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Advancements and challenges of artificial intelligence in cervical cancer diagnostics: A comprehensive review

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Abstract

Cervical cancer remains a significant global health concern, ranking as the fourth most common cancer among women and leading to substantial mortality, particularly in low- and middle-income countries (LMICs). The use of artificial intelligence (AI) in cervical cancer di- agnostics has gained attention for its potential to improve the ACC, efficiency, and accessibility of screening methods, including cytology and colposcopy. This paper provides a comprehensive review of AI-based diagnostic systems, analyzing their performance across various datasets and highlighting the advancements in deep learning models for detecting precancerous lesions. The discussion addresses the challenges associated with AI implementation, such as data availability, model generalization, cost, and ethical considerations. Despite these obstacles, AI shows great promise in revolutionizing cervical cancer screening, particularly in resource-limited set- tings, by reducing diagnostic errors and enhancing early detection. Continued research and innovation are needed to overcome existing barriers and ensure that AI can be effectively in- targeted into global healthcare systems.

Keywords: Cervical cancer, Artificial intelligence, Machine learning, Cytology, Colposcopy, Pap smear, Deep learning

Introduction

As the fourth most prevalent cancer diagnosed globally, cervical cancer has become a major health problem for women. About 604,000 new instances were recorded globally in 2020 alone, to provide an idea of the issue's scope [1]. It also ranks as the fourth most common cause of cancer-related mortality, taking 342,000 lives in a single year. Notably, areas like Southeast Asia, Melanesia, South America, and sub-Saharan Africa have the greatest death rate [1]. Cervical cancer is one of the most preventable and curable types of cancer if discovered at an early stage, despite these concerning statistics.

Human papillomavirus (HPV) infection is the main cause of cervical cancer [2]. Most occur- rences of cervical cancer are caused by this virus, which is quite common and easily spread through sexual activity or direct skin contact. Types 16 and 18 are considered high-risk strains of HPV and are the main causes of serious lesions and cancer among other strains [3]. These high-risk varieties are linked to aberrant cellular alterations in the cervix that may eventually give rise to malignant malignancies. Consequently, it is critical that women adopt preventative measures, such as routine screenings and HPV vaccines, in order to prevent and identify cervical cancer as soon as possible.

Cervical Intraepithelial Neoplasia (CIN), a disorder characterized by aberrant alterations in the cervix's squamous cells, is often the first step toward the development of cervical cancer. These cellular anomalies are closely associated with high-risk HPV infections. CIN is divided into two groups by the World Health Organization (WHO): CIN 1, which is regarded as low-grade, and CIN 2 or 3, which are classified as high-grade (Fig. 1).

Even while not all cases of CIN progress to cervical cancer, high-grade CIN has the potential to become invasive cervical cancer over time if treatment is not received. While CIN 2 and CIN 3 are classified as High-grade Squamous Intraepithelial Lesions (HSIL), CIN 1 is sometimes referred to as a Low-grade Squamous Intraepithelial Lesion (LSIL).

In otherwise asymptomatic women, CIN can be detected using a variety of screening methods, including Visual Inspection with Acetic Acid (VIA), Cytology (including Pap smears and liquid-based cytology), HPV testing, and Colposcopy [4].

Cervical cancer can be prevented in large part by using these tests to detect precancerous lesions, as treatment outcomes are significantly improved by early identification. Fig. 2 shows the entire cervical cancer screening and testing procedure.

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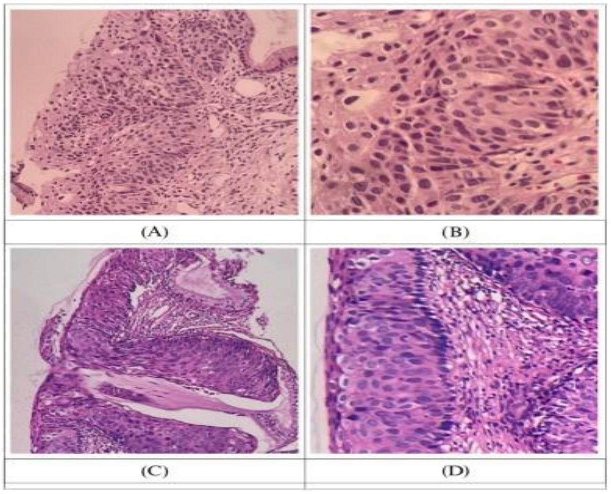

Figure 1: A, B are low-grade CINs, and C and D are high-grade CINs.

