Superior automatic screening for human helminthic ova by using self-supervised learning approach-based object classification

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**Abstract.** Human parasitic infections remain one of public health concerns for 1.5 billion people worldwide including Thailand. Conventional microscopic examination is a gold standard method and often used to identify the helminth ova and filariform larvae and also protozoa cyst in stool-dependent simple smear. The benefits of traditional techniques are diminished by time-consuming, complicated procedures, massive labor, and skilled and trained parasitologists. An automatically rapid screening of the most in need of treatment is considered to replace the conventional technique. Here, we aim to develop a deep convolutional residual network based self-supervised learning model to identify mostly common parasite ova in Thailand. Although small amounts of training data was used to train the proposed model, the result shows superior performance over 95% accuracy. As a result, low values of false positive and false negative based confusion matrix table found revealed the robustness of the proposed models. General accuracy of self-supervised learning based the area under a ROC curve proposed with greater than 94% is also support an outstanding model studied. Therefore, rank of 1% to 10% of fine-tuning data labelled used bring us about a comparable model to that of using a 100% labelled training data. The study's contribution is to implement it in remote areas where there is a lack of supportive lab equipment and skilled parasitologists. The deployment of an automatic screening device-based approach will hopefully help to aid clinical decision making of parasitic infections in patients.

**Keywords:** Helminthic eggs, Feature extraction, Similarity loss, Self-supervised learning, Object classification.

1. Introduction

Human parasitic infections remain one of public health concerns for 1.5 billion people worldwide including Thailand. The parasite can cause asymptomatic to severe conditions in gastrointestinal tract diseases (including abdominal pain, diarrhea, loss of appetite and malnutrition), and also affecting school-aged absent and developmental impairment in children. Specifically, more than 24% of global population affected soil-transmitted helminth (STH) infection, who’s commonly reported in Thailand such helminths (Ascaris lumbricoides, Hookworm, Strongyloides stercoralis, Taenia species and Opisthorchis viverrini) and pathogenic protozoa (Entamoeba histolytica, Giardia intestinalis and Blastocystis hominis) [1]. Several transmission modes of the parasite to human beings were reported which mainly include digestion of contaminated and uncooked food and drinking water and also skin contact with filariform larval stage. Life threatening by the pathogenic parasite infection can happen if not accurate diagnosis and treatment in time, especially in children, pregnant women, and immunocompromised patients.

Conventional microscopic examination is a gold standard method and often used to identify the helminth ova and filariform larvae and also protozoa cyst in stool-dependent simple smear. Genus and species characterization of pathogenic parasites can be conducted based on their morphology and structure [2]. Nevertheless, shared common traits and background interference (tissue-debris and colors) during microscopic observation led to mistaken identification. The benefits of traditional techniques are diminished by time-consuming, complicated procedures, massive labor, and skilled and trained parasitologists. An automatically rapid screening of the most in need of treatment is considered to replace the conventional technique.

Pattern recognition dependent pixel-wise classification to recognize any object with its structure, size, shape, and unique morphology is possibly used to overcome the conventional method described above. This pattern recognition technique is based on artificial intelligence (AI), machine learning (ML), and deep learning (DL) to compile with a whole slide scanner to help transfer the public-health services. ML is a scientific study of algorithms that deal with input under independent two-processes including feature extraction by engineer and learning transference by convolutional neural network (CNN). Previous study was proposed by [3] to characterize eggs of helminths, namely capillaria species deposited in institutional collections, by using logistic model tree algorithm combining with the majority voting algorithm resulting in high metric values [4]. DL, a current next generation of ML that both feature engineering and CNN learning are operated within a computerized system, was used to study 34 human parasite species based on various algorithm versions of You Only Look Once (YOLO). There are not only the proposed trained-model used to deal with the largest datasets, but state-of-the-art model also revealed performance with superior to localize and classify the helminths and protozoa with greater than 95% of both recall and precision, respectively [2].

The most effective and practical ML and DL applications tend to be supervised learning that requires a large sample size and high-quality trustworthy labels by skilled and trained doctors such as medical X-ray, CT scan, or MRI images. Self-supervised learning prone to a promising approach due to the technique can learn a bunch of datasets needing small proportions of labels ranging 1% to 10% of total data. Several self-supervised learning applications in a medical sector mainly used for histopathological images of cancer types [5]. These proposed the technique to estimate and diagnose interstitial pneumonia with a progressive course and poor prognosis due to poor reproducibility by pathologists reported [3]. The research result gave the prediction of pneumonia and a finding suggestive of progressive disease with high accuracy and AUC at 0.86. In addition, the classification of benign and malignant cells in lung cytological images with a weakly supervised deep learning method was also provided outstanding with 91.67% accuracy which comparable to senior and junior cytopathologist who have 98.34% and 83.34%, respectively [6]. As a result, the types of explainable AI can collaborate with human.

