

Application and Prospects of Artificial Intelligence in Schistosomiasis Prevention and Control

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Abstract. Schistosomiasis is a serious zoonotic parasitic disease affecting approximately 250 million people worldwide. Despite significant progress in China, challenges remain in snail surveillance, the low sensitivity of traditional diagnostics, and imprecise resource allocation. Recent advances in artificial intelligence offer new solutions. In snail monitoring, CNNs achieve over 90% accuracy in image recognition, and deep learning combined with remote sensing accurately identifies snail habitats. For diagnosis, mobile microscopy integrated with deep learning enables automated on-site egg detection. In strategy optimization, machine learning models (e.g., XGBoost) quantitatively evaluate intervention cost-effectiveness, and decision support systems simulate integrated control effects. Challenges include data quality, accessibility, and ethical privacy concerns. Future directions encompass multimodal diagnostic integration, transfer learning with foundation models, large language model (LLM)-assisted decision-making, and a "human-animal-environment" intelligent prevention and control system.

Keywords: Artificial Intelligence, Deep Learning, Schistosomiasis, Disease Surveillance, Smart Prevention and Control

1. Introduction

Schistosomiasis is a parasitic disease caused by flukes of the genus *Schistosoma* and remains a significant challenge in global public health. According to the World Health Organization, approximately 230–250 million people worldwide are infected, with the vast majority of cases occurring in sub-Saharan Africa [1]. The three main schistosome species infecting humans are *Schistosoma japonicum*, *Schistosoma mansoni*, and *Schistosoma haematobium*. *S. japonicum* is mainly found in Asia, particularly in the Philippines and China; *S. mansoni* occurs in Africa, the Middle East, and the Americas; and *S. haematobium* is mainly found in Africa and the Middle East [1].

In China, although schistosomiasis has been effectively controlled after more than seventy years of comprehensive prevention and control, and most endemic counties (cities, districts) have reached the standards of elimination or transmission interruption, due to the complex life cycle of schistosomes, the widespread distribution of intermediate host snails, and the difficulty of completely changing their breeding environment, coupled with the interaction of natural and socio-

economic factors, the risk of disease rebound always exists. Therefore, under the new circumstances, achieving precise monitoring and early warning of schistosomiasis and implementing intelligent intervention measures have become urgent problems in current schistosomiasis control. This article uses a literature review to systematically assess the progress of artificial intelligence applications in schistosomiasis prevention and control, and discusses their challenges and future development.

2. Bottlenecks of traditional prevention and control technologies and the basis of traditional models

2.1. Main problems faced by traditional prevention and control

The traditional prevention and control system faces certain limitations. The identification of intermediate host snails is influenced by environmental factors such as temperature, humidity, and aquatic habitats, necessitating on-site investigations by morphological specialists, which are notably time-consuming and labour-intensive [2]. In the human diagnostic phase, traditional methods depend on microscopic examination, which requires specialized equipment and trained personnel, limiting access in resource-limited rural areas [3]. Furthermore, the epidemic prediction phase relies on static epidemiological surveys and is devoid of spatiotemporal dynamic models.

2.2. Traditional models provide basic support for AI applications

Before the large-scale application of artificial intelligence in schistosomiasis control, traditional mathematical models had laid the foundation for quantitative research in this field. Gurarie and others developed the Stratified Worm Burden model, calibrated using longitudinal control trial data from Kenya, to simulate *Schistosoma* transmission dynamics and predict the long-term impact of mass drug administration on infection rates [4]. Simulation results indicate that only with high coverage ($> 70\%$) and at least one MDA per year can infection rates be significantly reduced within 10 years; if treatment is stopped, infection rates will rebound to baseline levels within 25–30 years. The study also points out that MDA alone is insufficient to achieve transmission interruption; snail control and improved environmental sanitation must be combined to achieve elimination goals [4].

3. AI applications in snail monitoring and identification

As the only intermediate hosts of schistosomes, snails are a key target for the prevention and control of schistosomiasis. Traditional manual snail surveys rely on experienced parasitologists conducting field investigations, covering approximately 6.557 billion square meters nationwide each year. This method is not only time-consuming and labor-intensive but also has a relatively high rate of missed surveys. In recent years, the rapid development of machine learning and deep learning technologies has provided a new technical approach for snail monitoring.

3.1. Snail and cercaria image recognition based on deep learning

Tallam and colleagues conducted a proof-of-concept study in the Senegal River basin, using convolutional neural networks (CNNs) to classify and identify schistosomiasis-related snails (*Biomphalaria pfeifferi*) and cercariae [2]. The research team collected over 10,000 labeled images across different lighting conditions, shooting angles, and background environments, and trained a CNN to distinguish between snails, cercariae, and non-target objects.

