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AI And Cervical Cancer Screening: A New Era In Women's Health. Review

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Abstract: Among cancers, cervical cancer is unique since it may be prevented and eradicated, primarily by vaccine and proactive screening. Nonetheless, many women in low- and middle-income nations still require cervical cancer screening. There are clear advantages and disadvantages to traditional cervical cancer screening methods in terms of sensitivity, specificity, timeliness, and cost. With an emphasis on machine learning (ML) and deep learning (DL) approaches, artificial intelligence(AI) has become widely used in recent years to assist medical practitioners in conducting comprehensive cervical cancer screenings. AI technology in conjunction with conventional screening techniques has demonstrated early efficacy in cervical cancer screening. However, there are a number of issues that must be addressed, including the lack of resources and technology, the complexities of integrating clinical processes, and the ethical and legal hazards associated with largescale community cervical cancer screening. This review initially discussed how AI improves the triage and diagnosis procedures for colposcopy and human papillomavirus (HPV), streamlines workflows, and helps with cytological segmentation and diagnosis. Next, we compiled the current clinical examples of AI used in widespread cervical cancer screening. Lastly, we talked about the difficulties and constraints of using AI to test for cervical cancer in big populations. By enhancing diagnosis accuracy, promoting early intervention, and boosting the overall effectiveness of cervical cancer screening programs globally, these discoveries may have the potential to revolutionize cervical cancer screening.

Keywords: Artificial intelligence, cervical cancer screening, deep learning, and machine learning.

I. Introduction

One of the most common malignancies that affect women is cervical cancer [1]. A remarkable five-year survival rate of 90% is associated with early-stage cervical cancer. The poor five year survival rate of 16.5% for advanced cervical cancer, however, emphasizes the significance of preventative health interventions in the fight against this illness [1, 2]. Cervical cancer is now the malignancy that can be targeted for eradication thanks to the development of HPV vaccination programs and the use of efficient screening techniques [3]. The World Health Organization (WHO) advocated for concerted international action to eradicate cervical cancer in May 2018 [4]. However, nations do not always succeed in reaching this objective. The objective is anticipated to be accomplished in the upcoming decades for industrialized nations. Less than 5% of women in the majority of low- and middle income nations get screened, and these nations have high rates of avoidable cervical cancer cases and deaths. Whether they can accomplish this before the end of this century is still up in the air [5].Promoting widespread cervical cancer screening in these nations is therefore crucial [6].In order to detect precancerous lesions and invasive malignancies early, cervical cancer screening now uses a number of clinical techniques. The most often used methods are colposcopy, HPV testing, and cytology (both liquid

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based and conventional Pap smears) [7].Every screening method has pros and cons that need to be weighed against patient preferences, professional recommendations, and healthcare resources [8].

AI has been used more and more in the medical field in recent years. It can identify complex clinical data and images and use algorithms to convert them into quantifiable and understandable clinical decisions, streamlining and improving clinicians' workflow [9, 10]. AI has been used more and more in gynecologic oncology to improve the precision and effectiveness of diagnostic procedures, particularly in the field of cervical cancer screening [11]. The use of AI in large-scale population cervical cancer screening is still in its early stages, despite the fact that it currently holds great promise and has the ability to completely transform screening procedures [4]. In order to improve early detection and eventually lower the incidence and death related to cervical cancer, it is imperative to address the obstacles and advance the use of AI in mass screening efforts [12].Without exploring how AI might be integrated with conventional cervical cancer screening methods to engage in different elements of cervical cancer screening activities, prior research has concentrated on summarizing the primary systems or algorithms of AI in cervical cancer screening. Furthermore, it has ignored the significance of AI in widespread community cervical cancer screening and pertinent research.

1. Conventional Techniques for Screening for Cervical Cancer

The Pap smear, which is the oldest technique for cervical cancer cytology screening, involves spreading cervix cells onto a microscope slide, staining them, and looking for any abnormalities in the cells [13]. The Pap smear has a 75% specificity and a 55.5% sensitivity [14]. Despite the Pap smear's relative simplicity and affordability, it is impossible to ignore the possibility of misleading results due to sampling errors, observer variations, or laboratory faults [15]. A contemporary method of screening for cervical cancer that enhances conventional Pap smear methods is liquid-based cytology (LBC) [16]. The cell samples were put into a vial with a liquid preservative that reduces blood and inflammatory cell contamination, resulting in a high specificity of 93.60% and more precise diagnoses [17,18,19]. However, LBC's drawbacks include lower sensitivity, higher costs, and the need for specific lab tools and techniques [19]. These elements might prevent LBC from being widely used. A key component of cervical cancer screening is HPV testing, which directly evaluates the virus that causes the majority of instances of cervical cancer [20,21, 22].

