International Journal of Advances in Data and Information Systems
Vol. 4, No. 2, October 2023, pp. 181~190
ISSN: 2721-3056, DOI: 10.25008/ijadis.v4i2.1305

Enhancing Soil-Transmitted Helminth Detection in Microscopic Images Using the Chain Code for Object Feature Extraction

Rio Andika Malik[1], Marta Riri Frimadani[2], Dwipa Junika Putra[3]
[1,3] Digital Business, Faculty of Economic Business and Social Sciences, University of Perintis Indonesia, Indonesia
[2] Integrated Natural Resources Management, Postgraduate Program of Andalas University, Indonesia

Article Info

Article history:

Received Aug 25, 2023
Revised Sep 28, 2023
Accepted Oct 20, 2023

Keywords:

Soil-Transmitted Helminths
Image processing
Image Retrieval
Chain Code
Object Feature Extraction

ABSTRACT

Soil-Transmitted Helminth (STH) infections are a grave global health issue, which involves particularly in countries that are developing with insufficient sanitation and limited access to healthcare. With better intestinal helminth egg detection technology, health facilities in areas with limited resources can identify and treat these infections more promptly. It is necessary to create a strong framework and an effective method to solve this challenge. The outcomes of this study could assist in parasite infection discovery and public health. Chain code-based feature extraction strategy can also be the foundation for the development of comparable approaches for diagnosing various parasitic diseases. Overall, the neural network design used in this study makes the model that is produced a good model that assigns well to never-before-seen data. The significance of image processing technologies in the medical field is shown by this study.

Corresponding Author:

Rio Andika Malik,
Digital Business, Faculty of Economic Business and Social Sciences,
University of Perintis Indonesia
Adinegoro Road KM15, Lubuk Buaya, Padang, West Sumatera, 25173, Indonesia.
Email: rioandikamalik@upertis.ac.id

1. INTRODUCTION

A category of parasitic worms known as soil-transmitted helminths (STH) are frequently present in soil and can infect people by coming into contact with contaminated soil, drinking contaminated water, or eating infected food [1][2][3][4][5]. STH infections are a serious all over the world health issue, particularly in developing countries with shoddy sanitation and inaccessible medical services [6][7][8][9][10][11][12]. According to projections, approximately 1.5 billion individuals, or 24% of the global population, are infected with illnesses set on by soil-transmitted helminths (STHs), making them a number of the most prominent infections in the world [7][8][13][14][15][5][16]. Due to the strong correlations between socioeconomic situations, individual cleanliness, and environmental factors in Indonesia, STH infections tend to be an ongoing issue [5][14][17][18][19][20][21][22]. In certain provinces, children aged between the ages of 1 and 12 have a worm-related spread rate that oscillates between 30% to 90% [13][14][17][23][24][25].

Reduced disease burden and minimization of potentially fatal repercussions arising from overlooked infections are made possible by early and precise STH infection identifying purposes [10][16][17][23]. Examining microscopic images obtained from specimens of human feces leads to the discovery of worm eggs, which can afterwards be enumerated and described [2][26][27][28]. Whilst microscopic examination of images has proven successful in spotting STH infections worm eggs, the procedure is time-consuming and labor-intensive, requires specialized human beings, and may be highly susceptible to human error. A more rapid and computerized method needs to be developed for identifying STH infections in microscopic imagery.

Neural Networks, in particular, have demonstrated tremendous promise in image processing during the past 10 years because to developments in artificial intelligence technology. The Neural Network architecture, which was advantageously utilized to deal with several kinds of pattern recognition challenges, including medical image analysis, is a superb example of a neural network manufactured artificially. Neural Network architecture was inspired by human visual processing. system's intricate workings, making them adept at detecting intricate patterns and features within images. The realm of medical image analysis is an illustrative case where have excelled, demonstrating their prowess in identifying anomalies and aiding healthcare professionals in diagnosing complex conditions.The application of chain code algorithm indicates appealing prospects for identifying infections caused by STH in microscopic pictures [7][15][29]. The neural network may be built to identify and differentiate STH worm eggs from various other characteristics in the images using image retrieval methods using datasets of precisely annotated microscopic images. This innovative approach can be further enriched by integrating image retrieval techniques.

Exciting possibilities exist for using neural network to diagnose infections brought on by Soil-Transmitted Helminth (STH) worms in microscopic pictures. In this situation, chain code algorithm can be designed to identify and separate STH worm eggs from other features in the image. This strategy makes use of an image retrieval technique and a dataset of precisely labelled microscopic images. In order to successfully diagnose STH worm infection in microscopic pictures, image retrieval technology makes use of neural network benefits for pattern recognition and image fit. By employing meticulously annotated datasets of microscopic images, the neural network can be trained to recognize subtle features indicative of STH infections.

