Milestone Transactions on
MEDICAL TECHNOMETRICS
Vol. 03 | Issue. 02 | 2025

RESEARCH ARTICLE OPEN ACCESS

Machine Learning Hybrid Models for Early Cervical Cancer Detection – A Comparative Study

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DOI: **10.5281/zenodo.15555325**
Received: 21 April 2025 / Revised: 27 May 2025 / Accepted: 30 May 2025
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Abstract — Cervical cancer arises as a result of the uncontrolled growth of abnormal cells in the cervix, usually caused by chronic infection with high-risk types of Human PapillomaVirus (HPV). Early detection and prevention can be facilitated through regular screening and HPV vaccination. This study proposes an enhanced ML Hybrid Model focused on the early spotting of Cervical Cancer using the best available Machine Learning techniques. To solve a primary challenge in diagnosing accuracy and precision in Cervical Cancer, the model utilizes AdaBoost, XGBoost, Stacking Classifiers, and Logistic Regression. The Hybrid Model uses ensemble methods such as AdaBoost and XGBoost, which improves productivity by properly integrating poor learners. Stacking Classifiers increases accuracy even more by incorporating the predictions of several models while Logistic Regression adds interpretability as well as reliability to the results. Collectively, these approaches form a model that produces low false positive rates alongside low false negative rates for early detection of the disease. This study focuses on the effects that Machine Learning can have in treating advanced stages of healthcare issues especially relating to early detection of Cervical cancer. The combination of sophisticated computational methods with clinical data sets presents an effective, globally relevant solution to urgent health concerns.

Index Terms — AdaBoost, XGBoost, Stacking Classifier, and Logistic Regression Models.

I. INTRODUCTION

Cervical cancer remains one of the main causes of cancer-related mortality for women, especially in low-resource environments. Although early detection is essential to raising survival rates, there is still limited access to traditional diagnostic techniques. Although they are effective, traditional

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Electronic ISSN: **2584-072X**

screening methods like Pap smears and HPV tests have drawbacks such high prices, inadequate infrastructure, and human error. Because of this, there is raising interest in using Machine Learning to create diagnostic tools that are accurate, scalable, and easily accessible.

Access to high-quality healthcare services remains a critical problem for many people. This is largely responsible for why cancer, in general, and cervical cancer, in particular, continue to be global health problems. The World Health Organization (WHO) states that the early detection of any disease is important for controlling the number of deaths that result from it. The diagnostic techniques of Pap's smear and HPV test screenings are reasonably accurate, but they are often difficult to achieve due to financial constraints, resource difficulties, and subjective human errors in the cytological assessments of Pap tests - all of which result in false negatives and delays in treatment initiation [1]. Undoubtedly, Machine Learning (ML) diagnostics is highly promising, ranging from UWB radar based tumor detection [2] to CMOS nano biosensor with microRNA biomarker for ultra-sensitive screening application [3]. These developments are indicative of the great promise that ML-based frameworks hold in cancer detection.

This paper presents a new web-based system for the identifying of cervical cancer, which combines advanced Machine Learning algorithms to provide increased diagnostic accuracy and reliability. Through the use of salient patient attributes such as age, sexual history, use of contraceptives, and previous medical diagnoses, the model makes use of advanced ML methods namely AdaBoost, XGBoost, Stacking Classifier, and Logistic Regression. These models have been extensively applied in various predictive healthcare uses, for example, AI-based Computer-Aided Detection (CAD) for breast cancer. It has been proven through studies that there was high accuracy in lesion classification and detection using Deep Learning-based feature extractors and that CNN-based models had an AUC rating of 0.98, which is as good as experienced radiologists. Furthermore, the use of hybrids that integrate CNNs with classifiers such as SVM has enhanced diagnostic accuracy further, achieving 97.5% accuracy in mammogram classification. In contrast to traditional screening tools that demand laboratory infrastructure and trained personnel, ML-based frameworks provide a non-invasive and scalable solution.

