Lymphatic Filariasis Detection Using Image Analysis

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Abstract. Elephantiasis is generally detected through microscopic examination of blood. Until now, this has been difficult because microfilariae only appear in the blood at night for a few hours (nocturnal periodicity). The lack of trained microscopy technicians is a serious problem. Due to the repetitive and tedious nature of diagnosis and the fact that there are few positive cases in a population of thousands. This is a contributing factor to increased detection errors. The main problem encountered is the high degree of difficulty and precision and the long time it takes to perform laboratory examinations. Image analysis method can be used as a way to identify Lymphatic Filariasis worms in the blood. Based on the description above, it can be said that the detection of Lymphatic Filariasis worms can be done with digital image analysis. This research will use the feature extraction method and Convolutional Neural Network to identify object features in the form of worms that cause elephantiasis (Lymphatic Filariasis) in digital images recorded by Trinocular digital microscope cameras. This study aims to determine the performance of image analysis methods used in the identification process of Lymphatic Filariasis worms using digital images recorded by a Compound Trinocular microscope.

Keywords: Lymphatic, Filariasis, Image Processing, CNN

1 Introduction

Filariasis (Elephantiasis) or often called elephantiasis disease is a chronic infectious disease caused by filarial worms, which attack the ducts and lymph nodes. This disease is not a lethal disease, but it is a chronic disease (chronic) and if you do not get treatment, it can cause body defects in the form of expansion, arms and leg genitals, both female and male[1]. Lymphatic filariasis is a disease caused by filarial worm infection. There are three species of worms that cause filariasis, namely Wuchereria brancofti, Brugia malayi and Brugia timori. Lymphatic filariasis (LF) is a parasitic disease that is a major cause of chronic disability in the developing world. According to the 2021–2030 road map for neglected tropical diseases (NTDs) published by the World Health Organization (WHO), the global goal for LF is elimination as a public health problem by 2030 through repeated rounds of mass drug administration (MDA)[2].

The spread of elephantiasis is transmitted by mosquitoes infected with filariasis lava. Unlike malaria and dengue fever, filariasis can be transmitted by 23 species of mosquitoes, including Anopheles, Culex, Mansonia, Aedes and Armager[3]. Elephantiasis disease is characterized by

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symptoms such as swelling of the body that has progressed slowly, which causes the legs to look like elephants. This disease is caused by a kind of white wire that is transmitted through mosquitoes. Symptoms of elephantiasis, filariasis) generally occur during childhood, where more than years will feel the development that occurs[4].

Thick blood smear staining is the gold standard method for filarial detection, however it is laborious and ineffective. Recently, pathogen detection technologies have been developed using microfluidic devices. Pathogen detection with microfluidic technology has various benefits, including point-of-care diagnosis, portability, small sample volumes, downsizing, and reduction in detection times. The development of a semi-automated microfluidic method to identify microfilariae of filarial parasites. A multichannel tank for sample loading and a multichannel microfluidic chip are included in the system. Microfilariae were found in the microfluidic chip during the testing of the semi-automated microfluidic system.[5].

Recently, novel immunologically-based diagnostic tools based on recombinant antigens have been created. The current study discusses the many recombinant antigens utilized in antigen and antibody capture assays as diagnostic tools for lymphatic ilariasis, highlighting their benefits and drawbacks as well as the primary commercial tests created based on them. The literary timeline spans the years 1991 through 2021. It begins by outlining the historical context around the identification of pertinent antigens and the production of the recombinant polypeptides utilized for the LF diagnosis, as well as highlighting characteristics unique to each antigen The use of those proteins to create antigen and antibody capture assays to identify LF is then covered in the section that follows[6].

At least six commercially available tests have been utilized so far in investigations on antibody capture assays, and more proteins have been used to create antigen capture tests. The five SXP/RAL2 family antigens examined in this work are BmSXP, Bm14, WbSXP1, Wb14, and WbL. The remaining antigens are BmShp1, Bm33, BmR1, BmVAH, WbVAH, BmALT1, BmALT2, and Wb123. The Global Program to Eliminate Lymphatic Filariasis is projected to benefit from continued development of tests combining sensitivity and specificity with cheap costs as a result of breakthroughs in research with these antigens (GPELF)[6].

The Global Program to Eliminate Lymphatic Filariasis' standard indicator for monitoring and surveillance is the prevalence of circulating filarial antigen (Ag), as determined by quick point-of-care assays. In 2015, the filariasis test strip (FTS), which has higher claimed sensitivity, took the place of the immunochromatographic test (ICT). Despite variations in sensitivity, when the FTS was implemented, the suggested surveillance targets remained unchanged. We carried out lymphatic filariasis surveys in American Samoa in 2016 using FTS, and compared to earlier surveys using ICT, we discovered a greater Ag prevalence[7].

