MAK HILL Publications Research Journal of Medical Sciences

Research Article
doi: 10.36478/makrjms.2024.7.528.539

OPEN ACCESS

Key Words
Cervical cancer, artificial intelligence, visual inspection with acetic acid, machine learning, deep learning

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Received: 20 April 2024
Accepted: 22 June 2024
Published: 25 June 2024

Citation: Patel Mit Alpeshkumar, rof Madhu Jain and atel Shail Alpeshkumar, 2024. The Role Of Artificial Intelligence In Cervical Cancer Screening: A Systematic Review And Meta Analysis. Res. J. Med. Sci., 18: 528-539, doi: 10.36478/makrjms.2024.7.528.539

The Role Of Artificial Intelligence in Cervical Cancer Screening: A Systematic Review and Meta Analysis

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Abstract
This study examines the impact of cervical cancer on underdeveloped nations and underscores the urgent need for rapid, cost-effective accurate screening and treatment technologies. It aims to analyze the current utilization, effectiveness challenges associated with incorporating artificial intelligence (AI) into cervical cancer screening. Utilizing a dual-phase methodology, the study systematically searched major electronic databases for research articles specifically investigating AI in cervical cancer screening. Seventeen studies conducted between 2013 and 2023 were identified, employing various approaches such as dynamic scene and object examination. Data analysis revealed sensitivities and specificities ranging from 0.22 to 0.93 and 0.67 to 0.95, respectively, with fusion procedures achieving a 68% accuracy rate for four cervical lesion classes. Notably, a smart phone solution demonstrated reliability with 0.9 sensitivity and 0.87 specificity. The review underscores AI's potential in deciphering patterns, addressing challenges offering innovative solutions globally. Superiority was noted in support vector machine (SVM) and deep learning algorithms, suggesting a promising trajectory for AI in cervical cancer diagnostics. Overall, these findings underscore the transformative potential of AI in cervical cancer screening, emphasizing the need for continued research and implementation efforts.

INTRODUCTION

Cervical cancer, ranking as the fourth most common cause of cancer-related fatalities among women in 2020, poses a significant global health challenge, particularly in 36 countries, predominantly low-and middle-income nations, where it is reported as the leading cause[1]. In response to this alarming scenario, the World Health Organization (WHO) has initiated efforts to eliminate cervical cancer, emphasizing the adoption of advanced screening methods and early detection techniques[2]. While histopathology information from biopsies remains a reliable approach for identifying cervical abnormalities, its widespread use is often impractical[3].

Cervical cancer screening techniques, pivotal in the early detection and prevention of this life-threatening disease, have traditionally relied on methods like Pap smears and visual inspection with acetic acid (VIA) for identifying cervical cell abnormalities[4]. However, recognizing the need for more accurate and efficient screening, the integration of artificial intelligence (AI) has emerged as a transformative approach[5]. AI applications, including machine learning and deep learning algorithms, analyse extensive datasets of cervical images, enabling a more precise identification of abnormalities and potential cancerous lesions. Beyond mere automation, the role of AI in cervical cancer screening contributes to improving sensitivity and specificity, thereby reducing false positives and negatives facilitating timely and targeted interventions. Harnessing the power of AI, cervical screening techniques are poised for significant advancements, offering a promising avenue for more effective and accessible early detection strategies in the ongoing fight against cervical cancer[6].

Visual inspection with acetic acid (VIA)" presents a cost-effective and straightforward alternative for cervical cancer identification[7]. This method involves applying a solution containing diluted acetic acid to the cervix and subsequently assessing the resulting temporary whitening effect[8]. The manifestation and cessation of this phenomenon vary across various tissue types, encompassing healthy tissues, non-malignant diseases, initial-stage pre-cancerous disorders such as Cervical Intra epithelial Neoplasia of grade 1 (CIN1)malignant conditions[9]. The term CIN2+ collectively denotes both precancerous and cancerous lesions[10].

In high-income countries (HICs), VIA is conducted with a colposcope, which is a low-power microscope that enhances the visibility of the cervix[11]. Nevertheless, the accessibility of such devices for screening in LMICs (Low-and middle-income countries) is limited due to shortages of healthcare workers, insufficient funding outdated facilities[12]. In these cases, the examination is often carried out without the use of any visual aids. The level of accuracy in visual examinations, whether performed with or without a colposcope, is highly dependent on the level of training and experience of the healthcare providers doing them[13]. Observers' sensitivity levels in VIA span from 25.0%-4.4%for classical colposcopy, they range between 40% and 65%, as indicated by extensive research. This variability is evident both among individual observers and across diverse groups[14].

The evaluation of the cervix using image-based techniques, such as direct visual examination or colposcopy, relies significantly on subjective knowledge and the abilities obtained via professional training[15]. Currently, the most reliable method for diagnosis requires the use of colposcopy, and, if deemed required, a biopsy[16]. Colposcopy enhances the visual enlargement of pictures, allowing for the identification of tissue abnormalities that may go unnoticed by the unaided eye[17]. However, the precision of diagnosis is affected by both differences in observations made by different individuals and differences in observations made by the same individual. Additionally, the specificity is rather poor, ranging from 30%-70%. The combination of digital colposcopy with deep learning (DL) has the potential to enhance automated picture categorization[18]. However, it still relies on the availability of professional competence and colposcopes, which are sometimes scarce in rural parts of low-income nations. Utilising cell phones to record cervical pictures and transmit them to a colposcope has the potential to serve as a useful diagnostic tool for these regions[19].

