TONGUE COLOUR DIAGNOSIS SYSTEM USING CONVOLUTIONAL NEURAL NETWORK

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DEDICATION

This project report is dedicated to my parents, who taught me never to give up and always strive to be the best. It is also dedicated to my siblings, who provided me with moral support throughout the entire length of the project.

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ABSTRACT

Tongue diagnosis is known as one of the effective and yet noninvasive technique to evaluate patient's health condition in traditional oriental medicine such as traditional Chinese medicine. However, due to ambiguity, practitioners may have different interpretation on the tongue colour, body shape and texture. Thus, research of automatic tongue diagnosis system is needed for aiding practitioners in recognizing the features for tongue diagnosis. In this project, a tongue diagnosis system based on Convolution Neural Network for classifying tongue colours is proposed. The system extracts all relevant information (i.e., features) from three-dimensional digital tongue image and classifies the image into one of the colour (i.e. red or pink). To increase the accuracy of the proposed system, a number of pre-processing and data augmentation are carried out and evaluated. Augmentation techniques evaluated consists of salt-and-pepper noises, rotations and flips. Synthetic one-sided flip has that proven that it increases the average accuracy from 75.41% to 75.72%. Thus, this technique is proposed for data augmentation in tongue diagnosis applications. The proposed system achieved accuracy up to 88.98% and average of 75.72% from 5-fold cross validation, and 0.05 seconds in processing time.

ABSTRAK

Diagnosis lidah ialah salah satu teknik yang berkesan tetapi tidak invasif untuk menilai kesihatan pesakit dalam perubatan tradisi timur seperti Perubatan Tradisi Cina. Tetapi, disebabkan oleh ketaksaan, pengamal perubatan akan mempunyai pentaksiran yang tidak sama dalam warna, bentuk dan tekstur lidah. Oleh itu, penyelidikan sistem diagnosis lidah adalah diperlukan untuk membantu pengamal perubatan dalam pengelasan ciri lidah. Dalam projek ini, sebuah sistem diagnosis lidah yang berasaskan Rangkaian Neural Konvolusi untuk pengelasan warna lidah telah dicadangkan. Sistem tersebut akan menyarikan semua maklumat berkaitan (seperti ciri-ciri) daripada gambar digital tiga-dimensi dan mengelaskan gambar tersebut kepada salah satu warna (iaitu merah atau merah jambu). Untuk meningkatkan ketepatan sistem tersebut, pelbagai teknik pra-pemprosesan dan pembanyakan data telah dilaksanakan and dinilai. Teknik pembanyakan data yang dinilai ialah hingar garam-dan-lada, putaran dan pembalikan. Pembalikan satu-belah sintetik telah dibuktikan bahawa ia boleh meningkatkan purata ketepatan dari 75.41% ke 75.72%. Oleh itu, teknik ini telah dicadangkan untuk aplikasi diagnosis lidah. Ketepatan sistem yang telah dicadangkan mencapai 88.98% dan purata 75.72% dari pengesahan silang 5-lipatan, dan 0.05 saat dalam masa pemprosesan.

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LIST OF ABBREVIATIONS

CNN	-	Convoultional Neural Network
SVM	-	Support Vector Machine
ReLU	-	Rectified Linear Units
TCM	-	Traditional Chinese Medicine
TKM	-	Traditional Korean Medicine

CHAPTER 1

INTRODUCTION

1.1 Background

In health care field, there are many ways to evaluate a patient's health condition. Tongue diagnosis is known as one of the effective and yet noninvasive technique to evaluate patient's health condition in traditional oriental medicine such as traditional Chinese medicine (TCM) [1] and traditional Korean medicine (TKM) [2]. Tongue diagnosis is performed based on the features on the tongue such as tongue body, colour, coating and fur. Tongue coating thickness is inspected to evaluate the condition of the stomach. Yellow fur and enlarged and thinning of the tongue body also a sign of unhealthiness. From the perspective of colour, tongue body colour can be pale, light red, red and deep red. The colour of a healthy person is light-red colour. Pale tongue colour indicates the sign *blood vacuity*, which is depletion of the blood in TCM. Red and deep red tongue colour indicates the repletion heat.

The practitioners of oriental medicine inspect the tongue features through visual inspection in order to perform tongue diagnosis. However, the predictions are made based on each practitioner's experience and observation and the prediction may varies. The prediction is also affected by the environmental factors such as brightness [3]. Due to ambiguity, there is a need for automatic digital tongue diagnosis system (TDS) in order to assist the medical practitioner in daily practices.

There are many methods implemented for TDS such as active contour based method, threshold tongue segmentation method, and machine learning. Generally, TDS is consists of three main steps: tongue image acquisition, pre-processing, feature extraction and disease classification. Deep learning is observed to have a lot of breakthrough recently due to the advancement of computation and its ability of feature learning and representation. One of the successful techniques for TDS is Convolutional Neural Network (CNN). This techniques have been applied in other image processing techniques such as facial expression recognition system [4] [5] and face recognition [6][7] as well. This technique could perform feature extraction and classification in one step.

In this work, the purpose of the project is to develop a high accuracy TDS based on CNN. Since building neural networks from scratch takes too long, the pre-trained framework TensorFlow is used.

1.2 Problem Statement

The research on tongue diagnosis has limited access of tongue image databases. From the related reviewed, the tongue images work, the data used are collected or obtained by the author. There is no standard data for evaluating the TDS and thus it is unfair compare to compare methods directly.

From previous works in [8, 9, 10], they do not evaluated the developed TDS in term of processing time and focusing on accuracy only . From reviewed related which evaluated execution time, it is found that CNN method take the longest computation time among the methods compared [11, 12].

Many existing methods are not robust to environment changes such as brightness [8, 13]. The accuracy of the developed TDS in the work is reported to be sensitive of brightness change or the data sample is taken strictly in the same brightness condition.

In most classification applications, features need to be extracted before the classification stage. The features are obtained in feature extraction stage. In non neural-networks methods [9, 13, 12], feature extraction is implemented separately and independently from the classification.

1.3 Objectives

The objectives of this project are:

1. To develop an accurate automatic tongue diagnosis system (TDS) using low complexity Convolutional Neural Network (CNN).
2. To investigate the impact of pre-processing and data augmentation methods on the developed system.
3. To compare with baseline SVM-based method on accuracy and processing time.

1.4 Project Scope

The scope of the project is limited to developed a TDS but the classification is based on tongue colour only. The TDS is based only CNN only. The developed TDS is aimed to classify tongue image from two classes (i.e. red and pink) only.

In this work, training and testing of the CNN based TDS is done by using Tensorflow 1.0 framework (Python 3.7) while the baseline SVM based TDS is trained and tested by using MATLAB 2019. The data used is limited to the data obtained from the works [12] [14] which is consists of 257 labelled tongue images. There are three classes of tongue images in the database (i.e. deep red, red and pink). The intensity of white coating on tongue is also labelled in the database. As baseline work classify tongue images into two classes only, this work is delimited to two classes classification only.

The evaluation of this work is based on accuracy and processing speed. However, the main focus is on accuracy while processing speed is the secondary focus.

1.5 Chapter Organization

Chapter 2 presents literature review. It contains the introduction of CNN, SVM and the conventional methods used for TDS. Different methods and approaches are compared and reviewed.

Chapter 3 describes the methodology. The overall project flow is presented and the details of each stage is also presented. This includes the baseline work reproduction, optimization process of the CNN model of this work, investigation of pre-processing and data augmentation.

Chapter 4 presents the result and discussion. Analysis is done based on the result. Chapter 5 conclude the project and future works is discussed.

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