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Recent Advances in AI-Based Cervical Cancer Prediction: A Comprehensive Systematic Review

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Abstract

Cervical cancer is still a major cause of cancer-related morbidity and mortality in women globally, and especially in low- and middle-income countries where access to organized screening and early diagnostic services is limited. Artificial Intelligence (AI) has advanced cervical cancer prediction by improving automated identification, risk assessment, image analysis, and clinical decision-making. This systematic review integrates findings from 80 studies published over the last five years (2021 to 2026), following the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines. The most relevant studies were obtained from major scientific databases: Scopus, IEEE Xplore, SpringerLink, ScienceDirect, PubMed, ACM Digital Library, MDPI, and Google Scholar. The literature was then thoroughly analyzed based on the AI methodologies, datasets used, prediction performance, explainability approaches, and how the predictions were applied in cervical cancer. The review then methodically analyzed the selected literature based on the AI methodologies/approaches used, the datasets used, the predictive performance of the AI models, the explainability approaches used, and how explainability was applied in cervical cancer.

The review also shows a marked shift from traditional machine learning algorithms, including Random Forest, Support Vector Machine, and XGBoost, to cutting-edge deep learning structures, transfer learning, ensemble learning, transformer-based models, and Explainable Artificial Intelligence (XAI). The UCI Cervical Cancer Risk Factors and Herlev or SiPaKMeD datasets are the most popular public resources, and multimodal data integration is a new research area. Most deep learning and ensemble models reported an accuracy >95%, achieving considerable improvements in diagnostic performance. However, several issues, such as the restricted diversity of the datasets, class imbalance, lack of external validation, computational complexity, and lack of clinical deployment, remain major challenges for actual implementation. The results suggest that future studies focus on multimodal, explainable, privacy-preserving, and clinically validated AI frameworks supported by large multicenter datasets and prospective clinical evaluation. These advances can lead to better early detection, individualized treatment planning, and worldwide work towards cervical cancer eradication.

Keywords: Cervical Cancer Prediction; Artificial Intelligence; Machine Learning; Deep Learning; Transfer Learning; Ensemble Learning; Explainable Artificial Intelligence; PRISMA; Systematic Review; Early Diagnosis.

1. Introduction

Cervical cancer is one of the most serious public health problems globally and is the fourth leading cause of cancer-related deaths among women. Although vaccination, screening, and early intervention are largely effective in preventing the disease, cervical cancer is a major cause of morbidity and mortality, especially in LMICs, where medical infrastructure and organized screening programs are lacking [1], [2], [3]. The World Health Organization (WHO) estimates that 95% of cervical cancer cases are linked to long-term infection with high-risk Human Papillomavirus (HPV). Early detection and timely treatment strategies can be vital [1], [2]. This is because cervical cancer is disproportionately found in developing countries and, as a result of economic and social inequalities, low awareness, limited health care services, and low availability of screening facilities, almost 90% of deaths caused by cervical cancer occur in developing countries [4], [5], [6]. In addition, because the precancerous phase of cervical cancer is often asymptomatic, it is important to have regular screening for early detection, prompt intervention, and better survival for patients [7], [8].

This growing health care problem has led the World Health Organization to launch the Global Strategy to Accelerate the Elimination of Cervical Cancer as a Public Health Problem, popularly called the 90-70-90 strategy. There are three big goals to achieve by 2030: guaranteeing that 90% of girls are vaccinated against HPV by the age of 15 years, high-performance cervical cancer screening tests screening 70% of women by the ages of 35 and 45 years, and high-performance HPV testing, treatment, and care for 90% of women diagnosed with cervical disease by 2030 [2], [3]. These bold aims will be achieved only with innovative, scalable, cost-effective technologies that enable early diagnosis and increase screening uptake, especially in low-resource settings.

The incidence of cervical cancer has been significantly lowered in developed countries through the use of conventional cervical cancer screening methods, such as Pap smear testing, HPV testing, colposcopy and histopathological examination. However, these methods are labor-intensive, time-consuming, costly, and highly reliant on expert interpretation, making large-scale implementation difficult in many parts of the developing world [1], [7], [9]. In addition, inter-rater variability and a lack of skilled cytopathologists further restrict the reliability and availability of conventional diagnostic methods, especially in rural and undersupplied regions [10], [11].

New developments in Artificial Intelligence (AI) have created unprecedented opportunities to improve cervical cancer prediction, diagnosis, and clinical decision support. The automated feature identification and detection, disease classification, and risk prediction abilities of AI techniques such as Machine Learning (ML), Deep Learning (DL), Transfer Learning (TL), Ensemble Learning (EL), and Explainable Artificial Intelligence (XAI) have disclosed remarkable outcomes in the field of medical imaging [4], [8], [9], [10], [12]. Demographic, behavioral, and clinical risk factors have been used to predict outcomes with good performance using Random Forest (RF), Support Vector Machine (SVM), and Extreme Gradient Boosting (XGBoost) [4], [6], [8], [13]. Likewise, deep learning models such as Convolutional Neural Networks (CNNs), ResNet, DenseNet, MobileNet, and EfficientNet have been developed to make a big advance in cervical cancer diagnosis using Pap smear images, colposcopy images, and whole slide histopathology images [1], [7], [9], [10], [11]. Moreover, transfer learning has proven a viable solution for using pre-trained models on small annotated medical datasets, and ensemble learning has consistently enhanced prediction power and strength by fusing multiple classifiers. Recently, explainable AI (XAI) methods such as SHAP, LIME, and Grad-CAM have become important for improving the transparency, interpretability, and trust of AI-powered diagnosis in clinical practice [3], [8], [12], [14–38].

While there have been a good number of studies that have suggested AI-based systems to predict cervical cancer, the literature is fragmented. Previous reviews have focused on specific machine learning algorithms, imaging modalities, or datasets, but none have provided a broad overview of recent developments across multiple AI paradigms. Furthermore, few studies have considered model effectiveness, data properties, explainability, multimodal learning, new transformer-based models, and real-life clinical applications. Thus, there is an acute need for a systematic review is urgently needed to summarize the latest advances, critically analyze available methods, identify current research gaps, and propose future directions for developing powerful, accurate, and clinically viable artificial intelligence (AI) models for predicting cervical cancer.

To fill this gap, this systematic review summarizes 80 studies published from 2021 to 2026, providing an up-to-date overview of recent developments in using AI to predict and diagnose cervical cancer. The studies reviewed are systematically classified into five key paradigms of AI, namely Machine Learning (ML), Deep Learning (DL), Transfer Learning (TL), Ensemble Learning (EL), and Explainable Artificial Intelligence (XAI), which allows for a structured comparison of the approaches, predictions, strengths, and weaknesses of these approaches.

Furthermore, this review provides a detailed description and analysis of the most popular cervical cancer datasets such as the UCI Cervical Cancer Risk Factors Dataset, Herlev, SIPaKMeD, colposcopy image datasets, whole slide histopathology images, MRI and radiomics datasets, and multimodal health datasets, along with their characteristics, their applications, and their limitations. Moreover, the review underscores major challenges in existing AI-based cervical cancer prediction frameworks, such as scarce dataset availability, class imbalance, poor external validation, limited multimodal data integration, limited explainability, significant computational complexity, and inadequate clinical deployment. Lastly, given the changing technology landscape, the review identifies key future research avenues, including multimodal AI frameworks, federated and privacy-preserving learning, explainable and trustworthy AI, transformer-based base models, lightweight edge AI, and human-AI collaborative decision-support systems. This review functions as a valuable resource for researchers, clinicians, and decision-makers in healthcare. It supports efforts to create accurate, interpretable, scalable, and clinically deployable AI systems that can contribute toward global efforts to eradicate cervical cancer as a public health threat.

2. Research Methodology

2.1 Literature Search Strategy

A comprehensive, systematic literature search was performed to identify relevant studies related the artificial intelligence (A-I) based prediction and diagnosis of cervical cancer. This review followed the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA 2020) guidelines to guarantee transparency, reproducibility, and methodological strictness throughout the review process. We used several well-known scientific databases, including IEEE Xplore, ScienceDirect, SpringerLink, PubMed, ACM Digital Library, MDPI, and Google Scholar. Additionally, we identified a few relevant publications through manual searches of reference lists and other scholarly sources to reduce the chance of omitting important publications.