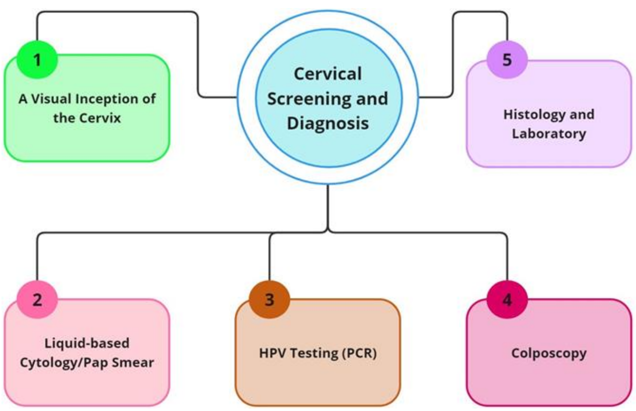

Figure 2: Procedures for diagnosing and screening for cervical cancer

VApplying 3–5% acetic acid to the cervix is the quick and effective Visual Inspection with Acetic Acid (VIA) cervical cancer screening procedure. This results in a transient whitened appearance of precancerous cells, making it easier for medical professionals to see aberrant regions. The inspection can be performed with the unaided eye or, for a closer look, with the use of a colposcope. VIA is accessible and affordable, especially in environments with low resources, and it may be carried out by mid-level healthcare professionals like nurses and midwives. Comparatively speaking to Colposcopy and Cytology, it is less sensitive. Both liquid-based cytology and the conventional Pap smear can be used for cytology screening. Cells from the cervix are taken and put on a slide for microscopic analysis in the Pap smear procedure. Similar methods include liquid-based cytology, which aims to increase Sensitivity (SEN) and accuracy (ACC) by preserving the cells in a liquid media prior to microscopic examination [5].

Cervical samples are collected with a tiny brush and spatula for HPV testing, another essential technique for identifying abnormalities in the cervical region. The samples are then sent to a laboratory for analysis. Polymerase Chain Reaction (PCR) and hybridization are the most widely used methods for HPV testing in laboratories [6]. While hybridization entails the attachment of HPV DNA to certain probes on a filter or microchip, PCR is a technique for identifying and amplifying specific DNA sequences, including those of the HPV virus [6]. A colposcopy with targeted biopsies is used to confirm the diagnosis if these screening tests find anomalies, such as cervical intraepithe- lial neoplasia (CIN). When performing a colposcopy, a gynecologist or other qualified healthcare provider uses a colposcope to magnify the cervix and closely check any problematic regions. A pathologist examines biopsy samples obtained during this process to check for the presence of aberrant or malignant cells.

According to the World Health Organization (WHO), women should start screening for cervical cancer at age 30, and they should get screened again every five to ten years [7]. Regretfully, screening programs are mostly in place in high-income nations, where more than 60% of women get tested on a regular basis. Comparatively, only around 20% of women in low- and middle-income nations have access to cervical cancer screening [8]; this is probably because these programs are expensive or lack sufficient resources or competence.

AI-based Cancer Diagnosis

The performance metrics and datasets used in AI-based diagnostics for PAP smear screening, as described in the reviewed literature, will be thoroughly compared in this section (Table 1). Summarizing the essential information on precancerous lesion identification in cervical cancer is the primary objective, since it is essential for both efficient treatment and prevention. Therefore, in order to increase the precision and effectiveness of detection, it is crucial to assess and examine the various techniques and technologies employed in PAP smear diagnostics.