Here, we aim to develop a deep residual neural network based self-supervised learning model to identify mostly common parasite ova in Thailand. The contribution of the study is to implement it in remote areas where there is a lack of supportive lab equipment and skilled parasitologists.

1. Architecture

**Fig. 1.** Process Overview. The BYOL process (green box) generates a pre-trained weight file utilized in the fine-tuning of a new classification model (yellow box). The traditional supervised learning method is depicted in the blue box for comparative purposes.

The green box (see Fig. 1) is the part of self-supervised learning (SSL) based the BYOL method [7]. During the process, the data loader required the Nvidia-DALI to assist it as the data input step. Second part of the SSL, the pre-trained weight (an output) would be used to fine-tune the selected classification model by using new labels during training in the down steam section. In our study, we designed two-experiments to find the suitable model and also adjust the cost and effect amount of training data. Accompanying the protocols above, the first experiment was done by comparing their model performance between the combination of pre-trained weight connecting to fine tune the classification models and an individual classification model, the ResNet backbones. In the second experiment, we want to find appropriate amount of training data in the downstream step to fine-tune the selected classification models, ResNet versions. Therefore, 1%, 10% and 20% of the labelled-training data were studied. Also, the compared result between that obtained from the second experiment and the single classification one could tell us the whether SSL is beyond the result of supervised learning (SL) model.

1. Materials and Method
   1. Dataset collection

All image data used in this studied were obtained from public dataset with url[[1]](#footnote-1) [8]. Totally, 11-classes were recruited including Ascaris lumbricoides, Capillaria philippinensis, Enterobius vermicularis, Fasciolopsis buski, Hookworm egg, Hymenolepis diminuta, Hymenolepis nana, Opisthorchis viverrini, Paragonimus spp., Taenia spp., and Trichuris trichiura. The microscopic images were obtained at two different magnification levels: 100× and 400×. Given the wide range of image ratios resulting from these different magnifications, we decided to focus on the specific objects of interest. To do so, we expanded the bounding box around each object by a factor of 1.2, which allowed us to effectively crop the images to just the region of interest. The cropped images were then resized to a standard dimension of 608 × 608 pixels and saved in the PNG format using square padding (see Fig. 2). In general, each class of parasites could be uniquely identified based on a combination of features such as the color of their egg-shell, the presence of certain organelles, and their size and shape [2].

**Fig. 2.** Genus and species of 11-helminth classes used in this study.

We started with a dataset comprising 13,228 images. For initial training, a BYOL model utilized 8,800 of these images. Fine-tuning of this model was accomplished via a classification approach, using smaller subsets (1%, 10%, and 20%) of the training data. A batch of 2,200 images was earmarked for validation purposes. Model performance was assessed using a distinct set of 2,228 images for testing, and the results were benchmarked against a full data supervised learning model.

**Table 1.** Distribution of image datasets in Supervised Learning (SL), Self-Supervised Learning (SSL), and fine-tuning processes.

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| Name | Processes | Label | Training | Validation | Testing |
| Dataset 1 | SL | Yes | 8,800 | 2,200 | 2,228 |
| Dataset 2 | SSL | No | 8,800 | - | - |
| Dataset 3 | Finetune | Yes | 1% of Data 1 | 2,200 | 2,228 |
| Dataset 4 | Finetune | Yes | 10% of Data 1 | 2,200 | 2,228 |
| Dataset 5 | Finetune | Yes | 20% of Data 1 | 2,200 | 2,228 |
| Dataset 6 | Finetune | Yes | 100% of Data 1 | 2,200 | 2,228 |

As seen in Table 1 presents a summary of how image datasets were distributed for various learning processes - Supervised Learning (SL), Self-Supervised Learning (SSL), and fine-tuning. In the 'Processes' column, the approach used for each dataset is identified. The 'Label' column indicates whether the data used in that process was labeled or not.

Dataset 1 was utilized for SL and involved labeled data. It comprised 8,800 images for training, 2,200 for validation, and 2,228 for testing.

Dataset 2, used for SSL, also contained 8,800 images for training. However, as SSL doesn't require labeled data, there was no validation set for this process.

Datasets 3, 4, 5, and 6 were all used in the fine-tuning process with labeled data. They differed in the proportion of Dataset 1 they incorporated for training 1%, 10%, 20%, and 100% respectively. Each of these datasets used 2,200 images for validation and 2,228 images for testing.