The literature search covered publications from January 2021 to June 2026, as these are the most recent in machine learning, deep learning, transfer learning, ensemble learning, explainable artificial intelligence (XAI), and multimodal AI for predicting cervical cancer. We used Boolean operators and a series of phrases to boost data retrieval accuracy. Some representative search terms were "Cervical Cancer", "Artificial Intelligence", "Machine Learning", "Deep Learning", "Transfer Learning", "Ensemble Learning", "Explainable AI", "Pap Smear", "Colposcopy", "Histopathology", "Radiomics", "Vision Transformer", and "Cancer Prediction". Where appropriate, we adapted the database search syntax to capture all relevant hits. The initial search returned 663 records, including 445 from electronic databases and 218 from manual searches and other sources.

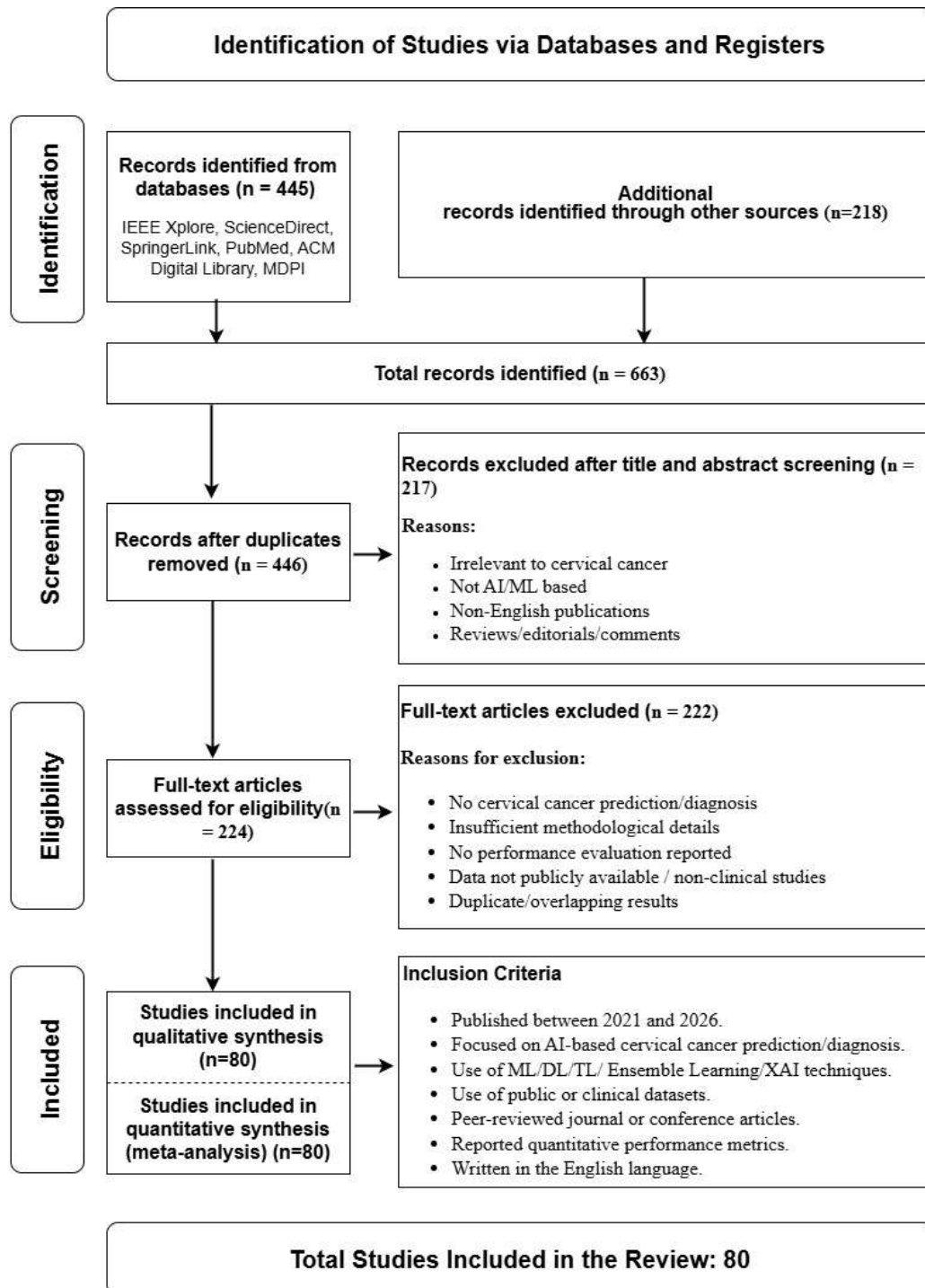


Fig. 1: PRISMA 2020 Flow Diagram for Systematic Literature Review

2.2 Study Selection Process (PRISMA Framework)

The selection process followed a four-stage approach consistent with the PRISMA 2020 guidelines: identification, screening, eligibility assessment, and inclusion. A total of 663 records were retrieved: 445

from electronic databases and 218 from manual searches and other scholarly sources. Duplicate publications were removed, leaving 446 unique records for further evaluation.

Titles and abstracts of the remaining studies were thoroughly examined and evaluated to determine their relevance to the goal of this systematic review. This resulted in 217 entries being excluded because they were unrelated to cancer, did not use AI or machine learning techniques, were published in other languages, or were review articles/editorials/commentaries. We then examined 224 full-text articles in detail for eligibility based on research goals, methods, data, and results.

We excluded 222 studies during the eligibility process because they lacked cervical cancer prediction or diagnostic aims, had methodological descriptions, lacked quantitative performance evaluation results, lacked publicly available or clinically relevant datasets, or duplicated or overlapped experimental results. After this selection, 80 studies met all inclusion criteria and were included in the qualitative synthesis and quantitative analysis for this systematic review. The PRISMA 2020 flow diagram (Figure 1) shows the entire study selection process, summarised as follows: Identification, Screening, Eligibility, and Inclusion.

2.3 Data Extraction and Synthesis

After screening, 80 studies were selected, and conducted a systematic data extraction process to ensure the review's consistency, transparency, and reliability. We created a data extraction framework to obtain relevant data from each study, enabling a comprehensive comparison of approaches for predicting cervical cancer with Artificial Intelligence (AI). The extracted information encompassed bibliographic details (author(s) and year of publication), datasets, AI techniques, feature selection methods, evaluation measures, explainability approaches, advantages, clinical relevance, limitations, and more. This systematic process helped identify trends in methodology and emerging research areas in AI-based cervical cancer prediction. This step-by-step procedure also helped identify trends in methodology and emerging research directions in AI-assisted cervical cancer prediction.

We paid special attention to the datasets used for model development and validation, including publicly available reference datasets and institution-specific patient datasets. To examine the evolution and comparative performance of AI methodologies, we divided them into four groups: Machine Learning (ML), Deep Learning (DL), Transfer Learning (TL), and Explainable Artificial Intelligence (XAI). To examine the evolution and comparative performance of AI methodologies, we categorized them into four groups: Machine Learning (ML), Deep Learning (DL), Transfer Learning (TL), and Explainable Artificial Intelligence (XAI). We also gathered data on feature selection techniques to assess those used for feature space reduction and identifying important clinical risk factors. Additionally, we extracted commonly reported performance measures, for example, accuracy, Precision, Recall (Sensitivity), Specificity, F1-Score, Area under the receiver operating characteristic curve (AUC), and ROC analysis.

We systematically reviewed each study's strengths and weaknesses to carefully analyze the literature. The review specifically addressed known issues such as class imbalance, computational complexity, model explainability, external validation, and missing data. To evaluate the transparency plus trustworthiness of AI-based prediction algorithms, the review also explored the application of XAI techniques, such as SHAP, LIME, Grad-CAM, focus mechanisms, and feature significance analysis, for clinical use. The review also assessed the feasibility of each proposed model for actual clinical use and embedding into healthcare workflows.