In addition to having a high sensitivity of 93.85%, HPV testing can extend the time between screens in the event that the findings are negative [22]. Nevertheless, HPV testing has a low sensitivity of 36.09%, cannot identify cervical cancer on its own, and may result in overdiagnosis and overtreatment when HPV infections are temporary [23].In women who have had abnormal cytology findings or positive HPV testing, colposcopy is performed to closely check the cervix, vagina, and vulva for evidence of illness [24]. Targeted biopsies may be carried out for additional pathological examination if any questionable lesions are found during colposcopy [25]. But it depends on the clinician's knowledge and could be interpreted differently. In addition to the possibility of problems including bleeding or infection, patients may feel uncomfortable during biopsies [26, 27].

Table.1 Current methods of cancer cervix screening

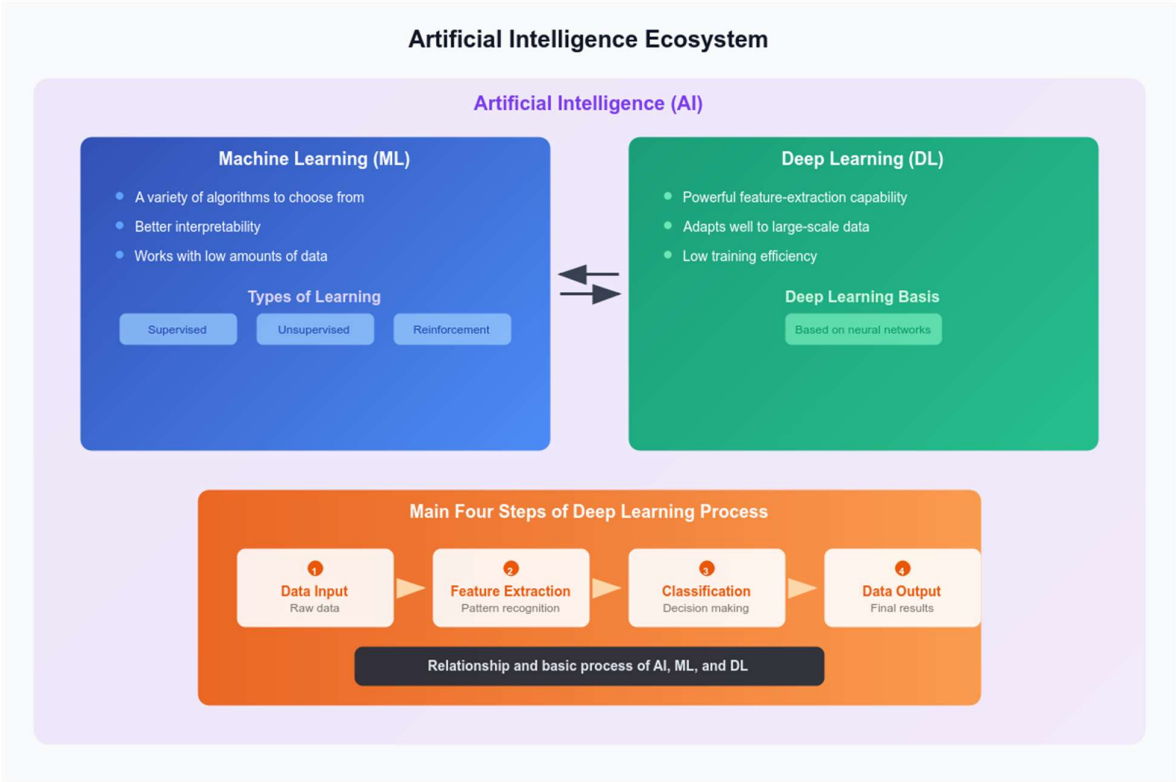
Method	Advantages	Disadvantages
• Liquid-based cytology	Specificity	Low sensitivity
	Accurate	Higher cost
		Special laboratory
		Equipment and processes
• Pap smear	simple	Sample errors
	Cost-effective	Laboratory inaccuracies
		Rely on observer
• HPV testing	Sensitivity	Low specificity
	Longer interval when	Over diagnosis

	the results are negative	Over treatment
• Colposcopy	Detail assessment	Rely on expertise
	Facilitate direct biopsy	Discomfort
	Accurate diagnosis and management	Complications