PAPNET, the original automatic screening system, was certified in 1992, although at first it was limited to being used as a re-screening tool for slides that cytologists had determined to be negative. Later, in 2004, a commercial screening tool called ThinPrep® imaging system (Version 1.0, Hologic, Marlborough, UK) was unveiled. It reduces pathologists' effort and improves diagnosis ACC by using a proprietary algorithm to identify the 22 most worrisome fields of view (FOV) [9]. Liquid-based cytology, which is used by ThinPrep®, has several benefits over traditional techniques, including improved cervix sample representation and the removal of labor-intensive manual fixation and staining, which can introduce variability.

According to recent research, the ThinPrep® imaging method has improved ACC and re- peatability over conventional cytology screening, and it may be more sensitive. Its capacity to identify minute cellular alterations linked to cancer greatly enhances the diagnostic procedure. But putting it into practice can be expensive and need specific operator training. Furthermore, the presence of mucous or hemoglobin might impede the ACC of a diagnosis. The FocalPoint GS imaging system was introduced in 2008, which was another significant advancement in cervical cytology. By identifying the top 10 most anomalous FOVs, our method improves efficiency and risk assessment [10]. Nevertheless, several researches suggest that the system's cost-effectiveness is restricted, which lessens its viability in developing nations [11]. Additionally, the technique still relies on final manual screening, underscoring the necessity for additional development [12].

The goal of AI integration in cervical cytology is to automate the screening procedure in order to lessen the workload of cytopathologists and increase efficiency and ACC. The application of AI might improve cost-effectiveness, especially in resource-constrained nations. Artificial Intelligence has the potential to improve the accessibility, efficiency, and cost-effectiveness of cervical cancer screening by automating the procedure.

Fuzzy c-means clustering was utilized by Chankong et al. [11] to segment single-cell pictures into three categories: background, cytoplasm, and nucleus for whole-cell segmentation. A different method achieved an ACC of 91.7% using Mask-RCNN by using a segmentation model based on nucleus localization and single-cell classification to discriminate between normal and pathological cells [13]. Traditional textural feature extraction and segmentation techniques have been replaced in cervical cell classification techniques in recent years. With over 93% ACC, a novel approach divides single-cell pictures into the nucleus, cytoplasm, and background before extracting morphological features for multi-label classification [14].

High ACC was proven by a novel method combining texture feature extraction and support vector machine (SVM) classification; nevertheless, further work has to be done since precision rates were only 50% at the stain plane and 60% at the unit plane [15]. Deep learning (DL) and transfer learning techniques are leading the way in the development of automated categorization approaches that eschew accurate segmentation strategies. These techniques exhibit remarkable performance. According to a research, deep learning models may achieve 98.3% ACC, 0.99 AUC, and 98.3% Specificity (SP). This suggests that sophisticated machine learning might potentially enhance the ACC of cell picture analysis in medical applications [16].

With 98.37% ACC, 99.80% SEN, 99.60% SP, and a 99.80% F-measure in the classification of cervical cells, graph convolutional networks have also shown great promise [17]. This highlights their potential in processing complicated medical pictures. An AI-assisted cytological diagnostic structure attained a total unplanned rate of 94.7% and a 5.8% increase in SEN when compared to manual examination in a different large-scale research involving 700,000 women going through cervical cancer screening, highlighting AI's potential for enhancing cervical detection of cancer [18]. The AIATBS system was built by Zhu et al. and demonstrated a SEN of 94.74% in identifying CIN, which was greater than that of human cytologists. This suggests that AI has the potential to considerably enhance diagnostic ACC [19]. The CytoBrain system, developed by Chen and colleagues, employs deep learning to classify and segment cervical cells. With an ACC of 88.30%, SEN of 92.83%, and precision of 82.26%, their CompactVGG classifier beat other models after analyzing 198,952 cervical cell pictures [20]. This suggests that it may be useful in improving cervical cancer screening.

When the lightweight YOLCO model was combined with the InCNet module, it showed impres- sive multi-scale feature extraction capabilities and outperformed conventional models in identifying aberrant, sparse cervical cells in whole slide images (WSIs) [20, 21]. A deep learning system was created by Cheng et al. that processed WSIs with amazing efficiency, matching experienced cy- topathologists' SP and SEN of 93.5% and 95.1%, respectively [22]. In comparison to previous state-of-the-art techniques, Wang et al.'s cascaded fully convolutional network model obtained 0.93 ACC and much quicker processing times [23].