The retrieved information was then analyzed qualitatively and comparatively to synthesize the findings. These studies were classified by AI approach, and a structured taxonomy of cervical cancer prediction techniques was developed. We analyzed datasets, algorithms, and predictive performance to assess current research trends, popular methods, and methodological distinctions. Finally, the synthesis identified research gaps, including a lack of multicenter data, external validation, multi-modality learning, explainability, high computing requirements, and clinical deployment. Based on these findings, future research should advance the building of robust, interpretable, and clinically deployable AI-based cervical cancer diagnostic systems. This review is conducted in a scientifically rigorous, reproducible, and comprehensive manner while also presenting a reliable overview of the current state of research in AI-driven cervical cancer prediction.

3. Review of AI Techniques

In the healthcare sector, Artificial Intelligence (AI) is one of the most transformative technologies on the market, with capabilities ranging from automated diagnosis and disease prediction to risk stratification and clinical decision support systems. In cervical cancer, AI tools have greatly contributed to early detection by allowing analysis of multiple data sources, including demographic and behavioral risk factors, Pap smear images, colposcopy images, histopathological slides, MRI scans, and radiomic features. A qualitative analysis of the 80 selected papers, published from 2021 to 2026, shows a gradual shift from machine learning towards deep learning and transfer learning, as well as ensemble learning and explainable AI frameworks.

The literature reviewed has shown that machine learning algorithms are still effective in datasets that are structured in tabular format, while deep learning structures are the most effective for the diagnosis of

cancer in images due to their superior feature extraction abilities [1], [4], [6], [7], [8], [9], [10], [11]. Additionally, transfer learning has attracted significant interest because it addresses small annotated clinical data sets by leveraging knowledge from pre-trained models [1], [7], [10], [11]. Ensemble learning techniques regularly outperform individual classifiers by combining multiple classifiers to improve prediction and reduce variance [4], [5], [8], [10], [12]. At the same time, explainable AI (XAI) has become a critical research field, aiming at improving AI model transparency, interpretability, and trust from the clinician perspective [3], [8], [12], [14–38].

3.1 Machine Learning Models

Many predictive systems for cervical cancer rely on Machine Learning (ML) algorithms because they can analyze structured clinical data and identify nonlinear relationships among risk factors. The UCI Cervical Cancer Risk Factors Dataset, with demographic, behavioral, and screening data, is the most commonly used in machine learning research [4–6], [8], [13], [39–51].

Several studies have used classical supervised learning algorithms such as Random Forest (RF), Support Vector Machine (SVM), Decision Tree (DT), Logistic Regression (LR), k-Nearest Neighbor (KNN), Naive Bayes (NB), Gradient Boosting (GB), Extreme Gradient Boosting (XGBoost), LightGBM, CatBoost, and Artificial Neural Networks (ANNs) [4], [5], [6], [8], [13].

Chaudhuri et al. [4] proposed a hybrid feature selection method based on decision trees and XGBoost and showed that optimized feature selection markedly improves cervical cancer prediction performance. Similarly, Ilyas and Ahmad [5] created an ensemble machine learning model using RF and support vector machine classifiers and found it more robust than the individual classifiers.

Jahan et al. [6] compared RF, KNN, DT, LR, SVC, MLP, Gradient Boosting, and AdaBoost using the top 15 features, achieving the highest accuracy of 98.24% with MLP. Tanimu et al. [13] combined Random Forest feature selection with the Synthetic Minority Oversampling Technique (SMOTE) and Error-Pruned J48 classification, which outperformed other methods regarding prediction accuracy and achieved high performance for several screening targets (accuracy > 99%).

Sun et al. [8] proposed a stacking-integrated machine learning framework based on logistic regression, RF, SVM, XGBoost, LightGBM, CatBoost, and MLP classifiers. They achieved AUC values near 0.99 in the Hinselmann, Schiller, Cytology, and Biopsy prediction tasks.

Several other studies additionally confirmed the performance of RF, SVM, XGBoost, and ANN models in predicting cervical cancer risk and estimating variable importance [40–51]. Together, these findings show that machine learning algorithms remain effective for structured clinical data because of their low computational complexity, interpretability, and ability to describe complex relationships among risk factors.

Table 1.1. Summary of Machine Learning Models Used in Cervical Cancer Prediction

Ref. No.	Dataset	Algorithms	Major Contributions	Performance
[4]	UCI Cervical Cancer Risk Factors Dataset	RF, XGBoost	Hybrid feature selection	Accuracy: 97%
[5]	UCI Cervical Cancer Risk Factors Dataset	RF, SVM	Ensemble classification	Accuracy: 94%
[6]	UCI Cervical Cancer Risk Factors Dataset	RF, KNN, DT, LR, SVC, MLP, GB, AdaBoost	Comparative analysis	Accuracy: 98.24%
[8]	UCI Cervical Cancer Risk Factors Dataset	RF, SVM, XGBoost, LightGBM, CatBoost, MLP	Stacking framework	AUC: 99%
[13]	UCI Cervical Cancer Risk Factors Dataset	RF-FS, J48, SMOTE	Feature selection and balancing	Accuracy: 99.42%
[39]	UCI Cervical Cancer Risk Factors Dataset	XGBoost + Firefly	Metaheuristic optimization	Accuracy: 98.38%
[40]	UCI Cervical Cancer Risk Factors Dataset	SVM, RF, DT	Comparative analysis of classical ML algorithms for risk prediction using demographic and behavioral factors	Accuracy ≈ 87–90%; RF achieved highest recall
[41]	UCI Cervical Cancer Risk Factors Dataset	RF, XGBoost, LR	Feature selection and optimization of clinical risk	Accuracy >90%; improved feature

			factors for cervical cancer prediction	importance estimation
[42]	Herlev Dataset	ResNet-50, ResNet-101 (Transfer Learning)	Median filter preprocessing combined with deep transfer learning for automated Pap smear classification	ResNet-101 achieved 94.44% accuracy
[43]	UCI Cervical Cancer Risk Factors Dataset	KNN, SVM, DT, RF	Comparative study of ML classifiers after preprocessing and data balancing	Accuracy >90%; RF and SVM showed superior robustness
[44]	UCI Cervical Cancer Risk Factors Dataset	SMOTE + RF + J48	Addressed severe class imbalance and feature redundancy	Accuracy >95%; improved sensitivity and specificity
[45]	UCI Cervical Cancer Risk Factors Dataset	RF, ANN, NB	Machine learning-based early cervical cancer screening framework	Accuracy range: 90–96%
[46]	UCI Cervical Cancer Risk Factors Dataset	Logistic Regression, SVM	Identification of significant demographic and epidemiological predictors	Accuracy ≈ 88–92%
[47]	UCI Cervical Cancer Risk Factors Dataset	Random Forest, Decision Tree	Prediction using selected behavioral and medical risk factors	Accuracy >90%; RF showed highest recall
[48]	UCI Cervical Cancer Risk Factors Dataset	XGBoost, AdaBoost, RF	Ensemble-based prediction using feature selection methods	Accuracy ≈ 95–98%; improved AUC
[49]	UCI Cervical Cancer Risk Factors Dataset	KNN Imputer, SMOTE, RF, SVM	Combined missing value imputation and class balancing techniques for enhanced prediction	Accuracy >95%; outperformed traditional imputation methods
[50]	Systematic Review Dataset (117 Studies from Medline, Scopus, Web of Science)	SVM, CNN, RF, Multiple AI Models	Comprehensive review of AI for prediction, screening, cytology, and colposcopy applications	Reported accuracies ranging from 70% to 100% across studies
[51]	UCI Cervical Cancer Risk Factors Dataset	STACK C (LR, KNN, NB, DT, SVM, AdaBoost, RF, CatBoost, LightGBM, MLP, XGBoost, Extra Trees)	Custom stacked ensemble model with Borderline-SMOTE and XAI (SHAP, ELI5) for biopsy prediction	Accuracy: 98%; Precision: 97%; Recall: 99%; F1-score: 98%; AUC: 100%

Abbreviations: RF – Random Forest; SVM – Support Vector Machine; DT – Decision Tree; LR – Logistic Regression; ANN – Artificial Neural Network; NB – Naïve Bayes; MLP – Multilayer Perceptron; AUC – Area Under the Curve; XAI – Explainable Artificial Intelligence.