2. Fundamental Ideas in AI for Screening for Cervical Cancer

The initial definition of artificial intelligence (AI) was put forth in 1956 and was described as computer systems simulating human intelligence processes [11,29]. The core element of AI is machine learning. By utilizing data or past experiences, it increases the effectiveness of computer programs and removes the need for direct programming by human operators [29, 30]. Supervised learning, unsupervised learning, ensemble learning, deep learning, and Bayesian learning are general classes of machine learning techniques [31].Even with minimal amounts of data, machine learning can produce good outcomes [32]. The most popular AI tool is deep learning (DL), a novel machine learning technique that has emerged in recent years. DL performs representation learning on data using neural networks as its architecture [33]. When compared to conventional ML models, the DL models are more adaptable. However, a significantly greater amount of training data is typically required for DL models [32]. Data input, feature extraction, classification, and data output are the four general processes in the ML and DL analysis process, all of which require little to no human participation [34].

Figure 1



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3. Uses of AI in cytology Screening for Cervical Cancer

3.1 Cervical Cytology Image Cell Segmentation

Separating the cytoplasm and nucleus from the overlapping cells is essential since the overlapping of sampled cervical cells can compromise the accuracy of investigations. While AI-based cell segmentation techniques provide great precision and low error rates, making them especially appropriate for large sample screenings, traditional manual segmentation techniques are ineffective and imprecise. In order to streamline workflows and aid in diagnosis, it is crucial to use AI technology to preprocess images of overlapping cervical cancer cells and extract important information [35]. Based on Mask RCNN and PointRend modules, Zhang et al. created a DL model that could separate overlapping cells and help pathologists diagnose patients quickly [36]. Additionally, Zhao et al. succeeded in fully segmenting Papanicolaou smear cells using the CNN-based SPCNet model [37]. However, a lot of labeled data is needed for DL-based cell segmentation techniques. Based on human visual simulation, Yang et al.'s HVS-Unsup model was an unsupervised cervical cell instance segmentation technique that could greatly increase segmentation accuracy and successfully lower the quantity of data labeling required [38].

Conversely, a CNN-based cell segmentation technique can provide false-positive findings. Liang et al. developed a global context-aware framework that could incorporate global context information, remove false positive samples, and enhance the precision and specificity of cell segmentation in order to optimize the existing approach [39].The most difficult part of cell segmentation is the overlapping cytoplasmic borders' inadequate intensity. In order to improve cell segmentation performance and drastically reduce incorrect segmentation results, Song et al. presented the restricted multi-shape evolution algorithm, which could segment overlapping cells based on local and global information priors [40]. Similarly, a method that uses deep ensemble learning techniques to automatically segment the cytoplasm and nuclei of cervical cells has been developed using U-Net and U-Net + + model architectures with ResNet34 and DenseNet121. The nuclear-cytoplasmic separation process was much improved by this method [41].

Efforts are being made to increase segmentation efficiency since it is challenging to use cell segmentation models in clinical settings due to the high computational load and lengthy processing time. In order to attain state-of-the-art performance with reduced computational complexity, Zhao et al. created a lightweight feature attention network (LFANet) that could precisely segment the nuclear and cytoplasmic regions in cervical pictures. This offered enhanced technical assistance for AI in cervical cancer screening by providing a straightforward and effective automatic cell extraction technique [42]. In a similar way, Luo et al. suggested a dual-supervised sampling network structure (DSSNet) that might greatly lower the computational load while maintaining segmentation accuracy [43].