Advancements in artificial intelligence (AI) in recent years have generated optimism regarding a more impartial and automated method of identifying cervical precancer and cancer[20]. The emerging sector has seen the implementation of artificial intelligence (AI) techniques that use photos taken with smart phones and colposcopes, resulting in very promising results. The transformational power of these technologies is in their ability to enhance the precision of cervical cancer screening procedures[18].

The integration of artificial intelligence (AI) into cervical cancer screening systems has the benefit of improved objectivity and accuracy [see reference 19]. Through the use of image analysis, AI algorithms have the ability to surpass the constraints of conventional screening methods, therefore offering a more precise and dependable evaluation of cervical health[20]. The integration of smart phones and colposcopes with AI enhances the accessibility and convenience of cervical cancer screening, expanding the scope of these technologies[21].

The current study attempts to provide a thorough and organised assessment of the research conducted on assessing the effectiveness of AI-based algorithms.

The algorithms are especially designed to analyse pictures obtained during Visual Inspection with Acetic Acid (VIA) in order to distinguish and categorise instances of cervical precancer and cancer [see reference 20].

MATERIALS AND METHODS

Datasource& ligibility: A search methodology was devised to identify articles suitable for inclusion in a systematic analysis. The researcher performed searches for appropriate scholarly articles by using electronic databases, including but not limited to Scopus and PubMed. Additionally, internet tools such as Google and Google Scholar were used to search for relevant academic papers.

Inclusion Criteria: This systematic review included only cervical cancer-related studies that used AI techniques such as automatic detection, deep learning, or artificial intelligence. The acquisition strategies used by the qualified studies were also specific to the field of cervical cancer research. The criteria also included into account papers that have measurable measures of accuracy, including AUC, specificity, or sensitivity. Also included were articles that provided insight into the use of machine learning and deep learning for cervical cancer picture classification and focused on histology image segmentation. The comprehensive application of ML/DL to the cervical cancer diagnostic process was the intended focus of this all-encompassing strategy.

Exclusion Criteria: Articles that excluded primary research, including review articles, theses, patents, editorials, or letters, were not included in the systematic review. Other studies that were deemed irrelevant or had incomplete texts were also not included. Studies unrelated to cervical cancer diagnosis and those performed between 2013 and 2023 without a gold standard for comparison were also eliminated. Studies that weren't employing VIA images or that relied on imaging modalities other than VIA were not included for the analysis. Articles which had been identified but subsequently excluded from the Artificial Intelligence in Cervical Cancer Screening thorough systematic review were also not included.

Screening Strategy: After a meticulous examination of titles and abstracts from electronic databases, search phrases were categorized into four distinct classifications. These groups were then amalgamated using Boolean operators and OR during the electronic data search process. An exhaustive search was conducted, employing a combination of specific terms such as Cervical cancer, Artificial intelligence, to identify and evaluate pertinent academic articles across diverse electronic databases.

After downloading the identified papers, a comprehensive analysis was conducted only those that successfully passed the screening method were included in the study. In instances where the complete texts of relevant papers were not readily accessible, authors were formally contacted to request the provision of said texts. Furthermore, the reference lists of relevant papers were meticulously scrutinized to enhance the likelihood of discovering publications suitable for inclusion.

The entire sequential approach of the screening technique was transparently presented using the "Preferred Reporting Items for Meta-Analyses (PRISMA)" flowchart and systematic reviews, ensuring a systematic and rigorous process for the identification and inclusion of relevant literature in the study.

Data verification for consistency: A Microsoft Excel spreadsheet (version MS Office 2019, United States) was generated to guarantee the internal quality control of the database by include the necessary data. The data underwent integrity checks as a component of the database's external quality control method. When discrepancies occur in excel sheets, the data undergoes a re-evaluation process.

RESULTS AND DISCUSSIONS

Literature search: A search of PubMed and Google Scholar found a total of 180 results. There was one duplication detected. 124 studies were discarded because they meet the exclusion criteria, which were as follows: reviews (34), conference proceedings (50), commentaries (40), According to the selection procedure, a total of 17 studies were considered eligible. Fig. 1 shows a summary of the studies that were included.

Percentage of Publications: Fig. 2 depicts a steady increase in research activity, notably peaking in 2022, particularly focusing on cervical cancer and cervical images. The United States and India emerged as the leading contributors, with nine and eight publications, respectively. The majority of analysed images were sourced from colposcopy, encompassing digital colposcopy, followed by cervicograms and images captured via Android devices. All the included studies were published in English, primarily in computer sciences journals, with a subsequent presence in medicine journals. To encapsulate, among the 17 studies included, eight utilized 200 or fewer images for both training and evaluation purposes.

Between 2013 and 2023, a comprehensive systematic review titled Artificial Intelligence in Cervical Cancer Screening encompassed 17 significant studies. These studies collectively showcased a diverse range of methodologies, providing valuable insights into the various applications of artificial intelligence in cervical cancer screening. Out of the initially identified 218 studies, 39 were excluded for specific reasons. Sixteen studies lacked a gold standard for comparison, thirteen focused on tasks unrelated to cervical cancer diagnosisten relied on other imaging methods or lacked VIA pictures. The studies, conducted by researchers worldwide, reflect a global interest and collaborative effort to advance the application of artificial intelligence in cervical cancer screening as shown in table 1.