In this situation, using image processing and image analysis tools can significantly improve the effectiveness and precision of STH infection identification. Chain code is a method that may be applied to extract object features from microscopic photographs. Chain coding, which represents the direction of change between adjacent pixels on an object's contour sequentially, can clearly and concisely depict an object's shape. This study uses chain code as an object feature extraction technique to enhance the detection of soil-transmitted helminth on microscopic pictures. It is envisaged that by employing this technique, the accuracy and effectiveness of worm egg identification can be increased. A chain code-based algorithm for feature extraction of objects in microscopic pictures will be developed in this study. The shape and size of the eggs will be reflected in a chain code representation created by this technique, which will recognise the worm eggs' contours in the image. Additionally, a pattern recognition model that can distinguish between worm eggs and other structures in the image will be trained using these attributes.

The primary objective of the current research is to further enhance the method for detecting STH infections applying image retrieval from microscopic images. The practical application of chain code algorithm is projected to boost diagnosis efficiency and precision while obviating the need for direct human involvement throughout the image analysis process [30][31][32][33][34][35][36][37][38][39][40]. The findings of this study are going to greatly contribute to efforts to prevent and control STH infections, particularly in areas with high prevalence rates [23][10][2]. The care of STH infections can be more prompt and successful with an automated and effective detection approach, inhibiting their detrimental effects on public health. Additionally, this discovery may open the door for the use of artificial intelligence technology in other healthcare disciplines that call for image analysis, thereby expanding the employment of AI in the healthcare industry.

2. RESEARCH METHOD

This study suggests creating chain code algorithms for worm egg extraction. In order to calculate the value of the chain, the length of the chain, and the probability of each object contained in each worm egg, which serves as the characteristics of a worm egg as well as can then be stored in a database, the basic idea is to track the contours of the worm eggs using Moore algorithms. A research methodology with numerous steps, similar those in the following figure 5, is necessary to design such a system. Consequently, there are 6 phases to this research.

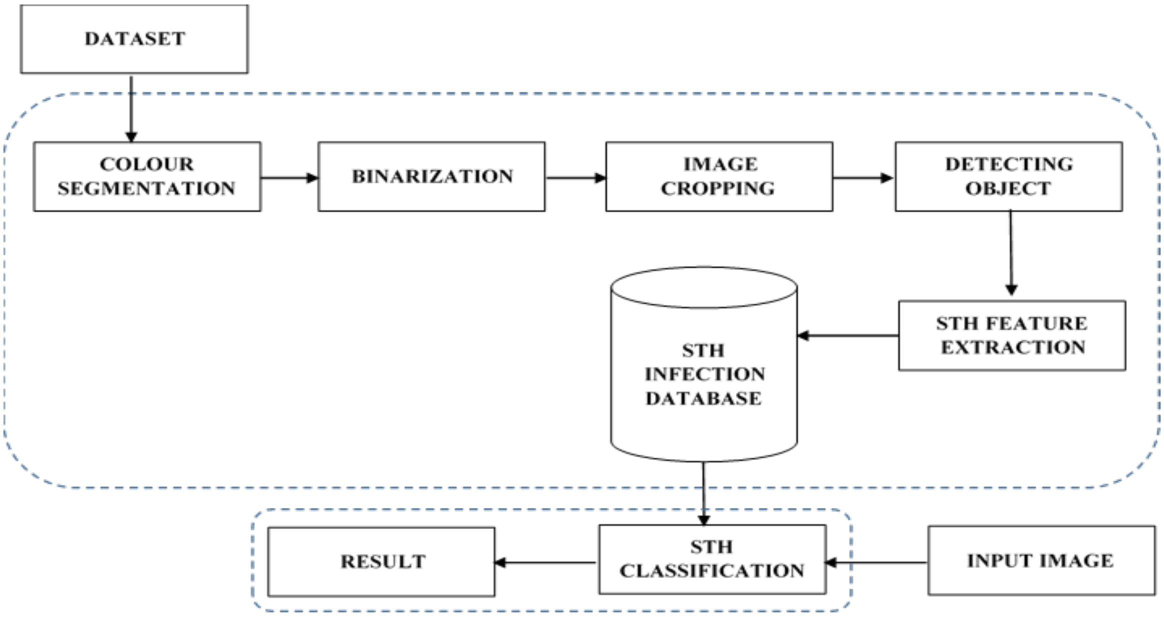
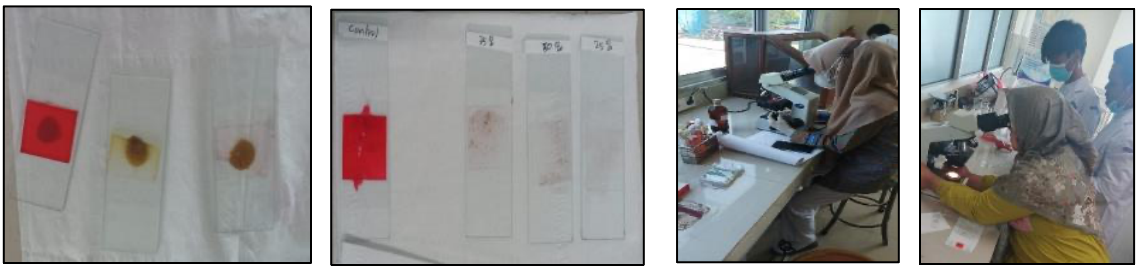


Figure 5. Feature extracting system phase [41]

A real-world instance of a deep neural network used for classifying images is a neural network ([30][42]. The problem-solving approach in this research is the utilisation of a Neural Network to optimise microscopic images in detecting Soil-Transmitted Helminths (STH) infections and conducting an in-depth analysis of how effective in detecting STH in microscopic images, as well as how this technology can enhance the efficiency and accuracy of STH infection detection. This study is experimental, aiming to improve accuracy and efficiency in detecting STH infections, with a focus on three types of STH, namely Ascaris lumbricoides, Trichuris trichiura, and hookworm [1][13][25][23][43][29].

