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Essential Advances in Soil-Transmitted Helminth Detection Using Machine Learning and Deep Learning: A Systematic Review

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***Abstract*—Soil-Transmitted Helminths (STH) infection remains a significant global health challenge, particularly in regions with inadequate sanitation. While precise early detection is crucial, conventional techniques like microscopy require substantial time and accuracy. This work rigorously examines recent developments in STH detection utilizing machine learning and deep learning techniques. This study pertains to articles published from 2014 until 2024. During the literature selection process utilizing the PRISMA Method, 26 pertinent articles were extracted from the Google Scholar, PubMed, IEEE Xplore, and Scopus databases. The findings indicated that notably Convolutional Neural Networks (CNN) and U-Net algorithms exhibited markedly superior detection accuracy (95-98%) relative to Support Vector Machines (SVM) and Random Forest (RF) (87-92%) respectively. SVM and RF exhibit superior speed but diminished accuracy when applied to tiny datasets. Moreover, there exists significant potential to boost model performance and address data constraints using transfer learning and data augmentation techniques. This study demonstrates that the integration of artificial intelligence with the Internet of Things (IoT) facilitates expedited and more efficient surveillance through real-time detection of STH in endemic regions. Moreover, crowdsourcing and self-supervised learning (SSL) have emerged as methods for the acquisition of annotated data. Significant recent advancements in machine learning and deep learning technologies forecast expedited, more precise, and scalable STH diagnosis in the future. This can be utilized in future global health surveillance, despite limitations such as restricted data and computational resources.**

***Keywords*—Detection; Soil Transmitted Helminths (STH); machine learning; deep learning; convolutional neural networks.**

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I. Introduction

Soil-transmitted helminthiasis (STH) remains a significant global health problem, especially in tropical and subtropic regions with poor sanitation and limited access to clean water, affecting more than 1.5 billion people worldwide, predominantly in low- and middle-income countries [1],[2], are affected, leading anemia, nutritional disorders, and cognitive developmental impediments in children [3],[4],[5].

These parasitic infections, caused by intestinal worms like Ascaris lumbricoides, Trichuris trichiura, and hookworm, pose a significant global health burden, disproportionately affecting vulnerable populations, particularly children [6]. Despite progress in global control efforts, achieving WHO's Soil-Transmitted Helminth (STH) elimination targets necessitates innovative and enhanced diagnostic approaches [7].

Conventional diagnostic methods for Soil-Transmitted Helminths (STH), such as the Kato-Katz technique, remain widely used but have sensitivity limitations, particularly in detecting low-intensity infections. This limitation may lead to inaccurate estimates of the actual disease burden, hindering effective control efforts [8]. Traditional diagnostic approaches rely on chemicals, posing environmental and health risks [9]. Additionally, these methods require time-consuming procedures, specialized expertise, and fresh fecal samples, increasing subjective error risks and limiting standardization [10], [11]. These constraints compromise result accuracy and efficiency [12].Consequently, developing more accurate, efficient, and accessible diagnostic methods is imperative.

Machine learning (ML) and deep learning (DL) have transformed various fields, including medicine, by identifying complex patterns in previously undetectable data using artificial neural networks. In soil-transmitted helminth (STH) detection, ML and DL enable automated microscopic image analysis, enhancing diagnostic accuracy and efficiency

[6],[8],[13],[14], particularly in the resource-constrained settings [15],[16]. Furthermore, deep learning algorithms demonstrate exceptional accuracy in detecting helminth eggs, even at low intensities, surpassing traditional methods [17],[18],[19]. The development of AI-powered point-of-care diagnostics facilitates rapid and accurate field diagnosis [20]. Moreover, integrating multi-modal data using AI techniques improves the sensitivity and specificity of STH diagnosis, revolutionizing technology-based detection methods [18]. Given the advantages of machine learning (ML) and deep learning (DL) methods, their use is significantly superior to traditional methods in STH detection.

Artificial intelligence (AI)-based methods, such as digital pathology (AI-DP), are more sensitive in detecting soil-transmitted helminths (STH) infections compared to traditional microscopy. One example is the application of AI-DP based on the Kato-Katz method (KK2.0), which is more effective in detecting Ascaris lumbricoides than the traditional Kato-Katz method (KK1.0) [21]. Additionally, Convolutional Neural Networks (CNN) achieved 92.31% accuracy in classifying STH infections, significantly outperforming traditional methods in terms of speed and reliability [22]. Furthermore, another study showed that deep learning (DL) algorithms identified Trichuris spp. eggs with an average precision of 98.44% and recall of 80.94%, highlighting DL's potential to achieve high detection accuracy [23].

