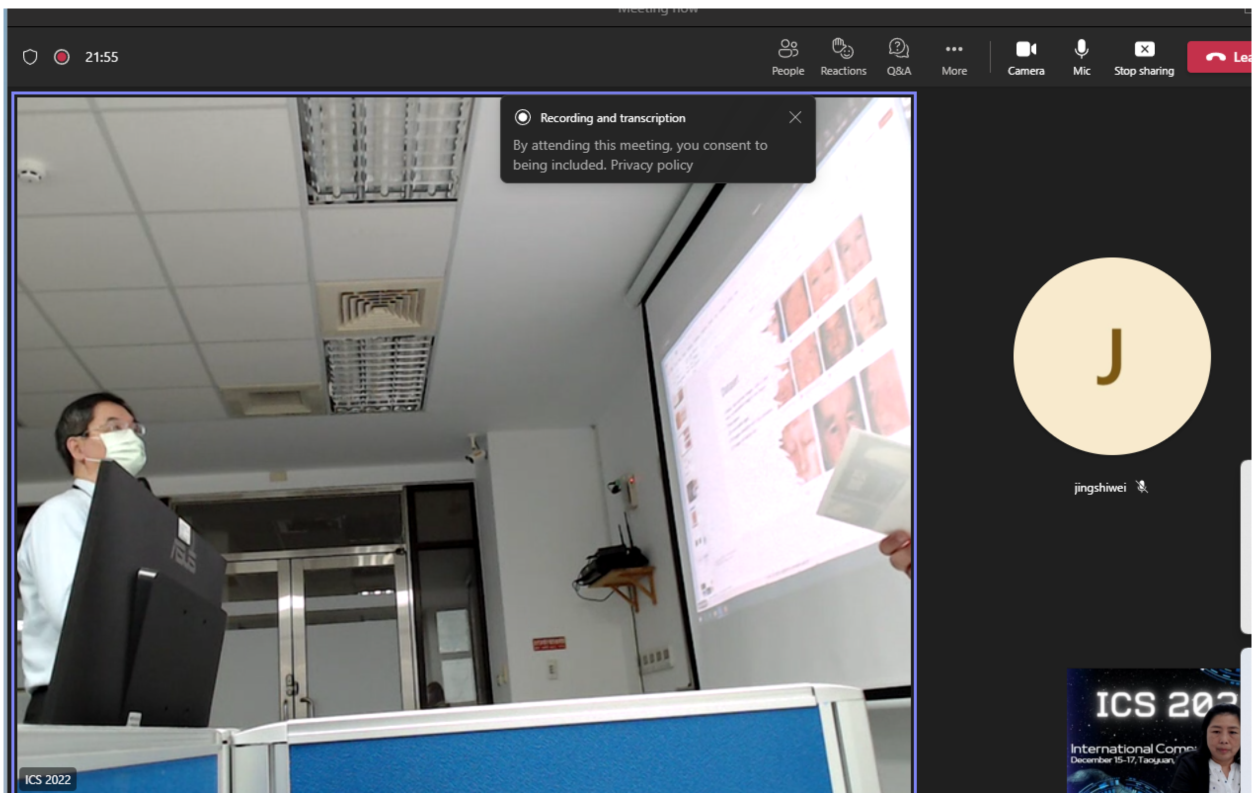
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Session Chair: Tomoyuki Yamakami, University of Fukui, Japan
Date: Dec. 16, 2022
Time: 15:30~17:30 (UTC+8)
Location: Room Bb 13 Gong Neng Building B1
#127 Tomoyuki Yamakami, Fine Grained Space Complexity and the Linear Space Hypothesis
#37 Yali Lv, Cheng-Kuan Lin, D. Frank Hsu and Jianxi Fan, A Comparison Diagnosis Algorithm for Conditional Fault Local Diagnosis of Multiprocessor Systems
#48 Meirun Chen, Cheng-Kuan Lin and Kung-Jui Pai, A tree structure for local diagnosis in multiprocessor systems under comparison model (Workshop Best Paper)
#129 Ruei-Sing Guan, Yu-Chee Tseng, Jen-Jee Chen and Po-Tsun Kuo, Combined Bayesian and RNN-based Hyperparameter Optimization for Efficient Model Selection Applied for autoML
#146 Juhi Chaudhary and Bhawani Panda, On Two Variants of Induced Matchings