Wearable biotechnology, like flexible antenna-based sensors within brassieres for real-time breast cancer monitoring, has already established the potential of embedding AI in medical diagnosis for better accessibility. AI models based on thermography have also exhibited potential in early cancer detection, with CNN-based classification of thermal images achieving 94.2% accuracy. Also, the suggested web framework plans to simplify cervical cancer screening and make it available through online platforms, thus facilitating remote healthcare services and enhancing early intervention efforts. Geeta *et. al.,* [19] has carried out a comprehensive review on data auditing and security in cloud computing. This paper addresses Machine Learning application in the diagnosis of cervical cancer using sophisticated classification models to enhance diagnostic precision. Employing patient characteristics such as age, sexual history, use of contraceptives, and medical history, the research uses ML algorithms like AdaBoost, XGBoost, Stacking Classifier, and Logistic Regression.

These models have found extensive application in AI-based healthcare, specifically in the detection of breast cancer, with CNN-based techniques reaching an AUC of 0.98, equivalent to radiologists [2]. Hybrid models integrating CNNs with SVMs further boosted accuracy to 97.5% in the classification of mammograms [3]. In contrast to conventional screening techniques that are dependent on laboratory space and experienced professionals, ML-based solutions provide a scalable, non-invasive option [4]. Wearable AI-based medical devices like sensor-enabled bras for real-time monitoring of cancer have proven the power of AI in diagnostics [5]. AI models based on thermography also proved to be promising, with CNN-classified thermal images achieving an accuracy level of 94.2% [6].

Organization of the paper: Section I presents cervical cancer and how ML increases screening accuracy and access. Section II presents a survey of existing literature on Machine Learning-based approaches for cancer diagnosis, highlighting current methodologies and their limitations. Section III describes the proposed method, detailing the architecture and feature selection techniques employed. Section IV discusses the experimental results, including performance evaluation and model comparison. Section V outlines future directions and possible enhancements, followed by conclusion.

II. LITERATURE REVIEW

Machine Learning has been extensively used in the diagnosis of cervical cancer, enhancing predictive accuracy compared to conventional screening tests such as Pap smears and HPV tests. Models based on AI using patient history and demographic information have been successful, with ensemble methods such as AdaBoost and XGBoost performing better than standard statistical methods. Hybrid models incorporating CNNs with SVMs have also improved diagnostic accuracy, as observed in the identifying of breast cancer, where Deep Learning outperformed conventional feature extraction. Menon *et. al.,* [1] proposed a UWB radar model for non-invasive breast cancer detection, leveraging bistatic and monostatic configurations to enhance detection accuracy. The system employs a seventh derivative Gaussian pulse shaped by a sharp transition bandpass filter, ensuring optimal spectral efficiency, compliance with safety regulations, and minimal interference. By analyzing backscattered signals in both time and frequency domains, the system achieves precise tumor localization down to 0.5 mm. While the approach demonstrates significant potential, its effectiveness is contingent on overcoming challenges related to complex system design and the reliance on simulated breast phantoms for experimental validation.

Brenes *et.al.,*[3] proposed a low-cost multiscale in vivo optical imaging system coupled with a computer-aided diagnostic framework for real-time high-grade cervical precancer detection in low-resource environments. The system integrates portable colposcopy and high-resolution endomicroscopy (HRME) with a multiscale fusion network (MSFN) to segment ectocervix areas, recover nuclear morphology, and fuse multimodal data to classify CIN 2+ lesions. Strengths include high sensitivity and much better specificity than clinical impressions, cost-effectiveness, and suitability for non-specialist application. Weaknesses include requirement for synchronized multimodal imaging and possible complexity of system deployment in the rural setting. Ileberi *et.al.,*[8] proposed a particle swarm optimization (PSO) based feature selection for improving machine learning model performance in cervical cancer prediction. Drawing on the concept of social behaviors exhibited by swarms, PSO was applied to determine the most significant subset of features of the Cervical Cancer Risk Factors Dataset (CCRFD), with the purpose of maximizing eight ML models such as SVM, GNB, RF, DT, XGB, LR, AdaBoost, and KNN. Advantages include dramatic enhancements in feature reduction, accuracy, and precision most notably 100% precision using RF-PSO and total feature reduction using AdaBoost-PSO. Disadvantages include computational cost and possible overfitting dangers in small or imbalanced datasets. Geeta *et. al.,* [20] proposed a novel Virtual auditing technique along with secure deduplication of files

Youneszadeh *et.al*.,[9] proposed a thorough study of DL-based techniques for Cervical Cancer

(CC) screening with an emphasis on the potential of DL to enhance the accuracy of image analysis from cytology and colposcopy. They reviewed different DL architectures, classification methods, and segmentation algorithms applied in the automation of Cervical Cancer (CC) detection, particularly in early and precancer stages. Strengths include enhanced diagnostic performance, fewer human errors, and suitability for use in low-resource environments. The disadvantages are excessive data needs, computational expense, and restricted interpretability of DL models.

