FASTER CONVOLUTIONAL NEURAL NETWORK INFERENCING FOR SCREENING RED BLOOD CELL DISEASE

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DEDICATION

This proposal is dedicated to everyone that helped me to come this far in life.

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ABSTRACT

The peripheral blood smear is a blood test, in which its purpose is to detect or confirm diseases in patients by identifying the morphological characteristic of the blood. The blood smear could only be interpreted through microscope by a skilled laboratory physician or haematologist which is time consuming and would result in other complication such as higher labour cost and error rate. In Malaysia particularly, the blood smear analysis is only performed in certain general hospital, which have a hematopathology unit, thus having more test to perform at once and ultimately further increases time. Hence, the approach taken to address this issue is by creating an automated blood smear screening tool. Typically feature extraction was done manually in computer vision to identify the disease but this method might introduce a drop in accuracy if the design was under or over segmented. Therefore, this research proposes a convolutional neural network (CNN) to screen diseases from the blood smear images. The focus would be on developing an optimized CNN model in terms of inferencing speed for faster object detection of sickle cell disease. Adopting a popular object detection CNN algorithm i.e., YOLOv3 which has a high inferencing speed, this research performed transfer learning, modify certain CNN attributes by adding a residual block and applying Gaussian filter prior to model training on blood smear images to optimize speed and accuracy. The proposed model, which is to train YOLOv3 with Gaussian filtered dataset achieved an inferencing speed of 379ms per image with a mean average precision of 72.74%. The algorithm had a fast-inferencing speed but suffers in term of accuracy due to insufficient dataset and failing to detect overlapping cells. To solve this, data augmentation technique and sharpening edge of the cell should be performed. In short, this project contributed towards existing literature by developing CNN that prioritize inferencing speed and implement YOLOv3 object detection for localization and classification of sickle cell disease.

ABSTRAK

Ujian darah periferal ialah sebuah ujian darah, yang bertujuan untuk mengesan atau mengesahkan penyakit dengan mengenalpasti morfologi darah pesakit. Ujian darah tersebut hanya boleh dijelaskan melalui microskop oleh pakar perubatan makmal atau pakar hematologi yang mengambil masa yang lama serta boleh mengakibatkan lain-lain komplikasi seperti kos buruh yang lebih tinggi dan kadar ralat yang lebih tinggi. Di Malaysia terutamanya, analisis darah periferal hanya dilaksanakan di sesetengah hospital umum, yang mempunyai unit hemapatologi, justeru mempunyai lebih banyak ujian untuk dilaksanakan serentak dan akan meningatkan masa lebih banyak. Oleh itu, langkah yang diambil untuk menyelesaikan isu ini adalah dengan mencipta alat saringan darah automatik. Kebiasaanya pengekstraan ciri darah dilakukan secara manual dalam dalam visi komputer untuk mengenal pasti penyakit tetapi kaedah ini boleh mengurangkan kadar ketepatan jika reka bentuk tersebut terkurang atau terlebih segmentasi. Oleh hal yang demikian, penyelidikan ini mengusulkan rangkaian saraf konvolusional, (*Convolutional Neural Network, CNN)*, untuk menyaring penyakit-penyakit daripada imej ujian darah. Tumpuan akan diletakkan dalam mencipta model CNN yang dioptimumkan khusus untuk kelajuan inferens untuk mengesan lebih laju penyakit sel sabit. Dengan mengguna pakai sebuah algoritma pengesanan objek CNN yang popular iaitu, YOLOv3 yang mempunyai kelajuan inferens yang tinggi, penyelidikan ini melaksanakan pembelajaran pindahan, mengubah suai sesetengah atribut CNN dengan menambah blok residual dan mengaplikasikan tapisan Gaussian sebelum latihan model dengan imej ujian darah untuk mengoptimumkan kelajuan dan kadar ketepatan. Model yang dicadangkan, iaitu YOLOv3 yang dilatih menggunakan set data tapisan Gaussian mencapai kelajuan inferens selaju 379ms untuk satu imej dengan purata ketepatan sebanyak 72.74%. Algoritma tersebut mempunyai kelajuan inferens yang laju tetapi teruk dalam kadar ketepatan kerana tidak cukup set data dan gagal mengesan sel yang bertindih. Bagi mengatasi masalah ini, teknik data augmentasi dan penajaman bucu sel perlu dilaksanakan. Akhir kata, projek ini menyumbang kepada penyelidikan sedia ada dengan pembinaan CNN yang mengutamakan kelajuan inferens dan menggunakan YOLOv3 untuk mengesan objek bagi penyetempatan dan pengelasan penyakit berkaitan sel darah merah.

