Enrichment of microscopic photographs by utilizing CNN regarding soil-transmitted helminths identification

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ABSTRACT

Soil-transmitted helminth (STH) infection remains a significant global health challenge, affecting millions of people, particularly in developing countries. A convolutional neural network (CNN) approach to optimize the detection of STH infections in microscopic images. The study aims to assess the effectiveness of the CNN model in identifying and classifying STH worm eggs accurately. The research employs MATLAB as the primary tool for conducting experiments and validation tests. By implementing image preprocessing techniques to enhance image quality and applying precise segmentation methods, the CNN model is trained on a dataset of microscopic images to learn and classify STH infections effectively. The validation test results demonstrate that the CNN model achieved a high accuracy rate of 92.31% in classifying STH infections. This accuracy surpasses traditional methods, which are time-consuming and susceptible to human errors. This study underscores the importance of integrating artificial intelligence, particularly CNN, into the healthcare domain to support detecting and diagnosing diseases requiring specialized expertise, such as STH infections. The findings of this research can serve as a valuable reference for researchers, medical practitioners, and data scientists in leveraging artificial intelligence to enhance the quality of healthcare services, leading to positive impacts on society worldwide.

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1. INTRODUCTION

Soil-transmitted helminth (STH) infections are significant and pose a substantial global health problem, especially in impoverished nations with subpar sanitation and limited access to healthcare facilities [1]–[7]. STH is a group of parasitic worms commonly found in the soil that can infect humans through direct contact with contaminated soil or by consuming food or water contaminated with worm eggs [8]–[12]. Infections induced by STH are among the most widespread infections in the world, with an estimated 1.5 billion infected people or 24% of the world's population [2], [3], [12]–[16]. In Indonesia, STH infections remain a major concern due to close links with socio-economic conditions, personal hygiene, and environmental factors [12], [14], [17]–[20]. The prevalence of worm infections among children aged 1-12 years in several provinces is relatively high, ranging from 30% to 90% [13], [14], [21].

The primary challenge that this research attempts to solve is how inadequate the present approaches are for identifying infections caused by STH, especially in areas with poor resources and restricted access to medical care. Even though STH infections are quite common and have a big effect on public health, the methods of identification that are now in use have a lot of drawbacks [22]. These include laborious procedures, a high risk of human error, and inefficiency.

Despite the scale of the problem, early and accurate detection of STH infections is hindered by the time-consuming and labor-intensive nature of traditional microscopic image analysis which is crucial for reducing the disease burden and preventing serious complications that may arise from undetected infections [5], [16], [17], [23]. One commonly used detection method involves analyzing microscopic images of human stool samples, where the presence of worm eggs can be identified and counted [9], [24]–[26]. Although microscopic image analysis has proven effective in detecting STH worm eggs, the process often requires significant time and effort as it needs to be carried out by skilled personnel and may be prone to human errors. The need for skilled personnel increases the likelihood of human errors, underscoring the urgency for a faster and more automated approach. Therefore, a faster and more automated approach is needed for detecting STH infections in microscopic images [22].

Recent advancements in artificial intelligence, specifically convolutional neural network (CNN), offer a promising avenue for addressing this challenge. In the past decade, particularly CNN has shown great potential in image analysis. A perfect illustration of a neural network created artificially is CNN architecture, inspired by human visual processing and has been used advantageously to solve a variety of pattern recognition concerns, including medical image analysis. In the context of detecting STH infections in microscopic images, the use of CNN holds promising solutions [2], [15], [27]. By training CNN on properly annotated microscopic image datasets, the neural network can learn to recognize and distinguish STH worm eggs from other elements in the images efficiently. The anticipated outcome is an automated and efficient detection method that minimizes the need for manual intervention in the image analysis process.

This research aims to optimize the approach of STH infection detection using CNN on microscopic images. The practical use of CNN is anticipated to enhance diagnosis speed and accuracy while eliminating requirements of personal involvement across the image analysis process [28]–[31]. The results of this research are expected to make a significant contribution to efforts in preventing and controlling STH infections, especially in regions with high prevalence rates [5], [9], [23]. With an automated and efficient detection method, the handling of STH infections can be more timely and effective, thereby minimizing their negative impact on public health. Moreover, this research may pave the way for the application of artificial intelligence technology in other healthcare fields that require image analysis, with the potential to expand AI applications in the healthcare sector. The current research changes the path to highlight the urgent need for automation and innovation in the domain of STH infection diagnosis in light of these difficulties. The awareness of the shortcomings of current methods serves as a stimulus for promoting a paradigm change for the adoption of more sophisticated and effective techniques. It lays out an explicit path for the next portions of the research, which will concentrate on using CNN abilities to transform the field of STH infection identification in microscopic photographs.

