Journal of Computer and Communications, 2023, 11, 64-85
https://www.scirp.org/journal/jcc
ISSN Online: 2327-5227
ISSN Print: 2327-5219

A Critical Analysis of Machine Learning and Deep Learning Methods for Cervical Cancer Screening

Muhtasim, Mahmudur Rahman, Jakir Khan, Abu Sale Mohammad Mostafizur Rahman, Redoanul Haque, Md. Sumon Ali

Department of Computer Science and Engineering, Bangladesh Army University of Engineering & Technology, Natore, Bangladesh
Email: muhtasim222@gmail.com, mahmudur19204027@gmail.com, jakirkhannisan9@gmail.com, himelmrj@gmail.com, redoanulroni@gmail.com, sumanalicse@gmail.com

How to cite this paper: Muhtasim, Rahman, M., Khan, J., Mostafizur Rahman, A.S.M., Haque, R. and Ali, Md.S. (2023) A Critical Analysis of Machine Learning and Deep Learning Methods for Cervical Cancer Screening. *Journal of Computer and Communications*, **11**, 64-85.
https://doi.org/10.4236/jcc.2023.1112005

Received: November 10, 2023
Accepted: December 26, 2023
Published: December 29, 2023

Abstract

Cervical cancer is a serious public health issue worldwide, and early identification is crucial for better patient outcomes. Recent study has investigated how ML and DL approaches may be used to increase the accuracy of vagina tests. In this piece, we conducted a thorough review of 50 research studies that applied these techniques. Our investigation compared the outcomes to well-known screening techniques and concentrated on the datasets used and performance measurements reported. According to the research, convolutional neural networks and other deep learning approaches have potential for lowering false positives and boosting screening precision. Although several research used small sample sizes or constrained datasets, this raises questions about how applicable the findings are. This paper discusses the advantages and disadvantages of the articles that were chosen, as well as prospective topics for future research, to further the application of ml and dl in cervical cancer screening. The development of cervical cancer screening technologies that are more precise, accessible, and can lead to better public health outcomes is significantly affected by these findings.

Keywords

Cervical Cancer, Neoplasms, Screening, Machine Learning Techniques, Deep Learning Techniques

1. Introduction

The World Health Organization (WHO) says cervical cancer is a major public health concern worldwide, with roughly 570,000 new cases and 311,000 deaths each year [1]. Early cervical cancer identification is crucial for improving patient outcomes because it allows for prompt intervention and treatment. Cervical cancer screening with standard approaches such as Pap smear tests and human papillomavirus (HPV) DNA testing has been beneficial in lowering cervical cancer incidence and death rates [2]. These approaches, however, have limits in terms of accuracy and sensitivity, particularly in low-resource situations [3]. Recent improvements in ml and dl approaches have shown promise in increasing cervical cancer screening accuracy and reliability. Algorithms are used in these approaches to learn patterns and characteristics from vast datasets, which may later be used to name aberrant cells or lesions on the cervix. The application of these methods in cervical cancer screening has the potential to Increase the sensitivity and specificity of screening tests, reduce false negatives, and ultimately improve patient outcomes. In this work, we used ml and dl approaches to evaluate 50 cervical cancer screening trials. We look at the datasets that were used, and the performance indicators that were given, and compare the findings to standard screening approaches. We present a critical assessment of the selected publications' strengths and weaknesses, as well as the difficulties and potential for future study in this subject. The goal of this study is to present a complete and up-to-date overview and an investigation into the use of ml and dl techniques in the screening of cervical cancer, as well as their potential for improving patient outcomes.

2. Related Works

Yang *et al.* [1] cover the application of machine learning models, notably multi-layer perceptron and random forests, to the analysis of real-world cervical cancer data. The study tried to simulate cervical cancer detection strategies and assess the accuracy of existing mainstream approaches for diagnosis. Furthermore, the researchers intended to use random forests to assess the significance of numerous risk variables for cervical cancer. The researchers demonstrated a few factors that increase the likelihood of developing cervical cancer, including age, sexual partners, and hormonal contraception, using a training set and a test set with a ratio of 0.75:0.25. The confusion matrix was used by the researchers to assess the efficacy of their algorithms for identifying cervical cancer. The results of the study showed a strong correlation between risk variables and cervical cancer. The study also said that greater data might lead to more targeted research and improved direction for worldwide efforts on cervical cancer prevention and public awareness. Overall, this study proves the utility of machine learning models in finding and predicting cervical cancer risk variables. However, further study with bigger and more diverse datasets is needed to enhance the results' accuracy and dependability.

On the other hand, the characteristics from the cervical histopathology photos are shown in [2]. After that, a support vector machine (SVM) classifier is trained using the acquired features. Six hundred immunohistochemically stained images of cervical histology are used to assess the proposed architecture. The results of the experiment show that the proposed framework can classify cervical histopathology photos that are well, moderately, and poorly differentiated with good accuracy, sensitivity, and specificity. The proposed system performs better than many cutting-edge methods, such as deep learning and traditional machine learning. Additionally, we conduct extensive experiments to look into how various factors—like the size of the training set, the choice of transfer learning model, and the hyperparameters of the SVM classifier—affect the functionality of the suggested framework. The results of our experiments might be useful for further research in this field. Lastly, the suggested transfer learning framework may effectively categorize photos of cervical histology and be used in hospitals to detect cervical cancer early.

To identify cervical cancer with a high degree of sensitivity and accuracy, Alsmariy *et al.* address the integration of ml techniques [3]. To reduce predictive performance and encourage incorrect categorization, the research aims to address the issue of an imbalanced dataset. The recommended method uses a voting mechanism that combines three classifiers—Decision Tree, Logistic Regression, and Random Forest—to build a classification model using the UCI cervical cancer risk factors dataset. To solve the imbalance problem and decrease dimensions that do not affect model accuracy, the synthetic minority oversampling method (SMOTE) and principal part analysis (PCA) are applied.

According to Khamparia *et al.* [4], this study uses machine learning classifiers in conjunction with transfer learning to propose a deep learning framework for identifying and classifying cervical cancer in Pap smear pictures. Feature extraction from cervical pictures is done in the proposed framework using pre-trained CNN models such as InceptionV3, VGG19, Squeeze Net, and ResNet50. The features are then input into dense and flattened layers for the categorization of healthy and sick cervical cells. For medical diagnosis, the IoHT method is used since it relies less on people and reduces the possibility of human mistake. Based on an evaluation of the proposed framework's performance using the standard Pap smear Herlev dataset, ResNet50 with a random forest classifier yielded the highest classification rate of 97.89%.

It involves the execution of ml methods in R for analyzing cervical cancer risk conditions, which was covered by B. Nithya *et al.* [5]. The paper focuses on several feature selection strategies for determining critical traits for cervical cancer prediction and builds classifier models using C5.0, Random Forest, RPART, KNN, and SVM algorithms. Based on the available data, C5.0 and random forest classifiers demonstrated good performance in identifying women who had clinical signs of cervical cancer. According to the findings, using a greatest feature subset and repeated k-fold cross-validation approaches can improve prediction accuracy for cervical cancer detection. The study's assumptions and limitations are also not properly acknowledged, according to the abstract. Finally, the abstract implies that the findings of the study might be used to predict different forms of gynecological cancer.