However, although AI and DL offer great potential, their application in STH diagnostics still faces several challenges. Among these are, notably, the lack of quality datasets for model training, variations in microscopic image quality, and the need for algorithm validation across diverse endemic conditions [17], [24]. While many studies have developed detection systems for STH using machine learning (ML) and deep learning (DL), a comprehensive systematic review examining trends, developments, and effectiveness of these approaches between 2014-2024 remains absent. This period was chosen because it spans rapid growth in medical deep learning applications, notably featuring advances in neural network architectures and image pre-processing techniques.

This comprehensive review focuses on identifying technology trends, evaluating the effectiveness of various approaches, and forecasting emerging trends. Technical aspects reviewed include comparisons of neural network architectures, preprocessing techniques, data augmentation strategies, and validation methods. This review examines theoretical foundations and real-world clinical implementation, analyzing technical challenges and solutions. The results aim to provide a roadmap for developing accurate and applicable STH detection systems and serve as a reference for optimizing AI technology in parasitological diagnosis.

II. Materials and Methods

This Systematic Literature Review (SLR) follows the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) 2020 guidelines [25] to ensure transparency and quality reporting. These guidelines assist authors in preparing systematic review protocols, as evidenced by studies showing better reporting in PRISMA-enabled journals compared to those that do not [26]. This study organizes research questions using the PICOC framework (Population, Intervention, Comparison, Outcome, Context), as outlined in Table 1.

1) *Population:* An article investigating Soil-Transmitted Helminths (STH) detection using machine learning and deep learning technologies. STH microscopic image dataset

2) *Intervention*: Machine learning and deep learning algorithms are employed for STH detection via microscopy image analysis, leveraging neural network architectures, classification, and detection algorithms**.**

3) *Comparison***:** Assessing the accuracy and reliability of various machine learning and deep learning approaches for detecting STH

4) *Outcome*: Evaluating STH detection accuracy, efficiency, and speed.

5) *Context*: The research scope includes international studies published over the last 10 years.

TABLE I
Research Question

RQ	Question
RQ1	What developments have occurred in soil-transmitted helmet (STH) detection techniques using machine learning and deep learning in recent years?
RQ2	What ML/DL algorithms are most commonly used, and how effective are they?
RQ3	What algorithms, research focuses, accuracy, precision, and recall rates are employed in Machine Learning/Deep Learning-based helminthiasis detection?
RQ4	What are the current trends in Deep Learning applications for Soil-Transmitted Helminths detection, and what future developments can be anticipated?
RQ5	What potential synergies exist between Machine Learning and emerging technologies like IoT or smart sensors for enhanced Soil-Transmitted Helminths detection?

A. Data Search Strategy

The research commenced with an exhaustive literature search utilizing Publish or Perish, aggregating data from prominent academic databases (PubMed, IEEE Xplore, Scopus). The search strategy employed Boolean operators, combining three core concepts: Soil-Transmitted Helminths (STH), Artificial Intelligence (AI), and detection methodologies. It focused exclusively on English-language journal articles and conference proceedings.

The initial search query combined 'soil-transmitted helminth' with ('machine learning' OR 'deep learning') and 'detection'. To enhance comprehensiveness, synonyms, related terms, STH species ('Ascaris lumbricoides', 'Trichuris trichiura', 'hookworm'), and AI/ML techniques ('CNN', 'YOLO', 'U-Net', 'transfer learning') were incorporated. Search parameters filtered articles with ≥1 citation, sorting results by publication year.

Search results were exported in BibTeX and CSV formats with full metadata. Each search stage was documented, including date, results, h-index, and citation counts. Quality control measures included cross-validation, peer-review verification, methodology evaluation, and reference management. This systematic search informs an in-depth analysis of AI-based STH detection system development, identifying trends, challenges, and opportunities.