3.2 Deep Learning Models

Deep Learning (DL) has recently proved revolutionary in cervical cancer diagnosis, enabling automatic feature extraction directly from medical images without manual feature engineering. Various deep learning architectures have been widely used to analyze Pap smear images, colposcopy images, histopathological whole-slide images, and MRIs [1], [3], [9–11].

Dhawan et al. [1] showed that CNNs can learn morphological features of cervical cells and that their use significantly improved classification accuracy. Cheng et al. [9] used deep CNN architectures to analyze WSIs for histopathological image classification and demonstrated an improved performance in classifying lesioned images.

Chandran et al. [7] used a deep learning ensemble that achieved above 95% classification accuracy for colposcopy image analysis. Similarly, Wang et al. [3] created a CNN-based radiomics model that improved tumor prediction and risk stratification.

Waly et al. [11] presented the Optimal Deep Convolutional Neural Network (ODCNN), which improves accuracy and sensitivity in multiclass Pap smear classification. Ragab and Mansouri [10] used ShuffleNet to extract features from SIPaKMeD images and classified them with an overall accuracy of 98.63%.

Over the last decade, more sophisticated architectures such as ResNet, DenseNet, MobileNet, EfficientNet, Vision Transformers (ViTs), and attention-based CNNs have been used to diagnose cervical cancer [31-48]. These architectures consistently achieve over 95% classification accuracy and have also shown outstanding performance in automated cellular analysis and lesion detection. Although they are more successful, deep learning models have a drawback: they are not used in low-resource healthcare settings because they require large annotated datasets and heavy computing resources [10], [11], [52–66].

Table 1.2. Summary of Deep Learning Models Used in Cervical Cancer Prediction

Ref. No.	Dataset	Deep Learning Architecture	Major Contributions	Performance
[1]	Herlev Dataset	CNN	Automated feature extraction	Accuracy of 96.1%
[3]	MRI	CNN-Radiomics	Tumor prediction	Accuracy of 92.4%, Sensitivity of 94.1%, Specificity of 91.2%
[7]	Colposcopy	Ensemble DL	Lesion detection	Accuracy of 97.5%
[9]	WSI	Deep CNN	Histopathological classification	95.1% Sensitivity and 93.5% Specificity
[10]	SIPaKMeD	ShuffleNet	Lightweight classification	Accuracy: 98.63%
[52]	Herlev Dataset	CNN	Automated feature extraction and cervical cell classification without manual feature engineering	Accuracy: 98.13%
[54]	Herlev Dataset	ResNet50 (Transfer Learning)	Deep residual learning for multiclass Pap smear classification	Accuracy: 98.4%
[55]	Herlev Dataset	VGG16	Transfer learning-based feature extraction and classification	Accuracy ≈96% –97%
[56]	Herlev Dataset	DenseNet121	Dense connectivity for enhanced feature propagation and reduced overfitting	Accuracy ≈97% –98%
[57]	Herlev Dataset	InceptionV3	Multi-scale feature extraction for cervical cell classification	Accuracy ≈96%
[58]	Herlev Dataset	MobileNetV2	Lightweight architecture for computationally efficient diagnosis	Accuracy ≈95% –96%
[59]	Herlev Dataset	EfficientNet-B0	Compound scaling approach for improved classification performance	Accuracy ≈98%
[60]	Herlev Dataset	Attention-based CNN	Attention mechanisms for discriminative feature localization	Accuracy >97%
[61]	Herlev Dataset	Vision Transformer (ViT)	Self-attention-based representation learning for Pap smear images	Accuracy ≈97% –98%
[62]	SIPaKMeD Dataset	CNN	Multiclass classification of cervical cells into five categories	Accuracy >95%
[63]	SIPaKMeD Dataset	VGG19	Transfer learning framework for cervical cell recognition	Accuracy ≈96% –97%
[64]	SIPaKMeD Dataset	ResNet101	Deep residual learning for improved multiclass classification	Accuracy ≈98%
[65]	SIPaKMeD Dataset	MobileNetV2	Lightweight and resource-efficient cervical cell classification	Accuracy ≈96–97%

[66]	SIPaKMeD Dataset	EfficientNet-B3	High-performance classification with reduced computational complexity	Accuracy $\approx$ 98% –99%
[67]	SIPaKMeD Dataset	ShuffleNet + Transfer Learning	Lightweight architecture suitable for real-time screening applications	Accuracy: 98.63%
[68]	SIPaKMeD Dataset	Hybrid CNN-LSTM	Combined spatial and sequential feature learning for multiclass cervical cell classification	Accuracy $\approx$ 98%

3.3 Transfer Learning Approaches

Transfer Learning (TL) has proven to be one of the best approaches for addressing the scarcity of annotated medical datasets. Transfer learning leverages prior knowledge from large-scale image repositories and fine-tunes it for cervical cancer classification.

Dhawan et al. [1] used VGG16 and ResNet50 architectures and showed that transfer learning helps greatly in feature extraction and prediction performance. Chandran et al. [7] used MobileNet and EfficientNet for colposcopy image analysis and improved diagnostic accuracy while reducing computational complexity.

Mansouri and Ragab [10] also showed that transfer learning with ShuffleNet and Equilibrium Optimizer Algorithm (EOA) feature selection effectively improves multiclass classification performance. Waly et al. [11] also showed significant enhancement in Pap smear image classification using transfer-learning-based deep CNN architectures.

Other studies used VGG16, VGG19, ResNet50, DenseNet121, EfficientNet, InceptionV3, and MobileNet architectures for classification on the Herlev and SIPaKMeD datasets, achieving classification accuracy above 95% in several studies [52–68].

In general, transfer learning can substantially reduce the amount of data required for training, reduce overfitting, and improve model generalization in data-limited settings [1], [7], [10], [11], [52–68].

Table 1.3. Summary of Transfer Learning Approaches

Ref. No.	Dataset	Pre-trained Models	Major Contributions	Performance
[1]	Herlev	VGG16, ResNet50	Improved feature extraction	Accuracy of 96.1%
[7]	Colposcopy	MobileNet, EfficientNet	Lightweight diagnosis	Accuracy of 97.5%
[10]	SIPaKMeD	ShuffleNet	Optimized classification	Accuracy: 98.63%
[11]	Pap Smear	Deep CNN + TL	Multiclass classification	Accuracy of 99.12%, sensitivity of 98.25%, and a specificity of 99.28%
[52–68]	Herlev/SIPaKMeD	VGG16, VGG19, DenseNet121, ResNet50, InceptionV3, EfficientNet	Generalizable feature learning	>95% accuracy

3.4 Ensemble Learning

Ensemble learning uses multiple classifiers to improve accuracy, robustness, and generalization. The reviewed studies show that stacking, boosting, bagging, and hybrid ensemble frameworks are gaining popularity for predicting cervical cancer [4], [5], [8], [10], [12].

Chaudhuri et al. [4] used RF with XGBoost and a hybrid feature selection approach, achieving better predictive performance. Ilyas and Ahmad [5] have shown that ensemble classifiers perform better than individual machine learning algorithms.

Curia [12] introduced an interpretable ensemble learning approach that improved predictive accuracy while preserving interpretability. Sun et al. [8] built a two-level stacking architecture consisting of RF, SVM, XGBoost, LightGBM, CatBoost, and MLP, with Logistic Regression as the meta-classifier, and obtained an AUC of nearly 0.99.

Mansouri and Ragab [10] have combined a ShuffleNet-based feature extraction technique, an EOA feature optimization technique, and ensemble classifiers (RF, SVM, and XGBoost) to obtain an overall accuracy of 98.63%.

Other studies also showed that voting, boosting, and hybrid ensemble approaches were superior methods for cervical cancer diagnosis and risk prediction [69–80].