Session B2: Cloud Computing and Big Data & Mobile Computation and Wireless Communication

Session Chair: Yue-Shan Chang, National Taipei University, Taiwan
Date: Dec. 16, 2022
Time: 15:30~17:30 (UTC+8)
Location: Room Bb 14 Gong Neng Building B1
#120 Rita Wiryasaputra, Chin-Yin Huang, Rio Willyanto and Chao-Tung Yang, Prediction of Middle-Aged Unhealthy Facial Skin using VGG19 and Support Vector Machine Models
#133 Sheng-Kai Wang, Wan-Lin You and Shang-Pin Ma, Semi-Automatic Chatbot Generation for Web APIs (Workshop on Cloud Computing and Big Data: Best Student Paper)
#142 Che-Wei Chang, Xinyu Zhang, and Hung-Chang Hsiao, Query Regrouping Problem on Tree Structure for GPUs Accelerated Platform
#28 Shashank Mishra and Jia-Ming Liang, Design and Analysis for Wireless Tire Pressure Sensing System
#108 Chun Hsiung, Fuchun Joseph Lin, Jyh-Cheng Chen and Chien Chen, 5G Network Slice Scalability

Prediction of Middle-Aged Unhealthy Facial Skin using VGG19 and Support Vector Machine Models

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Abstract. In human communication, the resource of primary information can be read from a human's face. Health problems occur in line with age, and one way to detect health issues is through changes in facial skin. People typically pay less attention to initial facial skin changes, even though the changes might be linked to a particular disease, such as Lupus. Treatment for Lupus takes time and is costly. Cutting-edge technology and Artificial Intelligence (AI) bring a new horizon to the medical field where a disease can be detected or predicted early. This paper presents the classification of training images for the early detection of middle-aged unhealthy facial skin. The Multi-Task Cascaded Convolutional Neural Networks (MTCNN) technique provides the face boundary box and the performance of face detection uses VGG19 architecture. The images dataset was divided into data training and data testing with a ratio of 80%: 20%, respectively, and the healthy or unhealthy face image was determined with a machine learning approach. The experimental results showed that the accuracy of the proposed Support Vector Machine classifier model was 92.2%.

Keywords: Face Detection · Machine Learning · MTCNN · SVM · VGG19

1 Introduction

It is undeniable that a person's first impression is reflected in the face. In human communication, the resource of primary information can be read from a human's face. Based on the World Health Organization (WHO), the age classification is as follows: young age (25-44 years old), middle age (44-66 years old), elderly age (60-75 years old), senile age (75-90 years old), elderly (above 60 years old) and long-livers who have more than 90 years old[6]. Many diseases merge in line with age, and one way to detect health problems is via facial skin. Most people typically do not notice the initial changes in their facial skin early on, even though some of the changes may be linked to diseases such as lupus, rosacea, herpes, erysipelas, and eczema. The cause of those skin disorders is ranging from viruses, bacteria, environment, or autoimmune problems. If a certain skin disorder is not detected early, the treatment cost could be high. For example, lupus is an autoimmune disease, and its symptoms often mimic another disease thus it is not easy to diagnose. Lupus also causes inflammation of particular body areas including the skin, joints, blood cells, kidneys, brain, heart, and lungs. The most distinctive sign of lupus is a facial rash that resembles the wings of a butterfly unfolding across both cheeks. There is no cure for lupus, but symptoms can be controlled through treatments. Advancements in technology and Artificial Intelligence (AI) particularly in the medical field offer new horizons to the healthcare world. Machine learning, as a subset of AI, has many models for classification and prediction purposes making early detection and screening of diseases possible. Convolutional Neural Network (CNN) is a machine learning unit algorithm. Based on a CNN, Multi-Task Cascaded Convolutional Neural Networks (MTCNN) enable the definition of the face into a boundary box as the first step of verification. MTCNN as a face detector is more accurate than DLIB. MTCNN can find faces at unfavorable angles whereas DLIB enables identification of the faces from the front [2]. The selection boundary box crop and extract with the VGG19 model to gain its feature. Previous studies have used VGG19 approach across various domains [1][7][14][13][8][10][11]. Moreover, underfitting issues are possible to experience with model. Underfitting is a phenomenon that occurs when the model cannot generate a low error value in the training set [18] To address the best result of classification, the Support Vector Machine (SVM) as the powerful machine learning classifier deals with complex datasets to recognize subtle and nondistinctive class [11]. The SVM classifier is also the most widely used in classification problem[3] [9]. The study objectives used ML methods to identify healthy and unhealthy middle-aged facial skin. The structure of this paper is as follows: the first section reviews the background, previous research is explained in section 2, and section 3 presents the research methodology. To deepen the understanding of the study's objective, section 4 features an experiment section. The conclusion is outlined in section 5 along with future research directions.