2. RESEARCH METHOD

The research methodology employed in this study leverages the CNN method, a dynamic and evolving approach within the realm of image analysis and pattern recognition [32]–[34]. The CNN known as CNN, is strongly influenced by the manner in which human visual perception operates. This method has brought significant changes in various applications related to image processing, including in the health sector, such as detecting STH infection in microscopic images. CNN is designed to process image data in the form of a pixel matrix and study the patterns and distinctive features contained therein [35]–[39] In contrast to traditional methods that require manual feature extraction, CNN can automatically extract important features from images during the training process.

There are some notable issues in the context of our work that require further attention and research. The following crucial elements stand for open issues and areas that need improvement. Even though STH can be detected using CNN, our study still faces difficulties in automatically extracting pertinent features from microscopic pictures [22]. Improving the network's capacity to recognize and extract minor but important elements on its own might improve STH classification accuracy even more. In the context of STH classification, it is necessary to enhance the interpretability and explainability of CNN decisions because they function as intricate, opaque models. More confidence and acceptance of the suggested strategy in clinical settings would result from the development of techniques to clarify the reasoning behind CNN-based diagnoses [22].

In this research, utilizing a CNN for classifying STH is a direct and effective method, highlighting the desirability of transfer learning [37], [40]–[42]. This approach enables faster implementation with reduced code and complexity. This research example showcases seven straightforward steps for implementing the STH classification: dataset loading, dataset splitting into training and validation sets (80:20

ratio), dataset resizing to fit the CNN's input layer size, examination of the network to identify the feature learner and classification layer, modification of these layers as necessary, definition of training options, and finally, training the network. The methodology presented in this study delineates seven straightforward steps for the STH classification implementation. These steps are as shown in this research are i) load the dataset, ii) divide the dataset in an 80:20 ratio into training and validation datasets, iii) resize the dataset to match the input layer size of the CNN, iv) inspect the network and identify the feature learner and classification layer, v) modify the feature learner layer and classification layer as needed, vi) define training options, and vii) train the network.

By following these steps, the CNN can be effectively utilized for classifying STH, saving time, and effort in the implementation process. Figure 1 illustrates the overview of the transfer learning process. CNN will update its weights based on the values of each image pixel in the training dataset and perform a convolution process on each predetermined filter [43], [44]. Then the convolution results will be processed using the activation function and used as input for the next layer. This process will continue to repeat until, finally, the model is sufficiently precise to the desired level [30], [45]. Once the CNN model has been trained, it may be applied to new microscopic photographs to generate predictions [46]–[48]. The image to be predicted will go through the same process as the test dataset: the convolution process, the activation function, and the next layer to produce the predicted output. In detecting STH infection, the prediction output of the CNN model will show the probability of STH infection in the faeces images. If the probability is above a predetermined threshold, the image can be classified as an STH-infected stool image. Conversely, if the probability is below the threshold, then the image can be classified as a stool image that is not infected with STH. Our CNN-based STH detection technology must be translated into real-world clinical situations, which means real-time deployment and execution issues. To enable realistic, rapid implementations in healthcare settings, more research is needed to optimize the computational efficiency and resource requirements of the model. By acknowledging and actively seeking solutions to these unsolved problems and areas requiring improvement, our manuscript aims to contribute not only to the advancement of STH detection methodologies but also to the broader field of medical image analysis and artificial intelligence in healthcare.