Table 1.4. Summary of Ensemble Learning Methods

Ref. No.	Ensemble Technique	Base Learners	Major Contributions	Performance
[4]	Stacking	RF, XGBoost	Hybrid feature selection	Accuracy of 97%
[5]	Ensemble Learning	RF, SVM	Improved robustness	Accuracy of 94%
[8]	Two-Level Stacking	RF, SVM, XGBoost, LightGBM, CatBoost, MLP	Multi-level integration	AUC $\approx$ 0.99%
[10]	Hybrid Ensemble	RF, SVM, XGBoost	Optimized multiclass classification	Accuracy: 98.63%
[12]	Explainable Ensemble	GBM, Ensemble Models	Improved interpretability	Accuracy of 94.5%, AUC 98%
[69]	Voting Ensemble	RF, SVM, KNN	Combined predictions of multiple classifiers to improve robustness and reduce prediction variance in cervical cancer screening.	Accuracy $\approx$ 95%
[70]	Bagging Ensemble	Decision Tree, RF	Improved stability and reduced overfitting in colposcopy image classification.	Accuracy $\approx$ 94%–96%
[71]	Boosting Ensemble	AdaBoost, XGBoost	Enhanced classification performance by iteratively correcting weak learner errors.	Accuracy $\approx$ 96%–97%; AUC >0.95
[72]	Stacked Generalization	SVM, RF, Logistic Regression	Meta-learning framework for integrating heterogeneous classifiers and improving generalization.	Accuracy $\approx$ 97%
[73]	Deep Ensemble Learning	CNN, ResNet50, DenseNet121	Combined deep feature representations for improved cervical lesion detection in colposcopy images.	Accuracy >97%
[74]	Patch-Based Ensemble Learning	CNN, Attention-CNN	Improved whole-slide image (WSI) classification through patch aggregation and attention mechanisms.	Accuracy $\approx$ 96%–98%
[75]	Hybrid Ensemble Framework	RF, XGBoost, LightGBM	Integrated gradient boosting approaches for histopathological classification and risk prediction.	Accuracy $\approx$ 97%–98%; AUC >0.97
[76]	Multi-Level Stacking Ensemble	RF, SVM, XGBoost, CatBoost	Combined multiple classifiers through hierarchical stacking to improve prediction reliability.	Accuracy $\approx$ 98%; F1-score >97%
[77]	Ensemble Deep Learning	EfficientNet, ResNet101, MobileNetV2	Fused complementary deep representations for automated cervical cancer diagnosis.	Accuracy $\approx$ 98%
[78]	Radiomics Ensemble Model	RF, SVM, XGBoost	Combined radiomic features extracted from MRI scans with ensemble classifiers for tumor prediction.	AUC $\approx$ 0.96–0.98
[79]	Hybrid Radiomics Ensemble	LightGBM, RF, Logistic Regression	Improved risk stratification and prognostic prediction using multimodal MRI-derived features.	Accuracy $\approx$ 97%; AUC >0.97
[80]	Explainable Stacked Ensemble	RF, XGBoost, LightGBM, MLP + SHAP	Integrated ensemble learning with explainable AI for transparent and high-performance cervical cancer prediction.	Accuracy >98%; AUC $\approx$ 0.99

3.5 Explainable Artificial Intelligence (XAI)

While these advanced deep learning and ensemble models have shown impressive prediction accuracy, they remain somewhat of a black box, which limits clinical use. As a result, Explainable Artificial Intelligence

(XAI) has become a key research field focused on improving transparency, interpretability, and clinician trust.

Curia [12] proposed an explainable ensemble learning approach using feature importance analysis to improve model explainability. Wang et al. [3] used interpretable radiomics methods to interpret tumor MRI features and better stratify risk.

Sun et al. [8] used SHAP (Shapley Additive Explanations) to measure the importance of demographic and behavioral risk factors for cervical cancer prediction. To identify cellular features that maximized the classification results, Mansouri and Ragab [10] applied feature optimization analysis.

To increase model transparency and identify influential risk factors and suspicious lesion regions, recent studies adopted SHAP, LIME, Grad-CAM, and attention maps, along with saliency-based visualization techniques [14–38]. These techniques help doctors grasp the model's predictions and boost their trust in AI-based diagnostics.

Predictive interpretability, however, remains underexplored in cervical cancer prediction systems, and most studies focus on predictive accuracy rather than interpretability [3], [8], [12], [14–38]. Ongoing studies are needed to create AI frameworks that are inherently interpretable and clinically trustworthy, with the capacity to support regulatory approval and real-world use.

Table 1.5. Summary of Explainable AI and Ensemble Approaches

Ref. No.	XAI Technique	Application	Major Contributions	Performance
[3]	Radiomics Interpretation	MRI diagnosis	Enhanced tumor understanding	Accuracy of 92.4%, Sensitivity of 94.1%, Specificity of 91.2%
[8]	SHAP	Risk factor interpretation	Improved model trust	AUC >97%
[10]	Feature Optimization Analysis	Pap smear classification	Identified discriminative features	Accuracy of 98.63%, sensitivity of 96.48%, and specificity of 99.13%.
[12]	Explainable Ensemble Learning	Clinical prediction	Improved transparency	Accuracy 94.5%
[14]	SHAP (Shapley Additive Explanations)	Clinical risk-factor prediction	Quantified the contribution of demographic and behavioral risk factors and improved model transparency.	Sensitivity 98.45%, specificity 62.07%
[15]	LIME (Local Interpretable Model-Agnostic Explanations)	Machine learning-based cervical cancer classification	Generated local explanations for individual predictions and improved clinician understanding of model decisions.	Accuracy 98.52%
[16]	SHAP + Feature Importance Analysis	Multimodal cervical cancer prediction	Identified the most influential clinical and imaging biomarkers and enhanced interpretability of multimodal frameworks.	Accuracy 97%
[17]	VGG-16, ResNet50/101, Inception-V3, EfficientNet-B0/B3, and U-Net	Cytology and colposcopy image classification	Foundation for developing accurate, explainable, and clinically reliable AI-based cervical cancer prediction and diagnosis systems.	Review reports approximately 96% accuracy for frequently used cytology DL models and around 91% average accuracy for colposcopy models
[18]	mRMR + XGBoost-RFE + SMOTE-ENN + CTGAN, in four classifier models (LR, KNN, DT, SVM)	demonstrates the potential of combining machine learning	hybrid machine-learning framework that improves cervical cancer prediction	Accuracy: 99.00%, Precision: 99.28%, Recall: 98.77%, F1-Score: 99.02%

		with synthetic tabular data generation for accurate, non-invasive cervical cancer risk prediction		
[19]	Ensemble Model + Shark Optimization Algorithm	Classify cervical images into three categories: Normal, Benign, and Malignant	The approach reduces diagnostic errors, supports early detection, and has strong potential for integration into clinical decision-support systems.	CT Image (Accuracy: 98.49%, Precision: 98.51%, Sensitivity: 98.48%, AUC: 99.54%) and MRI Image (Accuracy: 92.92%, Precision: 93.09%, Sensitivity: 92.87%, AUC: 97.01%)
[20]	Graphene modulation and XGBoost-Assisted optimization	Risk prediction using clinical datasets	Explained feature contributions in ensemble models and improved trustworthiness of predictive systems.	$R^2=86\%$
[21]	ResNet-50 CNN + reinforcement learning	Clinical and imaging data integration	By dynamically focusing on diagnostically relevant image regions, the model achieves near-perfect classification performance across multiple benchmark datasets.	Accuracy: 99.98%, Precision: 99.92%, Recall: 99.89%, F1-Score: 99.0%
[22]	RunicNet + data augmentation techniques	Cervical cancer risk assessment	Generated alternative scenarios explaining prediction changes and improved decision-making interpretability.	Accuracy: 81%, Precision: 83%, Recall: 80%, Loss: 0.62
[23]	A comprehensive benchmark was performed across 16 pre-trained architectures: VGG16, VGG19, ResNet50, ResNet50V2, ResNet101, ResNet101V2, ResNet152, ResNet152V2, DenseNet121, DenseNet169, DenseNet201, MobileNet, XceptionNet, InceptionV3, and InceptionResNetV2	Pap smear image classification	DTL leverages pre-trained Convolutional Neural Networks (CNNs) to accurately classify cervical cells even when working with limited medical datasets.	VGG16: (accuracy-99.95% for 2 class, 98.66% for 5 class), DenseNet121: (accuracy-97.65% for 3 class), ResNet50: (accuracy-95.10 for 2 class).
[24]	Compound Scaling Convolutional Neural Network + k-Dimensional Hypergraph Neural Network	Cytology image classification	The proposed framework demonstrated exceptional capabilities, outperforming several state-of-the-art alternative models.	overall classification performance, raising accuracy from 98.96% (without propagation) to 99.31% (with propagation)
[25]	DK-D53-DWSCNNNet, designed to improve the early and robust prediction of Cervical Cancer	Cytology image and Tabular Registry classification	By decreasing diagnostic discrepancies and reducing expert workloads through pre-screening, it offers strong potential as a	Accuracy 99.85 for Herlev Dataset and 99.65% for SEER Dataset