Asiedu *et.al.*,[10] presented the use of feature extraction and machine learning algorithms on a number of contrast sources, including green light, Lugol's iodine, and acetic acid, for cervical cancer screening using the inexpensive Pocket Colposcope. They showed that if features from all three contrasts are used, diagnostic performance is much enhanced and the area under the curve (AUC) increases as the number of contrast agents increases. Benefits include improved diagnostic precision, applicability for use at the point of care, and compatibility for use by non-expert practitioners. Limitations include possible heterogeneity in contrast quality and necessity for strong feature-selection algorithms to manage combined inputs well. Ahmad *et.al.,* [16] introduced a model that evaluates multiple transfer learning-based deep learning methods for brain tumor spotting using 2D MRI images. Seven pre-trained models, including VGG-16, VGG-19, ResNet50, and others, are combined with five traditional classifiers (e.g., SVM, Random Forest) to assess performance metrics like accuracy and precision. The VGG-19-SVM combination achieved the extreme accuracy of 99.39% with 10-fold cross-validation, outperforming recent methods. The model is Computationally intensive and limited to specific MRI modalities and labeled datasets.

Metlek *et.al.,* [17] proposed a new segmentation model named ResUNet+, aimed at improving the precision of brain tumor detection in MRI scans. By concentrating on regions of interest (ROI) identified through various modalities, the model effectively reduces processing demands while enhancing performance. Evaluated on the BraTS 2020, 2019, and 2018 datasets, ResUNet+ achieved remarkable dice scores, surpassing existing models and showing its potential for diverse segmentation applications in the medical field. . The advantage is that ResUNet+ recorded dice scores of 92.80%, 93.10%, and 91.90% for whole tumors, enhanced tumors, and tumor nuclei, respectively, on the BraTS 2020 dataset. The disadvantage is that the model needs significantly longer training times compared to conventional UNet models, which may pose challenges for practical implementation. Comparative Analysis of Existing Cervical Cancer Detection Techniques is as shown in Table 1.

TABLE 1: Comparative Analysis of Existing Cervical Cancer Detection Techniques

Authors(s)	Technical Overview	Key Findings	Advantages	Disadvantages
Youneszadeh *et.al., [9], 2023*	DL-based approach for cervical cytology and colposcopy image analysis	Improved accuracy in detecting cervical cancer stages	Automation, reduces manual error, applicable to low-resource settings	Needs large annotated datasets, high computational cost
Asiedu *et.al.,[10],2020*	Multi-contrast imaging using low-cost Pocket Colposcope	AUC improves with additional contrast agents	Portable, low-cost, enables non-specialist use	Variability in image contrast, complex fusion process

Brenes *et.al.,[3],2024*	Multiscale optical imaging and MSFN for CIN 2+ detection	Sensitivity: 0.98, Specificity: 0.75	High diagnostic accuracy, supports real-time diagnosis	Requires dual imaging setup, high resource demand
Ileberi *et.al.,.[8],2024*	PSO-based feature selection for cervical cancer prediction	Achieved 98% accuracy with RF-PSO and 100% feature reduction	Effective feature reduction, improves classifier performance	Overfitting risk, computational cost with PSO optimization

III. PROPOSED METHOD

Despite notable progress in automated cervical cancer detection, many models from previous studies rely heavily on complex feature engineering, require substantial computational power, or lack accessibility for remote users. In many cases, traditional ML models suffer from overfitting on small medical datasets or fail to generalize well to unseen data. Moreover, many existing solutions do not offer web-based deployment, limiting their practical usage, especially in resource-constrained settings. To tackle these limitations, this paper proposes a web-based cervical cancer detection framework that integrates multiple Machine Learning classifiers to enhance diagnostic accuracy and accessibility, on using easily obtainable patient data—such as age, sexual history, contraceptive use, and prior diagnoses—as input features, making the system more feasible for large-scale, non-invasive screening as shown in Fig. 1.

