PROTOTYPING AND EVALUATION OF A VISUAL IMAGERY ANALYSIS DEVICE FOR SICKLE CELLS

Jeffrey A. Co,
Eastern Samar State University, Borongan City, Philippines
Correspondence: [1]jeffreycoccs@gmail.com

ABSTRACT: *This study primarily aimed to develop a device prototype that can capture microscopic image of cells and determine whether they have sickle cell disease (SCD) though the integration of advanced data mining and predictive modelling. A regional convolutional neural network was utilized in the development of a model for sickle cell disease determination. Results revealed that based on the 100 shot image guided therapy method, the accuracy of the device is 98% accurate and its speed upon capturing and real-time display framerate is high. It was concluded that the use of the machine can lessen the laboratory test time consumption and most respondents approved the frequent use of automated sickle cell detection device with real time monitoring in terms of its Perceived usefulness, Ease of Use, Attitude and behavioral intention.*

Keywords: Sickle Cell Disease, FRCNN, SCD, CDC, Predictive Analysis

1. INTRODUCTION

Sickle cell disease (SCD) is a group of hereditary disorders that is characterized by having mostly hemoglobin S (HbS) in red blood cells which affects more than 3 million people globally [1, 2, 3]. According to the National Heart, Lung, and Blood Institute (NHLBI), sickle cell disease or anemia (SCD) is a group of inherited red blood cell disorders that can only be treated through early diagnosis, prevention of complications and management of end-organ damage. However, according to their research, only a small percentage of sickle cell disease patients are eligible for a transplant supported by stem cell therapy [4]. Sickle cell disease is more prevalent in areas where malaria is or was prevalent, according to data and statistics from the Centers for Disease Control and Prevention (CDC). Several regions in Africa and South Asia are thought to have given rise to the HbS mutation. SCD affects people with African heritage and is most common in sub-Saharan Africa, according to global statistics. But it can also be found in nations where malaria is endemic, like Italy, Greece, Turkey, and India. However, due to migration, the sickness and mutation are no longer localized to these regions [5]. The WHO (World Health Organization) defines malaria as a potentially fatal condition brought on by Plasmodium parasites and spread to humans through the bites of female Anopheles mosquitoes known as "Malaria Vectors" [6]. According to the DOH, there are currently four areas in the Philippines where the malaria pandemic is still going strong. These provinces are Sultan Kudarat, western Mindoro, Palawan, and Sulu. The majority of the locations in the provinces with the highest rates of malaria cases are inaccessible due to their remote location, which makes it more difficult to assess contagious illnesses or disorders that could potentially result in the transmission of such illnesses [7].The sickle cell disease is detected and tracked using a variety of methods and assays. These methods can be categorized into two groups: (1) those presently employed in the diagnosis of SCD; and (2) novel methods, the majority of which are still in the research phase. Some common techniques are complete blood count (CBC), peripheral blood smear (PBF), solubility sickle testing to name a few [3]. These data has been the primary driving factor of the researcher to innovate and develop an alternative and novel way of detecting sickle cells through a common compound microscope, a PI camera, and local storage unit. The device is able to take raw microscopic images of blood smears and automatically detect whether the smear has SCD by feeding to a model that has been pre-developed using regional convolutional neural network (RCNN). The shape of a projectile is generally selected on the basis of combined aerodynamic, guidance, and structural considerations. The choice of seeker, at supersonic speeds, careful selection of the nose and tail shapes is mandatory to ensure performance and operation of the over-all system.

2. OBJECTIVES OF THE STUDY

This research primarily aimed to develop a device that can detect sickle cells through a pre-developed model using CNN. Specifically this study aimed to:

a. Develop a predictive model in detecting sickle cells using regional convolutional neural network model.
b. Validate detection results using Image therapy procedures;
c. Design and develop a compact automated sickle cell detection device that;
d. Predict/ detect sickle cell disease present in blood smears;
e. Capture and save images for references or documentation purposes;
f. Support local recovery backup storage;
g. Evaluate the developed prototype using the Pugh Evaluation Method

3. METHODS

3.1 Framework of the Study

Figure 1 shows that all hardware components are connected to the Raspberry Pi 4. Pi camera is attached or mounted to the 25x1000 mm magnification lens of the compund microscope to acquire clear raw microscopic images from blood smears, and is automatically feed in to the raspberry pi to operate its sickle cell detection and counting using Faster RCNN algorithm. The touchscreen displays real-time surveillance and detection results including; number of cell detected, prediction scores, blood status i.e. positive or negative to the operator. If the operator decides to save the real-time frame the system recommends local storage using hard drives and flashdrives.