2.1 Material and Dataset

The first step in using neural network for STH infection detection is to create a faeces [7][13] image dataset using the Matlab software. Direct field observation and collaboration with the Public Health Centre in Padang City were used to obtain stool images. Medical laboratory professionals and analysts examined and analysed faeces samples under a microscope in the pathology laboratory to create a collection of microscopic images.



(a) (b)

Figure 2: (a) preparations on the slide; (b) checking STH infection detection preparations

To increase the number of datasets, the image will subsequently be processed using preprocessing techniques including normalisation, noise reduction, and image augmentation. In addition, the dataset will be split into three segments for training, validation, and testing. The human faeces microscopic image dataset that was used in this investigation was gathered from a number of hospitals and clinics in diverse locations with varying rates of Soil Transmitted Helminth (STH) infection. Microscopical images of STH Ascaris Lumbricoides, Trichuris Trichiura, hookworm eggs, and control samples devoid of worm eggs are included in the data set. The data collection depicted in Figure 3 pertains to the outcomes of STH infection detection by healthcare professionals.

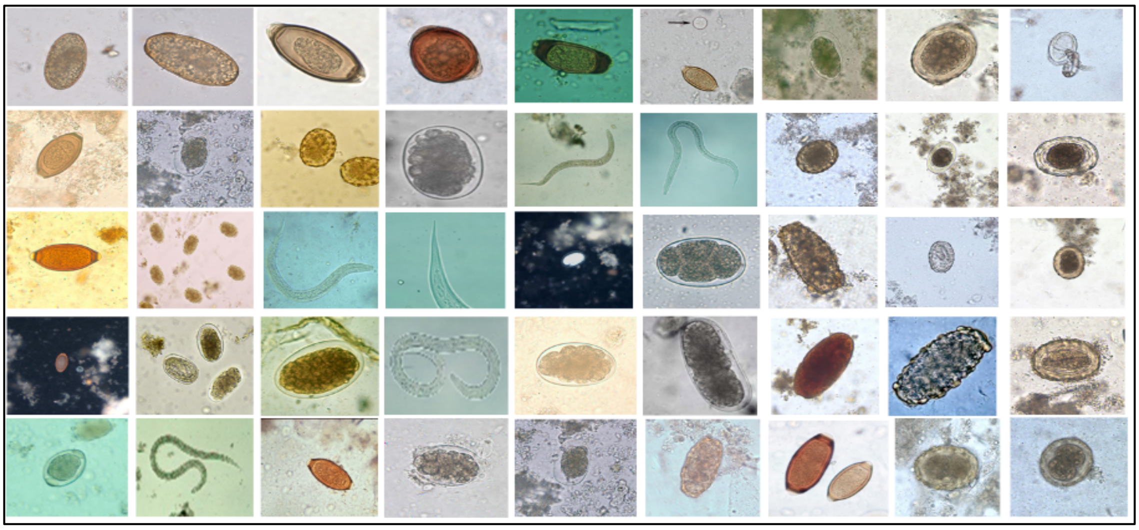


Figure 3: STH Dataset

With a focus on three varieties of STH, Ascaris lumbricoides, Trichuris trichiura, and hookworm, Figure 3 shows the classification of worm egg detection in detecting STH infections as a result of checking and validation by health workers and medical laboratory analysts.

(a) (b) (c)

Figure 4: (a) Ascaris Lumbricoides; (b) Trichuris Trichiura; and (c) Hookworm;

2.2 Image Colour Segmentation, Binarization, and Cropping

The essential yet difficult task of image segmentation in computer vision is to separate the input image into numerous disjoint subsets, each of which corresponds to a significant region. In many applications, including object recognition, picture editing, and medical image processing, it is an essential step. The essential yet difficult task of image segmentation in computer vision is to separate the input image into numerous disjoint subsets, each of which corresponds to a significant region. In many applications, including object recognition, picture editing, medical image processing, and many others, it is an essential step. The process of image segmentation involves locating areas of interest, which are typically an item or a section of a digital image. Each region must maximise the consistency of its pixel attributes (such as colour and texture) while also maximising the variances from nearby regions. Equations 1 mathematically denote the RGB colour space's colour gamut[41].

$$D = \sqrt{(R_{ref} + R_p)^2 + (G_{ref} + G_p)^2 + (B_{ref} + B_p)^2} \quad (1)$$

The segmented image is now subjected to a binary procedure with the intention of converting the colour pattern image to a grey image and subsequently to a binary image[44]. This tries to make each object's area boundaries clearer and make the subsequent analysis procedure easier. A noise removal step is necessary because the products of the binaryization process occasionally still contain noise in the form of tiny white dots. Next step is process of cropping is necessary for image processing because there are some parts of an image that can be removed if they are not needed. There are many different ways to crop, from manually selecting the areas you want to remove to using readily available tools like Photoshop and etc.

