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ORIGINAL ARTICLE

Classification Of Skin Cancer By Means Of Transfer Learning Models

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ABSTRACT – Skin cancer is a disease of human skin affected with abberrant or damaged cell and that lead to the formation of tumours. Skin cancer can be mainly classified into melanoma and non-melanoma, where melanoma is more deadly if misdiagnosis at the early stage. Traditional way of skin cancer classification required dermatologist to classify the cancer based on CT-scan, MRI or X-ray, which may promote risks of misdiagnosis. Hence deep learning is introduced to carry out the image feature extraction for the classification tasks by using the ISIC dataset. With the aids of InceptionV3 on different machine learning model, the skin cancer classification can be carry out by Artificial Intelligence. As a result of this study, Logistic Regression achieved overall classification accuracy of 78.3%, proven it has the ability to classify skin cancer based on skin lesion images.

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INTRODUCTION

Cancer is a condition in which some cells in the body develop abnormally and spread to other cells. Cancer may develop in practically any part of the human body. It arose from an aberrant or damaged cell, which can lead to the formation of tumours, or masses of tissue. Non-melanoma and melanoma skin cancers are the two most common kinds of skin cancer. Basal cell carcinoma and squamous cell carcinoma are non-melanoma skin cancers, whilst melanoma skin cancer is particularly fatal due to the high likelihood of tumour spread. The traditional way of skin cancer diagnosis is by using imaging test, stands from CT scan, X-ray or MRI. These test has been carried out for long time, but the downside of its is, it will require a dermatologist to observe and classify the skin cancer type. This may bring probability of misdiagnosis by the dermatologist.

Hence, deep learning were implemented in this study, that the diagnosis of skin cancer type is processed by a networks. The use of transfer learning carry out the feature extraction of the skin lesion images, where classification of skin cancer is utilised. Therefore, the proposed technique is expected to have a higher accuracy in classifying of the skin lesion type. Customised deep learning pipeline were used to classify the skin cancer through open sources skin lesion images.

The remainder of this paper is organized as follows: Section 2 briefly presents an overview of deep learning uses in diagnosis of skin cancer. Section 3 explains the method of transfer learning and machine learning algorithm used in this study. Section 4 provides the experimental settings and discusses the experimental results. Section 5 concludes the paper.

RELATED WORK

This part provides a brief overview of implementation of deep learning model in the work of classifying skin cancer by different means of convolutional network, which provided different feature extraction on the same skin lesion images. To investigate the uses of new model, an Adaptive Feature Learning Network (AFLN) model is proposed with a Difficulty-Guided Curriculum Learning to carry out the feature extraction from the images [1].The proposed model has the ability to overcome overfitting of data in training, hence showing better result in skin cancer classification

Another deep learning model is Multi-Scale Multi CNN (MSM-CNN) [2]. MSM-CNN was designed with 3-level fusion scheme. By level 1, the models is trained with images at fixed size and calculates its average classification probability vectors, then at level 2, the results were fused from individual networks and lastly level 3 will fuse the predicted probability vectors of various architecture to yield the final classification result.

The concept of CNN is brought to model a new architecture for feature extraction, namely Mask-RCNN [3]. The proposed architecture has the ability to extract deep features of the skin lesion images as it extract from the based segmentation. The study shows that the utilization of Mask-RCNN on a pretrained architecture will give big improvement on the classification accuracy than the normal pretrained model.

Generative Adversarial Networks (GANs) is another common architecture that used in machine learning. As GANs included 2 neural networks trained simultaneously, where the generator network transform random noise to the iamge, and a discriminator network will dsitinguish between real images with synthetic images produced by generator [4]. By doing so, the discriminator network is trained to distinguish between real samples and generated samples, and becomes a powerful classifier in differentiating images. While for generator network is trained to mislead the discriminator network and learn the pattern of real images distribution to prodce a better sample. The result of GANs provide a better quality of images, where the better images allows the transfer learning architecture to have a higher accuracy in classification task.