The CNN model achieved a 99% classification accuracy for snails and 91% for cercariae on the validation dataset, performing comparably to eight experienced parasitologists [2]. The study also deployed the model as a publicly accessible web application that supports offline use, making it particularly suitable for remote endemic areas with weak network infrastructure. This study indicates that CNN models can be deployed on low-cost mobile devices, providing a powerful tool for rapid on-site identification, environmental monitoring, and transmission risk assessment in resource-limited regions [2].

3.2. Remote sensing and UAV monitoring of snails

3.2.1. Deep learning satellite image segmentation

The distribution of schistosome host snails (*Bulinus* spp. and *Biomphalaria pfeifferi*) is closely related to specific aquatic vegetation, and identifying these plants can provide indirect indicators for mapping snail breeding sites. Liu et al. employed high-resolution remote sensing data (WorldView-2, 2.0-meter resolution) and deep learning semantic segmentation methods in the Senegal River Basin to identify aquatic vegetation linked to snail habitats [5].

The study compared the performance of the U-Net deep learning model with traditional machine learning methods such as random forests. The results showed that the U-Net model performed excellently in identifying snail-related aquatic vegetation, achieving an overall pixel accuracy of 94.5% on the test set and 82.7% on the hold-out validation set, significantly better than the random forest method (96.7% test, 67.8% validation). This technology produces high-accuracy segmentation maps of snail-associated aquatic vegetation with a spatial resolution of 2.0 meters, offering scientific evidence for health agencies to accurately identify environmental intervention strategies (such as vegetation removal and water management) and facilitating extensive mapping of snail breeding locations [5].

3.2.2. Machine learning spatial modeling to predict snail habitats

Zhang et al. conducted a study in Anhui Province to predict snail habitats using the random forest algorithm. The study collected data from 45,000 snail sampling points (including points with and without snails) and integrated 36 environmental variables (including remotely sensed vegetation indices, topographic factors, water proximity, soil types, etc.) to construct risk prediction models separately for two types of snail habitats: lake-type and hilly-type [6].

The random forest model performed excellently across all evaluation metrics: AUC (area under the curve) > 0.90, Kappa coefficient > 0.85, and classification accuracy > 90%. The model successfully identified high-risk lake-type areas along the Yangtze River (characterized by low elevation, proximity to water bodies, and abundant vegetation) and dispersed high-risk areas in the hilly regions of southern Anhui (characterized by specific elevation ranges and high ditch density). This study provides a scientific basis for precise snail inspections and resource optimization, guiding personnel to prioritize high-risk areas and potentially reducing the cost and manpower required for traditional manual snail surveys [6].

Glidden and colleagues conducted a nationwide study in Brazil using extreme gradient boosting regression tree species distribution models, combined with 30 years (1990-2020) of expert-collected records of *Biomphalaria* snail occurrences and high-resolution remote sensing data (including climate, land use, hydrology, vegetation, etc.) to map the habitat suitability distribution of three

Biomphalaria snail species (*B. glabrata*, *B. straminea*, *B. tenagophila*) at a spatial resolution of 1 km², and analyzed the spatiotemporal change trends over 30 years [7].

The study revealed, for the first time, the driving role of urbanization in snail distribution: in rapidly expanding informal settlements, due to inadequate water and sanitation facilities, new snail breeding habitats have formed, becoming potential transmission hotspots. Model predictions show that, over the past 30 years, suitable habitats for all three snail species have expanded toward urban peripheries. The study also found that climate warming has led to an expansion of potential snail distribution into higher altitudes and latitudes. This research provides a new perspective for precise monitoring and ecological interventions, with identified high-risk areas serving as priority targets for environmental modifications (such as improving drainage systems and hardening ditches) [7].

3.2.3. The application prospects of drones in snail monitoring

Drones can be equipped with various sensors for habitat monitoring. Although existing literature mainly focuses on mosquito breeding sites, their potential for mapping snail habitats for schistosomiasis has been confirmed. Drones can carry passive sensors (visible, near-infrared, thermal) for imaging, active sensors (LiDAR, radar) for 3D terrain characterization, and hyperspectral sensors for water detection even under turbid or vegetated conditions.

Compared to satellites, drones offer centimeter-level resolution, cloud-free operation, flexible acquisition, and low cost, making them ideal for monitoring snail habitats in remote, complex terrains (Mechan et al.) [8]. Future research could combine drone imagery with deep learning to enable automated identification of snail breeding sites.

4. AI applications in crowd infection diagnosis

4.1. On-site diagnosis integrating mobile digital microscopy and deep learning

In resource-limited schistosomiasis-endemic areas, traditional microscopic examination is constrained by the cost of equipment, a shortage of skilled personnel, and limited testing throughput. Holmström and colleagues conducted an innovative study in Tanzania, combining mobile digital microscopy with deep learning to develop an on-site automated detection system for schistosome and soil-transmitted helminth eggs [3]. This study utilized the MoMic portable digital microscope to digitally collect Kato-Katz fecal samples. The research team built a convolutional neural network model capable of automatically identifying the eggs of *Schistosoma haematobium*, hookworm, *Ascaris*, and *Trichuris*. The system achieved automated parasite detection in resource-constrained environments, with sensitivity exceeding 83% and positive predictive values ranging from 69.6% to 100%, showing good consistency with manual microscopic examination [3].