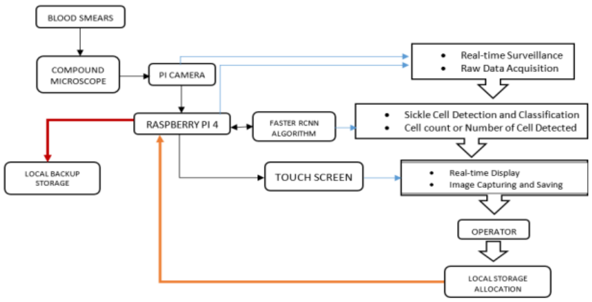

Figure 1. Framework of the Study

The first phase of the study commenced with gathering of existing blood smear images of healthy and SCD infected cells which were gathered from trusted sources such as Centers for Disease Control and Prevention [8], Image Bank of the American Society of Hematology [9], MicroscopyU Image Gallery [10] and World Health Organization (WHO). These images are then fed in an RCNN algorithm specifically a Faster RCNN which uses Regional Proposal Network that inputs the image feature maps from the convolution layer and proposes areas that a sickle cell might be present. The researcher then classified and labelled the image with annotations using Labeling. The annotations of the image are stored inside XML files with PASCAL VOC format, PASCAL VOC provides object detection data i.e. images with bounding boxes, each image will have a XML file because of that there will be numerous XML files, the researchers need to merge all the object detection data into two files (1) Train labels, the train labels consist of the object detection data that is for training the model and (2) Test labels, the test labels are the object detection data that is going to be used in testing the model, the ratio of splitting the data is important because the researchers must not overfit the model they're creating, overfitting cause the model to be inaccurate because the model memorizes the sequence of predictions instead of predicting based on object detection data. The object detection data is split 80% training label and 20% testing label to avoid overfitting, the train and test labels will be stored differently in a CSV file. The train and test label files provided the name, width, height, class, xmin, ymin, the train and test label are then needed to be converted to TFRecord file to be read by the algorithm for training the model and for better performance in training.

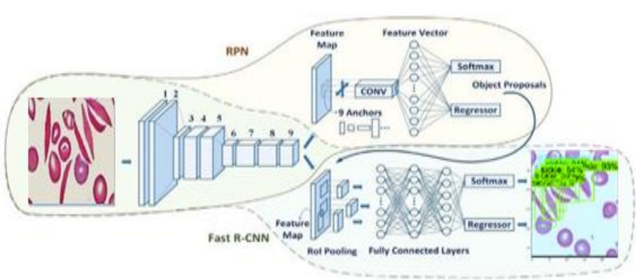

Figure 2. Faster RCNN architecture Layers for sickle cell detection [11]

TFRecord files are binary file format storage because it will take less space and thus result take less time for reading the data in hard disk. The researchers set the batch size of 20 and trained it for 2 hours. Figure 2 illustrates the Faster RCNN architecture and its CNN layers for automated sickle cell detection.

3.2 Data Gathering

The dataset of this study consist of 800 images, 640 with 80%, and 160 images with 20% of the total dataset population for training and testing respectively. The dataset is acquired via batch downloading procedures supported by Google images, through manual selection of images uploaded in medical websites including; CDC, NHLBI, WHO and other source of sickle cell anemia positive blood sample images including, researches, studies, books, article, etc. However, object detection accuracy depends on the available dataset. Thus, the images gathered through batch downloading underwent several cropping, flipping and rotating procedures to maximize data set and achieve a clearer and specified area of coverage by neglecting or removing the unnecessary pixels that does not present sickle cells.

3.3 100 Shot Images to Validate Detection Accuracy (Image Guided Therapy Approach)

Working on medical field acquires thorough investigation and accurate test results, to test medical diagnostics reliability. To validate the accuracy of initial object detection results, 100 shots of raw microscopic images can be used to test the accuracy and consistency of sickle cell detection. The 100 shot images will be gathered from different blood samples and type using compound microscope and camera. This is to verify that the object detection algorithm does not only work on specific blood type or sample, rather, detect cells at wide range of blood samples converted into images considering it's duration of exposure, humidity, temperature and other external or internal factors that affects blood tests [12].