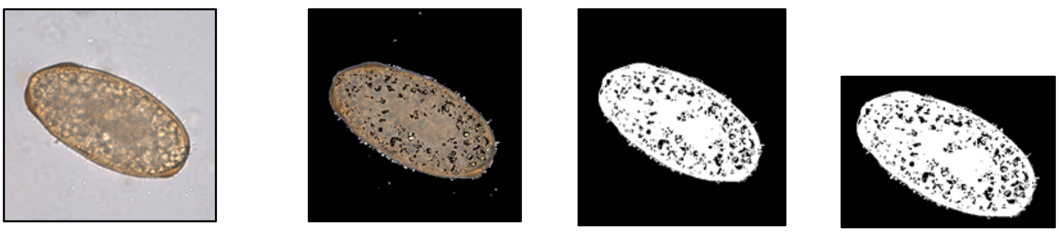
2.3 Object Detection and Feature Extraction

Image edge detection methods can be created using morphological procedures. The morphological dilation procedure, followed by the thinning process for object edge identification, is the morphological method selected at this step. Mathematical morphology is a method for performing image analysis that is based on topology and geometric shapes. It has found various uses as a tool to extract structures and geometric patterns. Morphological operations are frequently used to alter the structure of the shape of the objects contained in binary (black and white) images[45]. Morphological operations can really be applied to the picture grey level in addition to the binary image. Dilation and erosion are two fundamental activities in the process of mathematical morphology. A comprehension of set operations like intersection and joint is a requirement in order to comprehend morphological operations.

At this point, an image extraction procedure is applied to the image produced by the object detection process in order to acquire a value that will be used as a feature of the image. The contour tracing of Moore's technique is used to obtain the sorted contours from an image that may contain one or more items. After collecting the sorted contours, we use the chain code method to look for the value of the chain. Since this algorithm has not yet been developed, you will be requested to create it for your final assignment. The chain code algorithm produced the final value in the form as a result of the operation.

3. RESULTS AND DISCUSSION

The results of the segmentation, binarization, and cropping process are in the form of a binary image (as shown in fig. 5). Figure 5 (b) Utilising a similarity measurement methodology (colour similarity) and the value limit threshold technique, the segmentation procedure was carried out. Figure 5 (c) By removing small pixels from the binary image produced by the conversion to black and white mode, the location of the regarded objects will be identified.

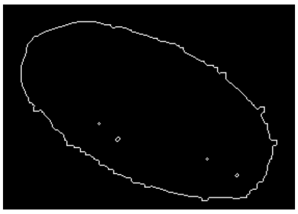
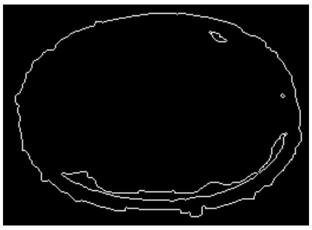


(a) (b) (c) (d)

Figure 5. (a) sample image (b) segmentation (c) binarization (d) cropping

Morphological operations can really be applied to the picture grey level in addition to the binary image. Dilation and erosion are two fundamental activities in the process of mathematical morphology. A comprehension of set operations like intersection and joint is a requirement in order to comprehend morphological operations. One of the cornerstones of morphology processing is the dilation procedure. The binary image's "lengthening" or "thickening" process is known as dilation. Structural components influence this unique way and the degree of thickening. Moore's contour tracking technique is used by inbound tracing to obtain contours. Objects that restrict the chain direction are represented using chain code. Additionally, determine the length of the value chain, the probability level of occurrence, and the rate of appearance of each 0–7 as shown as table 1.

Table 1. Yielded Values of Egg Extraction

Egg Name	Chains	Change Length	Probability Values
Ascaries Lumbricoides	0	692	0.21988
	1		0.04819
	2		0.12349
	3		0.09789
	4		0.24096
	5		0.03765
	6		0.12349
	7		0.10843
Trichuris Trichiura	0	530	0.12158
	1		0.13399
	2		0.20595
	3		0.03970
	4		0.11911
	5		0.15633
	6		0.19106
	7		0.03226
Hookworm	0	1100	0.21572
	1		0.08166
	2		0.11556
	3		0.08320
	4		0.22342
	5		0.07088
	6		0.12943
	7		0.08012

In order to gauge and assess the degree of picture similarity with the training data stored in the database, the outcomes of the image extraction process that have been stored in the database are tested with the original image at this step. There are two sections to algorithm, the first of which is the algorithm for the training process and the second of which is the method for the testing process. Backpropagation neural network algorithm is used during the training and testing procedure. This network's building parameters include the number of iterations (or "epochs"), learning rates (or "learning rates"), neurons in each hidden layer, and objectives. Figure 6 is a brief overview of the network used in this exercise.