3.2 Self-supervised learning and model training

BYOL algorithm of the self-supervised learning was used to accomplished our tasks, due to, its performance showed a greater than contrastive model (one of the state-of-the-art) [7]. We used three-ResNet versions to be our backbone, ResNet-50, ResNet-101 and ResNet-152 layers. As described as above, the well-pretrained weight file could be roughly assessed its performance by using the dimension reduction technique, namely Uniform Manifold Approximation and Projection (UMAP) to visualize the result of datapoint clustering. If the datapoints per class formed within a compact cluster, the pretrained weight would reach the excellent result at the downstream process finished (see Fig. 1).

### Solo-learn. library equipped with various self-supervised learning algorithms, useful for machine learning tasks. Its synergy with Nvidia DALI, a tool for data management, allows it to efficiently handle data input, streamline preprocessing pipelines, and manage hyperparameters. Nvidia DALI also accelerates computations, contributing to quicker model training and inference. The combination of Solo-learn with Nvidia DALI provides an efficient environment for visualizing and implementing self-supervised learning methods, ensuring high-quality learning representations and optimal model performance [9].

### Configuration. Our training condition of the SSL were described in Table 2. The condition comprised of using Nvidia DALI for data formatting and no required for data labelling. We fed batch size of 64, Tau base of 0.99, Tau final of 1.00, learning rate of 0.125, maximum epochs of 6000 and using Lars as for the optimization step. Almost parameters used were the same, except for the residual neural network backbone. In brief, we did vary the ResNet versions to find the suitable one for output representation.

**Table 2.** Hyperparameters and settings used in the Self-Supervised Learning (SSL) processes.

|  |  |
| --- | --- |
| Parameter | Value |
| Backbone | ResNet-50, ResNet-101, ResNet-152 |
| Data Format | Nvidia DALI |
| Label | No |
| Batch Size | 64 |
| Tau base | 0.99 |
| Tau final | 1.00 |
| Learning rate | 0.125 |
| Maximum epochs | 6000 |
| Optimizer | Lars |

### Loss in BYOL. Loss of BYOL method used is mean squared error by difference between L2 normalized online and target networks representations (see Fig. 1) [7].

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Model can be used to initially observe the graph of training loss to see if whether it reached the saturation. Briefly, as seen in Fig. 3 the first 2000 epochs gave an increasing of the trending line. Then, swing line represented for non-saturated training found during the epochs of 2000 to 4000. We observed it reached a steady state during 5000 epochs to 6000 epochs of the training phase and inferring the optimum training (see Fig. 3).

**Fig. 3.** Training loss of backbone ResNet-50, ResNet-101 and ResNet-152

### Dimension reduction. We used UMAP to achieve a hypothesis whether the pre-trained model has the capacity to differentiate to do clustering analysis of all datapoints per class. The UMAP of the ResNet-50 and ResNet-101 showed the most compact clustering of the datapoints more than ResNet-152(see Fig. 4). Therefore, both models may be evident of the similar performance in finding features and making a classification.

**Fig. 4.** UMAP of ResNet-50, ResNet-101, ResNet-152, respectively.

Downstream task and Supervised Learning (SL). The downstream task, set as a classification problem, was managed by a neural network fine-tuned with subsets of our labeled Dataset 1. This process initiated after the pre-training phase, in which we utilized the Bootstrap Your Own Latent (BYOL) method. Model architectures based on ResNet-50, ResNet-101, and ResNet-152 were employed, all fine-tuned with 11 helminthic labels. We used four subsets of Dataset 1 for this fine-tuning process: Dataset 3 (1% or 88 images), Dataset 4 (10% or 880 images), Dataset 5 (20% or 1,760 images), and Dataset 6 (100% or 8,800 images). Each subset was supplemented with 2,200 validation images and 2,228 testing images. In parallel, Supervised Learning (SL) was established as a benchmark process, where Dataset 1 was applied for training (8,800 images), validation (2,200 images), and testing (2,228 images). The comparison of the downstream task and SL allowed us to gauge the effectiveness of our fine-tuning approach versus traditional supervised learning, thereby helping us discern the optimal learning method and the ideal volume of training data required. The configurations used in our experiments are detailed in Table 3.