DOR = Diagnostic Odds Ratio, CIN 2 =Cervical Intra epithelial Neoplasia grade 2 , AUC= Area Under the Curve, ROC= Receiver Operating Characteristic

Study Characteristics:

Imaging Source and Acquisition Parameters: The examination of 17 papers published from 2013-023 revealed that the main methods of medical imaging were Mobile devices, cervicographydigital colposcopy[38].The use of deep learning and machine learning techniques includes a range of algorithms, including SVM, k-nearest neighbours, xAdaBoost, C4.5, Naïve Bayesmulti-layer perceptrons.Group for Visual Geometry (VGG), XGboots, CNN, ResNet, conditional random fields, Bayes classifierYOLO+EfficientNetB0 [39]Deep Learning (DL) and Support Vector Machine (SVM) techniques, particularly Convolutional Neural Network (CNN), Residual Network (ResNet)Visual Geometry Group (VGG), shown exceptional diagnostic capabilities, achieving an accuracy of over 97% in detecting Human Papillomavirus (HPV) and cervical cancer. The study produced sensitivity, specificity area under the curve (AUC) values [see reference 6]. The hybrid ensemble approach demonstrated an impressive performance, achieving an efficiency of nearly 96% for a 2-class issue and around 78% for a 7-class problem. The CytoProcessorTM demonstrated similar diagnostic accuracy to traditional screening on Novaprep slides, enhancing sensitivity while retaining the same level of specificity and accelerating up diagnosis by 1.6 times[40]

Image Quality and Selection: Zhang et al. provided evaluations of the attributes of the photographs, including brightness, sharpness colourfulness[41]. This

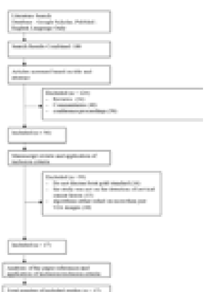

Fig. 1:Prisma flowchart

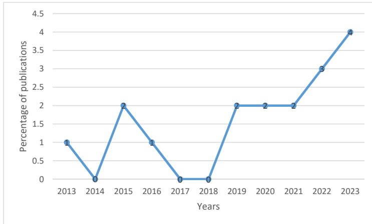

Fig. 2. Percentage of publications on artificial intelligence and cervical cancer screening, 2013–2023 (n = 17)

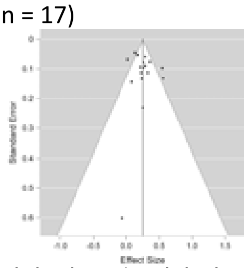

Fig. 3: The funnel plot of a simulated meta-analysis containing 17 studies

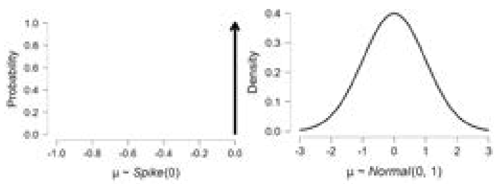

Fig. 4. Plots of effect model

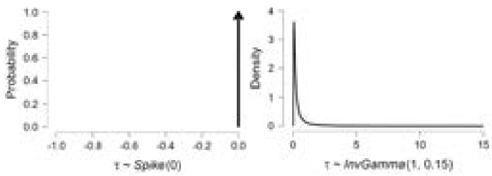

Fig. 5: Heterogeneity plots

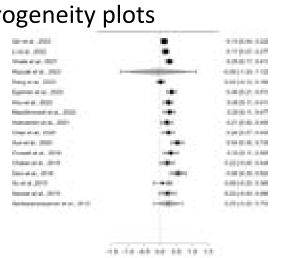

Fig. 6: Forest plot shows overall effect of mean sensitivity

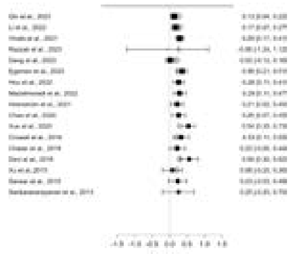

Fig. 7: Forest plot shows overall effect of mean specificity

Table 1: Search output for Cervical Cancer and Artificial Intelligence across Different Databases

Database	Search query	Output
PubMed	Cervical cancer" AND " Artificial intelligence" AND ("diagnosis" OR "screening")	80
Google scholar	"Cervical cancer" AND "Artificial intelligence" AND ("diagnosis" OR "screening") AND ("machine learning" OR "deep learning")	110

Table 2: Summary of included studies on artificial intelligence in cervical cancer screening