By performing paired testing on 179 people (63% FTS-positive) whose blood had been heparinized, we evaluated the concordance between FTS and ICT results to ascertain whether the rise was indeed occurring. ICT had a 93.8% sensitivity and 100% specificity for detecting FTS-positive individuals, and there was no relationship between any of these factors and sensitivity. Based on these findings, the results and interpretation of the 2016 surveys using ICT would have been comparable to those reported using FTS. Both tests would have resulted in American Samoa failing the Transmission Assessment Survey (TAS) of Grade 1 and 2 students, and the community prevalence would not have differed noticeably (4.1%, 95% CI, 3.3-4.9% with FTS vs. anticipated 3.8%, 95% CI, 3.1-4.6% with ICT)[7].

The availability of suitable technologies for disease mapping, monitoring, and surveillance is essential to accomplishing the global aim of eliminating lymphatic filariasis (LF). It can be difficult to create these tools for an illness that is often ignored like LF. Diagnostic manufacturers have no motivation to engage in this sector because there is no commercial demand for them and few people are aware of these disorders. A case study on how a multi-stakeholder, public-private partnership paradigm supported the development, assessment, and implementation of a new monitoring and surveillance tool for LF is provided by the creation of the filarial test strip (FTS)[8].

2 Method

It is possible to derive useful optical results from photos using image processing. They employed convolutional and recurrent neural networks to derive the structures' absorption spectra from photos of plasmonic structures. We ran 100,000 simulations with comparable settings and random topologies to get the data needed for the model. They developed a model for this deep network that can forecast the absorption response of any structure with a comparable arrangement. They extracted spatial information from the photos using convolutional neural networks, and we used that information along with recurrent neural networks to train the model to forecast the link between the spatial information and the absorption spectrum[9].

Recent advancements in deep learning have aided the medical imaging sector in the diagnosis of numerous ailments. Among machine learning algorithms, task CNN is the most popular and widely used for visual learning and image recognition (Hassan). Building a mobile robot that can perform a certain duty, such as navigation, surveillance, and explosive ordnance disposal, requires vision systems (EOD). The robot operator or controller will thereafter be aware of the surroundings and able to carry out the subsequent duties. The ability to effectively classify and detect the object has been made feasible by recent developments in deep neural networks for image processing. Convolutional Neural Networks (CNN) are capable of recognizing things in the surrounding area[10].

On a tiny dataset of 210 microfilarial pictures, we used Image Processing and Data Augmentation approaches. We used transfer learning to evaluate the accuracy of our scratched CNN model with previously trained VGG-16, ResNet-50, and Inception-v3 models. We trained them using a straightforward 8 Convolutional Layers CNN model. 150 photographs of microfilariae and 118 pictures of blood cells are part of the dataset. We divided our dataset into three independent training, validation, and testing parts. The validation data is sample data for model evaluation and model parameter tuning, whereas the training data is for model learning (Hassan). Test data are used to assess our model in its entirety. Our suggested process is divided into several steps.

In the stage of identifying an image using the Convotional Neural Network (CNN), there are several steps and processes required. The dataset is also needed as a database consisting of several examples such as the shape, size and color of the worm. Convolutional Neural Network is used to classify new image collections. So this method can identify objects with different shapes according to the dataset they have.

GoogLeNet or Axelnet has been trained on more than a million images and can classify images into 1000 categories of objects (such as keyboards, coffee cups, pencils, faces and many animals). The network has studied feature-rich representations for various images. The network takes an image as input and outputs a label for the objects in the image along with the probabilities for each category of objects.

Transfer learning is commonly used in deep learning applications. This process can take a trained network and use it as a starting point for learning new tasks. Fitting a network with transfer learning is usually much faster and easier than training a network with randomly initialized weights from scratch. Processes can more quickly transfer learned features to new tasks using fewer training images. In other words, the use of this feature will shorten the processing of new images.

Using the Open Source Computer Vision (CV) Canny Edge Detection algorithm, we removed the black edges from the images and only kept the brain part of the MRI scans. A multi-phase method called Canny Edge Detection is used to locate an object's edges in a picture. In Figure 2, only the brain portion of the image has been cropped after the margins of the Real MRI brain were revealed using the clever edge detection technique[11].

A technique for artificially boosting the volume and complexity of already-existing data is called data augmentation. We are aware that training a deep neural network requires lots of data in order to adjust the parameters. However, because the size of our dataset was so little, we used the data augmentation technique to add modifications to our photographs by flipping, rotating, and changing the brightness. It will expand the size of our training data and allow our model to learn more effectively and perform well on untried data because each of these minute changes will be treated as a separate image by our model[11].