2 Related Works

This section describes the literature study stage in which the papers assessed were from Google Scholar, Science Direct, and the IEEEXplore repositories. The research conducted by Taeb shows that augmented real and fake faces could be determined by conducting Custom CNN, DenseNet121, VGG19 approaches; the highest accuracy was achieved through the VGG19's performance [13]. Ahmed [1] found that the VGG19 had the best accuracy compared with other face recognition models. Goel [7] examined several models such as FaceNet, VGGFace, VGG16, and VGG19 in face recognition for sibling identification cases. Assessments on discrimination used cosine similarity, Euclidean distance, structured similarity, Manhattan distance, and Minkowski distance as the standard measures. The VGG16 and VGG19 models provided favorable results for foreheads. The accuracy of VGGFace classification reached more than 95% for the full-frontal face and eyes, but not for the nose. However, the FaceNet approach generated the best result for nose classification. Table 1 gives the related work of image classification.

Table 1. The related work of image classification

Reference	Model	Objective
[1]	AlexNet, MobileNet, VGG16, VGG19	A comparative study of several model Convolution Neural Network for face recognition
[7]	FaceNet, VGGFace, VGG16, VGG19	Classification with VGG19 in forehead
[14]	DenseNet, VGG16,VGG19	Classification with fruits images
[13]	DenseNet, VGG19	Comparing the common face detection classifiers
[8]	VGG16, VGG19, DenseNet	Classification using the limited size of the sample data sets from publicity data on modest hardware
[10]	VGG16, VGG19, DenseNet	Adjust densely-connected classifier with VGG19 pre-trained model
[11]	VGG16, VGG19, DenseNet	A method for multi-label classification with confusion matrices

3 Methodology

This section presents the research stages, encompassing the dataset collection process, the stage of feature extraction, and the image classification stage. The overall approach is illustrated in Figure 1.

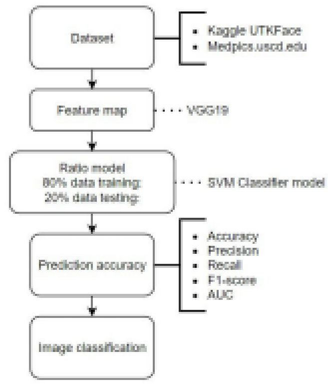


Fig. 1. Research Methodology

3.1 MTCNN

The MTCNN architecture has three serial layers - P-Net, R-Net, and O-net - as shown in Figure 2. This architecture facilitates and accelerates the fastest form of computation. The P-Net module was the most time-consuming in processing the full CNN to generate three outcomes [16] MTCNN applies Non-Maximum Suppression (NMS) to unite similar squares. The outcome from the P-Net module becomes the R-Net input module to improve decisions regarding the possibility of face segmentation, meanwhile, the NMS is applied to the output of the R-Net module. The main difference between P-Net and R-Net module is in the final layer in which the R-Net module features a fully connected layer for its last two layers [5].

3.2 VGG19

VGG19 is the variant of Visual Geometry Group (VGG) based on the CNN architectures which have 19 layers that consist of 16 convolution layers and 3 fully connected layers [8]. The feature extraction with the VGG19 algorithm has been widely used [13] and this is shown in Figure 3.

3.3 Support Vector Machine

Support Vector Machine (SVM) is used in regression tasks or classification tasks [17]. To avoid misclassification, SVM uses the concept of maximum margin so the model can be generalized [12] [4]. It has the following characteristics: the first is SVM's cut line has the largest margin. The second characteristic is the easiness to make non-linear lines (non-linear decision boundaries) by replacing the kernel function. Finding an optimal classifier for data with two different classes, yet separated by complex multidimensional boundaries[15].