Tested on extensive WSI datasets, deep learning models such as the one created by Kanavati et al. showed performance that was either equivalent to or better than semi-automated methods, with a ROC AUC range of 0.89–0.96, indicating the potential role of deep learning in standardizing screening [24]. With 97.4% SEN and 99.6% ACC, a hybrid system created by Hamdi and colleagues using ResNet50, VGG19, GoogLeNet, Random Forest, and SVM performed remarkably well in cervical cancer staging [25].

An ensemble of the best models demonstrated higher ACC across several classification tasks, with a recall (REC) of 0.96 for binary classification, according to Diniz et al.'s comparison of 10 convolutional neural networks (CNNs) for cervical cell categorization in PAP smears [26]. Tripathi et al. provided more evidence of the efficacy of transfer learning when they classified five different kinds of cervical cells using ResNet-152 attaining 94.89% ACC [27].

Zhou et al. established a three-step cervical screening strategy [28]. Cell detection, picture clas- sification, and case classification were all included in the framework, and each step was completed with notable SEN and ACC. These outcomes demonstrate the approach's therapeutic promise. Fi- nally, strong results on binary and multi-class datasets have been demonstrated by a transformer- based model named CervixFormer, indicating that it may be utilized for automated, scalable cervical screening [29].

In conclusion, cervical cytology has shown that AI systems offer excellent ACC and detection rates. Nonetheless, more investigation is required to investigate novel uses and enhance screening techniques, such artificial intelligence-assisted colposcopy and AI microscopes, which have the potential to transform cervical cancer diagnosis [30]. Alongside these developments in diagnosis, therapeutic approaches such as immunotherapy and targeted treatments also keep evolving [31].

Table 1: Comparative Analysis of AI-Based Diagnostic Methodsfor PAP Smear Screening

Year	**Author(s)**	**Datasets (Number of Images)**	**Methods Used**	**Performance Metrics**
2014	Chankong et al. [11]	ERUDIT (552), Herlev (917)	Bayesian Classifier, KNN, ANN	ACC: 93.78%–99.27%
2017	Zhang et al. [16]	Herlev (917), HEMLBC (2370)	CNN, Transfer Learning	ACC: 98.30%–98.6%; SP: 98.30%–99.00%
2019	Wang et al. [14]	Private (362)	Mean-Shift Clustering Algorithm	SEN: 94.25%; SP: 93.45%
2020	Bao et al. [18]	Cervical Cancer Screening Program (703,103)	Deep Learning	CIN1+ SEN: 88.9%; SP: 95.8%; CIN2+ SEN: 90.10%; SP: 94.80%
2021	Shi J et al. [17]	SIPAKMeD (4049)	Graph Convolutional Network (GCN)	ACC: 98.37%; SEN: 99.80%
2021	Zhu et al. [19]	Cytological Image Biopsy Diagnosis Proven (980)	AIATBS System	SEN: 94.74%

2021	Chen et al. [20]	WSI (198,952)	CompactVGG Network	ACC: 88.30%; SEN: 92.83%; SP: 91.03%; Precision: 82.26%; F1-s: 87.04%
2021	Wei et al. [21]	WSI (2019)	YOLCO (You Only Look Cytopathology Once)	ACC: 80.80%; SEN: 90.60%; SP: 71.00%
2021	Cheng et al. [22]	WSI (3545)	Recurrent Neural Network (RNN)	SEN: 93.50%; SP: 95.10%
2021	Wang et al. [23]	WSI (143)	Fully Convolutional Network (FCN)	Precision: 93.00%; REC: 90.00%; F1-s: 88.00%
2022	Kanavati et al. [24]	WSI (1605)	CNN, RNN	ACC: 90.00%; SEN: 86.00%; SP: 91.00%
2023	Hamdi et al. [25]	WSI (962)	Random Forest, ResNet50, VGG19	ACC: 99.00%; SEN: 97.40%; SP: 99.20%; Precision: 99.60%
2021	Diniz et al. [26]	CRIC (3233)	MobileNet, InceptionNet, EfficientNet	ACC: 96.00%; REC: 94.00%; SP: 97.00%; Precision: 94.00%; F1-s: 94.00%
2021	Tripathi et al. [27]	SIPAKMeD (966)	ResNet-152	ACC: 94.89%
2021	Zhou et al. [28]	WSI (237)	SVM, RetinaNet, Encoder	ACC: 90.50%; SEN: 89.10%; F1-s: 86.70%
2023	Khan et al. [29]	Mendeley (963), SIPaKMeD (4049), Dankook University Hospital (100,000), AI-Hub (20,000)	GRAD-CAM, Swin Transformer	ACC: 95.00%; REC: 95.00%; Precision: 97.00%; F1-s: 95.00%