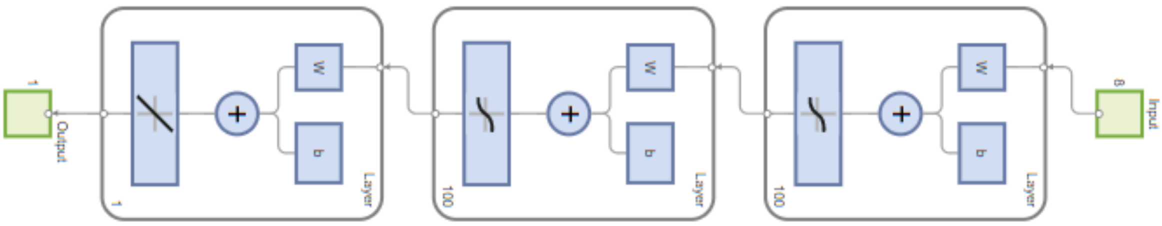
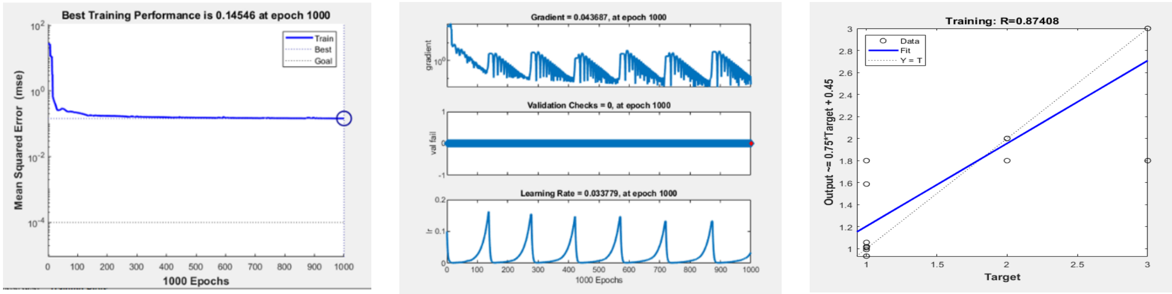


Figure 6. Neural Network Architecture

Figure 6 show a network architecture with 8 inputs, 2 hidden layers, 100 neurons in each layer, and 1 output is the first set of training parameters. The input layer's tantig activation function, the output layer's purelin activation function, and the network training functions with the quickest derivation method with variable understanding rate plus momentum are the activation functions that are employed.



(a) Performance (b) State (c) Regression

Figure 7. Training

Figure 7 the process of training an artificial neural network starting from performance, state and regression. Model tuning includes choosing the learning rate and the number of epochs. Based on the features of the data and the model's architecture, these parameters have been carefully adjusted. Performance gradient aids in keeping track of how much the model improves or degrades throughout training and Validation checks allow us to evaluate how the model will function beyond the training data and prevent overfitting (the model overfits the training data). How quickly or slowly the model learns during training depends on the learning rate. In the area of machine learning and statistics, the evaluation metric known as MSE (Mean Squared Error) is frequently utilised during the model training process. MSE assesses how closely the model being drilled corresponds to the training set or the intended target. The mean square error (MSE), which measures how well a neural network performs during training, is used to define epochs and learning rate as shown as figure 8.

Training Progress

Unit	Initial Value	Stopped Value	Target Value
Epoch	0	1000	1000
Elapsed Time	-	00:00:31	-
Performance	26.7	0.145	0.0001
Gradient	89.1	0.0437	1e-05
Validation Checks	0	0	6

Figure 8. MSE Training Process

Based on the training process, it can be inferred from Figure 8 that the process proceeds as anticipated and yields the expected outcomes in compliance with the established objectives and criteria. When the gradient value stops at 0.0437 with a target value of 0.00001, it indicates the algorithm has reached or is approaching the target value of 0.00001, which has been established with time passed, during an optimisation or training procedure. The model's target performance value indicator of 0.0001 shows that it has an exceptionally small error rate and that it exhibits no overvitting, allowing it to make generalisations successfully to new data start has lasted 31 seconds. Overall, the neural network design used in this study makes the model that is produced a good model that assigns well to never-before-seen data.

4. CONCLUSION

The field of public health and parasitic infection diagnosis may benefit from the results of this study. Health facilities in locations with limited resources can more quickly diagnose and treat these diseases with improved intestinal helminth egg detection capabilities. Additionally, this chain code-based feature extraction approach can serve as the basis for the creation of similar methods for identifying various parasite illnesses. The research also take into account a number of difficulties, including differences in the size and shape of worm eggs, fluctuations in lighting in microscopic images, and complexity in feature extraction on potentially overlapping items. To address this difficulty, a solid framework and suitable technique must be developed.