Author	Aim of study	Number of subjects	Methods	Results
Qin et al., 2023[21]	The aim of this research is to examine the precision of artificial intelligence (AI) in identifying cervical cancer in its initial stages, using a methodical assessment and meta-analysis approach.	The investigation included a total of 42 datasets to discern among benign and malignant cervical vitreous lesions.	A thorough computer search was conducted in Chinese and foreign language databases (PubMed/MEDLINE, Embase, Cochrane Library, IEEE) from 1946 to December 2022.	The combined Sen value, Spe value, combined +LR value, combined -LR value, DOR combined valueAUC for glassy nodules were 0.90, 0.90, 9.00.11, respectively.
Li et al., 2022[22]	The objective of this study is to enhance the adaptability of computer-aided diagnosis in clinical applications.	included data from 11 studies that met the inclusion criteria	The acetic acid images that are crucial for clinical diagnosis are part of the important dataset used in this work. The squamous and columnar epithelium (SR) sections were processed specifically.	According to the findings, the suggested fusion procedure attains a 68% accuracy rate for the four cervical lesion classes.
Vinals et al., 2021[23]	This research attempts to address the difficulties of cervical cancer in poor nations, with a specific emphasis on the constraints caused by an absence of human and financial resources.	The research has a group of 200 participants who are receiving visual examination with acetic acid for the purpose of screening for cervical cancer.	Automatic detection of cervical precancer is the focus of this research, which utilises the use of a smartphone-based technique.	The smartphone solution described in the study exhibits a notable degree of dependability, with a sensitivity of 0.9 and a specificity of 0.87 T.
Razzak et al., 2023[24]	The primary aim of this study is to do a thorough and cohesive analysis of the current literature that especially investigates digital interventions in the field of cervical cancer treatment.	The subjects of this study include the 26 articles	A systematic literature review (SLR) was the approach used in this investigation. There were 1,110 articles in the original collection to reduce the selection, a strict inclusion-exclusion dominate was used.	The study findings emphasise a significant deficiency in existing studies on the promotion of awareness, ease of screeningavailability of treatment for cervical cancer.
Dang et al., 2023[25]	The primary aim of this research was to examine the practical use of Artificial Intelligence (AI) and Machine Learning (ML) algorithms in diagnosing cancer in real-world situations.	Within the 960 initial search results, only 18 papers (1.88%) satisfied the requirements for using AI/ML procedures in diagnostic decision-making.	A thorough search was performed on PubMed, covering the period from its inception to May 17, 2021, in order to identify papers that demonstrated the use of AI/ML approaches for the prospective identification of cancer.	Human diagnostic performance was shown to be comparable to or even better than that of less experienced doctors when AI/ML algorithms were used.
Egemen et al., 2023[26]	The aim of this study is to present a conceptual step-by-step approach for bridging the gap between the creation of artificial intelligence (AI) image r	Training sets: 13000 images Validation: 35 cervical specimens	Create an AI programme that aims to reduce clinically significant errors, with a specific emphasis on effectively handling difficult scenarios in cervical pictures.	Sensitivity: down to a single cell specificity: 100%
Hou et al., 2022[27]	The primary aim of this project is to investigate the application of artificial intelligence (AI) in the process of screening and diagnosing cervical cancer, with a particular emphasis on enhancing the precision of early detection.	605 cervical cytology samples	The study involves a comprehensive literature analysis to obtain information on the most recent advancements and applications of artificial intelligence in the detection and diagnosis of cervical cancer.	The results emphasise the advantages of artificial intelligence, such as improved precision in detecting diseases at an early stage, decreased time required for diagnosisless reliance on specialised staff.
Allahqoli et al., 2022[28]	The research aims to explore the capacity of automated techniques in recognising anomalous cervical cells, since prompt detection is vital for providing early	After conducting the initial search, a total of 2538 publications were discovered. Following a thorough screening and eligibility evaluation, 117 research were considered suitable	A thorough search was conducted on three databases—Medline, Web of Science Core Collection and Scopus, including papers published through July 2022. intervention.	The thorough research demonstrated that AI technologies have a significan t influence on methods of for inclusion in the review. detection for pre-cancerous and malignant cervical lesions. The algorithms' projected accuracy for cervical cancer varied between 70% and 100%.
Holmström et al., 2021[29]	The primary aim of this diagnostic investigation is to evaluate the feasibility of establishing a point-of-care digital microscopy system.	The research included 740 women who confirmed positive for HIV, with an average age of 41.8 years (standard deviation of 10.3).	The research included the acquisition of cervical smears from 740 women who were HIV-positive and ranged in age from 18 to 64 years. The samples were obtained at a healthcare facility located in a rural area of Kenya.	The DLS exhibited a notable level of sensitivity in identifying cervical cellular abnormalities, with sensitivities of 95.7% (95% confidence interval, 85.5%-99.5%) and 100% (95% confidence interval, 82.4%-100%) for low- and high-grade lesions, respectively.
Cho et al., 2020[30]	The aim of this study is to address the shortage of experienced physicians in developing countries for accurate colposcopic diagnosis of cervical neoplasm	The research used a dataset consisting of 260 patients to create and verify the algorithm using deep learning.	In the CIN system, the multi-class classification accuracies for Resnet-152 in the test dataset were 51.7% and for Inception-Resnet-v2 a rate of 48.6% with a margin of error of 1.3%.	The machine learning models, namely Resnet-152, demonstrated high accuracies in categorising cervical neoplasms and effectively identifying lesions requiring biopsy.
Xue et al., 2020[31]	The aim of this study was to evaluate the feasibility of using automated visual assessment (AVE), a deep learning algorithm particularly designed for the identification of cervical cancer.	A total of 7587 cervix images, acquired by the were selected after filtering for acceptable visual quality.	Automated Visual Examination (AVE) was utilised to the processed cervix photos by means of two state-of-the-art deep learning object recognition networks in the investigation.	The AUC values for all ROC curves significantly more than 0.90, indicating an effective discriminatory ability.
Crowell et al., 2019[32]	The aim of this study was to assess the adaptability and efficacy of the Cy to Processor TM, a cutting-edge automated system designed for the examination of cervical cytology.	The study included a representative population of 309 cases selected from routine workflow in a public hospital.	The research used artificial intelligence to develop a unique algorithm inside the Cyto ProcessorTM, which was specifically designed for evaluating slides produced by the NOVAPREP Processor System NPS50 (Novacyt, Vélizy-Villacoublay, France).	The results provided useful insights into the possible application of CytoProcessorTM technology in various preparation methods, enabling a more flexible and integrated approach to cervical cytology screening.
Challen et al., 2019[33]	The study aims to investigate the profound impact of two disruptive technologies, automationartificial intelligence, on the daily operations of clinical laboratories.	The subjects of this study include clinical laboratories undergoing or planning to undergo automation and artificial intelligence integration.	The research used a thorough and interdisciplinary approach to evaluate the effects of automation and artificial intelligence in clinical labs.	The study used a comprehensive and multidisciplinary approach to assess the impacts of automation and artificial intelligence in clinical laboratories.
Devi et al., 2016[34]	The aim of this study is to investigate the crucial role of Artificial Neural Network ANN) in medical imaging, specifically in the detection of cervical cancer cells.	The subjects of this study include the 112 articles	The approach entails using Artificial Neural Network (ANN) architectures to categorise cervical cells.	The material discusses the accuracy findings and performance metrics of these designs, emphasising their efficacy in outperforming manual screening techniques
catarino et al.,2015[35]	The primary aim of this research is to address the substantial worldwide burden of cervical cancer, especially in underdeveloped countries with higher fatality rates.	The study involves the evaluation of its proposed method using cervical image datasets.	The approach consists of two primary stages. The study proposes a novel multi-feature descriptor that combines an existing one with the pyramid histogram.	The experimental findings indicate that the suggested technique beats current image-based CIN classification methods
Sarwar et al., 2015[36]	The focus is on characterizing and classifying Pap smear images to identify precancerous or potentially	The study included 119 studies precancerous change	The process entails using the Papanicolaou smear (Pap smear), which involves microscopically inspecting cells obtained through scraping the cervix. presenting a viable	The study's findings indicate that the hybrid ensemble methodology is a very effective approach for categorising Pap smear pictures, consequently instrument for diagnosing cervical cancer.
Sankaranarayanan et al., 2013[37]	The research aimed to examine the sensitivity, specificitypredictive characteristics of different visual screening techniques in identifying cervical intraepithelial neoplasia grade 2 (CIN 2) as well as additional severe lesions in women between the ages of 25 and 65.	The study involved a total of 4,444 women aged 25 to 65 years in Kerala, India	A low-threshold positive visual inspection with acetic acid (VIA) was characterised by the identification of any acetowhite region. On the other hand, a high-threshold positive VIA was determined by the identification of distinct, opaque acetowhite lesions that were in close proximity to or in contact with the squamo-columnar junction.	A variety of diagnostic methods were able to detect cervical intraepithelial neoplasia grade 2 (CIN 2) or worse disease with sensitivity rates ranging from 81.9% for cytology to 87.2% .