**Table 3.** Hyperparameters and settings used in the Supervised Learning (SL) and fine-tuning processes.

|  |  |
| --- | --- |
| Parameter | Value |
| Backbone | ResNet-50, ResNet-101, ResNet-152 |
| Data Format | Sub Folder |
| Label | Yes |
| Batch Size | 32 |
| Loss function | Cross-entropy |
| Learning rate | 0.0001 |
| Maximum epochs | 500 |
| Optimizer | Adam |

**Fig. 5.** Training accuracy and training loss of trained ResNet-50, ResNet-101, ResNet-152 algorithms. Each trained model was shown by small amounts of training data used including 1% and 10% of self-supervised learning approaches which is compared to that of a supervised learning model.

3.3 Evaluation metric

The optimized trained model were then evaluated its quality performance to detect the intestinal helminthic objects from testing image set (see Fig. 5). The confusion matrix table was used to assess the statistical metric of precision, recall, specificity, F1 score and general accuracy [10]. All analyzed four interpretation values retrieved from the confusion matrix table as follow; true positive (TP), true negative (TN), false positive (FP), and false negative (FN), respectively. These values were used to calculated four statistical metrics as follow;

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Receiver Operating Characteristic (ROC) curve was plotted based Scikit-learn library under python software version. An area under the ROC curve (AUC) calculated based 95% confident interval was revealed the generalized accuracy of the proposed trained model.

1. Results

Accompanying the procedure in material method section, the classification model and the pre-trained weight were fine-tuned by 11-helminthic labels. The quality performance of the trained models was initially assessed by using the confusion matrix table as follows;

In the confusion matrix table, the intensified diagonal pattern (from left to right) represented high degree of the TP values of each trained models found (see Fig. 6). Although the trained SL approaches seem to have a better pattern of TP values than the SSL approaches, the trained SSL has less training data than the SL, emphasizing the remarkably cutting-edge technique. Observing the results visually, it is clear that the SSL-ResNet-101 and SSL-ResNet-152 models outperform the SSL-ResNet-50 model. Although SL models appear to be superior to SSL, the SSL can be compared to the SL since all trained-SSL with merely 10% training data produced low FN and FP values.

* 1. General accuracies by confusion matrix tables

**Fig. 6.** Confusion matrix tables. The table show quality performance of trained SSL ResNet model versions and also represent them based on amounts of training data. Intensified color is positively correlated to degree of TP values.

Statistical metrics were calculated to measure the quality performance of the SSL and SL models based the ResNet backbones. Considering all metrics used in the SL, there are 82%, 91%, 97.9%, 99.1% and 87.7% of recall, precision, accuracy, specificity and F1 score, respectively (see **Error! Reference source not found.**). This suggested that SL-ResNet-152 is outstanding model. For our datasets, we found that the greater the number of convolutional layers, the higher the degree of all statistical metrics.

In SSL model, the performance of various training data based ResNet models is sporadic (see Table 4). For 1% training data, the ResNet-50 showed great value of 95.6% accuracy, 86.7% precision, and 99.1% specificity, the ResNet-101 for 66.6% recall and 74.4% F1 score, and the ResNet-152 for 96.2% accuracy.

For 10% training data, only ResNet-50 and ResNet-101 models gave highest value at 78.5% recall, 92.5% precision, 97.7% accuracy, 99.3% specificity and 87.9% F1 score.

For 20% training data, most statistical metrics at 97.7% accuracy, 99.1% specificity and 86.3% F1 score were measured from both the ResNet-101 and ResNet-152 models, respectively. Only two statistical metrics of 80.4% and 91.3% precision was obtained from the ResNet-101 model. In summary, significant correlation between the small amounts of training data ranging 1% to 10% and ResNet-50 and ResNet-101 models was observed. During limitation of biological variation and quality of its labels, these uncontrolled factors might be solved by using only 1% of the training data and then results in 86.7% precision, 96.2% accuracy and 99.1% specificity, respectively. The result indicated that the SSL technique is moving forward to undergo the opened-world datasets which are mostly unlabeled as effective.

**Table 4.** Evaluation metrics including recall, precision, accuracy, specificity and F1 score, respectively.

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| Evaluation metrics | Models | SSL | | | SL |
| **1%** | **10%** | **20%** | **100%** |
| Recall | ResNet-50 | 0.580 | **0.785** | 0.788 | 0.775 |
| ResNet-101 | **0.666** | 0.775 | **0.804** | 0.775 |
| ResNet-152 | 0.661 | 0.780 | 0.803 | **0.819** |
| Precision | ResNet-50 | **0.867** | 0.923 | 0.898 | 0.875 |
| ResNet-101 | 0.855 | **0.925** | **0.913** | 0.875 |
| ResNet-152 | 0.852 | 0.906 | 0.908 | **0.910** |
| Accuracy | ResNet-50 | 0.956 | **0.977** | 0.975 | 0.972 |
| ResNet-101 | 0.960 | 0.976 | **0.977** | 0.972 |
| ResNet-152 | **0.962** | 0.974 | **0.977** | **0.979** |
| Specificity | ResNet-50 | **0.991** | 0.992 | 0.990 | 0.988 |
| ResNet-101 | 0.986 | **0.993** | **0.991** | 0.988 |
| ResNet-152 | 0.988 | 0.990 | **0.991** | **0.991** |
| F1 score | ResNet-50 | 0.679 | **0.849** | 0.851 | 0.835 |
| ResNet-101 | **0.744** | 0.842 | **0.863** | 0.835 |
| ResNet-152 | 0.740 | 0.843 | **0.863** | **0.877** |