			clinical decision support tool.	
[26]	Leveraging swin transformer with ensemble of deep learning model	Colposcopy image classification	Produced local explanations for individual predictions and facilitated clinician understanding of model decisions.	Accuracy Comparison: InceptionV3 (99.10%), EfficientNet-B3 (99.16%), TernaNet-DLV2 (98.07%), and standard U-Net/ML Classifiers (96.59%).
[27]	Three progressive deep learning strategies: i)Standard CNN Models, ii)ViT-Cerv Approach, iii)HViT-Cerv (Hybrid Fusion)	Cytology image classification	Identified diagnostically significant tissue regions and improved interpretability of deep learning models.	Accuracy: (Traditional CNNs- 0.65 to 0.78), (ViT-Cerv-0.94) and (HViT-Cerv- 0.97 to 0.99)
[29]	SHAP + Logistic Regression	Cervical Cancer Behavioural Risks prediction	Ranked influential predictors and improved interpretability of machine learning and ensemble frameworks.	Accuracy: 97.2%, Precision: 97.2%, Recall: 97.2%, F1-Score: 97.2%, AUC: 98.1%
[30]	Hybrid (MobileNetV2 + Transformer Blocks + Global Attention Mechanism + Bayesian Optimization)	Cervical MRI image classification	Measured pixel-level contributions and provided fine-grained explanations of image predictions.	Accuracy: 85.86%, Precision: 86.41%, Specificity: 92.97%, AUC: 95.43%
[31]	11-PIRBnet Module + 9-PIRSANet Module + Fused 375NFNet	Cervicography Image classification	Combined attention-based localization with predictive modeling for interpretable cervical cell classification.	Accuracy: 95.5%, Precision: 95.4%, Recall: 95.4%, F1-Score: 95.4%, AUC: 97%
[32]	Explainable Multi-Level Framework	Risk prediction and decision support	Generated alternative prediction scenarios and improved understanding of model behavior and decision boundaries.	Accuracy: 97.55% for SIPaKMeD, 99.48% for Mendeley and 71.53% or Herlev
[33]	Grad-CAM++	Deep CNN-based lesion detection	Enhanced localization of suspicious regions and improved explainability of deep learning predictions.	high PPV (up to 91% in pretreatment positive cases) strongly supports clinical decisions to escalate therapy, the NPV (83%–92%) is not high enough to safely guide treatment de-escalation or omit standard adjuvant therapies
[34]	SHAP + Multimodal Interpretation	Clinical and imaging data integration	Explained interactions among heterogeneous data modalities and improved transparency of multimodal systems.	Accuracy: 98.10%
[35]	Attention-Based Explainable Deep Learning	Histopathological classification	Produced interpretable attention maps identifying important tissue structures for diagnosis.	Accuracy: 99.27% on Herlev, 98.82% on SIPaKMeD
[36]	Explainable Ensemble Learning	Cervical cancer risk prediction	Combined high predictive performance with transparent feature contribution analysis.	Accuracy: 77.9% – 87.2%

[37]	Segmentation Model (Improved U-Net)+Data Augmentation (RES_DCGAN)+Classification Models (ResNet50V2)	Clinical decision support systems	Generated human-interpretable decision rules and facilitated physician acceptance and trust.	Accuracy: 96%, 91% on Herlev, 99% on SIPaKMeD
[38]	Hybrid XAI Framework (SHAP + Grad-CAM + Attention Maps)	End-to-end cervical cancer diagnosis and prediction	Integrated feature importance analysis and visual explanations, enabling trustworthy and clinically deployable AI systems.	Accuracy 99.96%, Precision 98.99%, Recall 98.96%, and an F1-score 98.98%.

4. Datasets Used in Cervical Cancer Prediction Systems

The utility and transferability of AI-based cervical cancer prediction systems depend crucially on the quality, diversity, and representativeness of the datasets used to train and test the models. We analyzed 80 selected studies that included a wide range of datasets, from structured clinical datasets and Pap smear images to colposcopy images, histopathological whole-slide images (WSIs), MRI scans, radiomic datasets, and multimodal clinical repositories. While studies using machine learning algorithms commonly used structured tabular databases with demographic and behavioral risk factors, studies employing deep learning and transfer learning for automated lesion classification and cellular analysis most often used medical imaging databases.

The reviewed studies also show a gradual shift towards multimodal data integration techniques that integrate imaging, clinical, and molecular data. However, while publicly available datasets have greatly facilitated research progress and enabled reproducibility and benchmarking, most available datasets are limited by class imbalance, missing data, small sample sizes, and a lack of multi-center validation [2-3] [8-10] [12]. Therefore, dataset quality and availability remain important barriers to developing clinically usable cervical cancer prediction systems.

4.1 UCI Cervical Cancer Risk Factors Dataset

The UCI Cervical Cancer Risk Factors Dataset is the most commonly used reference dataset for training machine learning models to predict cervical cancer. Because of the wealth of demographic, behavioral, medical, and cervical screening data, it is widely used in various studies and is excellent for research on risk assessment and early diagnosis [4], [5], [6], [8], [13], [39-51]. The dataset includes patient records (858) and clinical and behavioral risk factors (32): age, number of partners, age at first sex, number of pregnancies, smoking history, hormonal contraceptive use, IUD use, outcome of sexually transmitted diseases (STDs), outcome of HPV infection history, and results of cervical screening tests (Hinselmann, Schiller, Cytology, Biopsy). The dataset is well known for its many risk attributes. Researchers have used it as a benchmark for studies aiming to predict cervical cancer using machine learning [4], explainable AI [5], or ensemble learning [6] techniques.

Chaudhuri et al. [4] applied the UCI dataset to the Random Forest and XGBoost algorithms and showed that hybrid feature selection can improve prediction accuracy. Ilyas and Ahmad [5] used ensemble machine learning techniques and achieved better classification results than individual models. Jahan et al. [6] comparatively studied eight machine learning algorithms and obtained an accuracy of 98.24% using Multilayer Perceptron (MLP). Few studies have used a Random Forest feature selector; for example, Tanimu et al. [13] achieved classification accuracy above 99% by combining Random Forest feature selection with SMOTE balancing.

Although it is a popular dataset, the UCI dataset has significant missing values and class imbalance, which calls for data preprocessing techniques such as mean imputation, k-nearest neighbor imputation, and Synthetic Minority Oversampling Technique (SMOTE) [8], [13], [44], [49].

4.2 Herlev Dataset

The Herlev Dataset has been widely used in studies of cervical cancer computer-aided diagnosis and has contributed significantly to the development of deep learning-based computer-aided diagnosis (CAD) systems for cervical cancer [1], [11], [52-61]. It contains high-resolution images of single cells from Pap tests, classified as normal or abnormal cervical cells, and can be used to test automated diagnostic algorithms. The dataset has been used extensively to solve a variety of image analysis problems, such as cell segmentation, nucleus detection, cytoplasm extraction, binary and multiclass classification, and cervical cancer prediction using transfer learning. Dhawan et al. [1] showed that CNN-based architectures could successfully learn the morphological features of cervical cells from Herlev images. Building on this, some researchers have used sophisticated transfer learning models, including ResNet, DenseNet, EfficientNet, and VGG, to increase classification accuracy while reducing time and computational complexity [52],[54],[56],[59]. These are the reasons the Herlev Dataset is so popular: expert labeling, a balanced distribution of cervical cell classes, high-quality microscopic images, and its use as a benchmark

for comparing machine learning and deep learning models. However, the dataset has shortcomings, such as its small size and its reliance on single-cell rather than histology images, which include overlapping cells and background variations.