4.2. AI optimization basics in serology and molecular diagnostics

In low endemic areas, the traditional Kato-Katz method has a high rate of missed diagnosis due to its low sensitivity (only 40-70% for a single slide test), creating an urgent need for more sensitive diagnostic methods. Cai et al. conducted a comprehensive comparative study in the Philippines, systematically evaluating the performance of antibody ELISA and droplet digital PCR (ddPCR) in the diagnosis of *schistosomiasis japonica* [9]. The study collected 412 fecal and serum samples from Leyte Island and compared three detection methods: the Kato-Katz technique (three thick smears), two recombinant protein ELISAs (combined detection of SjSAP4 and Sj23-LHD), and ddPCR based

on the *nad1* gene. The results showed that the detection rates of SjsAP4+Sj23-LHD-ELISA and ddPCR were similar, both exceeding 2.5 times that of the Kato-Katz method, indicating significant advantages in areas with low to moderate prevalence [9]. Although the study did not directly apply machine learning, its quantitative analysis of ELISA and ddPCR data provided a standardized data foundation for future AI-assisted diagnostics, which could integrate machine learning models to optimize antibody-antigen reaction pattern recognition and quantitative assessment of infection intensity.

5. AI-powered smart prevention and control system construction

5.1. Decision support system optimizes prevention and control strategies

Infectious disease prevention and control decision-making involves multiple complex factors, including disease characteristics, intervention measures, and community environment. Although various disease transmission models have been developed in academia, their complexity often poses a barrier to their use by grassroots decision-makers. Standley et al. developed a web-based decision-support tool to inform evidence-based decisions on integrated strategies for schistosomiasis and malaria control [10]. This tool collects local demographic, disease epidemiology, and intervention data through a user interface, runs parallel simulations and provides recommendations to public health decision-makers in an easily understandable format. Its application in Uganda indicated that by optimizing the timing of mass praziquantel chemotherapy and integrating malaria control measures, an additional benefit of more than a 5% reduction in malaria prevalence could be achieved [10]. This data-driven decision-support model provides a prototypical framework for building an AI-enabled intelligent prevention and control system.

5.2. Machine learning optimization elimination strategy

In the elimination phase of schistosomiasis, precisely allocating limited resources is a key challenge. Li et al. used seven machine learning models (XGBoost, Support Vector Machine, Generalized Linear Model, Random Forest, Gradient Boosting Machine, Neural Network, Regression Tree) to optimize China's schistosomiasis elimination strategy [11]. The study was based on nationwide schistosomiasis surveillance data and the implementation of intervention measures, using marginal benefit modeling to identify the most cost-effective combination of interventions.

The results showed that the XGBoost model performed best ($R^2 = 0.7306$), successfully identifying the optimal configuration of seven core interventions: risk surveillance, treatment, toilet construction, health education, snail control with molluscicides, animal slaughter, and livestock chemotherapy. Marginal benefit analysis revealed that risk surveillance yielded the highest marginal benefit, followed by snail control and treatment. This work offers a quantitative decision-making instrument for accurate resource allocation and the enhancement of elimination tactics, illustrating the practical utility of machine learning in refining prevention and control measures [11].

6. Conclusion

6.1. Limitations

This review is based on a selective literature analysis and does not include a systematic quantitative meta-analysis. Most cited studies are proof-of-concept rather than large-scale field implementations, and the generalizability of AI models across different epidemiological settings remains to be

validated. Additionally, ethical and privacy concerns related to AI-based diagnostics, surveillance systems, and large-scale data collection have also not been fully addressed in the current literature.

6.2. Summary and future perspectives

At the level of prevention and control strategies, Panzner emphasised that the elimination phase necessitates multi-faceted intervention strategies that incorporate chemotherapy, vaccination, health education, environmental modification, and thoroughly account for the effects of non-compliant populations, population mobility, and environmental alterations on transmission [12]. Based on this framework, future research could further introduce AI technology, incorporating human health, animal hosts, and environmental data into a unified platform to build a real-time monitoring network for cross-species transmission chains, achieving an intelligent prevention and control system that coordinates 'human-animal-environment' management. In drug development, AI is accelerating the discovery of new anti-schistosomiasis drugs. Moreira-Filho et al. reviewed applications of automated screening, computer-aided design, and machine learning—including QSAR-based virtual screening, molecular docking, deep learning for fragment library screening, and NLP for synthetic route prediction—which can significantly shorten the drug discovery cycle and address the risk of praziquantel resistance [13]. An effective transformation path from technology research and development to field verification and then to promotion and application should be established to ensure that AI technology effectively serves the ultimate goal of eliminating schistosomiasis.

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