Available Dataset

Cytology

Herlev Dataset: The Pap smear benchmark dataset comprises individual cell pictures tagged with ground truth data, and has been used extensively for deep learning applications since 2005. There are 917 cervical cell pictures in the collection; 248 are tagged as normal and 675 as aberrant. The trustworthiness of the data is ensured by adhering to conventional Pap smear and staining techniques during sample preparation. This dataset, which comes from Herlev University Hospital in Denmark, is broken down into seven different classes: (a) superficial squamous epithelia; (b) intermediate squamous epithelia; (c) columnar epithelia; (d) mild squamous non-keratinizing dysplasia; (e) moderate dysplasia; (f) severe dysplasia; and (g) carcinoma in situ. Classes (a) through (c) of these correspond to healthy cells, whereas classes (d) through (g) comprise aberrant cells [32]

SIPaKMeD Dataset: The Pap smear imaging collection, which was created in 2018, is separated into five categories: (a) metaplastic cells; (b) parabasal; (c) koilocytotic; (d) dyskeratotic; and (e) superficial-intermediate cells. Normal cells go into the first two groups, aberrant cells fall into the next two, and cells from the transition zone fall into the last category. 966 Pap smear slides and 4,049 single-cell pictures total—2,411 cytology-negative and 1,638 cytology-positive images—make up the dataset [33].

ISBI Dataset: The ISBI challenge datasets from 2014 and 2015 are often utilized in studies on overlapping cell segmentation. The 2014 dataset consists of 945 synthetic pictures with cell overlaps ranging from 2 to 5 and 16 actual cervical cytology EDF images. Nine authentic EDF cervical cytology photos with matching volume images—which show two to ten overlapping cells—are included in the 2015 collection.

Hussain et al. Dataset: The 963 pictures in this India-developed LCB dataset are divided into 350 aberrant cells and 613 normal cells. Based on the TBS categorization, the aberrant cells are further subdivided into 113 LSIL, 163 HSIL, and 74 SCC pictures. The public can access this dataset [34].

Colposcopy

Publicly accessible datasets are uncommon in colposcopy research; the majority of studies use private records. The "Atlas of Colposcopy: Principles and Practice" dataset from the International Agency for Study on Cancer (IARC), a division of the World Health Organization (WHO), and the "Intel & Mobile ODT Cervical Cancer Detection" dataset are two important datasets that can be accessed through the Kaggle platform [35, 36,42].

As of 2021, 1,481 cervix photos classified as abnormal or normal (non-cancerous) are available for download in the Kaggle dataset. Featuring photos from many case studies, the IARC's "Atlas of Colposcopy" highlights high-grade, low-grade, and normal colposcopies. With views featuring green filter, Lugol's iodine, and aceto-white effects, these photos provide a thorough tool for colposcopic examination. This dataset's access was updated in 2024.

Discussion

The application of artificial intelligence (AI) and machine learning (ML) technologies in cervical cancer diagnostics has shown significant promise, particularly in enhancing the ACC, efficiency, and accessibility of screening methods. Through the use of advanced algorithms, AI has been integrated into existing diagnostic methods such as cytology and colposcopy, with notable improvements in the detection of cervical abnormalities, including precancerous lesions. This discussion evaluates the impact of AI in these areas, identifies challenges, and suggests avenues for future research.