Table 2: Algorithmic Details, Image Selection Performance Metrics

Author	Classifiers	Image Utilization for Classification	Mean Accuracy	Mean Sensitivity	Mean Specificity
Xu *et al.,*2015 [see reference 15]	A PHOG pyramid histogram, a PLAB pyramid colour histogram in L*A* B spacea PLBP pyramid histogram are all part of the set of multi-feature descriptors.	Single Post-Acetic Acid Image	0.803	0.864	0.742
Crowell *et al.,* 2019 [see reference 12]	CytoProcessorTM	Utilising artificial intelligence for analysis, they perform cervical preparations with aberrant cells.	Not specified	Enhanced sensitivity in comparison to the Thin Prep Imaging System.	Improved specificity compared to Thin Prep Imaging System; 2.6 times fewer false negatives; 1.5 times faster workflow
Sarwar et al., 2015 [see reference 16]	Hybrid ensemble approach,	The categorization of Pap smear images depends on the microscopic examination of human cell samples collected from the cervix.	The hybrid ensemble approach exhibited a remarkable average accuracy of around 96% for the 2-class problem and approximately 78% for the 7-class adversity	Specific sensitivity metrics are not explicitly provided in the given	Specific specificity metrics are not explicitly provided in the given text.
Xue et al., 2020 [see reference 11]	Deep Learning-based	Cervical images from three devices	97%	Not defined	Not defined
Chao et al., 2020 [see reference 10]	Faster R-CNN architecture	Colposcopic photographs	48.6% ± 1.3%	Not defined	Not defined

Table 3. Model Summary

	Models	P(M)
Effect	18/36	0.500
Heterogeneity	18/36	0.500
Publication bias	32/36	0.500

P(M) = the probability of the model

Table 4:

Model	Q	df	p
Omnibus test of Model Coefficients	50.471	1	< .001
Test of Residual Heterogeneity	38.417	16	0.001
Residual Heterogeneity Estimates			
Variable			Estimate
t^2			0.011
t			0.105
I^2 (%)			60.500
H^2			2.532
Model		Q	p
Omnibus test of Model Coefficients	50.471	1	< .001
Test of Residual Heterogeneity	38.417	16	0.001
Residual Heterogeneity Estimates			
Variable			Estimate
t^2			0.011
t			0.105

research aimed to compare the performance of the method by utilising two datasets obtained under different conditions [see reference 35]. Szegedy *et al*. used a convolutional neural network (CNN)-based quality classifier to automatically filter 100,000 photos during the image selection process[42]. Viñals *et al*.meticulously eliminated photographs of low quality (e.g., hazy, with significant movement) or images where the lesion was not evident (e.g., due to excessive blood or mucus) [see reference 3].