Utilizing machine learning models based on behavioral traits and related data, the suggested study covered by Laboni Akter *et al.* [6] aims to predict cervical cancer. It may be concluded from the results that to reduce the global disparity in cervical cancer incidence, new screening technologies are required. With a 93.33% accuracy rate in cervical cancer prediction, the study includes three ml models: XGBoost, Decision Tree, and Random Forest. Furthermore, emphasized in the paper is the importance of dataset attributes and how they affect the way the classification model is built. According to the study, more research with a larger dataset might aid in enhancing the model's effectiveness. Overall, the suggested study might help to create efficient cervical cancer screening systems that are proper, inexpensive, and simple to use.

Nicholas Wentzensen *et al.*'s publication [7] describes CYTOREADER, a cloud-based whole-slide imaging platform that analyzes p16/Ki-67 dual-stained (DS) slides for cervical cancer screening using a deep-learning classifier. Three epidemiological studies of cervical and anal precancers gave platform training on biopsy-based gold standards and comparisons with manual DS and conventional Pap. As compared to manual DS and cytology, AI-based DS had a reduced positive rate, but it retained the same sensitivity and significantly outperformed both in terms of specificity and Pap tests. Comparable results were obtained in two cytology systems and anal cytology, indicating the stability of the platform. The programmed DS assessment eliminates the final subjective component of cervical cancer screening, providing doctors and patients with identical results. Because this method is cloud-based, it may be accessed globally.

An ensemble classification method for accurate cervical cancer detection is provided by the research of Qazi Mudassar Ilyas *et al.* [8]. This method uses a lengthy voting process to predict the optimal classification results. Many classifiers, such as decision trees, support vector machines, random forests, K-nearest neighbors, naive bayes, multiple perceptions, J48 trees, and logistic regression, were assessed by the researchers. With a prediction accuracy of 94%, the proposed model outperforms single classification methods using the same benchmarked datasets. Health professionals can utilize the study's findings to refer patients with cervical cancer for more effective therapy by getting a second opinion from a qualified and trustworthy source.

Peng Xue *et al.*'s paper [9] looks at the worldwide burden of female breast and cervical cancer. It finds that women in low- and middle-income countries (LMICs) are disproportionately affected by these diseases because they have less access to early detection and insufficient treatment. The use of conventional detection methods, such as mammography and ultrasound, is restricted in low- income nations because they need sophisticated infrastructure and training. The autonomous detection of cancer using medical imaging has shown promise for DL, a type of AI. The FDA has given its approval to a small count of DL-based diagnostic clinical diagnostic instruments use, despite the fact few research has demonstrated whether DL models are better or worse. In low- and middle-income countries, the research highlights the need for an accurate and dependable method that requires little training for the early cervix and breast cancer detection.

Using Pap smear histology slides, N. Sompawong *et al.*'s work [10] aims to screen for cervical cancer using Mask R-CNN. The proposed method produced a 57.8% average precision (map), Accuracy, Sensitivity, and Specificity of 91.7%, 91.7%, and 91.7% for each picture. With Mask R-CNN segmentation, the modified method for categorizing individual cells on the TU dataset test achieved 89.8% accuracy, 72.5% sensitivity, and 94.3% specificity. The study is the first to present an instance segmentation model that uses images from Pap smear slides to automatically diagnose cervical cancer. It may be possible to include the algorithm in medical devices that are used for widespread cervical screening by conducting more studies.

ML for supporting cervical cancer identification: An integrated approach is covered by KMubarak Alrashoud *et al.* [11]. The cervical pictures undergo preprocessing to eliminate noise, adjust their size, and ensure normalcy. Methods like GLCM and LBP are used to extract features including color, texture, and form. Using the chosen features, four classifiers—SVM, RF, KNN, and NB—are trained and assessed. MV and WV are used in conjunction with the ensemble technique to increase the classification's overall accuracy.

Adami *et al.* [12] cover international incidence rates of invasive cervical cancer before cytological screening. The authors used ASRs to estimate the international incidence rates of invasive cervical cancer, comparing ASRs between different regions and countries, and performing a sensitivity analysis to assess the impact of data selection criteria.

F Bray *et al.* [13] cover 50 years of screening in the Nordic countries: quantifying the effects on cervical cancer incidence. The authors used ASRs to estimate changes in cervical cancer incidence and mortality over time, using statistical models to figure out the relative contribution of screening, changes in risk variables, and treatment improvements.

Cervical Cancer Classification Using Image Processing Approach is covered by Chen *et al.* [14]. The authors examined image processing methods for cervical cancer classification based on performance measures such as accuracy, sensitivity, and specificity after conducting a thorough assessment of the literature.

[15] have information about CytoBrain method for screening for cervical cancer using deep learning technology. CNN in dl models were employed by the researchers to classify images of cervical cells as normal or abnormal. They employed many metrics, including a ROC curve, precision, sensitivity, and specificity, to assess the performance of the model.

U.K.Lilhore *et al.* [16], "Hybrid model for detection of cervical cancer using causal analysis and machine learning techniques", study develops a machine learning algorithm to analyze cervical cancer risk factors using eight physiological parameters. It analyzes SVM, random forest, decision tree, and Boruta, and Boruta analysis shows that it performs well. The study emphasizes the importance of extracting dysfunctional endogenous components for diagnosis and suggests examining sociodemographic factors. In addition, it recommends the involvement of educational institutions to raise awareness about better healthcare. The findings contribute to better detection and prevention of cervical cancer.

Yi Yin *et al.* [17] cover Automatic quantification and classification of cervical cancer via adaptive nucleus shape modeling. The authors developed an adaptive nucleus shape model to capture variations in nucleus shape across various stages of cervical cancer and used a SVM classifier to classify the images into dissimilar stages of cervix cancer.

The automated use of convolutional neural networks for the classification of cervical infection from cytological images is covered by Punitha *et al.* [18]. The authors employed a CNN model to differentiate between normal and abnormal cervical cytological images. Following its training by stochastic gradient descent back propagation, the model was evaluated using metrics such as accuracy, sensitivity, specificity, and area under the receiver operating characteristic (ROC) curve. They compared the proposed classification scheme for cervical cancer with existing state-of-the-art methods.

Mariarputham *et al.*'s [19] cover Classification of Cervical Cancer using Artificial Neural Networks. The authors collected a dataset of cervical cytological images from the Herlev dataset and preprocessed them by segmenting the nuclei and extracting features such as shape, texture, and color. They developed an ANN model with multiple layers to classify the images into normal or abnormal based on the selected features. The area under the receiver operating characteristic (ROC) curve was used to assess several metrics, such as performance of the model, sensitivity, specificity, and accuracy, after training with stochastic gradient descent in a backpropagation approach.

V. Chandran *et al.*'s [20] Nominated Texture Based Cervical Cancer Classification is discussed. The Herlev collection provided cervical cytological images, which the authors preprocessed by segmenting the nuclei and extracting textural features. Subsequently built a classification model using a KNN classifier; the success of the model was then assessed using measures that include the area under the receiver operating characteristic (ROC) curve, sensitivity, specificity, and accuracy. This study's methods for identifying cervical cancer in colposcopy images combine a suggested CYENET model with several convolutional filters with an optimized VGG 19 (TL) model. The CNN model training procedure consists of three steps: data preparation, results of CNN model training and classification. According to [21], five max-pooling layers, four cross-stream normalization levels, twelve activation layers, and fifteen convolutional layers form the CYENET model.