3.2 The Advancement of Cytology Microscopy with AI Assistance

It is often known that the most crucial instrument for cervical cancer cytology screening is the microscope. Following the acquisition of the cervical smear, a preliminary observation under a low magnification microscope is performed, and then suspicious spots are examined closely under a high magnification microscope [44]. Kurita et al. were able to separate negative specimens by accurately analyzing normal and abnormal images at low magnification using CNN based on DL; the model's accuracy may reach 87.3% [45].Tang et al. built an AI microscope using augmented reality. It helps pathologists diagnose cells by showing AI results directly on the microscope view [46].These helped doctors save time and streamline workflow by allowing cytologists ample opportunity to examine aberrant specimens under high magnification.

3.3 Using AI in Conjunction with Additional Detection Methods for Cytology Screening

For cervical cancer cytological screening, there are currently numerous alternative cutting-edge screening methods available in addition to Pap smears or LBC. First off, a straightforward and noninvasive technique for early cancer detection is raman spectroscopy.Raman spectroscopy can be used to categorize different types of cervical cancer tissues according to their proteins and nucleic acids [47].It was possible to screen and classify cervical precancerous lesions and early cervical cancer by combining Raman spectroscopy with DL and building an effective channel attention convolutional neural network (ECACNN) model. This approach had a high accuracy of 94.04% [48].In a similar vein, Yan et al. collected cervical tissue slice data using Raman

spectroscopy and classified and identified the tissue samples using a one dimensional hierarchical convolutional neural network (H-CNN) [49].

The nuclear morphology linked to cervical lesions can be seen using the high-resolution endomicroscope (HRME). When HRME and DL are combined, intraepithelial neoplasia grade 2 or above can be detected with sensitivity and specificity of 94% and 58%, respectively. Furthermore, the specificity of identifying cervical precancerous lesions could be greatly increased to 71% by combining diagnostic data with HPV test findings [50]. The FLIM-ML Model was created by combining ML techniques with Fluorescence Lifetime Imaging Microscopy (FLIM) technology. Using FLIM, our model assessed the metabolic status and fluorescence intensity of unstained exfoliated cervical cells. ML then examined the FLIM images. With a sensitivity and specificity of 90.9% and 100%, respectively, it could forecast the likelihood of developing cervical cancer. Future cervical cancer diagnosis, recurrence, and occurrence could all be predicted using the FLIM-ML Model [51]. Additionally, contemporary multimodal hyperspectroscopy (MHS), an AI-based method, greatly decreased the false negative rate in cervical screening by identifying abnormalities through the detection of metabolic and morphological indications inside cervical tissue [52].

3.4 Cervical Cancer Cytology Classification Using Transfer Learning

Transfer learning is a type of ML. Most machine learning needs huge datasets to work. Transfer learning fixes this by using less data [53]. The Swin-GA-RF model combines a Swin Transformer with a genetic algorithm and random forest classifier. This tool classifies cervical cancer results accurately and shows great potential for clinics [54]. Kurita et al. used a visual language model to check images quickly and with high precision. It ranks abnormal cases to make screening easier, which helps find and treat cancer earlier [55]. Allogmani et al. created the CPLDC-AOATL method. It uses the Archimedes optimization algorithm and transfer learning to process images, find features, and classify data. This makes it easier to spot cancer precursors [56].

3.5 Combining DL and ML Algorithms

DL is great at finding complex patterns in images. This helps ML algorithms work better. Mathivanan et al. used this by applying CNN architectures to the SIPaKMeD dataset to get key image features. They then used ML to diagnose and classify cervical cancer. This method reached 98% accuracy and could help screen large groups of people [57]. Different algorithms have different strengths and weaknesses. Mixing them can make screening better. Nambu et al. combined YOLOv4 and ResNeSt. First, YOLOv4 found atypical cells. Then, ResNeSt classified them. This two-step plan hit 90.5% accuracy for liquid-based cytology [58].

4. AI in HPV Testing

AI can make HPV detection more accurate than old methods. Sorting HPV-positive patients is a key part of screening [59]. Ahmed et al. used an automated visual evaluation system. They combined HPV typing and risk levels with predictive models. This created a reliable tool for sorting HPV-positive women [60]. Most HPV infections are short-lived. Very few lead to cancer [61]. Using cytology to sort these patients cuts down on too many colposcopies [62]. Xue et al. built an AI-LBC system using data from HPV-positive patients with abnormal results. This system sorts patients based on their cytology. AI-LBC had a sensitivity of 86.49%, which is similar to human experts and HPV16/18 typing. It also cut colposcopy referrals by 10% [63]. AI helps cytologists make better choices by looking at data patterns and molecular info. This reduces false positives and unnecessary tests. Table 7 shows recent AI systems used in HPV testing.