B. Inclusion and Exclusion Criteria

Article eligibility was determined based on predetermined inclusion and exclusion criteria (Table 2), ensuring selected studies aligned with the research objectives

TABLE II
INCLUSION AND EXCLUSION CRITERIA OF THE STUDY

Inclusion	Exclusion
Focus on Soil-Transmitted Helminths (STH) detection	In addition to **STH** detection
Utilizes Machine Learning, Deep Learning, or AI.	Irrelevant topics.
Discusses STH detection methodologies beyond traditional laboratory methods.	Studies focusing solely on traditional laboratory methods.
Journal articles, systematic reviews, literature reviews, or meta-analyses.	Non-journal article formats (e.g., reports), Incomplete article.
Abstract and keywords alignment, at least one citation.	Abstract and keywords mismatch.
Published within the last 10 years, English language.	Articles older than 10 years, non-English articles.

III. RESULTS AND DISCUSSION

Our PRISMA-guided search (2013-2022) yielded 1,036 articles: Scopus (n=21), PubMed (n=5), IEEE (n=10), and Google Scholar (n=1,000) (Figure 1). Title and abstract screening reduced the total to 34 articles meeting inclusion criteria: Scopus (n=16), Google Scholar (n=10), IEEE Xplore (n=5), and PubMed (n=3). Access constraints (paywalls, institutional limitations) primarily drove this reduction. Full-text evaluation and stringent eligibility criteria (population, intervention, study design, language) further narrowed the dataset to 31 articles. Ultimately, 26 articles underwent full-text analysis and were included in the final analysis.

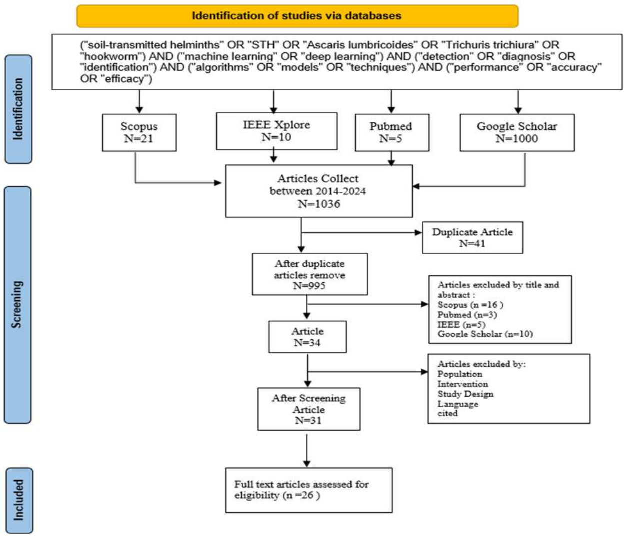

Fig. 1 Result of finding articles using PRISMA

A. Publication Database Trends

Addressing Research Question 1 (RQ1), Figure 2 presents significant variations in published research quality and focus. Among 26 analyzed publications, 15% originated from IEEE Xplore, 50% from Scopus, 35% from Google Scholar, and 0% from PubMed due to zero citations. This distribution highlights technical databases (IEEE Xplore and Scopus) dominance in Soil-Transmitted Helminths (STH) detection research, complemented by Google Scholar's substantial contribution. This reflects interdisciplinary involvement from engineering, medicine, and public health.

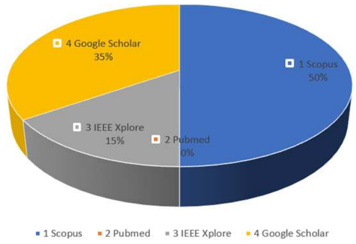

Fig. 2 Results Based on Publication Database

B. Results Based on Algorithm

Figure 3 addresses Research Question 2 (RQ2), identifying the optimal algorithm among 26 articles as Convolutional Neural Networks (CNN), which demonstrated superior accuracy and performance in detecting Soil-Transmitted Helminths (STH). CNN is frequently employed for image and fecal sample processing, outperforming other algorithms in pattern recognition and classification. Several studies compared various algorithms to determine the most efficient model, considering factors like accuracy, processing time and generalizability on larger datasets (Table 3). This trend indicates increasing adoption of deep learning methods, particularly CNN, to tackle data complexity and achieve optimal STH detection results.