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LIST OF ABBREVIATIONS

CNN	-	Convolutional Neural Network
NN	-	Neural Network
RBC	-	Red Blood Cell
WBC	-	White Blood Cell
SCD	-	Sickle Cell Disease
mAP	-	Mean Average Precision
YOLOv3	-	You Only Look Once Version 3
SSMD	-	Single Shot Multi-Box Detector
fps	-	Frame per Second
IoU	-	Intersection Over Union
TP	-	True Positive
TN	-	True Negative
FP	-	False Positive
FN	-	False Negative

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CHAPTER 1

INTRODUCTION

1.1 Introduction

The peripheral blood smear is a blood test that involves smearing patients' blood on a slide to obtain a microscopic image which would be analysed by an experienced haematologist or laboratory physician. From the image, the abnormalities in red blood cell, white blood cell, platelet and presence of parasite could be diagnosed. Although seemingly simple, blood smear is invaluable in the identification of multiple common diseases such as leukemia, anaemia, jaundice, malaria, lymphoma, thalassemia and several others [1]. A quick assessment of a blood smear on a healthy patient could be performed within a short period of time but an abnormal blood smear would take longer duration.

On top of that, in Malaysia particularly, the blood smear screening is only available in several hospitals which has unit specialized in pathology [2]. Therefore, if there were a high number of blood smear screening per day, it would be impossible for the haematologist or laboratory physician to complete within the given time frame. It is also widely accepted by WHO that a microscopist should only interpret a maximum of 30 – 40 blood smear slides per day, restricting the time frame further. The reason being is that the accumulation of fatigue would decrease the sensitivity and accuracy of the diagnosis [3]. Therefore, this study will propose a Convolutional Neural Networks (CNN) deep learning model that is capable of analysing blood smear autonomously and as time constraint is the motivation for this project, the CNN model should be optimized with respect to inferencing time while also maintaining its accuracy to prove the model's functionality.

Generally, literatures on automated blood smear analysis could be categorized into four different categories, which corresponds to the type of cells that exists in human body. Namely the white blood cells (WBC), red blood cells (RBC), platelets, and foreign parasites such as Malaria [9 - 12]. This study is only limited to RBC analysis to simplify the scope of this project. Furthermore, the only disease that would be examined is the sickle cell disease (SCD) whereby some of the RBC's shape is elongated. In SCD analysis, haematologists would investigate the characteristics of the RBC which is the average size and shape of the cell [4]. However, a simple image classification might not be sufficient as it would only take the blood smear image and classify what kind of disease that the patient is diagnosed with. Instead, object detection should be performed as it implements both classification and localization. By also providing the location of the elongated RBC, it would be easier for haematologists to spot those abnormal cells in a given blood smear. Besides that, as each location of RBC is given, it could also serve to count the ratio of elongated RBCs to normal RBCs. With these in mind, this study proposes to develop a CNN for object detection instead of image classification.

1.2 Problem Statement

Prior to the popularization of neural network, most research tend to automate the analyzation of blood smear through conventional image processing, which is by enhancing, restoring, segmenting, feature extraction and classification of the blood smear image. However, during designing the feature extraction for identifying disease on the blood smear images, over segmentation or under segmentation will reduce the results accuracy [5]. Moreover, the process of designing image segmentation and feature extraction is challenging and requires deep understanding in analyzing the morphological characteristic of the blood smear images [6, 7]. One possible way to solve this is by replacing conventional image processing with a neural network (NN).

As previously mentioned, manual disease classification by haematologist is a time-consuming and arduous process. As time increases, fatigue would increase linearly, and haematologist will be more prone to making error. This would directly affect the person's reliability in giving a qualitative analysis. Furthermore, only trained haematologists are able to manually perform manual blood smear analysis. This means that the more time they spend, the higher the labour cost would be [8]. In Malaysia, not each hospital would have a hematopathology unit and thus, they would have a huge number of blood smear analysis to be performed at a same time [2]. Lastly, inferencing time is prioritized over accuracy in this research because majority medical computer vision is only used for screening purposes and as doctor's second opinion only [1]. The final decision would still be performed by a specialist.