The datasets reviewed, including the Herlev, SIPaKMeD, ISBI, and others, provide a foun- dation for developing AI-driven diagnostic models. These datasets have played a crucial role in training and validating deep learning models, enabling automated image analysis for cervical cell classification and lesion detection. The comparative analysis of various AI models (e.g., CNN, RNN, and transformer-based models) shows that AI can achieve a high degree of ACC, SEN, and SP in detecting abnormalities in Pap smear and colposcopy images. For instance, deep learning models like the Graph Convolutional Network (GCN) and CompactVGG have demonstrated high precision and SEN, particularly in handling complex cytological images [17, 20].

However, several limitations must be addressed. One challenge is the variability in the quality of datasets across different regions, which can lead to inconsistencies in model performance. While publicly available datasets such as Herlev and SIPaKMeD are beneficial, there is still a scarcity of high-quality, diverse datasets from low- and middle-income countries, where cervical cancer screening is most needed. This limits the generalizability of AI models in real-world applications. Moreover, some AI technologies, such as the ThinPrep® and FocalPoint GS imaging systems, have high implementation costs, making them less feasible for resource-constrained healthcare systems [11, 12].

The purpose of AI in colposcopy is still limited compared to cytology, there are much fewer pub- lic dataset to use in research. Although Intel & mobile. ODT Cervical Cancer Screening dataset and IARC's "Atlas of Colposcopy" dataset are rich resources for AI development in colposcopy, problems still exist, such as the inconsistency of variables across datasets. Furthermore, the explanation capability that involves explaining why the image is suspicious in the case of colposcopy has not been well advanced.

AI can help to decrease cytopathologists' and physicians' workload concerning the recurrent cervical cancer screening and can broaden the scope of the approach. Using a highly specific diagnostic signature based on consequent whole slide images data analysis, AI can improve the diagnostic process especially in the areas with scarce healthcare provision. However, to implement the AI more often, the following should be considered: There is a need to train the operator, and the process of model deployment should not be so complicated; besides, the cost of the AI has to be affordable.

Considering the future developments of AI in cervical cancer diagnostics, the future endeavors will to incorporate diverse data into AI model and to deploy explainable AI systems into use. Furthermore, there is a need to investigate the integration of AI with other novel techniques in treating diseases, including immunotherapy and targeted therapies, with a view of offering precision medicine. AI researchers, health care professionals, and policymakers will work together to refine use of AI diagnoses to increase widespread cervical cancer screening.

All in all, current cervical cancer screening through AI is advancing rapidly to provide better results but further improvement is still needed. When these gaps are addressed and good access to AI technologies is given, healthcare systems will be able to enhance early detection and early treatment of cervical cancer reducing the burden of cervical cancer around the world.

Challenges

The implementation of artificial intelligence (AI) in cervical cancer diagnostics, though promising, faces several significant challenges that need to be addressed for its full potential to be realized. One of the foremost obstacles is the availability and quality of data. Many AI models rely on existing datasets such as the Herlev and SIPaKMeD datasets, which are limited in both size and diversity. This creates a problem in model training and testing, as datasets from low- and middle-income countries (LMICs) are often scarce, resulting in AI systems that may not perform as effectively across different populations or regions. Without comprehensive and diverse datasets, AI models risk developing biases, making their real-world application less reliable.

In addition to data limitations, the generalization of AI models presents another major chal- lenge. AI systems trained on specific datasets or under controlled conditions may not generalize well when exposed to new populations, clinical environments, or variations in screening methods. Factors such as differences in image quality, patient demographics, and the equipment used for sample collection can significantly affect the ACC and SEN of these models. The ability of AI systems to maintain performance consistency across various healthcare settings remains a crucial issue that needs to be addressed to ensure that these technologies are robust and adaptable.

Despite the fact that the use of AI in cervical cancer diagnostics has already shown distinct potential for presenting excellent results, there are several obstacles that the methodology has to overcome in order to reach its full potential. The first of them is consistency and reliability of data usage Limited and poor data are some of the significant challenges that organizations face to implement baselines. Most of the AI models are based on relatively small and diverse set of databases including Herlev and SIPaKMeD databases. This becomes an issue in model development where datasets from LMICs are usually limited thus developing AI systems that aren't as efficient in the different populations or developed areas. This could be because when training machine learning algorithms, data is segmented and divided into so many categories that without detailed data sets, AI models are bound to have some sort of bias and therefore their impact in the real world will not be accurate.