This research draws attention to the relevance of image processing technology in the medical and health fields. The use of image-based algorithms can change the way we approach disease diagnosis and analysis, opening the door for further innovation in medical practice. The results of this study can be the basis for further research in the development of more complex and sophisticated pattern recognition techniques. Integration with technologies such as machine learning and deep learning can improve the capabilities of models in automatically recognizing objects. Researchers in the future could concentrate on creating more complex machine learning models that can identify intestinal worm eggs using attributes taken from microscopic photographs. Convolutional neural networks (CNN) and deep learning are a few instances of machine learning methods that can enhance the accuracy and speed of worm egg assessment.

ACKNOWLEDGEMENTS

The University of Perintis Indonesia ought to be appreciated by the author for providing resources and expertise during the research. We also appreciate with admiration the funds provided by The Directorate of Research Technology and Community Service (DRTPM) of the Ministry of Education and Culture of the Republic of Indonesia, which supplied funding to operate the novice lecturer research scheme (PDP) in 2023.

REFERENCES

[1] P. M. Jourdan, P. H. L. Lamberton, A. Fenwick, and D. G. Addiss, "Soil-transmitted helminth infections," *Lancet*, vol. 391, no. 10117, pp. 252–265, 2018, doi: 10.1016/S0140-6736(17)31930-X.

[2] S. Ame *et al.*, "Impact of preventive chemotherapy on transmission of soil-transmitted helminth infections in Pemba Island, United Republic of Tanzania, 1994–2021," *PLoS Negl. Trop. Dis.*, vol. 16, no. 6, pp. 1–11, 2022, doi: 10.1371/JOURNAL.PNTD.0010477.

[3] A. A. Adegoke, I. D. Amoah, T. A. Stenström, M. E. Verbyla, and J. R. Mihelcic, "Epidemiological evidence and health risks associated with agricultural reuse of partially treated and untreated wastewater: A review," *Front. Public Heal.*, vol. 6, no. DEC, pp. 1–20, 2018, doi: 10.3389/fpubh.2018.00337.

[4] V. A. Welch *et al.*, "Mass deworming to improve developmental health and wellbeing of children in low-income and middle-income countries: a systematic review and network meta-analysis," *Lancet Glob. Heal.*, vol. 5, no. 1, pp. e40–e50, 2017, doi: 10.1016/S2214-109X(16)30242-X.

[5] S. Vaz Nery *et al.*, "The role of water, sanitation and hygiene interventions in reducing soil-transmitted helminths: Interpreting the evidence and identifying next steps," *Parasites and Vectors*, vol. 12, no. 1, pp. 1–8, 2019, doi: 10.1186/s13071-019-3532-6.

[6] I. D. Amoah, G. Singh, T. A. Stenström, and P. Reddy, "Detection and quantification of soil-transmitted helminths in environmental samples: A review of current state-of-the-art and future perspectives," *Acta Trop.*, vol. 169, pp. 187–201, 2017, doi: 10.1016/j.actatropica.2017.02.014.

[7] E. Dacal *et al.*, "Mobile microscopy and telemedicine platform assisted by deep learning for the quantification of Trichuris trichiura infection," *PLoS Negl. Trop. Dis.*, vol. 15, no. 9, pp. 1–14, 2021, doi: 10.1371/journal.pntd.0009677.

[8] D. Wimmersberger *et al.*, "Efficacy and Safety of Ivermectin Against Trichuris trichiura in Preschool-aged and School-aged Children: A Randomized Controlled Dose-finding Trial," *Clin. Infect. Dis.*, vol. 67, no. 8, pp. 1247–1255, 2018, doi: 10.1093/cid/ciy246.

[9] L. Steinbaum *et al.*, "Detecting and enumerating soil-transmitted helminth eggs in soil: New method development and results from field testing in Kenya and Bangladesh," *PLoS Negl. Trop. Dis.*, vol. 11, no. 4, pp. 1–15, 2017, doi: 10.1371/journal.pntd.0005522.

[10] J. Kabatende *et al.*, "Prevalence, intensity, and correlates of soil-transmitted helminth infections among school children after a decade of preventive chemotherapy in Western Rwanda," *Pathogens*, vol. 9, no. 12, pp. 1–20, 2020, doi: 10.3390/pathogens9121076.

[11] B. Le *et al.*, "The impact of ivermectin, diethylcarbamazine citrate, and albendazole mass drug administration on the prevalence of scabies and soil-transmitted helminths in school-aged children in three municipalities in Timor-Leste: a before–after assessment," *Lancet Glob. Heal.*, vol. 11, no. 6, pp. e924–e932, 2023, doi: 10.1016/S2214-109X(23)00134-1.

[12] A. Prüss-Ustün *et al.*, "Burden of disease from inadequate water, sanitation and hygiene for selected adverse health outcomes: An updated analysis with a focus on low- and middle-income countries,"

Int. J. Hyg. Environ. Health, vol. 222, no. 5, pp. 765–777, 2019, doi: 10.1016/j.ijheh.2019.05.004.