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The deep learning network has also been introduced on low specification devices, such as mobile phones. The light-weight neural network architecture has been designed to compress the deep architectures by avoiding full connections in the network [5]. Two approaches were included, first is to optimise the network parameters, down sampling, network representation and pruning of weights. Secondly, design the small architecture by directly reducing the kernel size, which effectively reduce the convolution and the number of channels. The study shows that the classification accuracy were maintained at high level while minimizing the network.

METHODOLOGY

Process Flow Chart

The study were separated into four phases. The data acquisition and data pre-processing were the first phase of the process. This phase included data collection, data labelling and data resizing to prepare the dataset for the next phase.

Second phase of the process is preliminary benchmarking. A pretrained convolutional neural network is selected and is passes through 3 different machine learning model, namely SVM, kNN and Logistic Regression. This phase is to make sure the study posses the ability of classification of skin lesion images.

Parameter fine tuning is the third phase of the study. By fine tuning of the parameter, the machine learning model could achieve better classification result compared to the second phase.

The final phase is the final evaluation of the result. All the models will be evaluated based on their classification accuracy.

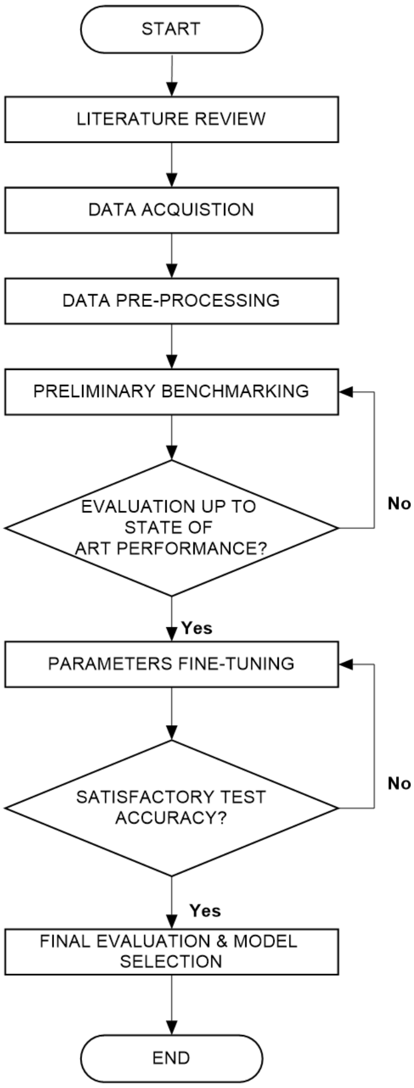

Figure 1. Process Flow Chart

Dataset

The dataset used in this study is the International Skin Imaging Collaboration (ISIC) dataset: The dataset is an open source public access dataset that initiated to facilitate the application of digital skin imagaing to help reducet melanoma mortality. ISIC works to achieve the goals of engaging dermatology and computer science towards an improved diagnosis, by serving as a resource of images for teaching, researching and testing of artificial intelligence algorithms, as machine learning. The dataset included 2,357 skin lesion images from 9 different diseases. In this study, only 3 types of diseases is used, with total number of 663 images.

The dataset were then resized based on the requirement of the transfer learning architecture, as for different models required different size of images. After this, the data were splitted into 3 set, with 70% of the images into training set, 15% to the validation set and the last 15% is for testing.

Transfer Learning

Transfer Learning deals with how a programs can easily adjust the algorithm to the new task. It allowed machine learning models to carry out tasks even with small dataset. Conventional Neural Network (CNN) usually made up the Transfer Learning models, as it is a pretrained network and is well-known in it robustness in computer vision with its outstanding performance.

The Transfer Learning model used in this study is InceptionV3. It is a CNN which assisting in image analysing and object detection, hence it is widely used in image recognition as its performance is outstanding compared to the others. The architecture is made up of symmetric and asymmetric building blocks as shown in Figure 2.

By using InceptionV3, the feature extracted from the data images can be direct to the machine learning model for the classification task to proceed.