* 1. Performances of various models

In consistent to those described as above, the AUC supported the performances of 10% of training data-based SSL-ResNet-50 (AUC = 0.944) and SSL-ResNet-101 (AUC = 0.946) model revealed outperform when comparing to others (see Fig. 7). Interestingly, only 1% of training data reproduced the AUC equal to 89.9%, which suggesting high enough to employ the trained model in a real situation. The idea was supported by the result seen in Fig. 8. Also, the positive correlation between 10% of training data-based SSL-ResNet-101 model was shown (see Fig. 8). Although the utilization of small neural network layers by the ResNet-50 model was trained with 1% data, the AUC still showed similar result to SL model. This indicated that the SSL technique is superior to the SL model.

**Fig. 7.** ROCs for assessing general accuracy of supervised comparing to self-supervised models.

**Fig. 8.** Comparison of AUC among SSL against SL models. We highlighted small amounts of labelled training data ranking 1% to 10%.

1. Discussion and conclusion

In this study, 11-common human-helminthic eggs in Thailand were automatic screening by using self-supervised learning approach. As workflow and architecture, our proposed algorithm contained two main components, namely online network that function to prepare feature extraction without class labelling and do data clustering-based similarity loss function. In our experiment, then, the result from previous section were used to do classification under labelling with multiclass-classification processes. Remarkably, the model trained with the advanced BYLO method outperformed the supervised learning model using ResNet. This was achieved even when a small fraction of the dataset, ranging from 1% to 10%, was employed for training and validation, highlighting the efficiency of the BYLO method in leveraging limited data resources. As mentioned as above, SSL approach for classifying our unseen image dataset is comparable to previous works based only on object detection [10-12], suggesting the superior model to supervised ones. This is because our SSL approach used trained data less than and equal to 10% of training data and reveal ranging of 87% to 99% accuracy, precision and specificity, respectively. According to the result mentioned as above, it can be assured that SSL is beneficial to solve the biological and medical tasks with still affecting by some serious issues such as high variation and a large amount of deposited data such as chest X-rays, CT-scans, MRI images, and whole slide images which these had been intensively investigated based on supervised learning network. In addition, the corrected prediction result of supervised learning model is depending on sample size with needs qualitative labels by expert clinicians [13, 14]. If the trained model was consumed garbage labels, the results would give the garbage output found.

Nevertheless, the training SSL model might experience with some limitations such as well-trained model could require the numbers of feature extracted and the more number feature vector such as either 1024 or 2048 vectors, the higher performance received than less one such as 64 vectors. Furthermore, even though the SSL approach uses a smaller sample size with less data labeling during training and validation, the optimized model required a potential region with high variation[15]. Nevertheless, this step could be fixed by implementing the augmentation function before doing training data. Lastly, computational speed still requires, specifically training with a large validation.

In conclusion, we proposed the outstanding the classification algorithm-based SSL approach to solve the biological and medical tasks including a large unstructured/ structured data. In Thailand, incidence of human helminth infection is currently reported along rural area from several sources such as Thai’s CDC, ministry of health and also academic publications. Although, current anti-helminth drugs are available with convenient accessible at any drug store, ignorant behavior for stool examination during annual check-up and traditional meal with raw cook remains an existing transmission of the parasite in Southeast Asian countries. Automatic screening device (for example; smartphone application) based deployed SSL approach is new hope to support the clinical-decision making in remote area where is lack of expert technicians.

Competing interests

The authors declare no competing interest.

Data availability

The data that support the findings of this study are upon requested to the corresponding author.

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**Author’s contribution.**

N.P., and S.C. conceived and designed the research study; N.P., and V.K. wrote the manuscript; N.P. performed the computational experiment; N.P., V.K., S.C., and S.B. performed data analysis; N.P., R.J., K.J., and S.C. collected data; T.T., S.C. and S.B. conducted the computer’s platform. S.B., and S.C. read and approved the final manuscript.

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