5. AI Applications in Colposcopy

Colposcopy results depend on the skill of the doctor. Many clinics lack enough experts to meet patient needs quickly [64]. Ouh et al. built CerviCARE AI to analyse cervicography images. It classifies lesions with 98% sensitivity and 95.5% specificity [65]. An automated visual evaluation (AVE) system uses images for fast screening. It has 85% sensitivity and 86% specificity. While limited, it helps with acetic acid inspections and shows future promise [66]. Chandran et al. created the Colposcopy Ensemble Network (CYENET). This model uses deep learning to find cancer with 92.3% accuracy [67]. Xue et al. made CAIADS to help junior doctors. The system finds biopsy sites using deep learning and performed well on large datasets [68]. Takahashi et al. built a system that checks 12 areas of the cervicovaginal region. It had an 89.7% accuracy rate and helps find CIN lesions [69].

The cervical transformation zone is where most cancers start. Its type affects how doctors grade results and pick treatments [70]. Cao et al. used a deep learning network to identify these zone types. It hit 88.49% accuracy, aiding better screening [71]. AI models alone cannot fully screen for cancer. Fu et al. combined saline, iodine, and acetic acid images in a logistic regression model. They added cytology and HPV tests to make a cross-modal system. This model reached an AUC of 0.921 for precise screening [72]. Table 8 lists these AI algorithms and systems.

6. Applications of AI in Cervical Cancer Diagnosis

Colposcopy-guided biopsy and FIGO standards are used to diagnose and stage cervical cancer (73). In 2018, FIGO allowed imaging and pathology for staging . AI helps with colposcopy and MRI to stage cancer with good results.

6.1 Colposcopy

Colposcopy and pathology results often disagree. This leads to wrong or missed diagnoses. Unskilled clinicians can cause bleeding, pain, or infection. Doctors need long training to become proficient. A lack of trained staff makes it hard to use colposcopy for cancer diagnosis (74).

6.1.1 AI Boosts Image Classification Performance

Deep Learning (DL) is now common in medical imaging (75). Using DL to classify colposcopy images helps fix old bottlenecks and makes diagnosis more accurate. Miyagi et al. trained a CNN AI to tell LISIL from HSIL. The AI achieved accuracy, sensitivity, and specificity of 0.823, 0.800, and 0.882, while an oncologist scored 0.797, 0.831, and 0.773 (76). Another DL classifier used HPV types and images to identify HSIL/LSIL with 0.941 accuracy (77). Xue et al. made a tool called CAIADS to grade findings and guide biopsies. CAIADS matched pathology results 82.2% of the time, beating traditional colposcopy at 65.9% (78). Yuan et al. built a ResNet model with 85.38% sensitivity and 82.62% specificity to aid biopsy choices (79). Yue et al. used a C-RCNN algorithm to classify lesions. By extracting time and space features, they reached 96.13% accuracy and 98.22% specificity (80).

6.1.2 AI Helps Detect High-Grade Cervical Lesions and Guides Biopsy

Clinicians must separate normal or CIN 1 tissues from CIN 2/3+. Patients with CIN 2/3+ need treatment. CIN 1 is mild and often goes away on its own after a year, so it needs less care. Kim et al. built an algorithm using colour and texture. It had 74% sensitivity and 90% specificity in finding high-grade lesions (81). Hu et al. studied 9,406 women over 7 years. Their fast R-CNN model had an AUC of 0.91 for CIN 2+, which beat both human evaluators and Pap smears (82). Cho et al. made a binary model to decide if a biopsy was needed for CIN+ or LSIL+ lesions. Their RESNET-152 model had an AUC of 0.947 and 85.2% sensitivity (83). This helps new doctors decide when to biopsy or refer a patient. AI image analysis handles large datasets well. It makes detecting lesions and placing biopsies more accurate, which lowers misdiagnosis rates (84,85,86).

6.2 Pelvic MRI

MRI is very accurate for staging cervical cancer before surgery (73, 74). It is the top choice for local staging, checking treatment success, finding recurrence, and patient follow-up (87). Doctors use MRI mainly to find tumors spread and lymph node metastasis (LNM) (88).