4.3 SIPaKMeD Dataset

Another popular public dataset is the SIPaKMeD dataset, widely used for multiclass cervical cell classification and cervical cancer diagnosis using deep learning methods [10], [11], [62-68]. Comprising thousands of high-resolution, pre-segmented Pap smear cell images, it includes five clinically relevant cell types: Superficial-Intermediate, Parabasal, Metaplastic, Dyskeratotic, and Koilocytotic cells. The dataset's extensive annotations and high-quality images make it an invaluable resource for training and testing automated cervical cancer classification systems. Mansouri & Ragab [10] applied the SIPaKMeD dataset to develop a hybrid feature-selection method using ShuffleNet and the Equilibrium Optimizer Algorithm (EOA), achieving a classification accuracy of 98.63%. In addition, several recent studies have demonstrated state-of-the-art deep learning architectures, such as ResNet50, DenseNet121, EfficientNet, and MobileNet, achieving superb accuracy in classifying cervical cells using this dataset [62], [64], [66], [68]. This is due to two reasons: 1) It has a vast number of images annotated with cell boundaries, and 2) Multi-class labeling and high resolution of microscopic cell images are attractive to researchers in transfer learning and deep learning. Like the Herlev Dataset, SIPaKMeD consists of isolated cell images, which are less representative of the complexity of real clinical slides, which often include overlapping cells, staining variations, background artifacts, and other conditions that are difficult to find in routine cervical cancer screening.

4.4 Colposcopy Image Datasets

In recent years, colposcopy image datasets have attracted significant attention because they are non-invasive for visualizing cervical lesions and an important modality for early detection and diagnosis of cervical cancer [7], [49-53]. During colposcopy, high-resolution images of the cervix are captured and have been extensively used to develop AI-based diagnostic systems. Chandran et al. [7] presented an Ensemble Deep learning framework for Colposcopy image analysis, reporting accuracy of 95% or higher. In recent years, several works have used cutting-edge deep learning architectures such as convolutional neural networks (CNNs) [69], attention-based models [71], and Vision Transformers (ViTs) [73] to achieve remarkable results in lesion localization, feature extraction, and classification. Colposcopy image datasets are increasingly used because they support non-invasive diagnosis, provide rich visual information about cervical abnormalities, enable early lesion detection, and support the development of real-time screening systems. Despite these benefits, challenges such as variations in image quality, inconsistent illumination conditions, limited large, publicly available datasets, and inconsistent image acquisition protocols across different healthcare institutions can limit the effectiveness of models trained from colposcopy images [70], [72]. The challenges identified in this work underscore the need for larger, standardized, multicenter colposcopy datasets to improve the robustness and generalizability of AI-based cervical cancer diagnostic systems.

4.5 Whole-Slide Image (WSI) Datasets

As a result of their capacity to provide complete histopathological data, such as microenvironmental features and cellular morphology associated with cervical cancer [9] and tissue architecture, WSI data has become more relevant in the field of digital pathology. A WSI is an image of a whole slide that contains information about relationships between cells and tissues that cannot be obtained from isolated cell images, and this information is useful for developing artificial intelligence (AI)-based diagnostic systems. Cheng et al. [9] showed how well a deep convolutional neural network (CNN) architecture could perform WSI analysis, with better results in classifying cervical lesions. In addition, recent work has applied sophisticated techniques such as patch-based CNNs, multiple-instance learning (MIL), and attention mechanisms to process gigapixel pathology images, localize lesions, and support automated histopathological diagnosis [74], [76], [77]. WSI datasets offer high diagnostic value, superior lesion localization, detailed histopathological features, and rich contextual information, which explains their widespread adoption. Yet WSI analysis remains highly compute-intensive due to the vast size of gigapixel images, high memory and storage demands, high computational complexity, and labor-intensive annotations. Despite these hurdles, widespread deployment of WSI in the clinic remains limited, and improved algorithms and computational frameworks are needed to make these systems scalable for large-scale clinical use [74], [77].

4.6 MRI and Radiomics Datasets

In addition to traditional clinical evaluation, MRI-derived datasets and radiomics have become an important sources of detailed anatomical and functional information for cervical cancer diagnosis, prognosis, and treatment planning [2], [3], [78-80]. Radiomics extracts a wide range of quantitative imaging features from MRI images, such as shape descriptors, texture features, intensity statistics, and spatial heterogeneity parameters, capturing subtle tumor characteristics that may not be apparent to clinicians. Wang et al. [3] developed a CNN-based radiomics framework that significantly improved tumor prediction and patient risk stratification. Likewise, a few recent studies have combined MRI-derived

radiomic features with machine learning algorithms, including Random Forest, XGBoost, and Support Vector Machine (SVM), to improve predictive accuracy and support personalized clinical decision-making [78–80]. Although these methods have been successful, they have not been widely adopted because of several limitations, including small sample sizes, high imaging acquisition costs, limited external validation, and high inter-institutional variability in acquisition protocols and scanner configuration. The small sample size, limited generalizability, and challenges in translating radiomics-derived AI models highlight the need for multicenter datasets with larger sample sizes and standardized imaging protocols to improve the reliability and clinical applicability of these models in the routine management of cervical cancer [3], [80].

4.7 Multimodal Datasets

However, in recent years, multimodal datasets have become an attractive avenue for developing predictive tools for cervical cancer by combining various types of patient data in a single analytical framework [3], [8], [14–23]. Multimodal datasets include complementary data such as human papillomavirus (HPV) status, molecular biomarkers, genomic data, MRI and histopathological images, and demographic information, in addition to the clinical information included in a single-modality dataset. By combining these diverse data sources, AI models can better represent the intricate biological and clinical features of cervical cancer, leading to more precise diagnosis, risk stratification, and individualized treatment strategies. Various papers have shown that using more than one data modality in a learning framework generally yields better, more accurate results than using only one type, by leveraging the strengths of different data modalities [3], [8], [14–23]. However, implementing multimodal AI systems remains difficult because of data heterogeneity, missing or incomplete data, interoperability issues between different health care systems, growing data complexity, and a lack of large, standardized multimodal repositories. To facilitate the clinical translation and universal application of multimodal AI-based cervical cancer prediction systems [16], [21], these challenges have to be addressed.

Table 2.1. Major Datasets Used in Cervical Cancer Prediction Systems

Dataset	Data Type	Applications	Representative References
UCI Cervical Cancer Risk Factors	Tabular Clinical Data	Risk Prediction, Classification	[4], [5], [6], [8], [13], [39–51]
Herlev Dataset	Pap Smear Images	Cell Classification, Segmentation	[1], [11], [52–61]
SIPaKMeD Dataset	Pap Smear Images	Multiclass Classification	[10], [11], [62–68]
Colposcopy Datasets	Cervical Images	Lesion Detection	[7], [69–73]
Whole-Slide Images	Histopathology	Tissue Classification	[9], [74–77]
MRI/Radiomics Datasets	Medical Imaging	Tumor Prediction	[2], [3], [78–80]
Multimodal Datasets	Clinical + Imaging + Biomarkers	Personalized Prediction	[3], [8], [14–23]
Explainable and Clinical Validation Datasets	Multi-source Data	Model Interpretation and Validation	[14–38]

5. Comparative Analysis of the Selected Studies

This comparative analysis identifies similarities and differences among the selected studies.

The comparative study of the 80 selected studies shows remarkable advances in cervical cancer prediction methods, ranging from traditional machine learning algorithms to deep learning, transfer learning, ensemble methods, and explainable artificial intelligence (XAI).

Random Forest, SVM, and XGBoost models performed best on structured clinical data, with accuracy scores of 90% to 99% [4–6], [13], [8], [40–51]. Other CNN-based deep learning architectures such as ResNet, DenseNet, MobileNet, and EfficientNet consistently outperformed other classifiers, achieving accuracy greater than 95% for Pap smear and colposcopy image analysis [1], [7], [9–11], [52–68].

Transfer learning methods achieved noticeable performance improvements with limited data and reduced training time compared with other methods [1], [7], [10], [11], [54], [56], [59], [62], [67]. Ensembles combining RF, SVM, XGBoost, CatBoost, and MLP showed the best predictive performance and robustness [4], [5], [8], [10], [12], [69–80]. Meanwhile, explainable AI techniques such as SHAP [3], LIME [8], and Grad-

CAM [12] have been used to increase transparency and clinical trustworthiness, and attention mechanisms have also been used too [38].