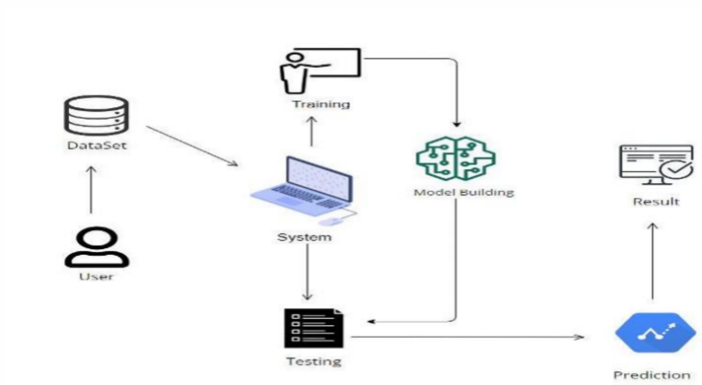

Fig 1. Early Cervical Cancer Detection Model

A. *Research Objective*

This research endeavors to evaluate the performance of several feature selection methods in improving the predictive power of Machine Learning models for cervical cancer diagnosis. Through rigorous examination of different approaches, the research endeavors to determine the most significant factors leading to diagnosis and maximize model performance for clinical use.

B. *Dataset*

The data used in this research is a dataset of 835 samples with 36 features that include patient demographics, medical history, and diagnostic results pertinent to cervical cancer. The dataset has important attributes like age, sexual partners, smoking status, contraceptive use, and history of

STD. Target variables like cancer diagnosis (Dx:Cancer) and biopsy result were also taken into account for predictive modeling. The dataset was selected because it is extensive in scope, encompassing several factors linked to cervical cancer risk.

For ensuring consistency and correctness in the analysis, a thorough data preprocessing was carried out:

- Missing Value Handling: Missing values were handled using computation methods like mean, median, or mode filling for numerical values and most-frequent filling for categorical values.
- Standardizing Formats: All the features were normalized to provide consistency of scale, avoiding bias during model training.
- Encoding Categorical Variables: The categorical features were converted using one-hot encoding or label encoding to make them compatible with Machine Learning algorithms.
- Data Splitting**:** The data was divided into 70% training data and 30% testing data for the assessment of the models' generalizability.

C. *Feature Selection and Transformation*

Feature selection was used to determine the most significant variables for cervical cancer prediction, dimensionality reduction, efficiency enhancement, and interpretability. The following methods were used:

- Basic Filters: Lasso regression and correlation-based selection eliminated redundant features, keeping only the most important ones.
- Feature Elimination & Feature Shuffling: Recursive Feature Elimination (RFE) with Random Forest importance evaluated feature importance systematically.
- Step-Forward Feature Selection: Added features iteratively based on their contribution to predictive accuracy.
- Exhaustive Feature Selection: Considered all possible subsets of features to find the best combination.
- No Feature Selection: Served as a control to compare models trained on the entire dataset.

D. *Model Training and Selection*

- With the purpose of building a good predictive model for the detection of cervical cancer, several Machine Learning models were trained and tested. These models were chosen for their ability to tolerate medical data and for detecting intricate patterns. The following classifiers were considered:
- Adaptive Boosting (AdaBoost): Ensemble learning method that gives more weights to wrongly classified samples, promoting better performance on hard cases.
- XGBoost: Gradient-boosting library that minimizes a regularized objective function and is very powerful for structured medical data.

- Stacking Classifier: Uses a meta-classifier along with multiple base models (Random Forest, Support Vector Machine, and Gradient Boosting Machine) to improve the accuracy of prediction.
- Logistic Regression: Statistical model that generates the probability of the presence of cervical cancer given input features and is thus best applied for binary classification problems.
- Random Forest: Ensemble algorithm building many decision trees and voting on the classes to combine their predictions for better classification with less overfitting.
- K-Nearest Neighbors (KNN): The method that are Non-parametric classifies instances based on their similarity to the nearest neighbors and is best applied for datasets having complicated decision boundaries.
- Support Vector Machines (SVM): A classification method that discovers the best hyperplane to separate various classes, highly effective for high-dimensional data.