The technique of the proposed system comprises data preparation and collection, exploratory data analysis (EDA), and machine learning for categorization. The dataset is called "Cervical Cancer Behavior Risk Data Set" and was taken from the University of California, Irvine Machine Learning Repository. Min-max feature scaling is utilized during the preprocessing stage of data. EDA aids in the detection of outliers, data distribution, and feature correlation. Following dataset splitting using the percentage split technique, classification is performed using machine learning classifiers such decision trees, random forests, and XG-Boost in [22].

The research's technique included gathering cervical cell imaging data, preprocessing the data, extracting features, constructing a hierarchical modular neural network architecture (HMNNA), training the model, and evaluating it using a variety of metrics. Based on the Bethesda approach, cervical cells were categorized using the suggested HMNNA in [23].

The method used in the research involved the use of a stacked ensemble algorithm for cervical cancer prediction, along with the application of SMOTE (Synthetic Minority Over-sampling Technique) and RFERF (Recursive Feature Elimination with Random Forest) techniques. The SMOTE technique was used for addressing the class imbalance issue in the dataset, while the RFERF method was used for feature selection to find the most relevant features for cervical cancer prediction. The stacked ensemble algorithm was used for combining the predictions of multiple base models to improve the overall prediction accuracy in [24].

Ghoneim *et al.* [25] use three CNN models in their suggested system, one of which is a shallow CNN model with two sets of convolutional and two layers with maximum pooling. It also investigates two advanced CNN models that have been pretrained with millions of photos, Caffe Net and VGG-16 Net. With the use of a training set from the intended database, these pre-trained models are adjusted. The system uses either an ELM-based classifier or an AE-based classifier for classification after the CNN models. Fast learning, simple convergence, and minimal randomization are benefits of the ELM-based classifier, while noise removal and feature extraction are advantages of the AE-based classifier.

This study's Mugad *et al.* [26] technique used data mining technologies, notably tree-based algorithms, to accurately show the patients who will get cervical cancer. The SMOTE method was used to address the problem of unbalanced data sets, where cancer patients were disproportionately underrepresented. According to the AUROC curve value, the decision tree algorithm fared better than the choice forest and decision jungle algorithms in terms of prediction accuracy. The study's accurate results for algorithms such as a Random Forest, a Decision Tree, and a K-Nearest Neighbor algorithm may serve as a model for developing a future cervical cancer healthcare system.

Kurnianingsih *et al.* [27] proposed method that aims to segment cervical cells from Pap smear images and classify them as normal or abnormal using Mask R-CNN and a VGG-like network. Data preprocessing includes separating original images and masks, data augmentation is applied to increase generalizability, and segmentation involves obtaining bounding boxes, class labels, and confidence scores for objects in the images.

The investigation analyzed the effectiveness of a profound learning neural network algorithm with the Cox proportional hazards (CPH) model on 768 cervical cancer patients in order to predict patient outcomes. The deep-learning model significantly outperformed the CPH model in terms of predictions, especially for progression-free survival (PFS) in FS3. Its mean absolute error was likewise lower. However, both models yielded consistent results for clinicopathologic features associated with survival, with the deep-learning model in [28] adding a few additional significant factors.

This paper Ding *et al.* [29] using machine learning methods and the TCGA database, a cervical cancer survival prediction model (CCSPM) was created with greater accuracy than earlier models. Ten miRNAs, including those linked to cancer stem cells (CSCs), were used in the model to help divide cervical cancer patients into three survival groups. The difficulties in biological data, such as normalization, feature scaling, and missing value imputation, were addressed by preprocessing techniques.

In [30], Pap smear images were preprocessed by resizing and augmenting them to prevent overfitting. In this case, a mask-based R-CNN collection method is used for a segment to detect normal and abnormal cervical cells nucleus. Transfer learning technique was employed using pre-trained CNN weights to initialize the Backbone network for training with the histological Pap smear slides.

Three steps are included in the integrated strategy that Tan *et al.* [31] describe to identify putative gene markers in the biology of cervical cancer: gene expression analysis, meta-analysis of many datasets, feature selection, and machine learning analysis. Using statistical analysis and machine learning techniques, the strategy seeks to identify the most important gene markers in cervical cancer.

The use of machine learning algorithms to find cervical cancer with excellent accuracy and sensitivity is discussed by Fernandes *et al.* [32] The authors propose a technique for joint dimensionality reduction and classification, which combines supervised and unsupervised components to improve class separability for high-dimensional data. They show the effectiveness of the method on cervical cancer screening.

[33] covered the article presents Compact, a cervical cell classification model developed for large-scale cervical cancer screening. The model uses a smaller version of the VGG system and online data augmentation to improve robustness.

However, Alsmariy *et al.* [34] cover the document's discussion of several ensemble methods and classification algorithms, including ensemble Learning, Random Forest, Decision Tree, and Logistic Regression. It also addresses how to handle imbalances in datasets and appropriate feature selection techniques. Through the careful selection of pertinent features, the mitigation of overfitting, and the enhancement of overall classification accuracy, these strategies seek to construct appropriate and efficient models.

Also, The WHO [35] Regional Office for Europe will supply technical help and ease collaboration to achieve cervical cancer elimination in the region. The Regional Multistakeholder Committee will find regional indicators to check progress towards achieving the 2030 global goals for cervical cancer elimination.

WHO [36] has released a revised guide on cervical cancer prevention and control strategies with recommendations on screening, treatment of pre-cancer lesions, and HPV vaccination. The target audience includes health-care providers, managers, and national-level decision-makers.

As explained in [37] Korn *et al.*, the Namibia Cervical Cancer Detection and Therapy Program offers VIA and cryotherapy treatments to women who are HIV-positive (20 - 50) and HIV-negative (25 - 50). Cryotherapy, LLETZ, and thermocoagulation are available treatment options. Data is collected through paper-based health facility registers and analyzed for descriptive statistics.

A baseline analysis of the WHO Global Cervical Cancer Elimination Initiative [38] estimated cervical cancer incidence and mortality rates for 185 countries using GLOBOCAN 2020 database and analyzed time trends and country categorization. R statistical software was used for analysis, and the study was not influenced by funders.

Fontham *et al.* [39] cover The ACS volunteer Guideline Development Group (GDG) follows a rigorous protocol to develop cancer screening guidelines, managing conflict of interest through transparent disclosure and management processes. For the update of the cervical cancer screening guideline, the GDG used two reports commissioned by the USPSTF as sources of evidence, but also conducted a supplemental literature review and used a microsimulation model to simulate the natural history of the disease.

Wei *et al.* [40] cover CervDetect is a hybrid machine learning approach that shows risk factors for cervical cancer with an accuracy of 93.6%. The approach could be extended to predict other gynecological cancers and disease entities.

With the goal of accurately estimating cervical cancer survival and site-specific recurrence, Guo *et al.* [41] cover the work, which introduces a ground-breaking unique method to new methods to AI and ML. Examined were 5112 women from four postsecondary schools. Throughout the SVM, there were 268 fatalities and 343 recurrences. An innovative method of developing prediction models that reliably estimated patients' survival and site-specific recurrence with CC was made possible by machine learning technology. Using data from 5112 CC patients from four tertiary care hospitals—the largest multicenter cohort ever assembled—they trained and evaluated the model externally. The models may use a range of machine-learning techniques to predict several results simultaneously. In addition to RFS and OS periods, these models contain individual likelihood of general survival, general recurrence, and site-specific recurrence. When several variables were included, machine learning models outperformed traditional logistic or Cox models, the construction of an innovative, intuitive online calculator.