3.4 Image Capturing and Saving

A 5MP megapixel raspberry Pi camera, 7 inches HDMI touchscreen display, and SCROT python script is used to capture images (computer frame). SCROT is a Linux Command Python library that supports image capturing that automatically save image frames when the command is typed manually through keyboards. Using Python SCROT command are converted variables allowing the operator to save image content to the system memory automatically by clicking the converted variable command reducing it operational complexity.

3.5 Local Backup storage System for Recovery and Data Accessibility

Flash drives and Hard disk drives will be used for local recovery system in case of disasters and transmission or accessibility of data and information of saved images from blood samples for references and documentation especially at areas where internet connectivity is not available applicable at remote areas.

3.6 Real-Time Surveillance Display and Monitoring

A 5MP PI Camera is mounted to the x25 mm magnification lens with 40/ 0.65 objective lens of An Amscope 40x-2500 LED, compound Microscope 3D machine, to acquire raw microscopic images and real time blood surveillance, supplied by 220 Volts via power cord. The pi camera is connected to a Raspberry Pi board Microprocessor 4 model BI that has boardcom BCM2711 Quad-core cortex-A 72(ARMS8) 64-bit and 1.5Ghz frequency, operated using Raspbian OS to support LabelImg for image classification and annotation of ROI in the images presented. Finally, to display real-time surveillance and sickle cell detection results, cell detection count and blood status, a 7inch HDMI display touch screen that has HDMI, and USB cables is connected to the Raspberry pi 4 providing HMI support function.

3.7 Sickle Cell Detection ProcessReal-Time

Figure 3 shows the process of sickle cell detection. To identify sickle cell disease, the researchers used raspberry pi 4 as the hardware for running all the software that is need to detect sickle cell disease. Raspbian OS is the operating system that is going to be installed into the raspberry pi 4, Tensorflow and OpenCV will be installed in python 3.7 that is from the Raspbian OS, the researchers will use tensorflow library for training and testing the model together with OpenCV library for manipulating the Pi Camera that is connected to the raspberry pi 4, the real time detection will be displayed in the touchscreen that is also connected in the raspberry pi 4.

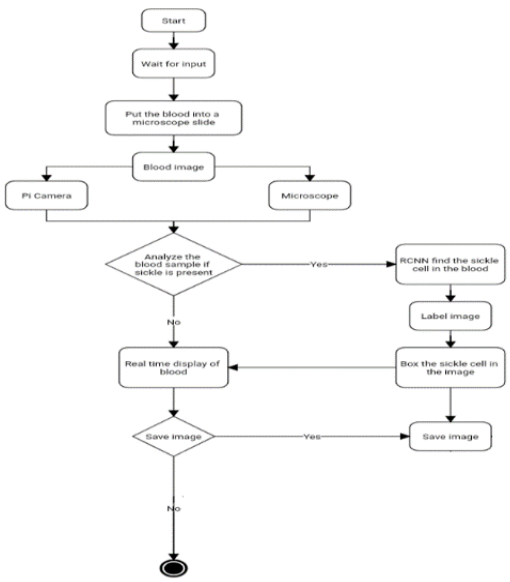

Figure 3. Sickle Cell Detection Process.

3.7 Hardware Design

Using a 3D modelling software, a mock design developed, as shown in figure 4, to enable the researcher to see how the entire device would look like. The design contained a part to hold the HDMI display touch screen for easy navigation and the PI camera which will be mounted at the top portion of the device. Sufficient space was provided for the compound microscope, ensuring that the eyepiece of the microscope meets the PI camera.

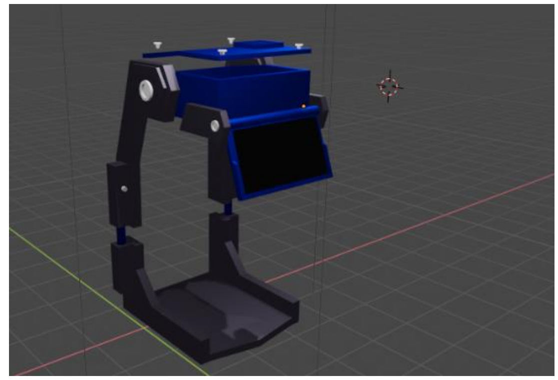

Figure 4. Project Hardware Design Simulation Perspective View

4. RESULTS

After the development and evaluation of the prototype, the following results were obtained:

4.1 Concept Evaluation

The researchers evaluated the various concepts generated concerning the objectives of this project. For the evaluation, the researchers chose the Pugh Evaluation Method. Manual generation of raw microscopic images and sickle cell detection procedures are used as a reference. The researchers listed different criteria for comparing with the recommended concepts. The researcher constructed a decision matrix based on the comparison and are shown below:

Legend:

- +7 to +8 meets criterion extremely better than datum
- +4 to +6 meets criterion much better than datum
- +1 to +3 meets criterion better than datum
- 0 meets criterion as well as the datum
- -1 to -3 meets criterion not as well as the datum
- -4 to -6 meets criterion much worse datum
- -7 to -8 meets criterion far worse than the datum

Table 1. Decision Matrix

OBJECTIVES	DATUM	CONCEPT 1	CONCEPT 2
Sickle Cell detection Capacity	Manual	+	+
Accuracy	Manual	-	+
Speed	Manual	-	+
Ease of Use	Manual	+	+
Multipurpose	Manual	+	+
Durability	Manual	+	+
Storage	Manual	-	+
Cost	Manual	+	+
Total number of (+)	n/a	**+4**	**+8**
Total number of (-)	n/a	**-3**	**0**

Table 1 suggest which concepts is functional and is more likely to achieve most of the objectives using Pugh Evaluation method. Concept 1 has a total score of +1 which means that it meets the criterion better than datum, whereas Concept 2 scores +8 which means that it meets the criterion extremely better than the datum. Since concept 2 has the maximum positive score than Concept 1 the researchers considered Concept 2 as the final solution.

4.2 Hardware Development Result

Figure 5 shows the complete connections of the compound microscope, which is connected to the Pi Camera. In order to choose the proper components that will be used for designing the hardware, the researchers conducted hardware testing to avoid using the wrong components. The Pi Camera is mounted to the 25x 1000mm magnification lens of the compound microscope to obtain clear raw microscopic images from the blood smears. The Pi Camera module comprises a sensor and get instructions from the raspberry pi for surveillance that have a high quality 5 mega pixel camera for raspberry pi, that's capable of 3280x2464 pixel static images and also supports. Furthermore, figure 6, shows the ability of the device to capture cells and detect whether it contains sickle cell disease.

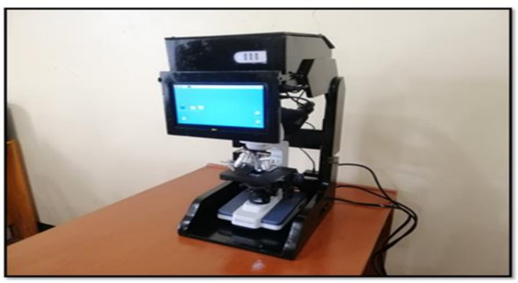

Figure 5. The Complete working Prototype

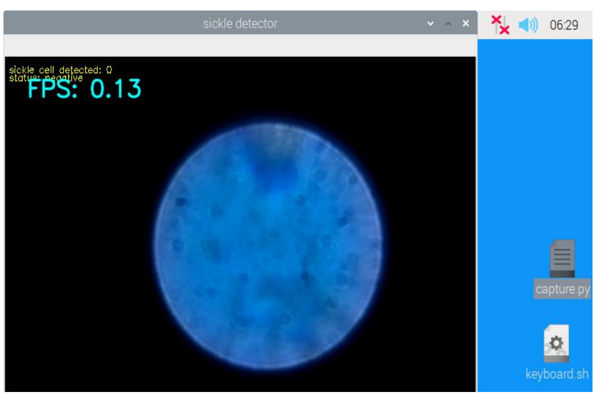

Figure 6. Cell Detection.

5. CONCLUSIONS

The designing of automated sickle cell detection, local backup storage support, image capturing and saving, real-time display and monitoring functions were successfully met by the researchers. The Evaluation indicates that the main objectives of the study are met with some limitations and exemptions. The researchers was able to design image capturing functions and storage backup allocation without the aid of application which could result to greater cost, however, remote access to the device can be made possible with the use of some readily available applications downloadable in Appstore such as tMviewer etc. Based on the survey and the 100 shot image guided therapy method, the accuracy of the device is 98% accurate and its speed upon capturing and real-time display framerate is high. It was concluded that the use of the machine can lessen the laboratory test time consumption and most respondents approved the frequent use of automated sickle cell detection device with real time monitoring in terms of its Perceived usefulness, Ease of Use, Attitude and behavioral intention.

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