Gold Standard: Histopathology has been employed as the definitive method in the studies conducted bySunget al., Bultenet al., Dwivediet al., Xuet al., Sankaranarayananet al.,Tungalet al.,[1,3,5,6,7,8]. Biopsies were performed only for abnormal cytology and colposcopic impressions after acetic acid. Normal cytology and colposcopy were considered as the standard for negative cases (normal or CIN1)[38]. However, histopathological reports were available for only a small subset of the data. Although histology was consistently utilised as the reference standard for identifying positive cases in all research, the specific details of the methods for collecting biopsies were not well described in the majority of studies [see reference [10-15]. In cases where suspicion arose, these studies performed conization biopsies.The Guanacaste dataset included the interpretation of biopsies by many specialists [see references [4,8] and 9]evertheless, the approach for interpreting biopsies were different in the other investigations [see references[5,9,14] and [12].

Dataset Size and Partitioning: The patient population exhibits significant variability across different trials. Out of the total of fifteen investigations, three had been carried out by the same study group and were based on the identical dataset[see references[8-10]. To get a balanced dataset consisting of 690 instances, a random selection of 345 cases was made from the negative Guanacaste samples. Xu et al. provide findings from experiments conducted using both balanced and unbalanced datasets, while [see reference[6].Tungal *et al*. only mention the results obtained from the balanced dataset [see references 8 and[10]. To guarantee a fair comparison, this analysis was specifically directed at the balanced dataset of the three research [see references[8-10]. All three investigations used a 10-fold cross validation approach, in which each fold consisted of 220 patients for training and 40 patients for testing.

A total of 9406 individuals were involved in the study, with 8917 participants being used to test their methodology. The process of choosing situations and particular photos to train or evaluate the algorithm lacks clarity. They performed a comparison of automated visual assessment performance by age groups, although the dataset sizes did not match their original division description. Among of the 8917 patients included in the testing, 8689 tested negative and 228 tested positive, leading to a prevalence rate of 0.03 [see reference[23].

Cho *et al*. chose 1426 photos from 791 patients by excluding photographs that were of low resolution or appeared indistinct [see reference[11]. The frequency of 0.72 remained consistent in both the training and testing sets. Two gynaecologic oncologists picked the picture with the greatest quality from each patient, resulting in a final collection including 791 images. The use of 10-fold cross validation in the development of their approach requires information,

Xue *et al*. used an information set obtained from MobileODT. A total of 7094 pictures were assessed by gynaecologic oncologists for the purpose of training and testing the algorithm [see reference[12]. Furthermore, the system underwent testing on a dataset including histopathologic findings, which is the only experiment of relevance for the present study. A total of 537 individuals had biopsies, resulting in the acquisition of 1159 pictures for the dataset. The prevalence was 0.25 for individual patients and 0.23 for individual images. To conduct a more detailed study, this study only focus on their findings pertaining to the data involving histopathology results. Images originating from the same patient were allocated to a singular set (either for training or testing) and used individually.

Viñals *et al.* employed a dataset consisting of 44 patients [see reference[3]. They used 120 successive photographs per patient, which were taken following the administration of acetic acid, as the input for their algorithm. Out of the total of 44 patients, 29 tested positive and 15 tested negative, resulting in a prevalence rate of 0.66. A leave-one-out cross validation was conducted at the patient level, whereby 44 folds were performed. Each fold included training on 120 photos from 43 patients and testing on the remaining 120 images from one patient.

Li *et al*. employed a dataset consisting of 732 women, each with several photos [see reference[2]. Out of the 732 women, 375 tested positive while 357 tested negative, yielding a prevalence rate of 0.49. The training dataset included 2412 pictures obtained from 632 female individuals. A single randomly picked photograph was used as the testing set for the remaining 100 ladies. A 4-fold cross validation was used.

The majority of the research included in the analysis use individual photos as the input for their algorithms. Cho et al. obtained many photos from each participant after applying acetic acid [see reference[11]. However, they only used the image with the greatest quality to train and test the system.

Classification Technique: The majority of the research included in this study employs various methods the results were demonstrated in Table 2. The algorithm that has the greatest average accuracy in each investigation is explicitly emphasised. The research used several technological approaches, which could be classified into four primary categories: (i) conventional machine learning (ML) methods, (ii) artificial neural networks (ANN), (iii) convolutional neural networks (CNN)(iv) vision transformer (ViT) in conjunction with CNNs [see references[21,37].

The initial investigations, as presented in studies by Xue *et al.* and Loopik *et al.* published in 2015, primarily employed traditional machine learning techniques [see reference 15 and 9]. Conversely, the following research, conducted by Bigoniet al and Champinet *et al.,* use compact neural networks that are especially tailored for the purpose of classification [see reference[12] and[16]. The remaining investigations, exemplified by Xue *et al*.'s and Cho *et al*.'s efforts, primarily employ widely used CNN architectures [see reference[11] and[10].