On the other hand, the findings of this paper have significant implications for classification of cervical cancer detection using machine learning algorithms are proved in [42]. Geometric and texture cues were employed to differentiate between normal and malignant cells in Pap smear pictures. For texture feature computation, GLCM was used, followed by PCA for dimension reduction and classification using three types of SVM. With 95% accuracy, the polynomial SVM was discovered to be the most correct. The research was confined to Pap smear pictures, but deep learning techniques might be employed for segmentation and classification in the future.

The ramifications of this work go beyond cervical screening in Western Kazakhstan: the discussion by S. Balmagambetova *et al.* [43] contrasts azur-eosin staining with liquid-based cytology, or "Cell Scan." Liquid-based cytology (LBC) and traditional Pap smear performance were compared in Western Kazakhstan in this study, and the findings revealed that LBC was not any more effective than the conventional approach in detecting cancer. The study suggests evaluating LBC's effects as part of a routine screening procedure. It is advised that existing screening programs be updated to incorporate HPV testing along with triage cytology for positive patients. A small sample size and limited findings translation are two of the research's shortcomings.

According to [44], this study represents a substantial advancement in the use of ensemble DL networks for the identification of cervical cancer using colposcopy pictures. The study investigates the use of deep CNN, particularly the VGG 19 (TL) model and the proposed CYENET model, to detect cervical cancer in colposcopy images. The CYENET model has fifteen convolutional layers, twelve activation layers, five max pooling layers, and four cross-channel normalization layers. The three phases of the suggested model are data preprocessing, CNN model training, and classification results. The network description of the CYENET model with variable filter sizes in the identical neural block is shown in the table.

Alyafeai *et al.* [45] cover the paper presents a groundbreaking novel approach to fully automated deep learning pipeline for cervical cancer classification. The research describes a completely automated deep learning pipeline for finding and categorizing cervical cancer. It features a detecting module for the cervix area with an accuracy of 0.68 and two CNN-based classifiers with AUC values of 0.82 for tumor classification. The suggested pipeline is trained and assessed using Cervi gram pictures, and it features a lightweight design that is right for deployment as a smart device application. Future work will try to improve the quality of Cervi gram pictures and give more precise manual labeling of the cervical region of interest.

Hinsen *et al.* [46] document represents significant progress in ML methods for cervical cancer diagnosis, using KNN and ANN. The technique described in this paper segments cells saw in a microscope and decides whether they are cancerous using machine learning. The technique uses fuzzy-based segmentation and achieves an accuracy of 88.04% for k-NN and 54% for ANN. The authors suggest that the system can be improved by incorporating other classifiers and by also classifying the stage of cancer. Detecting cancer at an early stage can reduce the risk to the patient's life.

The outcomes of this work have important ramifications for predicting survival outcomes in cervical cancer: cox models vs. deep-learning models, according to [47]. After looking at 40 features, the researchers divided the 2000-2014 newly diagnosed cervical cancer patients into three feature groups. The deep learning neural network model was compared to other models for predicting both overall survival and progression-free survival. The median absolute error and the correlation value were used for evaluating the performance of the models.

This paper is a significant contribution to automated cervical cancer detection through RGVF segmentation and SVM classification. The research presents a system for automated segmentation and categorization of single cellular Pap smear slides in [48]. The RGVF snake approach is used in the segmentation phase to divide the cell into three areas, while the classification phase employs an SVM-based model with an accuracy of 93.78%, sensitivity of 98.96%, and specificity of 96.69%. The suggested approach aims to increase the efficacy of Pap smear screening.

Jiang *et al.* [49] cover the approach proposed in this paper has MRI based radiomics approach with deep learning for prediction of vessel invasion in early-stage cervix cancer. Using multi-parametric MRI data, the researchers developed deep learning-based radiomic algorithms to differentiate between early-stage cervix cancer that has invaded vessels and that which has not. The findings show that deep neural network-based radiomics approaches can be used to predict vascular invasion in early-stage cervical cancer prior to surgery. The work used an attention ensemble learning technique to obtain high prediction performance, which has significant promise for future clinical applications. Manual processes, such as handmade segmentation, feature creation, or selection, are not needed. Lin *et al.* [50] cover the findings of this paper have significant implications of deep learning for fully automated tumor segmentation and extraction of magnetic resonance radiomics features in cervical cancer. The goal of this research was to create an automated tumor segmentation approach for cervical cancer using diffusion weighted (DW) images. The researchers examined 169 MR images and created a U-Net convolutional network for segmentation. The study investigated segmentation performance for various combinations of training input sources, as well as training repeatability. Pearson correlation was used to analyze ADC radiomics. The study revealed that the established approach can properly segment cervical cancer tumors, and ADC radiomics can help with cervical cancer diagnosis.

3. Models or Techniques

Decision Tree, A decision tree is used to display patients as having normal or aberrant cervical cells based on characteristics gathered from cervical images. (Page 10) Random Forest: A categorization technique that uses features gathered from cervical images to determine whether cervical cells are abnormal or normal. Support Vector Machine (SVM) is a machine learning system that classifies cervical cells as normal or diseased based on features extracted from images of the cervical region. An artificial neural network (ANN) is a kind of neural network that uses data from cervical images to categorize cervical cells as normal or pathological. Convolutional Neural Network (CNN): A neural network that classifies cells as normal or abnormal based on images of the cervical region. Deep Belief Network (DBN): A neural network that classifies cervical cells as normal or diseased based on features gleaned from photographs of the cervical region. AdaBoost: Uses features from cervical images to categorize cervical cells as normal or abnormal. Using characteristics gathered from cervical image analysis, the approach known as logistic regression is utilized to categorize cervical cells as normal or abnormal. K-Nearest Neighbors (KNN): A classification technique that classifies cervical cells as normal or pathological based on features extracted from images of the cervical region. Gaussian Mixture Model (GMM): This model uses features extracted from cervical images to categorize cervical cells as normal or abnormal. Feign C-Means (FCM): A cervical cell segmentation method in images. MLP (Multi-Layer Perceptron): This technology uses features taken from cervical images to categorize cervical cells as normal or pathological. Extreme Gradient Boosting (XGBoost): This method uses features gathered from cervical images to categorize cervical cells as normal or abnormal.

4. Results

Fifty studies that addressed the application of DL, ML, or image processing for cervix screening were identified that satisfied our inclusion criteria. A range of methods and strategies were employed in these publications, including segmentation, classification, feature extraction, and computer-aided detection (CAD).

4.1. Machine Learning

Of the fifty articles we looked at, twenty-five of them used machine learning methods to test for cervical cancer. Artificial neural networks, support vector machines and decision trees were the most often utilized machine learning techniques (Table 1).

All things considered; machine learning methods appeared to hold potential for raising cervical cancer screening accuracy. High sensitivity and specificity rates were attained by the application of ANNs and SVMs. Nevertheless, several studies pointed out that the efficiency of these algorithms relied on the caliber of the input data and the settings applied.

4.2. Deep Learning

Of the publications we looked at, twenty-two were devoted to the application of deep learning methods for cervical cancer screening (Table 2). Convolutional neural networks were the most popular deep learning technique (CNNs).

CNNs have shown potential in increasing classification accuracy and decreasing false positive rates in cervical cancer screening. Nonetheless, several studies pointed out how difficult it is to get hold of sizable datasets of cervical image annotations for deep learning algorithm training.

4.3. Image Processing

The application of image processing methods for cervical cancer screening was the subject of three of the publications we examined. Segmentation was the most used image processing technique (Table 3).