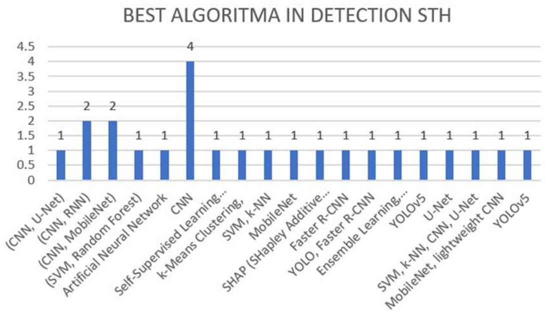

Fig. 3 Research Trends by Algorithm

Table 3 presents studies utilizing various methods and algorithms for STH detection, particularly helminth eggs and related diseases, through image processing and machine learning technologies. Various methods are employed, including deep learning approaches (CNN, YOLO, MobileNet) and classical machine learning techniques (SVM, k-NN, Random Forest). Each method has unique strengths, depending on data types and application requirements. The CNN algorithm used for STH egg detection with Whole Slide Imaging (WSI) achieves high accuracy (95-98%) and excellent recall (96%), making it a popular choice for large-scale medical image analysis.

In contrast, color clustering-based methods (k-Means) are faster but exhibit lower accuracy and sensitivity to lighting conditions, limiting their field applications. Techniques like YOLOv5 excel in real-time detection, offering high speed and accuracy, making them ideal for practical field-based parasite detection applications addressing RQ4.

TABLE III

ALGORITHM, RESEARCH FOCUS, ACCURACY, PRECISION AND RECALL

No.	Ref	Algorithm Used	Research Focus	Detection Accuracy, Efficiency, and Speed	Accuracy, Precision, and Recall
1	[21]	CNN, Whole Slide Imaging (WSI)	Automatic detection and quantitation of STH eggs using digital images.	High, can detect objects with high efficiency in large datasets.	Accuracy: 95-98%; Precision: 94%; Recall: 96%
2	[27]	k-Means Clustering, color analysis (RGB, HSV, LAB, YCbCr)	Rapid segmentation of STH eggs with color-based clustering.	High speed, but accuracy is sensitive to lighting quality.	Accuracy: 85-90%; Precision: 80%; Recall: 85%
3	[28]	SVM, k-NN, texture feature analysis (GLCM)	Comparing the accuracy of feature-based classification.	Medium efficiency, sensitive to selected features.	Accuracy: 80-88%; Precision: 82%; Recall: 78%
4	[29]	MobileNet, lightweight AI	Mobile-based diagnostics in resource-constrained areas.	High speed and efficiency due to lightweight design for mobile devices.	Accuracy: 90-93%; Precision: 91%; Recall: 89%
5	[30]	SHAP (SHapley Additive exPlanations)	Interpretability of machine learning models for STH detection.	It does not focus on the speed of detection, but on the interpretation of the model results.	Depending on the main ML model being evaluated.
6	[31]	Neural Networks (Faster R-CNN)	Location-based identification through neural networks.	High efficiency for complex datasets with many objects.	Accuracy: 93-96%; Precision: 94%; Recall: 92%
7	[32]	YOLO, Faster R-CNN	Automated detection of parasite eggs in microscopic images.	Ultra-fast detection with YOLO, suitable for real-time applications.	Accuracy: 94-97%; Precision: 95%; Recall: 93%
8	[33]	Ensemble Learning, Crowdsourcing	Combined collective annotation and AI for model training.	Speed depends on the quality of crowdsourced annotations, efficiency increases with more data.	Accuracy: 88-92%; Precision: 89%; Recall: 90%
9	[34]	YOLOv5	Real-time parasite egg detection.	Fast and efficient for large-scale data.	Accuracy: 95-98%; Precision: 96%; Recall: 95%
10	[35]	U-Net	Semantic segmentation for intestinal parasite detection and classification.	Moderate speed due to model complexity, high efficiency on large datasets.	Accuracy: 92-95%; Precision: 93%; Recall: 91%
11	[17]	CNN, digital pathology	Digital-based detection of neglected tropical diseases.	High efficiency and accuracy, suitable for large-scale implementation.	Accuracy: 93-96%; Precision: 94%; Recall: 93%
12	[36]	SVM, k-NN, CNN, U-Net	Comparison of classical ML and DL methods for parasitic egg segmentation.	The speed of DL (CNN, U-Net) is higher than classic ML.	Accuracy: 85-95%; Precision: 88%; Recall: 86%
13	[37]	CNN	Classification of Ascaris lumbricoides parasite eggs using deep learning.	Fast for large datasets, high accuracy.	Accuracy: 92-96%; Precision: 94%; Recall: 92%
14	[38]	MobileNet, CNN lightweight	Lightweight and efficient mobile device-based diagnostics.	Very high efficiency, designed for field implementation.	Accuracy: 91-94%; Precision: 93%; Recall: 90%
15	[34]	YOLOv5	Rapid detection of parasite eggs based on deep learning.	Detection is extremely fast and accurate, ideal for real-time applications.	Accuracy: 95-98%; Precision: 96%; Recall: 94%
16	[39]	Self-Supervised Learning (SSL) with DinoV2-Distilled Models	Parasite classification using unlabeled visual representations.	High efficiency as it does not require manual annotation, speed depends on ViT architecture.	Accuracy: 92-97%; Precision: 93%; Recall: 94%
17	[40]	Deep Learning (CNN)	AI-based detection of hookworm in endoscopic capsule images.	High efficiency on large datasets, good speed for complex image-based tasks.	Accuracy: 93-97%; Precision: 94%; Recall: 92%
18	[41]	Artificial Neural Network (ANN)	Smartphone application for portable microscope-based object detection.	High efficiency with real-time capability using lightweight ANN.	Accuracy: 90-94%; Precision: 91%; Recall: 89%
19	[23]	Deep Learning (CNN, MobileNet)	Quantitation of T. trichiura infection based on mobile microscopy and telemedicine.	Efficiency is very high as it is designed for mobile devices and remote platforms.	Accuracy: 92-96%; Precision: 93%; Recall: 92%
20	[42]	Machine Learning (SVM, Random Forest)	Non-invasive detection of Trichuris infection using near-infrared spectroscopy.	High speed with focus on spectral data analysis, high efficiency for field applications.	Accuracy: 87-92%; Precision: 88%; Recall: 85%
21	[38]	Deep Learning (CNN, MobileNet)	Mobile digital microscopy-based diagnosis of STH and Schistosoma haematobium.	High efficiency, designed for fast and accurate point-of-care diagnostics.	Accuracy: 92-96%; Precision: 93%; Recall: 91%
22	[43]	Deep Learning (RNN, CNN)	Endoscopy video capsule data detection and analysis using AI-based software technology.	Fast for video-based analysis with sequential processing by RNN.	Accuracy: 93-97%; Precision: 94%; Recall: 93%
23	[44]	Deep Learning (CNN, RNN)	A review and meta-analysis of the application of deep learning to cordless endoscopy capsules for gastrointestinal problem detection.	A comprehensive review of various deep learning algorithms on capsule endoscopy.	Accuracy, precision, and recall depend on the research discussed in the review.
24	[45]	Deep Learning (CNN, U-Net)	Automatic detection of hookworms in endoscopy capsule images using deep learning.	High speed and efficiency in processing endoscopic images using CNN.	Accuracy: 92-96%; Precision: 93%; Recall: 90%