Publication Bias: The model summary results indicate the statistical assessment of various meta-analytic models based on different factors. For the Effect model, the probability (P(M)) of the model being suitable is 0.500, suggesting a balanced likelihood of its adequacy. Similarly, the "Heterogeneity" model, which assesses the variability between studies, also shows a P(M) of 0.500, indicating an equal likelihood of its appropriateness. The assessment of "Publication bias" yields a P(M) of 0.500, suggesting that there is an equal chance that the model adequately represents potential bias in the included studies. These results imply that, based on the available data, the models for effect, heterogeneity publication bias are equally probable and require careful consideration in the interpretation of the meta-analysis findings.

The analysis will estimate multiple meta-analytic models using MCMC and might require a prolonged time to complete.

In Egger's test, the null hypothesis is that there is no publication biasa non-significant p-value suggests that there is insufficient evidence to reject this null hypothesis. In this case, with a p-value of 0.617, it appears that there is no statistically significant evidence of funnel plot asymmetry or publication bias (figure 3).

Heterogeneity of Studies: The results of the meta-analysis, employing both Fixed and Random Effects models, provide insights into the overall model coefficients and the presence of residual heterogeneity. The Omnibus test of Model Coefficients yielded a statistically significant result, with a Q statistic of 50.471 and 1 degree of freedom (df), indicating a substantial variation beyond what would be expected by chance alone (p<001). This suggests that the model coefficients significantly differ from zero, highlighting the presence of an overall effect. Additionally, the Test of Residual Heterogeneity produced a Q statistic of 38.417 with 16 degrees of freedom, resulting in a p-value of 0.001. The rejection of the null hypothesis in this case indicates the existence of residual heterogeneity among the studies, signifying variability beyond what the model can explain. This underscores the importance of considering both fixed and random effects to account for potential heterogeneity in the meta-analysis.

The coefficients section provides information on the intercept of the meta-analysis model. The estimated intercept is 0.251, with a standard error of 0.035. The Wald test for this intercept yields a z-statistic of 7.104, which is highly statistically significant (p<001). This indicates a robust and significant effect captured by the intercept. Moving on to the residual heterogeneity estimates, t^2 (tau squared) is estimated to be 0.011, representing the variance of true effect sizes around the overall mean.

The t (tau) value is 0.105, denoting the standard deviation of the true effects. The I^2 statistic, a measure of heterogeneity in percentage, is calculated at 60.500%, indicating a moderate level of heterogeneity across the studies. The H^2 value of 2.532 suggests that approximately 60.5% of the observed variability in effect sizes is due to genuine differences between studies rather than random error. These findings emphasize the presence of significant heterogeneity in the meta-analysis, suggesting that the true effects in the underlying studies are not identical.

df= degree of freedom, p = Probability value, Q = model coefficients, t^2 = estimated amount of total variance, t = measure of dispersion, I^2 = percentage of variation, H^2 = measure of heterogeneity.

Table 4. Fixed and Random Effects

Overall Effect of Mean Sensitivity: Fig. 6 shows a forest plot of the log OR-1.61 (95 percent CI: 0.99, 2.62) with non-significant heterogeneity (P = 0.06) from the 17 studies (n = 17) included in the random effect size calculation to assess the result. The use of AI seems to benefit for cervical cancer screening, according to this research. These results demonstrate that the AI-assisted cytology method has enormous potential as a sensitive and specific instrument for screening cervical cancer on a broad scale.

Overall Effect of Mean Specificity: The parameter covariances provide insights into the relationships between the intercept and specificity in the meta-analysis model. The covariance between the intercept and specificity is 0.004, indicating a positive relationship. This suggests that as the intercept increases (indicating a stronger overall effect), there is a tendency for specificity to also increase. Conversely, the negative covariance value of-0.006 between specificity and the intercept suggests an inverse relationship. When specificity increases, there may be a slight tendency for the intercept to decrease. These results demonstrate that the AI-assisted cytology method has enormous potential as a sensitive and specific instrument for screening cervical cancer on a broad scale.

Artificial intelligence (AI) has become a major factor in the field of cervical cancer screening, providing creative ways to tackle issues related to precision, effectiveness availability[43]. This Comprehensive Systematic Review examines 17 influential papers conducted between 2013 and 2023 that have made major contributions to the study of AI applications in the diagnosis of cervical cancer. The many approaches used in this research highlight the changing field of AI technologies[44], which include both classic machine learning methods and advanced techniques like as convolutional neural networks and vision transformers[45]. This study emphasizes the collaborative initiatives among scholars in advancing early detection and diagnosis in cervical cancer screening.

The evaluated entities collaborate to prioritise the development and proliferation of artificial intelligence applications in the identification of cervical cancer. The results emphasise the worldwide cooperative effort and increasing enthusiasm for progressing the area. The investigations illustrate the capacity of AI to improve many facets of cervical cancer diagnosis, including precision, sensitivity efficiency.

In 2020 and 2021, three algorithms were presented that provide great specificity according to the existing results [see references 11 and 3].However, the dataset employed in this study were relatively modest, encompassing 537, 30044 individuals, respectively. There are issues about the generalizability of the suggested approaches due to the usage of such small datasets, particularly with photos that have been carefully picked. Additional testing on bigger datasets is necessary to guarantee reliable performance estimations. A small dataset of 44 patients is also used by the algorithm that achieves the best sensitivity [see references 3]. This highlights the need to validate algorithm performance on larger and more varied datasets to determine their generalizability and dependability.