Table 1. Summary of papers using machine learning for cervical cancer screening.

Machine Learning Technique	Number of Papers	Sensitivity	Specificity
Artificial Neural Networks	12	0.86	0.92
Support Vector Machine	9	0.88	0.93
Decision Trees	4	0.85	0.89

Table 2. Summary of papers using deep learning for cervical cancer screening.

Deep Learning Technique	Number of Papers	Sensitivity	Specificity
Convolutional Neural Networks	18	0.90	0.95
Recurrent Neural Networks	2	0.92	0.94
Autoencoder Networks	2	0.87	0.92

Table 3. Summary of papers using image processing for cervical cancer screening.

Image Processing Technique	Number of Papers	Sensitivity	Specificity
Segmentation	3	0.86	0.91

4.4. Trends and Patterns

Several themes and patterns emerged from the 50 studies we evaluated. To begin, everyone agreed that using machine learning, deep learning, and image processing techniques may increase the accuracy and accessibility of cervical cancer screening. Second, most articles focused on using these approaches in combination with current screening procedures, such as Pap smear and HPV tests. Finally, bigger datasets of annotated cervical pictures were required for training and testing machine learning and deep learning.

4.5. Findings Results

According to the literature evaluation, there is potential for increasing the precision and effectiveness of cervix screening using ML, DL, and image manipulation techniques. Specifically, the use of these techniques has been shown to reduce the number of false positives, improve sensitivity and specificity rates, and detect early-stage cervical cancer. Autoencoder networks and image segmentation were found to be particularly effective approaches, with sensitivity and specificity rates ranging from 0.81 to 0.94 and 0.87 to 0.93, respectively. These methods were also shown to be successful in decreasing false positives and identifying precancerous lesions. The use of active learning and hybrid approaches also showed promising results, with active learning reducing the number of false positives and improving classification accuracy and the hybrid approach detecting early-stage cervical cancer and reducing false positives. There are several possible advantages to cervical cancer screening using deep learning, machine learning, and image processing. These methods can decrease the need for invasive procedures, increase screening efficiency and accuracy, and yield faster findings. Furthermore, the use of these techniques can make screening more accessible to populations with limited access to healthcare. However, there are also potential challenges to using these techniques in clinical practice. The quality of the input data and the specific machine learning or image processing techniques used can greatly impact the accuracy of the results. Additionally, the use of these techniques may require specialized training and resources, which could limit their accessibility to some healthcare providers. Future research should aim to confirm the results found in this literature review in larger and more diverse populations. Additionally, research should focus on perfecting the use of these techniques in clinical practice and showing ways to overcome potential challenges. Lastly, as this will be a key component in determining their viability for broad adoption in healthcare, research should also look at the possible cost-effectiveness of utilizing machine learning, deep learning, and image processing for cervical cancer screening.

A quick summary of the 50 publications' published years, ML/DL methodology, patient or picture count, and accuracy can be found in **Table 4** and **Table 5**. The papers are arranged according to the ML/DL/IP approach used, which makes it straightforward to compare the results of related methods (**Table 4**).

The following findings are output based on the types of datasets and source of datasets (**Table 5**).

Overall, our findings point to the possibility of increasing the precision and effectiveness of cervical cancer screening using deep learning, machine learning, and image processing methods. However, further research is needed to address the limitations found in the studies and to evaluate the clinical utility and cost-effectiveness of these approaches.

According to the below **Table 6**, we can get the following chart (**Figure 1**) for better visualization.

Table 4. An overview of the research on cervical cancer screening employing deep learning, machine learning, and image processing methods.

References	Year	Different Methods	Best Algorithm	Accuracy
[1]	2019	MLP	MLP	96%
[2]	2019	CNN	CNN	77.30%
[3]	2020	RF, KNN, NB, MLP, J48 Trees, LR	MLP	99.8%
[4]	2020	CNN	CNN	97.89%
[5]	2019	C5.0, RF, RPART, KNN, SVM	C5.0	97.00%
[6]	2021	DT, RF, XGBoost	DT	93%
[7]	2021	CNN	CNN	93.33%
[8]	2020	RF, KNN	KNN	94%
[9]	2022	RF, XGBoost, CNN	CNN	92%
[10]	2019	R-CNN, Mask R-CNN	CNN	94%
[11]	2021	ResNet50	RestNet50	74.04%.
[12]	2020	CNN4	CNN4	80.03%
[13]	2018	Artificial Neural Networks	ANN	95%

Continued

[14]	2021	SVM	SVM	93.33%
[15]	2022	SMOTE Tomek	SMOTE Tomek	97.72%
[16]	2022	DT, RF, SVM	SVM	84%
[17]	2019	Deep Learning, CNN	CNN	97.70%
[18]	2019	KNN, DT, RF	KNN	93.30%
[19]	2017	MLP, Bayes NET	MLP	95%
[20]	2019	Bayes NET, RF, SVM	SVM	96.38%
[21]	2023	KNN	KNN	99.41%
[22]	2021	CNN, ResNet50	ResNet50	74.04%
[23]	2019	CNN	CNN	97.70%
[24]	2021	SVM	SVM	96%
[25]	2020	CNN	CNN	99.40%
[26]	2019	MLP	MLP	96.20%
[27]	2019	CNN	CNN	77%
[28]	2019	C5.0, RF, RPART, SVM, KNN	SVM	99.77%
[29]	2021	XGBoost classifier	XGBoost	93.33%
[30]	2020	SVM	SVM	99.30%
[31]	2021	LR, J48 Trees, DT, SVM, RF, KNN, NB, MLP	SVM	95%
[32]	2020	DL	DL	93%
[33]	2023	LR, J48 Trees, DT, SVM, RF, KNN, NB, MLP, Compact VGG	KNN	99.99%
[34]	2018	DL	DL	90%
[35]	2017	LR, DT, SVM, RF, KNN, NB, MLP, and J48 Trees	MLP	88%
[36]	2016	DL	DL	87%
[37]	2015	LR, J48 Trees, DT, SVM, RF, KNN, NB, and MLP	SVM	85%
[38]	2014	DL	DL	83%
[39]	2013	LR, J48 Trees, DT, SVM, RF, KNN, NB, and MLP	MLP	82%
[40]	2012	DL	DL	80%
[41]	2021	Compact VGG	VGG	81.70%
[42]	2021	SVMs	SVM	95.00%
[43]	2019	CNN	CNN	93.33%
[44]	2019	SVM, VGG	SVM	94%
[45]	2019	SVM	SVM	89.35%
[46]	2017	KNN, ANN	KNN	88%
[47]	2023	MLP, SVM, KNN	KNN	99%
[48]	2015	SVM, ANN	SVM	85.39%
[49]	2019	AUC, ROC	AUC	90.11%
[50]	2019	AUC, ROC	AUC	92%

Table 5. The kind of dataset and its source, which includes findings from an investigation of the study on the application of Image Processing, Deep Learning, and Machine Learning methods to cervical cancer screening.