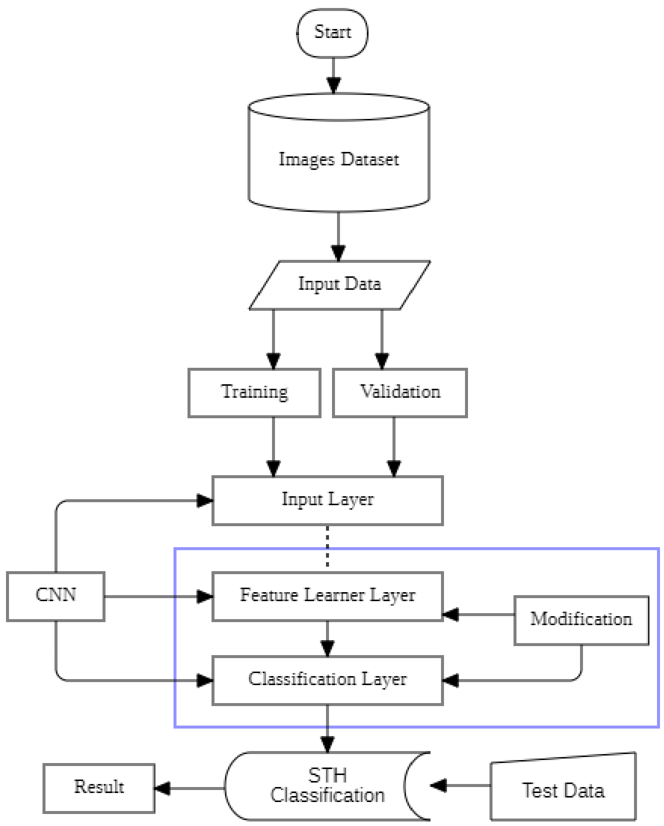

Figure 1. STH detection using CNN

3. RESULTS AND DISCUSSION

In this study, the CNN method can be used to detect STH infection in microscopic faeces images using processed faeces image datasets. The CNN model training process is carried out by updating the weights on each image pixel in the training dataset and performing a convolution process on each predetermined filter. After being trained, the CNN model can be used to make predictions on new faeces images by showing the probability of STH infection in the faeces images using the parameter shown in Table 1.

To test for the presence or failure to detect Ascaris lumbricoides, trichuris trichiura, and hookworm eggs in the faeces, descriptive cross-sectional MATLAB code was utilized in this experiment. The training and validation loss and accuracy graphs shown in Figure 2 provide insight into how a CNN model performs during the training and testing process. In this study, we have monitored the loss and accuracy graphs to understand to what extent the CNN model successfully recognizes and classifies STH infection on microscopic images using MATLAB. Figure 2 shows the accuracy graph of how the CNN model improves its ability to recognize STH infections over time. Initially, the accuracy value in training and validation may be relatively low because the model is not yet effective in classifying infections. However, as the epoch progresses, the accuracy increases as the model learns and improves the classification of STH infections.

Table 1. GoogleNet architecture parameter used

Parameter	Value
Mini batch size	5
Max epochs	6
Initial learn rate	0.0003
Optimizer	adam
Weight learn rate factor	10
Bias learn rate factor	10

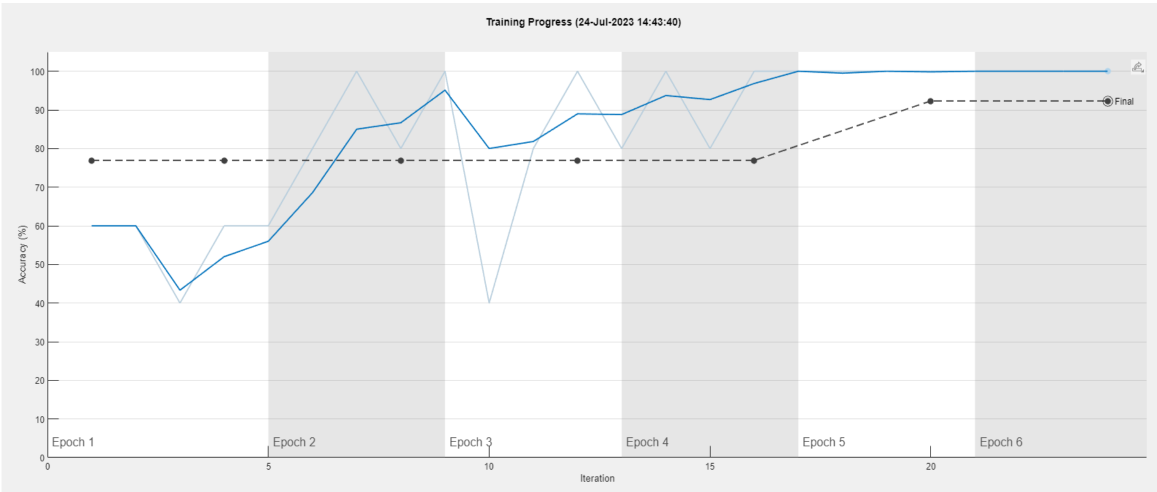

Figure 2. Training and validation of accuracy

The loss graph, as shown in Figure 3 is the change in the value of the loss function at each epoch during the training and validation process. At the beginning of training, the Loss value tends to be high because the model has not yet received a proper representation of the features of STH infection. However, as the epoch progresses, loss values gradually decrease as the model learns to recognize the distinctive patterns and features associated with STH infection.