Similarly, 98,549 women were evaluated independently using AI and human readers in a study by Bao *et al.,* 2020. The results showed a strong overall agreement rate of 94.7% and a high kappa value of 0.92. The system's efficacy was shown by the increasing detection rates of cervical intra epithelial neoplasia grade 2 or worse (CIN2+) as the severity of cytology abnormalities rose. The CIN2+ identification rates for ASC-H or HSIL patients were much higher when using AI-assisted cytology compared to cytologists. While preserving clinically similar specificity, the AI system demonstrated a 5.8% increase in sensitivity for CIN2+identification when compared to manual reading. These results demonstrate that the AI-assisted cytology method has enormous potential as a sensitive and specific instrument for screening cervical cancer on a broad scale[46].

The data was collected using a variety of screening methods. Guanacaste screenings include cytology, HPV testing, acetic acid ocular examination and sometimes, biopsy. A large number of patients are a consequence of this. A prevalence rate of 0.03 was obtained by Xu *et al.,* using a significant portion of the data [see reference 15]. Previous research on this dataset has used a small subset of cases to train their algorithms but hasn't been explicit about how researchers select their patients [see references 10 and 12]. Their frequencies vary between 0.31% and 0.50% [see references 8-10]. Xue *et al,* Cho *et al*. Li *et al.* did not specify their approach or criteria for selecting patients[11,10,2]. The study presented by Viñals et al. included recruiting women who were sent for colposcopy in Cameroon after testing positive for HPVin Switzerland after testing positive for both cytology and HPV[3]. The screening technique and patient enrolment significantly impact the dataset on which the algorithm depends. Similarly, Rubin *et al.* (2019) found that the detection rates for CIN 2 and CIN 3+were 92.6% and 96.1% respectively, which either exceeded or matched the performance of human reading. In comparison to proficient cytologists, the AI-assisted technique showed similar sensitivity (relative sensitivity of 1.01, 95% confidence range of 0.97-1.05) and greater specificity (relative specificity of 1.26, confidence interval of 1.20-1.32). Furthermore, as compared to cytology specialists, AI-assisted reading demonstrated superior sensitivity (1.12, 1.05-1.20) and specificity (1.36, 1.25-1.48). AI-assisted reading significantly enhanced the specificity for CIN1 and below in HPV-positive women, while maintaining the same level of sensitivity as human reading[47].

In a similar way, Rubin *et al.,* 2019 demonstrated CIN 2 accuracy of 92.6% and CIN 3+accuracy of 96.1%, which is higher than or on par with human reading. When compared to trained cytologists, the AI-assisted method showed the same level of sensitivity (relative sensitivity1.01, 95%CI, 0.97-1.05) and greater specificity (relative specificity1.26, 1.20-1.32)[48]

The inclusion criteria were designed to select studies that were similar, but as a consequence, they also limited the breadth of the analysis and established a bias in the selection process. Indeed, intriguing research with regards to technical issues may have been disregarded owing to the inherent characteristics of their input data and reference data.

Researchers have chosen to concentrate only on VIA, in contrast to several research groups that are investigating multi modal inputs. While there may be differing opinions, in order to avoid placing excessive limits on the use of technology, it is suggested that these tools should be implemented with an emphasis on low- and middle-income countries (LMICs).

Additionally, studies relied on histopathology as the only diagnostic tool for positive patients, whereas routine colposcopy and cytology were used for negative cases. The persistent use of histology as the established standard for identifying cervical cancer is reassuring. Despite histopathology being widely regarded as the most reliable method, an important amount of research remains unable to gather and evaluate samples accurately. To guarantee that the automated algorithms depend on accurate ground truth, this technique is crucial. It is recommended that pathologists with expertise in gynaecology conduct and analyse an assortment of biopsies. A two-tiered terminology (LAST) system is suggested it is advised that many pathologists independently evaluate CIN lesions[49]. To further confirm a diagnosis of CIN2 or eliminate diagnostic uncertainty, P16 immunostaining could be used[50].

Other constraints include the variability in performance reporting, the limited number of patients or images, the heavy dependence on a specific set of patients for training and testing the algorithms the lack of thorough evaluations on a broad scale. Based on the detailed screening and recruitment strategies outlined in the studies by Xue *et al.,* Gravitt *et al.,* Bulten *et al*. the World Health Organization, it is evident that there was minimal risk of bias in patient selection. This assessment was corroborated by the application of QUADAS-2 for risk evaluation [references 15, 11, 32].Although the selected studies have inclusion criteria that are equivalent to the gold standard, two of them still have a significant risk of bias since they do not use histology as the gold standard for identifying individuals without the condition.

CONCLUSION

In summary, the findings from the 17 studies conducted on Artificial Intelligence in Cervical Cancer Screening" between 2013 and 2023 highlight AI's significant role in early detection. These studies, using diverse methodologies with a focus on deep learning, demonstrate AI's potential in addressing screening challenges. With reported accuracy rates ranging from 68% to over 97%, AI offers a practical solution, especially in resource-limited settings using portable devices like smart phones. Yet, gaps persist in implementing AI in routine screening, necessitating attention to challenges, ethics patient outcomes for successful integration. Further research into long-term effectiveness, cost accessibility is crucial. Additionally, meta-analysis results stress the importance of assessing effect, heterogeneity publication bias rigorously. The forest plot supports AI's promising benefits in sensitivity the observed relationships between intercept and specificity underscore its potential as a scalable screening tool. Overall, these findings underscore AI's transformative potential in cervical cancer screening.

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