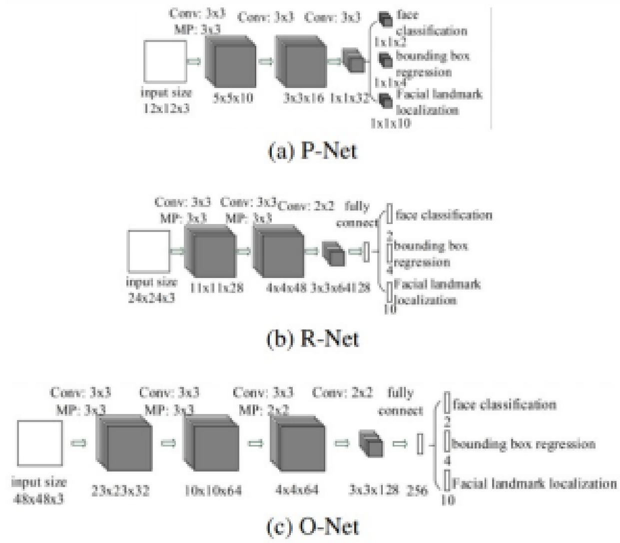


Fig. 2. MTCNN Architecture

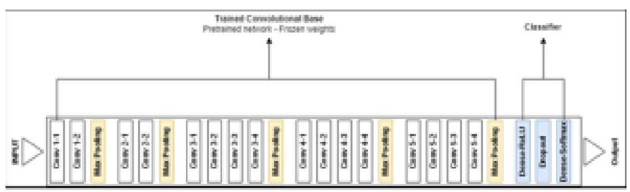


Fig. 3. VGG19 Architecture

3.4 Model Evaluation

The model was evaluated with confusion matrices in the simplest form of a table with two rows and two columns, which represents four possibilities of a classification outcome: True Positive (TP), False Positive, True Negative (TN) and False Negative (FN) [11]. The model evaluated the confusion matrices form as well as, measured the model in terms of accuracy, precision, recall, and the F1-score. The equations refer to equations1, 2, 3, 4 respectively.

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{1}$$

$$Recall = Sensitivity = \frac{TP}{TP + FP} \tag{2}$$

$$Precision = \frac{TP}{TP + FN} \tag{3}$$

$$F1 - score = \frac{2 * Precision * Recall}{Precision + Recall} \tag{4}$$

4 Experiment

This section covers the efficacy of the proposed model which was tested by carrying out experiments as described in the previous section. All experiments were generated using Google collaboration tools. The experiment used two resources of image datasets. The first dataset was Kaggle's UTKFace which consists of over 20,000 face images, and the other was images from the medpics.uscd.edu website. The unhealthy images are images of faces with skin disorders due to a disease. To ensure the outcome of a good result, the image collection was screened. The chosen images were classified as non-blurred images, with a clear tone, and no redundant image in one frame. The images were labeled as one of the three classes (healthy, unhealthy, non_middle- aged). The labeling images are depicted in Figure 4. Every class had various sizes of images. The total

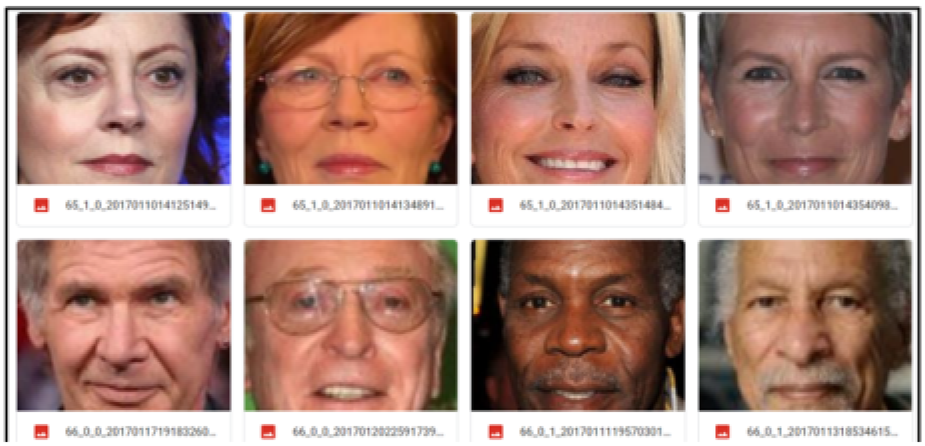


Fig. 4. Labelling images

images consist of 629 images with 223 non_middle-aged images, 179 images of middle age healthy images, and 227 images of adult unhealthy images. Examples of unhealthy facial skin are shown in Figure 5. Detector MTCNN cropped and resized the images. The purpose of resizing is to adjust the image size so they have the same pixel (224 as the input default for the VGG19 approach). The input image features were detected or retained in the feature map with the VGG19 model pre-trained without using its own classifier. Commonly, a feature map that is closest to the input provided small details while a feature map most similar to the model output captures more general features. Figure 6 shows the feature map that was processed by VGG19. Using this approach, the amount