From the training and validation graphs of loss and accuracy, we can conclude that the CNN model in this study successfully identified STH infection on microscopic images with a high degree of accuracy. The graph shows that the model effectively learns the characteristic features of STH infection and can classify them appropriately. In addition, high validation accuracy demonstrates the ability of the model to generalize to new data, highlighting the model's accuracy and dependability in spotting STH infection in general as shown in Figure 4.

CNN testing using MATLAB with training data of more than 1,500 images resulted in an accuracy rate of STH detection reaching 92.31%, as shown in Figure 3. The achieved accuracy of 92.31% demonstrates the efficacy of using CNN for detecting STH infections in microscopic images. This high accuracy rate showcases the CNN model's ability to learn and recognize distinctive features associated with STH worm eggs, enabling precise classification.

The accuracy level achieved in this study highlights the reliability of CNN for enhancing the efficiency and accuracy of STH infection detection. Compared to traditional methods, which often require manual intervention and may lead to errors, the CNN-based approach is more robust and less prone to human biases. Furthermore, the high accuracy rate achieved in this research indicates the possibility of employing this CNN model as an assistive tool for healthcare professionals. By automating the STH detection process, the CNN can potentially save valuable time and resources, eventually allowing prompt treatment and earlier, more precise diagnostics.

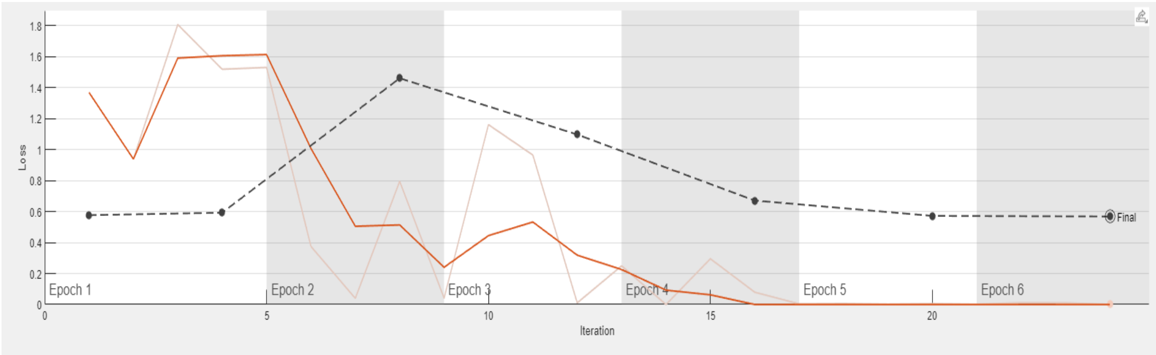

Figure 3. Training and validation of loss

Results	
Validation accuracy:	92.31%
Training finished:	Max epochs completed
Training Time	
Start time:	24-Jul-2023 14:43:40
Elapsed time:	11 sec
Training Cycle	
Epoch:	6 of 6
Iteration:	24 of 24
Iterations per epoch:	4
Maximum iterations:	24
Validation	
Frequency:	4 iterations
Other Information	
Hardware resource:	Single GPU
Learning rate schedule:	Constant
Learning rate:	0.0003

Figure 4. Result of training and validation loss and accuracy

4. CONCLUSION

Based on the results of the conducted research, it can be concluded that optimizing microscopic image detection of STH infection using a CNN is a highly promising and effective approach. By implementing image preprocessing techniques to enhance image quality and employing accurate segmentation techniques, the CNN model can identify and classify STH worm eggs in microscopic images with a high level of accuracy. The incorporation of clinical data, such as patient demographics and associated symptoms, could significantly enrich the context of STH infection detection. Integrating this information into the CNN model presents an area for improvement, potentially enhancing the diagnostic capabilities and contributing to a more holistic understanding of infection patterns. Using CNN to detect STH infections in microscopic images offers significant advantages over traditional methods that are time-consuming and prone to human errors. This technology provides a quick, accurate, and efficient solution for diagnosing STH infections, aiding in global disease control and management efforts. Furthermore, this research also highlights the importance of using artificial intelligence technology in healthcare, particularly in supporting the detection and diagnosis of diseases that require specialized expertise, such as STH infections. It is hoped that this study can serve as a valuable guide for researchers, medical practitioners, and data scientists in harnessing artificial intelligence to improve the quality of healthcare services and positively impact society globally.

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