There is another massive challenge associated with the generalization of AI models, apart from the data limitations, that are discussed above. Specifically, the AI systems involved in developing and refining a screening process may not perform as expected when applied to a new population, different clinic settings or changed manner of screening. In our study, the variations in image quality, predominantly with the patient's demographic characteristics, and sample collection equipment influencing the performance of the proposed models in terms of ACC and SEN have been identified. Another challenge that has been found with reference to AI systems is the ability to develop and retain performance that will be common to different settings within the health-care system; This is an important issue that has to be resolved fully to ensure that the technologies are solid.

The second challenge facing organisations is the price as well as availability of AI-based diagnostic devices. These include; the improvements in the ACC performances of enhanced screening processes such as ThinPrep® and FocalPoint GS. To begin with, infrastructure in terms of equip- ment, software among others, and the technical knowledge that health care providers needs makes these systems very expensive and hence cannot be implemented in a lean environment. Even in the situation when LMICs bear the highest burden of cervical cancer, financial resources do not allow for the implementation of AI-based technologies.

In addition there is also the technicality of integrating AI systems in already established heath care infrastructure that is also a challenge. It is understood that most healthcare systems even in the developed part of the world let alone those in the developing world do not possess the technical savvy, the digital support or integration abilities required to support AI solutions. Consequently, the effectiveness of AI technologies also goes beyond model ACC; that is, incorporating AI tech- nologies into clinical practices and workflows, the privacy of data used in training AI models, and artificial intelligence system compatibility with existing structures.

Finally, issues of ethics and possible regulatory barriers will form the last section of this paper on the application of AI in the healthcare sector. The precise regulation of issues related to the confidentiality of personal information, explain-ability of AI's choices or responsibility for mistakes made by the algorithm are innovative and complicated questions. Therefore as AI advances further within the medical practice there need to be well set rules and enactments that check on the advancement in order to safeguard the lives of patients besides checking on the principles of medical practice.

Solving these issues are crucial for the means of using AI in cervical cancer diagnosis in regions of low access. If implemented correctly which includes the collection of credible data, reduction of costs, and strong policies on artificial intelligence cervical cancer is set to reduced throughout the world due to artificial intelligence.

Conclusion

AI's highly promising in increasing diagnostic accuracy, the ACC of cervical cancer, and the ef- ficiency and accessibility of techniques used for screening. In cytology and colposcopy, the AI is proved to be capable of identifying cervical pathologic changes including precancerous lesions with high accuracy and SEN. Incorporation of such technologies as deep learning models, in combination with better image analysis, has improved the ability of identifying cells that look abnormal in both traditional Pap smear tests and the newer whole slide images (WSIs). Such technologies represent a hope in the inability to alleviate the load on health care workers and optimize the diagnostic process.

However, several barriers must be mastered for AI to be as efficient in clinical environments as shown in the foregoing figures. Some are requirement of more data from diverse and including LMICs, requirement for AI models to perform across different population and other health sys- tems. Expenses of implementation of AI solutions, as well as the demands for the development of infrastructure and training sessions needed to integrate AI systems continue to function as a ma- jor constraint to the application of AI solutions in large-scale human-led organizations, including those characterized by low resources. However, the ethical factors like the protection of data, the introduction of responsibility when AI makes decisions, becomes more critical when dealing with these technologies as they extend their usage in the health care field.

As for the further development of AI in the cervical cancer diagnostics, all depends on the development of AI technologies and different collaborations. Thus, removing current shortcomings and enhancing the AI approaches, one will increase the early detection rates, decrease the possibility of misdiagnosis, and enhance the accessibility to screening for women across the globe. AI is capable of improving cervical cancer care given that the right approaches are applied which include generic approaches capable of enhancing cervical cancer care in developing countries and Least developed nations hence reducing the mortality rate posed by cervical cancer thus better patient outcomes.

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