6.2.1 Segmentation of Cervical Cancer Lesions

MRI shows soft tissue better than CT. It shows tumor size, pelvic structures, and if the cancer hit the uterus or vagina (81). Lin et al. used a U-Net CNN to map cervical carcinoma in DWI scans. They found a dice coefficient of 0.8 and 0.89 sensitivity (89). AI is faster and more objective than humans. Wang et al. used T2WI and DWI images to predict if a tumor spread. The AUC was 0.780 for T2WI alone and 0.921 when combined with DWI (90).

6.2.2 Diagnosis of Cervical Cancer

LNM AI helps find LNM early. CT and MRI accuracy for lymph nodes is about 83% to 85%, though specificity is high at 66% to 93% (69). In 2018, staging rules changed to include lymph node status. Cancer with LNM is now stage IIIC (61). Wu et al. used

preoperative MRI to predict LNM. T1WI models had an AUC of 0.844, but a hybrid model using DL and MRI reports reached 0.933 (91).Radiology now links imaging with precision medicine. It uses image tools and stats to find hidden data (92). Wu et al. used MRI radiomics to improve LNM diagnosis. Combining T2WI with a decision tree worked best, reaching 100% sensitivity in validation (84). Wang et al. also found that T2WI and DWI predict pelvic LNM well in early cancer (78).

7. Limitations and Future Directions

AI excels at computing and image analysis. This makes it useful for medical research. It helps doctors make decisions, cuts their workload, and lowers misdiagnosis rates. AI makes screening more accurate. It solves problems with time and a lack of trained staff. It also removes human bias. This allows cervical cancer screening in poor areas, which can lower the disease rate.AI has some hurdles. Data is a big one. Machine learning needs millions of examples to work well. Current clinical data is often scarce, poor quality, or lacks markers. Managing this data is hard for automated tools. We need large, standard databases. Data security and overfitting are also risks. These can lead to wrong results and overdiagnosis. Most AI models are not used in clinics yet. We need more studies to prove they work. AI cannot replace doctors. It is a tool to help them. Technical failures can happen, so we need skilled staff to maintain the systems.

AI shows promise in cervical cancer screening. Its use in cytology is quite advanced. However, segmentation is still hard. This part is key for classification. AI struggles with overlapping nuclei, non-target cells, and slide dyeing differences. Some methods skip segmentation entirely. This avoids extra steps and may be the way forward. AI can also help with treatment, prognosis, and prevention. More research on these areas will lead to better decisions and help end the disease globally. AI should also be used for rare types like adenocarcinoma. It can help tell cervical cancer apart from other diseases without invasive tests. Better AI will improve cancer prediction, staging, and patient outcomes.

8 . Perspective and challenges of AI applied to large-scale population screening

Large-scale AI screening needs high-power computing. It must cover many regions to find high-risk people fast. Small-scale screening focuses on known lesions or specific patient needs. This requires AI techs and pathologists to work together. Less than 5 percent of women in low-income countries get screened. We must expand screening to find high-risk groups early.AI-assisted screening has great potential. It processes images and data quickly. It finds small signs that humans miss. This lowers the chance of missing a diagnosis. In poor areas, AI on smartphones can fix resource gaps. This helps distribute health resources better and helps the global goal to end cervical cancer.

Challenges remain. AI needs huge amounts of data. Current images and data lack a single standard. The people collecting data have different skill levels, which hurts accuracy. Current algorithms have different pros and cons. We need one efficient, general system. The way doctors use the machines also changes the results. Patient privacy and ethics need clear laws.AI screening is likely cost-effective and accurate over time. It handles hard data and cuts labor costs. But it costs a lot to start. Traditional methods are cheaper at first and well known. They are slow and cost more in labor during large screenings. Mixing both methods might work best. This paper has gaps. We need to test more AI models to see which one's doctors should pick. We also need better ways to move these models into clinics.

II. Conclusion and Directions

AI algorithms are maturing. Large-scale AI screening should happen soon. Future work should focus on faster algorithms for better accuracy. We need large, high-quality data from many centres. AI must fit easily into clinic workflows. Multi-centre trials should check long-term costs and effects. Finally, AI should work with other new tech to make screening automatic.

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Conflict of Interest

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Author Contribution

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