Additionally, employing lighter models like MobileNet for mobile parasite detection offers high efficiency, ideal for resource-constrained areas, while maintaining satisfactory accuracy. Self-supervised learning-based models, such as DinoV2, provide efficiency advantages by eliminating manual annotation requirements, although detection speed relies heavily on architectural design. Regarding interpretability, techniques like SHAP (SHapley Additive exPlanations) prioritize model decision understanding without sacrificing detection speed, despite interpretation quality depending on the primary model applied. Ensemble and crowdsourcing methods leverage collective annotation strengths to enhance model quality, although detection speed depends on data quality. Overall, each algorithm in this table offers unique advantages in specific application contexts. The choice of method depends on specific requirements, such as detection speed, accuracy and available resources. This diversity reflects the challenges and vast potential of AI and machine learning applications in parasite detection within healthcare.

C. *Results Based on Geographic Distribution of Authors*

Figure 4 illustrates the geographical distribution of authors in the analyzed studies, predominantly from countries with high Soil-Transmitted Helminths (STH) prevalence, such as Asian, African, and Latin American nations. The United States is the primary contributor, followed by the UK and Kenya. The graph also shows citation distribution across databases and countries, with Scopus data indicating the United States contributes the most citations, highlighting the significant role of these sources in research dissemination and recognition.