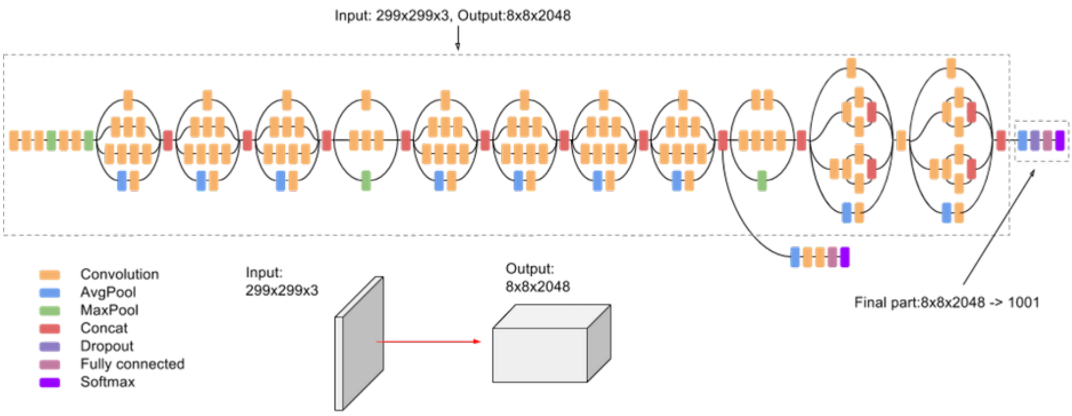

Figure 2. Architecture of InceptionV3.

Machine Learning Model

The Machine Learning model in this study is where the extracted features from the skin lesion images is classified to each classes. The models uses in this study is Support Vector Machine (SVM), k-Nearest Neighbours (k-NN) and Logistic Regression.

Support Vector Machine is a set of supervised learning methods used for classification. The model is effective in high dimensional spaces and the uses of subset of training point in the decision function, making it memory efficient. SVM will builds a model that assign the new data to a category, mapping the training set to a point to maximise the gap between classes and then mapped the new data into the gap to predict its class.

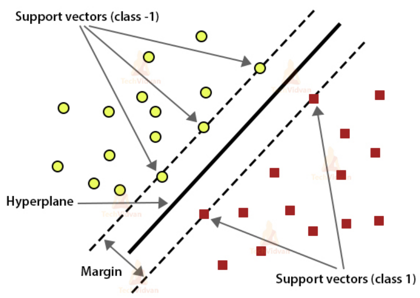

Figure 3: SVM

k-Nearest Neighbours is a classification method with non-parametric. The data is classified by plurality vote of its neighbours, with the data is assigned to the most common class among the k value, which is the class of the data. The function is approximately locally, and the computation is yield to function evaluation. The algorithm is rely on the distance metrics.

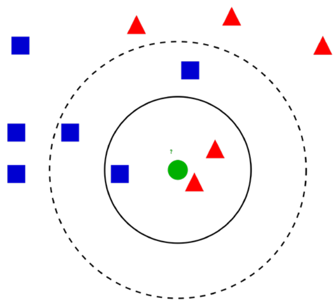

Figure 4: k-NN

Logistic Regression is a statiscal model that estimating the parameters by understanding the relationship between a dependent variable with one or more independent variables.

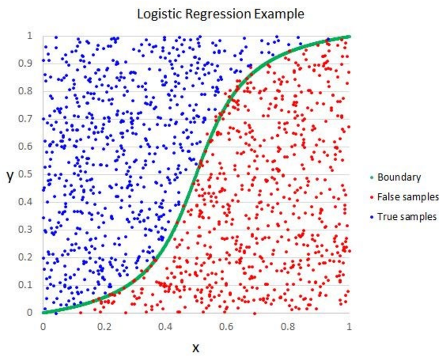

Figure 5: Logistic Regression

Performance Metrics

The result of the classification tasks done by the 3 machine learning models is to be presented on a confusion metric. The confusion metric shows the result of classification by presenting the number of correct or incorrect labelling of the data. From confusion metric, the data can be divided into True Positive (TP), True Negative (TN), False Positive (FP) and False Negative (FN). By knowing these data, the classification accuracy can be calculated and therefore suggesting the best model.

Confusion Matrix		Predicted		
		Class 1	Class 2	Class 3
Actual	Class 1	A	B	C
	Class 2	D	E	F
	Class 3	G	H	I

True positives; True Negatives; Misclassified cases.

