CLASSIFICATION OF SKIN CANCER BASED ON DEEP LEARNING

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ABSTRACT

Skin cancer is a common and dangerous disease. This project aims to assist doctors in effectively diagnosing skin cancer using a neural network trained on the Skin Cancer MNIST: HAM10000 dataset. Using the Resnet18 pre-training model and some adjustments, the project achieves a 96.47% accuracy rate. This model can reduce diagnosis time and material cost, ensuring patients receive accurate and timely treatment.

INTRODUCTION

The most common form of cancer in humans is skin cancer. Skin cancer accounts for one-third of all cancer cases reported to the World Health Organization (WHO), and the prevalence rate is rising globally.
The diagnostic accuracy report of clinical dermatologists has shown 62% accuracy with the clinical experience of three to five years. A dermatologist with more than 10 years of experience, however, has a diagnostic accuracy of 80%.

DATASET

Images of various image classes from HAM10000 dataset. The image of various diseases are as follows
(A) Melanocytic Nevi,
(B) Benign Keratosis-like Lesions,
(C) Dermatofibroma,
(D) Vascular Lesions,
(E) Actinic Keratoses and Intraepithelial Carcinoma,
(F) Basal Cell Carcinoma,
(G) Melanoma, and
(H) Normal skin image are presented.

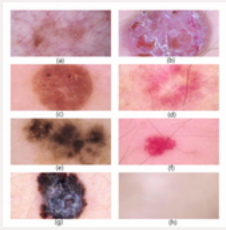

Fig 1: HAM10000 data sample

classes: 7
numbers: 10015
training set: 60%
validation set: 20%
testing set: 20%

DATA PROCESSING

SMOTE (Synthetic Minority Over-sampling Technique) is a popular oversampling technique used to address the class imbalance problem in machine learning datasets [2].

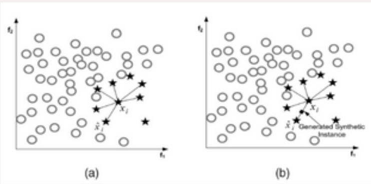

Fig 2: SMOTE oversampling algorithm logic [2]

METHODOLOGY

ResNet-18 is a type of deep neural network architecture used for image recognition tasks. It consists of 18 layers with residual connections, which help address the vanishing gradient problem that can occur in deep networks [1]. The network is composed of four stages, each with several blocks of convolutional layers, batch normalization, ReLU activation, and pooling layers. ResNet-18 has achieved high accuracy in image classification tasks, and has been used as a base for many other deep learning models.

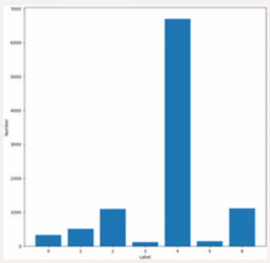

Fig 3: Unprocessed data distribution

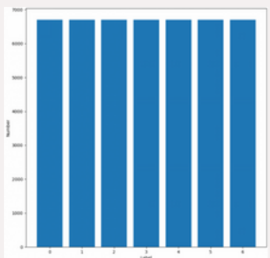

Fig 4: Data distribution after processing

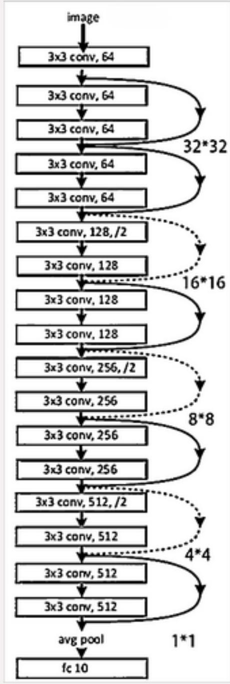

Fig 5: Structure of resnet18 [1]

RESULT & DISCUSSION

This project used the deep learning model adjusted by several experiments and evaluated its performance on the data set. Four indexes, including accuracy, precision, recall and F1 score, were used to evaluate the performance of the model. On the data set, the accuracy rate of the model is 95.93%, the precision is 96.08%, the recall rate is 95.88%, and the F1 value is 95.88%. This shows that the model has high accuracy and reliability in label recognition. In addition, this project plotted the confusion matrix to better understand the performance level of the model. The confusion matrix can help us better analyze the performance of the model.

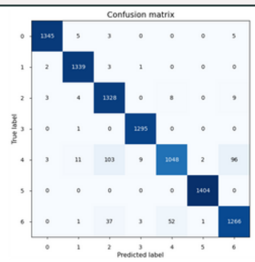

Fig 6: Confusion matrix result

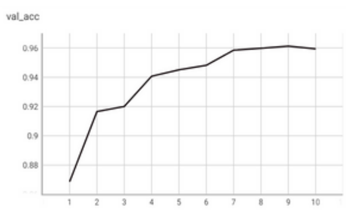

Fig 6: accuracy curve

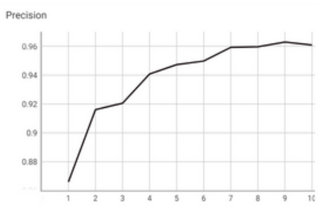

Fig 7: precision curve

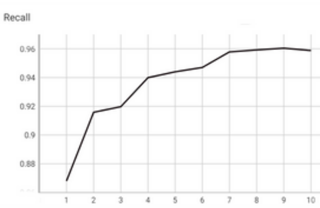

Fig 8: recall curve

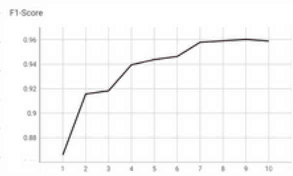

Fig 9: F1 score curve

FUTURE WORK

As future work, there is significant potential for the ResNet18 architecture to be utilized in various areas of computer vision beyond image classification. Its residual connections could assist in addressing issues associated with multi-scale object detection or improve the accuracy of semantic segmentation. Future research could also explore alternative nonlinear activation functions, variation in depth, width, or size of residual blocks, and improving transfer learning capabilities of the ResNet18 architecture.

GUI

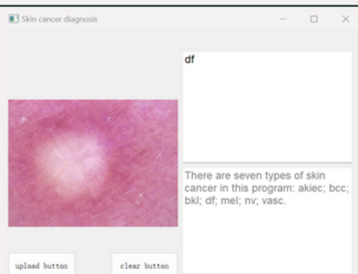

Fig 10: A user interface with detection capabilities

REFERENCES

1. He, Kaiming, et al. "Deep Residual Learning for Image Recognition." Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, 2016, DOI: 10.1109/CVPR.2016.90

2. Chawla, N. V., Bowyer, K. W., Hall, L. O., & Kegelmeyer, W. P. (2002). SMOTE: Synthetic minority over-sampling technique. Journal of artificial intelligence research, 16, 321-357. DOI: 10.1613/jair.953.