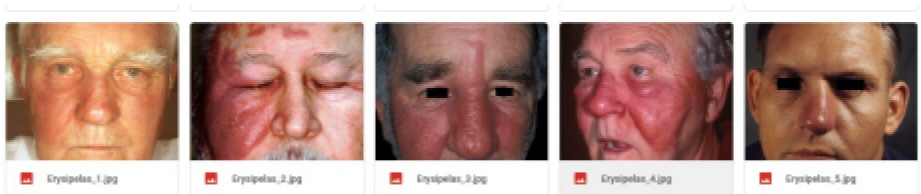


Fig. 5. Unhealthy

of images resulting from the feature map process was separated with a ratio of 80% accounts for the training set and the remaining accounts for the testing set. The SVM model was given sets of data training and data testing, so the

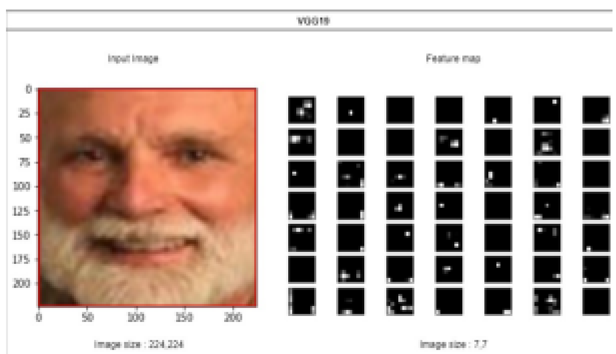
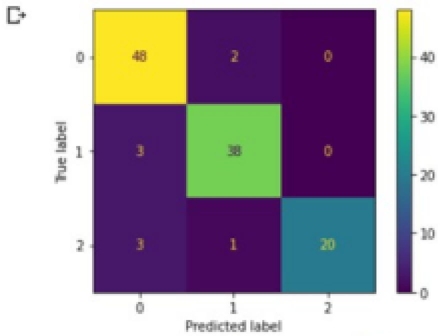


Fig. 6. Feature Map

classifier can distinguish the images. Receiver Operating Characteristic (ROC) is the probability curve and Area Under Curve (AUC) represents the degree or measure of separateness. The higher the AUC value, the better the model prediction. To assess whether a machine learning algorithm can distinguish between the classes, in the confusion matrices, the precision value is obtained from the right guess. True Positive (TP) means an actual object of interest was identified correctly. The high precision value is affected when there is no false positive (FP). Meanwhile, a high recall value is affected when there is no false negative (FN). F1-score is the accuracy value of each existing class. The combinations of value data training and data testing with interval 10 were explored to gain more insight. Table 2 shows the higher value of the training data or the smaller value of the testing data in getting accurate results and the AUC came close to number 1. Due to a 92.2% accuracy result, the dataset used can be studied by the model. Several SVM kernel parameters such as Linear, RBF, Poly, and Sigmoid were evaluated in different ratio data testing and data training, shown in table 3. The best accuracy was achieved by linear kernel. Table 4 shows

Table 2. Accuracy with different ratio data testing and data training

Data Testing	Data Training	Accuracy	Train AUC
10%	90%	0.965	0.999
20%	80%	0.922	0.997
30%	70%	0.907	0.991
40%	60%	0.908	0.990
50%	50%	0.895	0.930

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              precision    recall  f1-score   support