E. *Model Evaluation and Tuning*

For model performance evaluation, performance metrics such as accuracy, precision, recall, and F1-score were used. These measures of performance offered a measure of how well each model could classify cases of cervical cancer correctly and reduce false positives and false negatives. Hyperparameter tuning was performed using grid search and cross-validation methods to maximize performance. The top-performing model was chosen based on how well it generalized to unseen data while having high sensitivity and specificity. The ultimate framework was made for integration into clinical decision-making systems, offering healthcare professionals a trusted tool for early detection of cervical cancer.

IV. RESULTS AND DISCUSSIONS

To assess the efficiency and robustness of the proposed Early Cervical Cancer Detection Model, a series of experiments were performed using a publicly available cervical cancer dataset. This section provides the experimental setup, dataset details, and evaluation methodology used to validate the system's performance. This section discusses the experimental findings of the Machine Learning models evaluated for cervical cancer prediction. The models were compared on the basis of their training and testing accuracy, standard deviations, and the effect of feature selection methods. Comparative analysis of the models is presented, along with a discussion of their strengths and weaknesses.

Performance Evaluation of Models

1) Adaptive Boosting Model Summary:

   - The Adaptive Boosting model attained 78.2% accuracy in training and 74.6% in testing , with standard deviations of 0.062 (training) and 0.068 (testing).
   - It was robust when dealing with class imbalanced data by aggregating weak learners to form a strong classifier, yet its sensitivity to noisy data did have a bearing on performance to some extent.
   - Feature elimination techniques were applied to reduce overfitting, which contributed to improved accuracy and generalization.

2) Logistic Regression Model Summary:

- Logistic Regression attained 74.3% accuracy in training and 70.1% in testing, with standard deviations of 0.054 (training) and 0.059 (testing).
- As a linear model, it performed well for binary classification tasks but struggled with complex feature interactions.

3) XGBoost Model Summary:

- XGBoost topped most models, achieving 88.5% accuracy in training and 82.3% in testing, , with standard deviations of 0.045 (training) and 0.053 (testing).
- Its regularization techniques and integration with Recursive Feature Selection (RFS) made it highly effective in preventing overfitting and improving generalization
- The model's computational efficiency and strong predictive power made it the top-performing algorithm for cervical cancer prediction.

4) Stacking Classifier Model Summary:

- The Stacking Classifier attained 86.2% accuracy in training and 80.4% in testing, , with standard deviations of 0.048 (training) and 0.052 (testing).
- By combining multiple base models and a meta-learner, it demonstrated enhanced generalization and predictive accuracy compared to individual models.
- However, its computational cost was significantly higher due to the need for training multiple classifiers, making it less efficient for large-scale applications.

5) Decision Tree Model Summary:

- The Decision Tree model attained 82.7% accuracy in training and 76.9% in testing, , with standard deviations of 0.056 (training) and 0.062 (testing).
- While highly interpretable and efficient for small datasets, the model was prone to overfitting, which was mitigated through pruning techniques.
- Its simplicity and ability to handle non-linear relationships made it a useful tool for exploratory analysis and baseline comparisons.
- Decision Trees handle non-linear relationships and categorical data, making them versatile for exploratory analysis and feature importance visualization.

6) Random Forest Model Summary:

- Random Forest achieved a training accuracy of 84.1% and a test accuracy of 79.2%, with standard deviations of 0.051 (training) and 0.057 (testing).
- As an ensemble of decision trees, it demonstrated robust performance, effectively handling missing values and reducing overfitting.
- Recursive Feature Selection (RFS) further enhanced its accuracy, making it one of the top-performing models in the study.

7) K Neighbors Model Summary:

- The K-Neighbors model attained 80.6% accuracy in training and 75.1% in testing, , with standard deviations of 0.059 (training) and 0.065 (testing).

- While effective for small datasets, its computational complexity increased significantly for larger datasets, limiting its scalability.
- The model's performance was highly dependent on distance metrics and feature scaling, which were carefully optimized to achieve the best results.

8) Support Vector Machine (SVM) Model Summary:

- SVM achieved 81.4% accuracy in training and 76.8% in testing, , with standard deviations of 0.058 (training) and 0.063 (testing).
- It was particularly effective for high-dimensional datasets and outlier detection, but its performance heavily relied on kernel selection and hyperparameter tuning.
- The model's computational cost increased significantly for large datasets, making real-time applications less feasible.