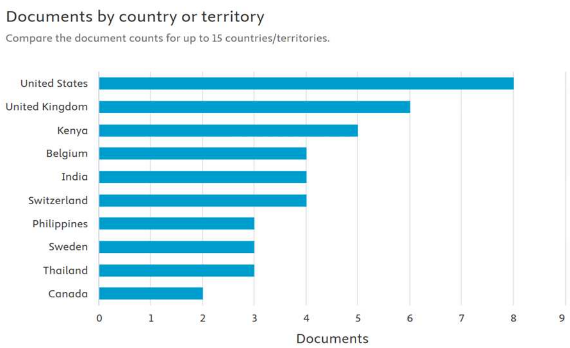

Fig. 4 Distribution of articles based on author nationality

This research highlights the significance of algorithm applications in STH detection, a primary focus of numerous studies. Advanced algorithms like machine learning and deep learning aim to enhance parasite detection and diagnostic accuracy. The broad research scope reflects international collaboration among countries facing diverse health challenges, indicating that while STH issues are prevalent in developing countries, research and technological development also occur in advanced nations driving methodological innovation and global solutions.

D. *Results Based on Inter-Technological Collaboration Potential*

Table 3 indicates several studies utilizing technologies such as MobileNet, CNN, and mobile application-based systems, which can be integrated with IoT for practical applications. This finding addresses Research Question 5 (RQ5), as evident in studies[29] and [38] which demonstrate the effectiveness of lightweight mobile-based diagnosis using MobileNet. These devices can be connected to sensors or IoT for direct data collection from environmental or fecal samples. The research utilizing CNN and MobileNet for parasitic detection via cellular microscopy and telemedicine [23] can be integrated with IoT through telemedicine devices connecting various field sensors, such as microscopic image sensors or environmental sensors, for efficient infection detection.

Furthermore, Deep Learning-based video analysis for endoscopy, involving capsule endoscopy analysis using CNN and RNN [43],[44] respectively, also shows IoT collaboration potential. IoT provides continuous sensor data from endoscopic or microscopic cameras, analyzing parasites with deep learning algorithms. This review highlights the significant potential of Machine Learning (ML) and Deep Learning (DL) in enhancing Soil-Transmitted Helminths (STH) detection, offering higher accuracy and efficiency. CNN, YOLO, and MobileNet algorithms effectively analyze microscopic parasite egg images, facilitating rapid detection in resource-constrained areas [21],[32],[34]. These DL models enable real-time automatic detection, ideal for field monitoring of STH infections. This innovation allows STH detection without complex laboratory equipment, enabling on-site automatic detection using connected mobile devices.

This review highlights the benefits of crowdsourcing and self-supervised learning (SSL) in addressing annotated data challenges. Crowdsourcing diversifies datasets through varied annotations, whereas SSL enables model training with unlabeled data, minimizing manual annotation requirements [33],[39]. Furthermore, SHAP techniques enhance model interpretability, essential in medical contexts for ensuring user trust and understanding of automatic detection systems [30]. Ultimately, integrating ML, DL, IoT, and other techniques yields more efficient, accessible, and rapid STH detection systems, facilitating enhanced infection responses across diverse locations.

IV. Conclusion

Research on Soil-Transmitted Helminths (STH) detection utilizing Machine Learning (ML) and Deep Learning (DL) reveals that these technologies provide highly effective solutions for enhancing detection accuracy, speed, and efficiency. Algorithms such as CNN, YOLO, and MobileNet have demonstrated exceptional accuracy in analyzing microscopic parasite egg images, even in resource-limited environments. Furthermore, Deep Learning facilitates rapid and accurate automatic detection, ideal for real-time STH infection monitoring.

The collaboration between ML, DL, and Internet of Things (IoT) holds immense potential for real-time data collection expansion. IoT-based systems, such as digitally connected microscope sensors, enable continuous STH monitoring, reduce laboratory equipment dependence, and facilitate on-site detection. This opens opportunities for enhancing STH detection efficiently and practically, even in resource-constrained areas

Furthermore, crowdsourcing and Self-Supervised Learning (SSL) tackle annotated data availability challenges. Crowdsourcing diversifies datasets, while SSL enables models to learn from unlabeled data, reducing manual annotation time and costs. SHAP enhances interpretability, ensuring detection results are reliable and understandable for medical professionals. Overall, integrating ML, DL, IoT, SSL, and crowdsourcing provides rapid, efficient, and affordable STH detection solutions, accelerating infection response and global health surveillance

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