[13] P. A. Zendejas-Heredia, V. Colella, S. F. Hii, and R. J. Traub, "Comparison of the egg recovery rates and limit of detection for soil-transmitted helminths using the kato-katz thick smear, faecal flotation and quantitative real-time pcr in human stool," *PLoS Negl. Trop. Dis.*, vol. 15, no. 5, pp. 1–18, 2021, doi: 10.1371/journal.pntd.0009395.

[14] Y. Xu *et al.*, "The prevalence of soil transmitted helminths and its influential factors in Shandong Province, China: an analysis of surveillance data from 2016 to 2020," *Infect. Dis. Poverty*, vol. 12, no. 1, pp. 1–13, 2023, doi: 10.1186/s40249-023-01100-4.

[15] P. Ward *et al.*, "Affordable artificial intelligence-based digital pathology for neglected tropical diseases: A proof-of-concept for the detection of soil-transmitted helminths and Schistosoma mansoni eggs in Kato-Katz stool thick smears," *PLoS Negl. Trop. Dis.*, vol. 16, no. 6, pp. 1–16, 2022, doi: 10.1371/JOURNAL.PNTD.0010500.

[16] M. Z. Tee *et al.*, "Efficacy of triple dose albendazole treatment for soil-transmitted helminth infections," *PLoS One*, vol. 17, no. 8 August, pp. 1–21, 2022, doi: 10.1371/journal.pone.0272821.

[17] N. Salam and S. Azam, "Prevalence and distribution of soil-transmitted helminth infections in India," *BMC Public Health*, vol. 17, no. 1, 2017, doi: 10.1186/s12889-017-4113-2.

[18] M. Hesham Al-Mekhlafi, J. Surin, A. S. Atiya, W. A. Ariffin, A. K. Mohammed Mahdy, and H. Che Abdullah, "Pattern and predictors of soil-transmitted helminth reinfection among aboriginal schoolchildren in rural Peninsular Malaysia," *Acta Trop.*, vol. 107, no. 2, pp. 200–204, 2008, doi: 10.1016/j.actatropica.2008.05.022.

[19] C. M. Scavuzzo *et al.*, "Feature importance: Opening a soil-transmitted helminth machine learning model via SHAP," *Infect. Dis. Model.*, vol. 7, no. 1, pp. 262–276, 2022, doi: 10.1016/j.idm.2022.01.004.

[20] N. Miswan, G. V. Singham, and N. Othman, "Advantages and limitations of microscopy and molecular detections for diagnosis of soil-transmitted helminths: An overview," *Helminthol.*, vol. 59, no. 4, pp. 321–340, 2022, doi: 10.2478/helm-2022-0034.

[21] M. Beknazarova, H. Whiley, and K. Ross, "Strongyloidiasis: A disease of socioeconomic disadvantage," *Int. J. Environ. Res. Public Health*, vol. 13, no. 5, 2016, doi: 10.3390/ijerph13050517.

[22] N. Fauziah, M. A. Ar-Rizqi, S. Hana, N. M. Patahuddin, and A. Diptyanusa, "Stunting as a Risk Factor of Soil-Transmitted Helminthiasis in Children: A Literature Review," *Interdiscip. Perspect. Infect. Dis.*, vol. 2022, 2022, doi: 10.1155/2022/8929025.

[23] M. Werkman *et al.*, "Testing for soil-transmitted helminth transmission elimination: Analysing the impact of the sensitivity of different diagnostic tools," *PLoS Negl. Trop. Dis.*, vol. 12, no. 1, pp. 1–20, 2018, doi: 10.1371/journal.pntd.0006114.

[24] W. Moser, C. Schindler, and J. Keiser, "Efficacy of recommended drugs against soil transmitted helminths: Systematic review and network meta-analysis," *BMJ*, vol. 358, pp. 1–10, 2017, doi: 10.1136/bmj.j4307.

[25] K. I. Azzopardi *et al.*, "Detection of six soil-transmitted helminths in human stool by qPCR- a systematic workflow," *PLoS One*, vol. 16, no. 9 September, pp. 1–17, 2021, doi: 10.1371/journal.pone.0258039.

[26] A. Montresor *et al.*, "The global progress of soil-transmitted helminthiases control in 2020 and world health organization targets for 2030," *PLoS Negl. Trop. Dis.*, vol. 14, no. 8, pp. 1–17, 2020, doi: 10.1371/journal.pntd.0008505.

[27] E. T. Donkoh *et al.*, "Evidence of reduced academic performance among schoolchildren with helminth infection," *Int. Health*, vol. 15, no. 3, pp. 309–317, 2023, doi: 10.1093/inthealth/ihac044.

[28] O. Holmström *et al.*, "Point-of-care mobile digital microscopy and deep learning for the detection of soil-transmitted helminths and Schistosoma haematobium," *Glob. Health Action*, vol. 10, no. 3, 2017, doi: 10.1080/16549716.2017.1337325.