3 Result

The data used as the test sample is the result of a digital microscope recording in the form of a digital image. A sensor is mounted on one of the microscope lenses to record the observed images in the form of images. Then, the image recorded by the sensor is digitized to obtain image data in digital form. Digital images recorded by digital microscopes are used as input in the object identification process using image analysis techniques.

Image data were collected using the OLYMPUS BX 51 Compound Trinocular Microscope with Camera Photo DP21. The image data collection process was carried out during the day at the Technical Center for Environmental Health and Disease Control in Medan. The image used as input has an object in the form of a worm that causes elephantiasis in the blood. The number of samples used is 150 images consisting of 3 categories. Figure 1 below shows some images recorded by a digital microscope.

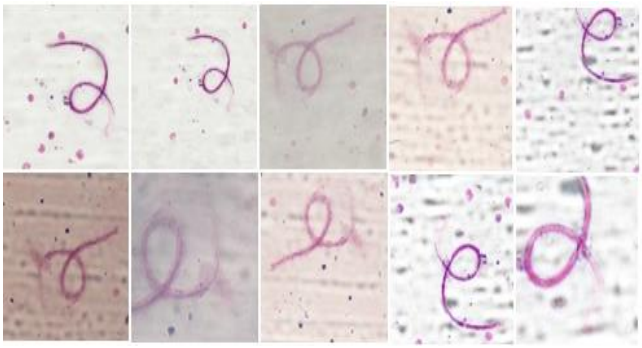

Fig 1. Image of Digital Microscope Recorded

In this CNN Model using Pretrained CNN, after the Model has been compiled, then the next is the Training process, where in this training process is a process where Machine Learning works so that the algorithm that we have defined can remember the pattern of each class in the data that we will train. . The blue graph in Figure 3 is the train process that gets good accuracy (Accuracy is identified), while the orange graph in Figure 4 shows the training process cannot manage the dataset properly (Loss).

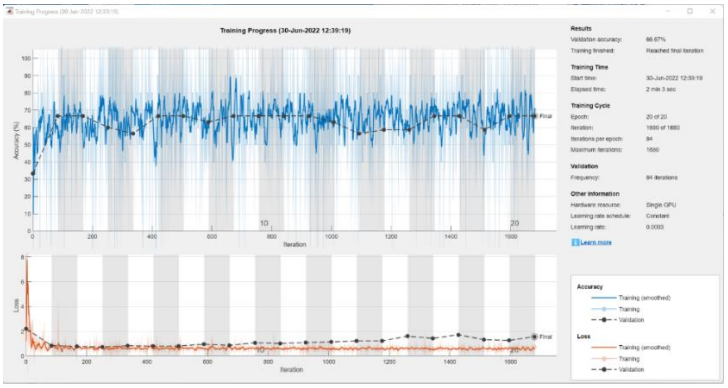

Fig 2. Accuration of Identification

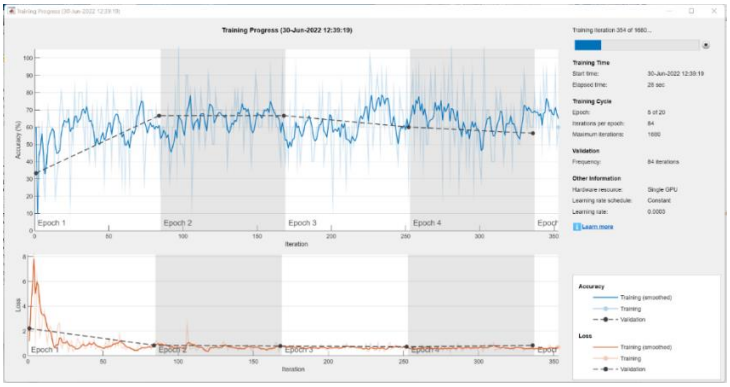

Fig 3. Loss Accuration

Features of an object in an image can be seen based on the distribution of values contained in the cumulative matrix. The value in the cumulative matrix is the relationship between the pixel values of an object in the image. Tests were carried out on 250 input images, with three categories based on the magnification size. The first category is the image with 150 times the microscope magnification, the second category is the image with 200 times the microscope magnification and the third category is the image with 400 times the microscope magnification. To simplify the complex calculation process, used tools in the form of software for testing. Test results can be seen in Figure 4.

Fig 4. Filarial image detection results

4 Conclusion

The CNN algorithm proposed in this study is able to detect worms in digital images with an accuracy of 70%. The training process takes a long time because of the large dataset. In addition, the detection failure is also caused by the presence of blood cell images that become noise during the training process. Similarity in shape, size and color can be an indicator of the success of the detection process. For further research, it is necessary to separate the datasets. The dataset used is a color image and a black and white image.

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