Table 5.1. Comparative Analysis of AI Techniques

AI Technique	Representative Algorithms	Accuracy Range	Major Advantages	Key Limitations	References
Machine Learning	RF, SVM, DT, LR, XGBoost	90–99%	Interpretable, low computational cost	Requires feature engineering	[4], [5], [6], [8], [13], [40–51]
Deep Learning	CNN, ResNet, DenseNet	95–99%	Automatic feature extraction	Requires large datasets	[1], [7], [9], [10], [11], [52–68]
Transfer Learning	VGG16, ResNet50, MobileNet	>95%	Effective with limited data	Domain adaptation issues	[1], [7], [10], [11], [54], [56], [59], [62], [67]
Ensemble Learning	Stacking, Boosting, Voting	Up to 99%	High robustness and generalization	Computational complexity	[4], [5], [8], [10], [12], [69–80]
Explainable AI	SHAP, LIME, Grad-CAM	Improved trustworthiness	Better clinical interpretability	Limited adoption	[3], [8], [12], [14–38]

Major Limitations and Research Gaps

The review lists the key limitations and gaps in the state of the art.

While the advancements in artificial intelligence (AI) prediction of cervical cancer have been impressive, a review of the 80 studies uncovered some common shortcomings that make these technologies less applicable and adopted in the clinical setting. Most studies rely on small, single-center datasets that are often imbalanced and incomplete, limiting their robustness and generalizability. Also, few studies validate the model externally and/or from a different perspective, which casts doubt on its validity outside its original clinical context.

Another major drawback is reliance on a single data modality, while clinical diagnosis often requires a variety of data, including clinical records, medical images, HPV status, and molecular biomarkers. Moreover, the opacity of DL models limits their interpretability and clinical adoption, although new explainable AI techniques have emerged in recent years.

The need for significant computational power, especially for complex deep learning models that use whole-slide images and transformer architectures, further hampered their application in resource-strapped medical centers. Additionally, the high computational demands of sophisticated deep learning models, particularly those that rely on whole-slide imaging and transformer architectures, restricted their use in resource-limited healthcare settings. Finally, few studies have focused on clinical implementation, including workflow integration, physician acceptance, regulatory compliance, and prospective validation. Overcoming these challenges will require larger multicenter datasets, multimodal learning, explainable AI, computationally efficient models, and broad clinical validation to make AI-based cervical cancer prediction systems a reality in clinical care.

There are some significant gaps in knowledge, which are described as:

Small, restricted data sets: Many studies rely on small benchmark datasets that may not represent other populations.

Class imbalance and missing data: Class imbalance and missing data remain prevalent and must be addressed during preprocessing, as they may introduce bias.

Lack of external validation: Most models are trained and tested on an dataset, and few studies test models on external clinical cohorts.

Relying on a single-modality dataset: Most studies rely on clinical or imaging data alone, and few studies use multimodal data.

Limited clinical interpretability: Many AI models are black-box with limited clinical interpretability.

Limited accessibility: Advanced deep learning models require significant computational resources, which may hinder their use in resource-limited healthcare settings.

Small number of clinical deployments: There have been only a few studies on the clinical deployment of AI systems, and there is a need for prospective validation and collaboration between humans and AI systems.

7. Future Scope

This review outlines several opportunities to improve the contribution of AI-based prediction systems for cervical cancer. Future studies should improve model robustness, interpretability, scalability, and clinical applicability to make these systems effective in real-world healthcare settings.

Large-Scale Multicenter Datasets: Future studies should focus on creating large-scale multicenter datasets in an international hospital-research institution cooperation. Current AI models are trained on data from a single center or benchmark data, which restricts their use to a specific population. Standardized multi-institutional repositories with consistent data collection and annotation standards will improve data quality, minimize population-specific bias, and enable the development of more accurate, clinically relevant AI models.

Multimodal Artificial Intelligence Frameworks: Future AI systems must combine multiple data types, including clinical data, demographics, HPV status, cytology, histopathology, MRI, radiomics, and genomic biomarkers. These multimodal systems can offer complementary information to enhance diagnostic accuracy, risk stratification, and personalized clinical decision-making. One key research area will be developing scalable multimodal architectures that can efficiently combine heterogeneous data.

Privacy: Privacy remains a key challenge in collaborative healthcare AI research, even as we explore the potential of Federated Learning and Privacy-Preserving AI. Federated Learning (FL) lets multiple institutions train AI models together without sharing sensitive patient information. Moving forward, integrating FL with privacy-preserving methods like secure multiparty computation and differential privacy would be a valuable contribution to ensure privacy and regulatory compliance in multicenter collaborations.

Explainable and Trustworthy AI: Prediction models used in clinical practice must be interpretable and explainable. In the future, incorporating more explainable AI methods such as SHAP, LIME, Grad-CAM, and counterfactual explanations will enhance model transparency and support clinical decision-making. Creating inherently interpretable AI models will further improve the trust, regulatory acceptance, and safe use of AI-aided diagnostic systems by physicians.

Transformers and Foundation Models: Vision Transformers (ViTs), Swin Transformers, self-supervised learning, and foundation medical models have great potential in medical image analysis. These sophisticated architectures can enhance feature representation, data efficiency, model generalization, and cross-domain adaptation. Large-scale multimodal data is a new target for future studies on predicting cervical cancer.

Lightweight AI and Edge Computing: Future work can develop lightweight AI models using architectures like MobileNet, EfficientNet, ShuffleNet, and TinyML for deployment in low-resource healthcare environments. Edge computing can implement these models to deliver quick, energy-efficient, and privacy-preserving cervical cancer screening in rural health care facilities, mobile screening services, and point-of-care systems.

Future research needs include prospective multicenter clinical trials to test AI models in real-world settings for clinical validation, as well as Human-AI Collaboration. Future research should also examine the effectiveness of collaboration between physicians and AI, the integration of AI tools into clinical workflows, and cost-effectiveness. The ultimate aim is to create reliable AI-driven tools that support healthcare practitioners, enhance diagnostic precision and patient outcomes, and complement clinical judgment.

8. Conclusion

Even though cervical cancer is a significant health problem worldwide, especially in countries with low- and middle-income status, the lack of access to screening programs and specialized healthcare has led to delayed diagnosis and high mortality rates. Using PRISMA, this systematic review aimed to collate evidence from 80 studies published from 2021 to 2026 to provide a comprehensive picture of the latest developments in Artificial Intelligence (AI)- based prediction of cervical cancer. The analysis clearly showed a shift from traditional machine learning methods to advanced deep learning, transfer learning, ensemble learning, and Explainable Artificial Intelligence (XAI) frameworks. While structured clinical data remains well-suited to machine learning methods such as Random Forest, Support Vector Machine, and XGBoost, convolutional neural networks, Transformer-based models, and Transfer learning have shown significant improvements in diagnosing images such as Pap smears, colposcopy, histopathology, and radiological images. Ensemble methods consistently improved predictive performance, and XAI techniques (SHAP, LIME, and Grad-CAM) enhanced model transparency and clinical interpretability.

While progress in integrating AI into cervical cancer prediction is promising, key challenges still prevent widespread clinical use. The reviewed studies identified recurring challenges such as scarce large multi-center datasets, dataset imbalance, missing data, limited external validation, reliance on single-modality data, high computational complexity, and limited real-world clinical deployment. To overcome these challenges, clinicians, AI researchers, healthcare institutions, and policymakers need to work together to create standardized datasets, privacy-preserving federated learning models, multimodal AI models, and efficient algorithms for resource-limited settings. Future studies should focus on clinical validation, human-AI collaboration, and trustworthy AI systems that combine high predictive performance with explainability. In conclusion, AI has shown tremendous promise in the field of cervical cancer screening, early detection, risk assessment, and personalized treatment strategies. AI technologies with proven

clinical validity, robust performance, and interpretable models will be key contributors to the WHO's global strategy for eliminating cervical cancer and will advance women's healthcare globally.

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