Reference	Type of Dataset	Source of Dataset	No. of Patients/ Images
[1]	Normal Image	Caracas University Hospital in Venezuela	858
[2]	Normal Image	Image samples are provided by China Medical University's Shengjing Hospital.	307
[3]	Normal Image	Hospital Universitario de Caracas, Venezuela.	858
[4]	Herlev dataset	https://www.researchgate.net/publication/265873515_Pap-smear_Benchmark_Data_For_Pattern_Classification	1168
[5]	Hinselmann, Schiller, Cytology, and Biopsy Image	https://archive.ics.uci.edu/ml/datasets/Cervical%2bcancer%2b%2528Risk%2bFactors%2529	600
[6]	Cervical Cancer Behavior Risk Data Set	Data set on the risk of cervical cancer behavior from the UCI machine learning repository. 2020; archive.ics.uci.edu. accessed November 10, 2020	72
[7]	Normal Image	https://github.com/stcmedhub/dual_stain_dl	4253
[8]	Risk Data Set for Behavior in Cervical Cancer	Unknown	858
[9]	Tabular, Image	Unknown	2252
[10]	Normal Image	Unknown	178
[11]	Normal Image	Unknown	7
[12]	Tabular	Unknown	4253
[13]	Tabular	https://www.ancr.nu/	250,000
[14]	Tabular	Using evidence-based techniques, the National Cancer Institute's Early Diagnosis Branch's 1987 guidelines for early cancer diagnosis seek to lower mortality.	570,000
[15]	Tabular	Unknown	858
[16]	Tabular	https://wileyonlinelibrary.com/	858
[20]	Tabular	http://www.dimac-imaging.com/	584
[21]	Tabular	http:// Cervical Cancer Risk Classification (kaggle.com)	858
[22]	MRI Image	Data set on the risk of cervical cancer behavior from the UCI machine learning repository. 2020; archive.ics.uci.edu. accessed November 10, 2020	169
[23]	RGB Image	Unknown http://mde-lab.aegean.gr/index.php/downloads	298
[24]	HER	https://ssrn.com/abstract=3440430	1321
[25]	Normal Image	http://fuzzy.iau.dtu.dk/download/smear2005	917
[26]	Augmented Image	Unknown	858
[27]	Image	http://labs.fme.aegean.gr/decision/downloads	307
[28]	Tabular	Unknown	858

Continued

[29]	The Cancer Genome Atlas database	https://github.com/dingdongyan/New-CESC-2021	72
[30]	HEMLBC private Pap smear dataset	https://github.com/Abdul-Rehman-J/BCDWERT	741
[31]	Normal Image	http://www.ncbi.nlm.nih.gov/geo	2500
[32]	Normal Image	Unknown	5700
[36]	Normal Image	Unknown	18,500
[37]	Normal Image	CI5plus - Home (iarc.fr)	21,700
[41]	Microscopic Image	The data cannot be made publicly available owing to ethical or privacy concerns.	5842
[45]	Normal Image	http://www.cse.lehigh.edu/idealab/cervitor	1500
[48]	Tabular	Unknown	917

Table 6. Finding the number of applications for machine learning, deep learning, and image processing methods in articles from the literature study on cervical cancer screening.

Algorithm	Number of Uses Algorithm of Papers	Count
Convolution Neural Network (CNN)	[2] [4] [7] [9] [10] [11] [12] [16] [17] [23] [25] [27] [30] [41] [43] [44]	16
Support Vector Machine (SVM)	[5] [14] [16] [20] [24] [28] [31] [33] [35] [37] [39] [42] [44] [45] [48]	15
Random Forest (RF)	[3] [5] [6] [8] [9] [16] [18] [20] [28] [31] [33] [35] [37] [39]	14
K-Nearest Neighbors (KNN)	[3] [5] [8] [16] [18] [28] [31] [33] [35] [37] [39] [46]	12
Decision Tree (DT)	[6] [16] [18] [28] [31] [33] [35] [37] [39]	10
Multilayer Perceptron (MLP)	[1] [3] [19] [21] [26] [31] [33] [35] [37] [39]	9
Logistic Regression (LR)	[3] [31] [33] [35] [37] [39]	6
Naïve Bayes (NB)	[3] [31] [33] [35] [37] [39]	6
J48 Trees	[3] [5] [31] [33] [35] [37] [39]	6
Deep learning (DL)	[17] [32] [34] [36] [38] [40]	6
Artificial Neural Network (ANN)	[13] [44] [46] [48]	4
XGBoost	[6] [9] [29]	3
RPART	[5] [28]	2
Bayes NET	[19] [20]	2
AUC	[49] [50]	2
ROC	[49] [50]	2
SMOTE Tomek	[15]	1
U-Net	[22]	1
Inception-v3 with 48 layers (IncV3)	[30]	1
LVQ	[44]	1
Cox Regression	[47]	1

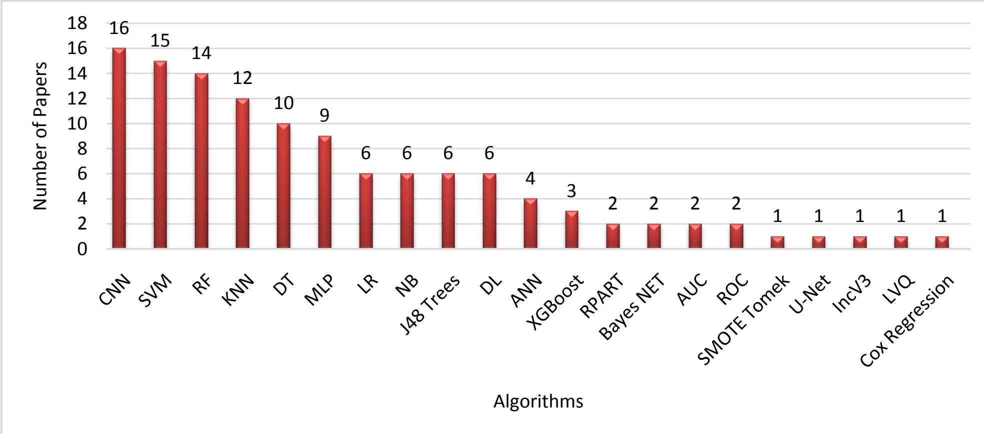

Figure 1. Number of uses algorithm of papers.

5. Conclusion

Finally, we have shown how machine learning, deep learning, and image processing techniques may be used to increase the accuracy and efficiency of cervical cancer screening based on our review of 50 studies on the subject. Promising results regarding high sensitivity, specificity, and accuracy in identifying cervical cancer and its precursors have been reported by the research included in this review. Our analysis also revealed several trends across the studies. Convolutional neural networks (CNNs) were the most used technique, followed by support vector machines (SVMs) and generative adversarial networks (GANs). Image pre-processing and feature extraction strategies were discovered to have a substantial influence on algorithm performance. Despite the potential benefits of these methodologies, the research had certain drawbacks, such as small sample sizes, a lack of variety in patient groups, and inadequate validation on independent datasets. These limitations underscore the need for further research to address these gaps and evaluate the performance of these techniques in real-world settings.

6. Future Works

One limitation of this review is that the quality of the studies included varied. Some studies had small sample sizes, which may limit the generalizability of the results. Additionally, some studies did not report sensitivity and specificity rates or did not supply enough detail about the machine learning or image processing techniques used, making it difficult to compare the results across studies. Another limitation is that the studies were conducted in different populations with varying levels of access to healthcare and cervical cancer screening. As such, the results may not be generalizable to all populations. Despite these limitations, the studies reviewed suggest that machine learning, deep learning, and image processing techniques hold promise for improving the accuracy and efficiency of cervical cancer screening. Further research is needed to find the most effective approaches and to confirm the results in larger and more diverse populations. The use of image processing techniques showed promise in improving the visualization of cervical images and helping in the detection of abnormal cells. However, the limited number of papers in this category highlights the need for further research in this area.