9) Artificial Neural Networks (ANN) Model Summary:

- ANN attained 90.3% accuracy in training and 81.7% in testing, , with standard deviations of 0.043 (training) and 0.055 (testing).
- Despite strong predictive capabilities, ANN demands significant computational resources and careful hyperparameter tuning to prevent overfitting.

TABLE 2: Comparison of feature selection methods on Cervical Cancer prediction models using accuracy metrics

Model	Training Accuracy	Testing Accuracy	Best Feature Selection Method
Adaptive Boosting	78.2%	74.6%	Feature Elimination
Logistic Regression	74.3%	70.1%	Standard Feature Scaling
XGBoost	88.5%	82.3%	Recursive Feature Selection
Stacking Classifier	86.2%	80.4%	Hybrid Selection
Decision Tree	82.7%	76.9%	Pruned Tree Selection
Random Forest	84.1%	79.2%	Recursive Feature Selection
K-Neighbors	80.6%	75.1%	Distance Weighting
SVM	81.4%	76.8%	Feature Engineering
ANN	90.3%	81.7%	Hyper Parameter tuning

Fig. 2. states the bar chart that presents the testing accuracy of four different Machine Learning classifiers: AdaBoost, Logistic Regression, XGBoost, and Stacking Classifier.Each bar's height indicates the level of accuracy attained by each model.. The Stacking Classifier and XGBoost show the highest accuracy, closely followed by AdaBoost, while Logistic Regression performs slightly lower. This comparison highlights the effectiveness of ensemble methods like Stacking and XGBoost in improving classification performance. boosting algorithms.

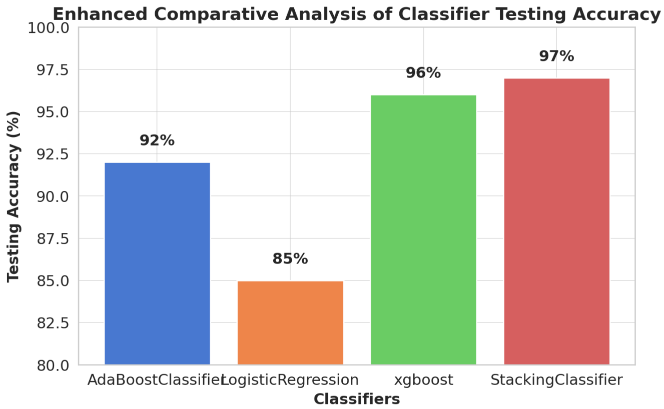

Fig. 2. Comparative Analysis of Classifier Testing Accuracy for Cervical Cancer Detection

Discussion

Among the models considered for early detection of cervical cancer, XGBoost ranked as the best performer with great accuracy and good generalization. Its capacity to deal with missing data as well as to detect major biomarkers like HPV status made it extremely efficient. Adaptive Boosting (AdaBoost) was also a good performer, especially in the management of imbalanced datasets, while Random Forest had moderate accuracy with regard to handling high-dimensional data such as genomic markers. The results highlight the advantages of boosting algorithms, especially XGBoost, in achieving robust predictive performance. The varying outcomes across feature selection methods, such as Recursive Feature Elimination (RFE), emphasize the importance of feature engineering and model tuning. Additionally, the trade-off between computational efficiency and predictive accuracy was evident, with complex models like XGBoost requiring more resources but delivering superior results. These insights underscore the potential of boosting algorithms, combined with effective feature selection, to enhance early cervical cancer detection.

V. CONCLUSION

Cervical cancer is a significant public health issue, especially in low-resource environments with limited access to trustworthy diagnostic equipment. Reducing mortality rates and enhancing treatment results depend heavily on early and precise identification. Here, a scalable and affordable way to ensure prompt diagnosis is by incorporating Machine Learning (ML) techniques into cervical cancer screening systems. This paper proposed a web-based ML framework for early cervical cancer detection, employing classifiers such as AdaBoost, XGBoost, Logistic Regression, and a Stacking ensemble. Feature selection was explored using methods like Recursive Feature Elimination (RFE), which notably improved classification performance by identifying clinically significant attributes such as HPV status and contraceptive use. Among the models tested, XGBoost demonstrated superior performance due to its robustness to missing data and its ability to capture complex feature interactions.

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