           0       0.89      0.96      0.92        50
           1       0.93      0.93      0.93        41
           2       1.00      0.83      0.91        24

    accuracy                           0.92       115
   macro avg       0.94      0.91      0.92       115
weighted avg       0.93      0.92      0.92       115
```

Fig. 7. Accuracy with 20% data testing

Table 3. Evaluation of Different SVM Kernel

Data Testing	Data Training	Linear	RBF	Poly	Sigmoid
10%	90%	0.928	0.920	0.856	0.900
20%	80%	0.930	0.921	0.835	0.916
30%	70%	0.920	0.912	0.815	0.902
40%	60%	0.912	0.898	0.810	0.898
50%	50%	0.916	0.891	0.786	0.881

Table 4. Comparison between optimizer in different Epoch

Epoch	Adam	Adamax	Adadelta	SGD
15	0.461	0.417	0.426	0.400
30	0.435	0.417	0.409	0.357
50	0.409	0.400	0.365	0.417
100	0.400	0.426	0.391	0.439

the comparison optimizer in different epoch. The comparison optimizers that were namely used, the: Adam, Adamax, Adadelta, SGD optimizers began with 15 epochs until 1000 epochs. The result of the validation accuracy value generated by each optimizer was similar or did not change significantly. The Adadelta

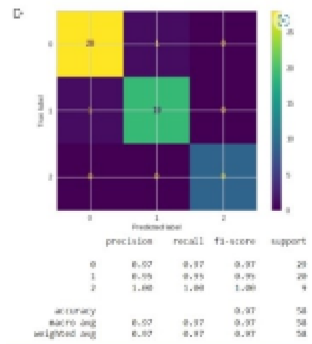

Fig. 8. Accuracy with 10% data testing

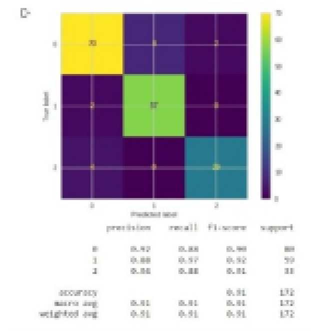

Fig. 9. Accuracy with 30% data testing

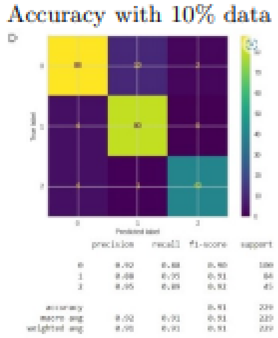

Fig. 10. Accuracy with 40% data testing

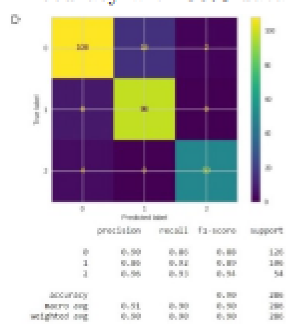

Fig. 11. Accuracy with 50% data testing

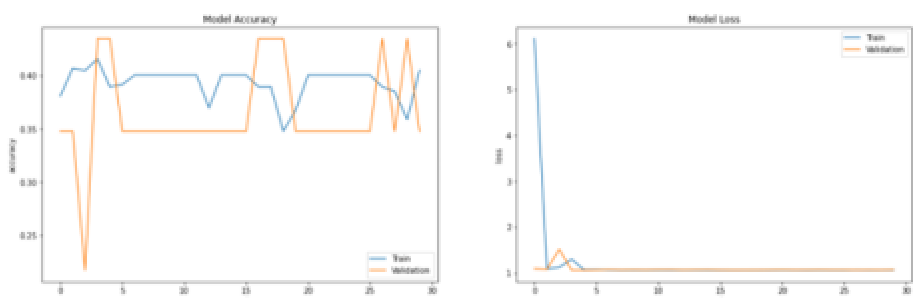

Fig. 12. Epoch30

optimizer had the smallest accuracy during an experiment with several epochs. Running the VGG19 model in 50 epochs and 100 epochs, the SGD optimizer gained the highest value. In essence, the epoch value correlates with the accuracy value; more epochs means better accuracy. Without an SVM classifier, the performance of VGG19 experienced an underfitting circumstance. The graph in Figure 12 demonstrates the Adam optimizer with 30 epochs. During the VGG19 training process, the loss value decreased to 1 and remained constant until the end. This scenario shows that the model did not study the given dataset properly thus the accuracy of VGG19 approach had a lower value.

5 Conclusion

Technological advancements have introduced new paradigms to the field of medicine. Based on the results and discussion, the proposed model's accuracy reached 92.2% with the ratio of data training and data testing as 80% and 20% respectively. The high accuracy results with a minimum of 90% mean that the dataset which is used can be studied by the proposed model. The applied model may possibly detect a middle-aged person's face and classify it under healthy or unhealthy facial skin because there is a process where the model used is not classified as an underfitting model. Further research efforts will be necessary to compare and integrate with another model for conducting in edge computing.

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