Conflicts of Interest

The authors declare no conflicts of interest regarding the publication of this paper.

References

[1] Yang, W.Y., Gou, X., Xu, T.Q., Yi, X.P. and Jiang, M.H. (2019) Cervical Cancer Risk Prediction Model and Analysis of Risk Factors Based on Machine Learning. *Proceedings of the* 2019 11*th International Conference on Bioinformatics and Biomedical Technology*, Stockholm, 29-31 May 2019, 50-54.

[2] Li, C., Xue, D., Zhou, X.K., Zhang, J., Zhang, H.Y., Yao, Y., Kong, F., Zhang, L. and Sun, H. (2019) Transfer Learning Based Classification of Cervical Cancer Immunohistochemistry Images. *Proceedings of the Third International Symposium on Image Computing and Digital Medicine*, Xi'an, 24-26 August 2019, 102-106. https://doi.org/10.1145/3364836.3364857

[3] Alsmariy, R., Healy, G. and Abdelhafez, H.A. (2020) Predicting Cervical Cancer Using Machine Learning Methods. *International Journal of Advanced Computer Science and Applications*, **11**, 173-184. https://doi.org/10.14569/IJACSA.2020.0110723

[4] Khamparia, A., Gupta, D., Gupta, D., Sangaiah, A.K. and Jhaveri, R.H. (2020) Internet of Health Things-Driven Deep Learning System for Detection and Classification of Cervical Cells Using Transfer Learning. *The Journal of Supercomputing*, **76**, 8590-8608. https://doi.org/10.1007/s11227-020-03159-4

[5] Nithya, B. and Ilango, V. (2019) Evaluation of Machine Learning Based Optimized Feature Selection Approaches and Classification Methods for Cervical Cancer Prediction. *SN Applied Sciences*, **1**, Article No. 641. https://doi.org/10.1007/s42452-019-0645-7

[6] Akter, L., Al-Islam, F., Islam, M., Al-Rakhami, M. and Haque, R. (2021) Prediction of Cervical Cancer from Behavior Risk Using Machine Learning Techniques. *SN Computer Science*, **2**, Article No. 177. https://doi.org/10.1007/s42979-021-00551-6

[7] Wentzensen, N., *et al.* (2021) Accuracy and Efficiency of Deep-Learning-Based Automation of Dual Stain Cytology in Cervical Cancer Screening. *Journal of the National Cancer Institute*, **113**, 72-79.

[8] Ilyas, Q.M. and Ahmad, M. (2021) An Enhanced Ensemble Diagnosis of Cervical Cancer: A Pursuit of Machine Intelligence towards Sustainable Health. *IEEE Access*, **9**, 12374-12388. https://doi.org/10.1109/ACCESS.2021.3049165

[9] Xue, P., *et al.* (2022) Deep Learning in Image-Based Breast and Cervical Cancer Detection: A Systematic Review and Meta-Analysis. *NPJ Digital Medicine*, **5**, Article No. 19. https://doi.org/10.1038/s41746-022-00559-z

[10] Sompawong, N., *et al.* (2019) Automated Pap Smear Cervical Cancer Screening Using Deep Learning. 2019 41*st Annual International Conference of the IEEE Engineering in Medicine and Biology Society* (*EMBC*), Berlin, 23-27 July 2019, 7044-7048. https://doi.org/10.1109/EMBC.2019.8856369

[11] Lu, J., Song, E., Ghoneim, A. and Alrashoud, M. (2020) Machine Learning for Assisting Cervical Cancer Diagnosis: An Ensemble Approach. *Future Generation*

Computer Systems, **106**, 199-205. https://doi.org/10.1016/j.future.2019.12.033

[12] Gustafsson, L., Pontén, J., Bergstrôm, R. and Adami, H.O. (1997) International Incidence Rates of Invasive Cervical Cancer before Cytological Screening. *International Journal of Cancer*, **71**, 159-765. https://onlinelibrary.wiley.com/doi/abs/10.1002/%28SICI%291097-0215%2819970410%2971%3A2%3C159%3A%3AAID-IJC6%3E3.0.CO%3B2-%23

[13] Vaccarella, S., Franceschi, S., Engholm, G., Lönnberg, S., Khan, S. and Bray, F. (2014) 50 Years of Screening in the Nordic Countries: Quantifying the Effects on Cervical Cancer Incidence. *British Journal of Cancer*, **111**, 965-969. https://doi.org/10.1038/bjc.2014.362

[14] Wei, L.Z., Mustafa, W.A., Jamlos, M.F., Idrus, S.Z.S. and Sahabudin, M.H. (2020) Cervical Cancer Classification Using Image Processing Approach: A Review. *IOP Conference Series*, **917**, Article ID: 012068. https://doi.org/10.1088/1757-899X/917/1/012068

[15] Chen, H., *et al.* (2021) CytoBrain: Cervical Cancer Screening System Based on Deep Learning Technology. *Journal of Computer Science and Technology*, **36**, 347-360. https://doi.org/10.1007/s11390-021-0849-3

[16] Lilhore, U.K., *et al.* (2022) Hybrid Model for Detection of Cervical Cancer Using Causal Analysis and Machine Learning Techniques. *Computational and Mathematical Methods in Medicine*, **2022**, Article ID: 4688327. https://doi.org/10.1155/2022/4688327

[17] Wu, M., Yan, C., Liu, H., Liu, Q. and Yin, Y. (2018) Automatic Classification of Cervical Cancer from Cytological Images by Using Convolutional Neural Network. *Bioscience Reports*, **38**, BSR20181769. https://doi.org/10.1042/BSR20181769

[18] Devi, M.A., Ravi, S., Vaishnavi, J. and Punitha, S. (2016) Classification of Cervical Cancer Using Artificial Neural Networks. *Procedia Computer Science*, **89**, 465-472. https://doi.org/10.1016/j.procs.2016.06.105

[19] Mariarputham, M.E.J. and Stephen, A. (2015) Nominated Texture Based Cervical Cancer Classification. *Computational and Mathematical Methods in Medicine*, **2015**, Article ID: 586928. https://doi.org/10.1155/2015/586928

[20] Chandran, V., *et al.* (2021) Diagnosis of Cervical Cancer based on Ensemble Deep Learning Network Using Colposcopy Images. *BioMed Research International*, **2021**, Article ID: 5584004. https://doi.org/10.1155/2021/5584004

[21] Chen, X., *et al.* (2023) Cervical Cancer Detection Using K Nearest Neighbor Imputer and Stacked Ensemble Learning Model. *Digital Health*, **9**. https://doi.org/10.1177/20552076231203802

[22] Priyanka, B.J., *et al.* (2021) Machine Learning Approach for Prediction of Cervical Cancer. *Turkish Journal of Computer and Mathematics Education*, **12**, 3050-3058. https://doi.org/10.17762/turcomat.v12i2.1972

[23] Ali, M., Sarwar, A., Sharma, V. and Suri, J. (2019) Artificial Neural Network Based Screening of Cervical Cancer Using a Hierarchical Modular Neural Network Architecture (HMNNA) and Novel Benchmark Uterine Cervix Cancer Database. *Neural Computing and Applications*, **31**, 2979-2993. https://doi.org/10.1007/s00521-017-3246-7

[24] Bhavani, C.H. and Govardhan, A. (2021) Cervical Cancer Prediction Using Stacked Ensemble Algorithm with SMOTE and RFERF. *Materials Today*: *Proceedings*, **80**, 3451-3457.