Figure 6: Confusion Metrics

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

Figure 7: Formula for Classification Accuracy

RESULTS

The pretrianed model, InceptionV3 were trained and tested using the ISIC dataset as mentioned above. Classifiers for each run has been changed to the three machine learning models as explained above, so that to identify the differences in the classification accuracy. The result of every classifiers is as shown below.

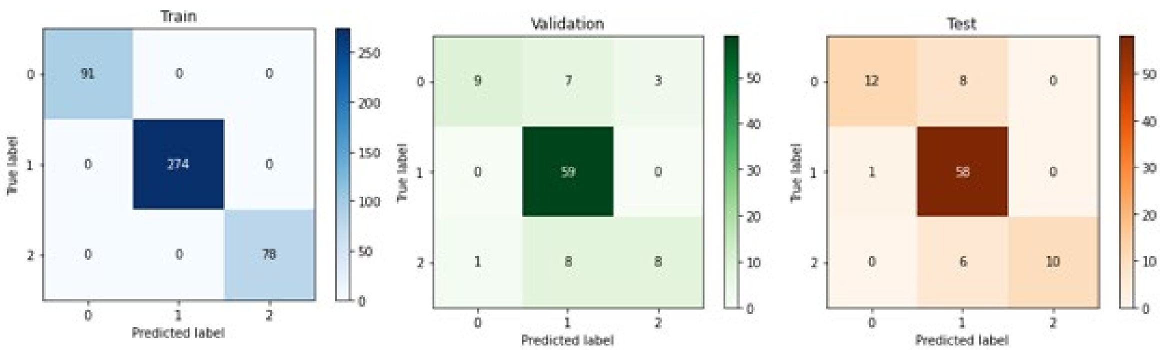

Figure 8: Confusion Matrix for InceptionV3 on Logistic Regression

	SVM	k-NN	Logistic Regression
Training	96%	80%	100%
Validation	69%	68%	80%
Testing	76%	71%	84%
Overall	66.8%	68.4%	78.3%

Table 1: Result of InceptionV3 on 3 Machine Learning Models

CONCLUSION

From the result above, the InceptionV3 covered on Logistic Regression posses the highest classification accuracy among the other methods, with 78.3% of overall accuracy. This is due to the simplicity of Logistic Regression in implementation, interpretation and effect in training. Logistic Regression is also easy to extend its classes to multiple, hence providing a natural probabilistic view of the class predictions.

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REFERENCES

[1] P. Tang, X. Yan, Q. Liang, and D. Zhang, "AFLN-DGCL: Adaptive Feature Learning Network with Difficulty-Guided Curriculum Learning for skin lesion segmentation," *Applied Soft Computing*, vol. 110, p. 107656, 2021, doi: https://doi.org/10.1016/j.asoc.2021.107656.

[2] A. Mahbod, G. Schaefer, C. Wang, G. Dorffner, R. Ecker, and I. Ellinger, "Transfer learning using a multi-scale and multi-network ensemble for skin lesion classification," *Computer Methods and Programs in Biomedicine*, vol. 193, p. 105475, 2020, doi: https://doi.org/10.1016/j.cmpb.2020.105475.

[3] M. A. Khan, T. Akram, Y.-D. Zhang, and M. Sharif, "Attributes based skin lesion detection and recognition: A mask RCNN and transfer learning-based deep learning framework," *Pattern Recognition Letters*, vol. 143, pp. 58–66, 2021, doi: https://doi.org/10.1016/j.patrec.2020.12.015.

[4] Z. Qin, Z. Liu, P. Zhu, and Y. Xue, "A GAN-based image synthesis method for skin lesion classification," *Computer Methods and Programs in Biomedicine*, vol. 195, p. 105568, 2020, doi: https://doi.org/10.1016/j.cmpb.2020.105568.

[5] E. Goceri, "Diagnosis of skin diseases in the era of deep learning and mobile technology," *Computers in Biology and Medicine*, vol. 134, p. 104458, 2021, doi: https://doi.org/10.1016/j.compbiomed.2021.104458.