To recapitulate, the first problem statement is that conventional image processing requires too deep understanding in blood smear analysis and might have reduced accuracy. Ideally, researchers or engineers do not require in depth understanding on par with a doctor for analyzing blood smear. However, conventional image processing techniques requires such comprehension to increase the accuracy of the computer vision system. Besides that, over designing or under designing will introduce error in the system and would cause medical misdiagnosis. The second problem statement is that time is a major issue as analyzing blood smear is time consuming and would results in other complication such as fatigue, labor cost and reduced accuracy. Besides that, hematologist's time frame in Malaysia for analyzing blood smear is restricted as Malaysia has limited resource on number of hospital unit that could perform this test. Following WHO's guidelines, hematologists are only able to examine a maximum of 40 blood smear samples per day, which further limit the time frame. Therefore, this research will develop an object detection CNN model for replacing conventional image processing and as time is a major issue, the CNN model should have a fast-inferencing speed.

1.3 Research Question

To address all these issues, several matters need to be considered in this research, including:

(a) What are the methods to analyze blood smear without having to perform conventional image processing and what are the existing works done which is related to it?

(b) Is neural network a feasible approach to replace conventional image processing?

(c) Is it possible to develop a neural network with popular CNN which optimizes inferencing speed as its base line in analyzing blood smear?

(d) What are the methods to improve accuracy in a neural network and how severe is the speed to accuracy trade off?

1.4 Research Objectives

According to the problem statement and research question, the main objectives to be achieved in this research are:

(a) To develop a CNN model which could successfully detect and classify sickle cell disease in blood smear images to replace conventional image processing.

(b) To optimize the CNN model's inferencing speed (latency or throughput) while maintaining a mean average precision of more than 90% .

1.5 Research Scope and Limitation

This study focuses on developing a CNN model prioritizing inferencing speed to detect and classify SCD in blood smear images. To achieve mentioned research objectives, the scope and limitation for this project must be narrowed down which is:

(a) Although blood smear contains RBC, WBC and Platelet, this research scope will only identify diseases related to RBC which is sickle cell disease whereby the cell is elongated.

(b) The output of the neural network would only be the location and classification of three types of RBC which is normal RBC, elongated RBC or others. The amount or ratio of each cell type in a blood smear image will not be reported and is not considered in this research scope.

(c) In general, most research regarding CNN revolves around 5 metrics to determine its' performance which is accuracy, time, energy, programmability, and hardware cost such as area, storage, and process technology. These metrics would get traded off among each other during optimizing one of the metrics [9]. In this research, the only CNN performance criteria that would be considered are time and accuracy.

(d) Only the inferencing speed during blood smear analysis is accounted for and hence, CNN model training time will not be reported.

(e) This research would use mean average precision (mAP) as the model's accuracy performance metrics which is a standard evaluation criterion for object detection. The intersection over union parameter for this project is set to be more than 0.5.

(f) The hardware side in a neural network will not be optimized in this research.

1.6 Contribution

The limited literatures regarding the prioritization of time over accuracy for blood smear analysis has prompted me to work on this research. Moreover, to the best of my knowledge, there are no works that was done using “You Only Look Once”, (YOLOv3) as a CNN model for detection of SCD which represents the novelty of this research. Although some literatures utilized YOLOv3 for blood smear, it was for classification of WBC or for a complete blood count (CBC) analysis [5, 10].

1.7 Thesis Organization

The structure of the report would be as follows. Chapter 1 would discuss on the motivation, problem background, objectives, scopes, and the contribution of this project. The next section, Chapter 2, would talk about literatures that are related to this study. Then, the research methodology will be presented in Chapter 3, whereby 3 phases and this project timeline were discussed. Chapter 4 is about the results obtained from the experiments, discussion on those results, reasons for failure and suggestions that should be taken. Finally, in Chapter 5, conclusion of this report was made.

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Appendix A Python Code Used In This Project

The whole script is included in this GitHub repository:

https://github.com/zafri7410/master_project