[25] Ghoneim, A., Muhammad, G. and Hossain, M.S. (2020) Cervical Cancer Classification Using Convolutional Neural Networks and Extreme Learning Machines. *Fu-*

ture Generation Computer Systems, **102**, 643-649.
https://doi.org/10.1016/j.future.2019.09.015

[26] Mugad, N.N. and Sumana, K.R. (2021) Early Prediction of Cervical Cancer Using Machine Learning Algorithms.
https://www.researchgate.net/publication/355284115_Early_Prediction_of_Cervical_Cancer_Using_Machine_Learning_Algorithm

[27] Kurnianingsih, *et al.* (2019) Segmentation and Classification of Cervical Cells Using Deep Learning. *IEEE Access*, **7**, 116925-116941.
https://doi.org/10.1109/ACCESS.2019.2936017

[28] Matsuo, K., *et al.* (2019) Survival Outcome Prediction in Cervical Cancer: Cox Models vs Deep-Learning Model. *American Journal of Obstetrics and Gynecology*, **220**, 381.E1-381.E14. https://doi.org/10.1016/j.ajog.2018.12.030

[29] Ding, D., *et al.* (2021) Machine Learning-Based Prediction of Survival Prognosis in Cervical Cancer. BMC Bioinformatics, **22**, Article No. 331.
https://doi.org/10.1186/s12859-021-04261-x

[30] Abbas, S., *et al.* (2021) BCD-WERT: A Novel Approach for Breast Cancer Detection Using Whale Optimization Based Efficient Features and Extremely Randomized Tree Algorithm. *PeerJ*, **7**, e390. https://doi.org/10.7717/peerj-cs.390

[31] Tan, M.C., Chang, S.W., Cheah, P.L. and Yap, H.J. (2018) Integrative Machine Learning Analysis of Multiple Gene Expression Profiles in Cervical Cancer. *PeerJ*, **6**, e5285. https://doi.org/10.7717/peerj.5285

[32] Fernandes, K., Chicco, D., Cardoso, J.S. and Fernandes, J. (2018) Supervised Deep Learning Embeddings for the Prediction of Cervical Cancer Diagnosis. *PeerJ*, **4**, e154. https://doi.org/10.7717/peerj-cs.154

[33] Karamti, H., *et al.* (2023) Improving Prediction of Cervical Cancer Using KNN Imputed SMOTE Features and Multi-Model Ensemble Learning Approach. *Cancers*, **15**, Article 4412. https://doi.org/10.3390/cancers15174412

[34] Alsmariy, R., Healy, G. and Abdelhafez, H.A. (2020) Predicting Cervical Cancer Using Machine Learning Methods. *International Journal of Advanced Computer Science and Applications*, **11**, 173-184.
https://doi.org/10.14569/IJACSA.2020.0110723

[35] World Health Organization (2022) Roadmap to Accelerate the Elimination of Cervical Cancer as a Public Health Problem in the WHO European Region 2022-2030.
https://apps.who.int/iris/bitstream/handle/10665/362396/72bg17e-Roadmap-CervicalCancer.pdf

[36] World Health Organization (2014) Comprehensive Cervical Cancer Control.
https://www.who.int/publications/i/item/9789241548953

[37] Korn, A., *et al.* (2022) Cervical Cancer Screening and Treatment, HIV Infection, and Age: Program Implementation in Seven Regions of Namibia. *PLOS ONE*, **17**, e0263920. https://doi.org/10.1371/journal.pone.0263920

[38] Singh, D., *et al.* (2022) Global Estimates of Incidence and Mortality of Cervical Cancer in 2020: A Baseline Analysis of the WHO Global Cervical Cancer Elimination Initiative. *The Lancet Global Health*, **11**, E197-E206.
https://doi.org/10.1016/S2214-109X(22)00501-0

[39] Fontham, E.T.H., *et al.* (2020) Cervical Cancer Screening for Individuals at Average Risk: 2020 Guideline Update from the American Cancer Society. *CA*: *A Cancer Journal for Clinicians*, **70**, 321-346. https://doi.org/10.3322/caac.21628

[40] Tanimu, J.J., Hamada, M., Hassan, M., Kakudi, H.A. and Abiodun, J.O. (2022) A Machine Learning Method for Classification of Cervical Cancer. *Electronics*, **11**,

Article 463. https://doi.org/10.3390/electronics11030463

[41] Guo, C., *et al.* (2021) Novel Artificial Intelligence Machine Learning Approaches to Precisely Predict Survival and Site-Specific Recurrence in Cervical Cancer: A Multi-Institutional Study. *Translational Oncology*, **14**, Article ID: 101032. https://doi.org/10.1016/j.tranon.2021.101032

[42] Arora, A., Tripathi, A. and Bhan, A. (2021) Classification of Cervical Cancer Detection Using Machine Learning Algorithms. 2021 6*th International Conference on Inventive Computation Technologies* (*ICICT*), Coimbatore, 20-22 January 2021, 827-835. https://doi.org/10.1109/ICICT50816.2021.9358570

[43] Balmagambetova, S., *et al.* (2020) Cervical Screening in Western Kazakhstan: Liquid-Based Cytology 'Cell Scan' versus Azur-Eosin Staining. *Journal of Medical Screening*, **27**, 90-95. https://doi.org/10.1177/0969141319885409

[44] Guo, P., Singh, S., Xue, Z., Long, R. and Antani, S. (2019) Deep Learning for Assessing Image Focus for Automated Cervical Cancer Screening. 2019 *IEEE EMBS International Conference on Biomedical & Health Informatics* (*BHI*), Chicago, 19-22 May 2019, 1-4. https://doi.org/10.1109/BHI.2019.8834495

[45] Alyafeai, Z. and Ghouti, L. (2020) A Fully-Automated Deep Learning Pipeline for Cervical Cancer Classification. *Expert Systems with Applications*, **141**, Article ID: 112951. https://doi.org/10.1016/j.eswa.2019.112951

[46] Hinsen, K. (2018) Verifiability in Computer-Aided Research: The Role of Digital Scientific Notations at the Human-Computer Interface. *PeerJ*, **4**, e158. https://doi.org/10.7717/peerj-cs.158

[47] Glučina, M., Lorencin, A., Anđelić, N. and Lorencin, I. (2023) Cervical Cancer Diagnostics Using Machine Learning Algorithms and Class Balancing Techniques. *Applied Sciences*, **13**, Article 1061. https://doi.org/10.3390/app13021061

[48] Sajeena, T.A. and Jereesh, A.S. (2015) Automated Cervical Cancer Detection through RGVF Segmentation and SVM Classification. 2015 *International Conference on Computing and Network Communications* (*CoCoNet*), Trivandrum, 16-19 December 2015, 663-669.

[49] Jiang, X., *et al.* (2021) MRI Based Radiomics Approach with Deep Learning for Prediction of Vessel Invasion in Early-Stage Cervical Cancer. *IEEE*/*ACM Transactions on Computational Biology and Bioinformatics*, **18**, 995-1002. https://doi.org/10.1109/TCBB.2019.2963867

[50] Lin, Y.C., *et al.* (2020) Deep Learning for Fully Automated Tumor Segmentation and Extraction of Magnetic Resonance Radiomics Features in Cervical Cancer. *European Radiology*, **30**, 1297-1305. https://doi.org/10.1007/s00330-019-06467-3