[29] L. Lin *et al.*, "Combining collective and artificial intelligence for global health diseases diagnosis using crowdsourced annotated medical images," *Proc. Annu. Int. Conf. IEEE Eng. Med. Biol. Soc. EMBS*, pp. 3344–3348, 2021, doi: 10.1109/EMBC46164.2021.9630868.

[30] N. Kalaivani, N. Manimaran, S. Sophia, and D. D. Devi, "Deep Learning Based Lung Cancer Detection and Classification," *IOP Conf. Ser. Mater. Sci. Eng.*, vol. 994, no. 1, 2020, doi: 10.1088/1757-899X/994/1/012026.

[31] W. Ayadi, W. Elhamzi, I. Charfi, and M. Atri, "Deep CNN for Brain Tumor Classification," *Neural Process. Lett.*, vol. 53, no. 1, pp. 671–700, 2021, doi: 10.1007/s11063-020-10398-2.

[32] E. Guirado, S. Tabik, M. L. Rivas, D. Alcaraz-Segura, and F. Herrera, "Whale counting in satellite and aerial images with deep learning," *Sci. Rep.*, vol. 9, no. 1, pp. 1–12, 2019, doi: 10.1038/s41598-019-50795-9.

[33] T. M. Ghazal *et al.*, “Alzheimer disease detection empowered with transfer learning,” *Comput. Mater. Contin.*, vol. 70, no. 3, pp. 5005–5019, 2022, doi: 10.32604/cmc.2022.020866.

[34] J. Wang, H. Zhu, S. H. Wang, and Y. D. Zhang, “A Review of Deep Learning on Medical Image Analysis,” *Mob. Networks Appl.*, vol. 26, no. 1, pp. 351–380, 2021, doi: 10.1007/s11036-020-01672-7.

[35] A. Fuentes, S. Yoon, S. C. Kim, and D. S. Park, “A robust deep-learning-based detector for real-time tomato plant diseases and pests recognition,” *Sensors (Switzerland)*, vol. 17, no. 9, 2017, doi: 10.3390/s17092022.

[36] S. Sarkar, A. Sunil Menon, G. T, and A. K. Kakelli, “Convolutional Neural Network (CNN-SA) based Selective Amplification Model to Enhance Image Quality for Efficient Fire Detection,” *Int. J. Image, Graph. Signal Process.*, vol. 13, no. 5, pp. 51–59, 2021, doi: 10.5815/ijigsp.2021.05.05.

[37] H. J. Yu, S. R. Cho, M. J. Kim, W. H. Kim, J. W. Kim, and J. Choi, “Automated Skeletal Classification with Lateral Cephalometry Based on Artificial Intelligence,” *J. Dent. Res.*, vol. 99, no. 3, pp. 249–256, 2020, doi: 10.1177/0022034520901715.

[38] N. Tajbakhsh *et al.*, “Convolutional Neural Networks for Medical Image Analysis: Full Training or Fine Tuning?,” *IEEE Trans. Med. Imaging*, vol. 35, no. 5, pp. 1299–1312, 2016, doi: 10.1109/TMI.2016.2535302.

[39] X. Ma, Z. Dai, Z. He, J. Ma, Y. Wang, and Y. Wang, “Learning traffic as images: A deep convolutional neural network for large-scale transportation network speed prediction,” *Sensors (Switzerland)*, vol. 17, no. 4, 2017, doi: 10.3390/s17040818.

[40] M. Havaei *et al.*, “Brain tumor segmentation with Deep Neural Networks,” *Med. Image Anal.*, vol. 35, pp. 18–31, 2017, doi: 10.1016/j.media.2016.05.004.

[41] Yuhandri, S. Madenda, E. P. Wibowo, and Karmilasari, “Object feature extraction of songket image using chain code algorithm,” *Int. J. Adv. Sci. Eng. Inf. Technol.*, vol. 7, no. 1, pp. 235–241, 2017, doi: 10.18517/ijaseit.7.1.1479.

[42] R. Hashemzehi, S. J. S. Mahdavi, M. Kheirabadi, and S. R. Kamel, “Detection of brain tumors from MRI images base on deep learning using hybrid model CNN and NADE,” *Biocybern. Biomed. Eng.*, vol. 40, no. 3, pp. 1225–1232, 2020, doi: 10.1016/j.bbe.2020.06.001.

[43] S. H. Farrell *et al.*, “Investigating the effectiveness of current and modified world health organization guidelines for the control of soil-transmitted helminth infections,” *Clin. Infect. Dis.*, vol. 66, no. Suppl 4, pp. S253–S259, 2018, doi: 10.1093/cid/ciy002.

[44] Z. Liu *et al.*, “Improved Kiwifruit Detection Using Pre-Trained VGG16 with RGB and NIR Information Fusion,” *IEEE Access*, vol. 8, pp. 2327–2336, 2020, doi: 10.1109/ACCESS.2019.2962513.

[45] V. Khare and S. Kumari, “Detection of Brain Tumor Based on Multimodality Brain Image Fusion Using Dual Branch Convolution Neural Network,” *Ing. des Syst. d’Information*, vol. 28, no. 2, pp. 475–482, 2023, doi: 10.18280/isi.280224.