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Analysis of Computational Methods for Diagnosis of Cervical Cancer – A Review

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Abstract: The PAP test, a simple screening method, detects cervical cancer early, preventing fatality. Uterine, cervical, and fallopian tube cancers are common among women, making prevention vital. Despite over 60 years since its inception, attempts to automate this process have aimed at saving time and costs. Automated cell sample screening, available since 2000, minimally impacted screening expenses. Cervical cancer is a leading cause of death in poor nations, but technological advancements enable faster, cost-effective screening and treatment. However, screening procedures may still be cumbersome, especially in low-income countries. This study reviews current screening methods and introduces computational techniques for cervical cell analysis, including automated quality assessment, segmentation, and classification, addressing practical challenges.

Keywords: Cervical cancer, Human Papilloma Virus(HPV), Prevention, CYENET

1 Introduction

This disease is more common in low-income countries because it disproportionately affects women. Cervical cancer claims the lives of 570,000 women each year, the majority of whom live in countries with low or moderate incomes. Women die most frequently from breast cancer in 55 different nations. African, Asian, and Latin American women confront particular difficulties. It's because they don't have effective prevention and fair access to early diagnosis and treatment programmes that their death rates are so high.

Researchers are developing CADx systems for the early detection of cervical cancer because these under-resourced health facilities lack specialised personnel and equipment. Computer vision and machine learning techniques already employed in CADx systems could be utilised to automate the inspection of cervical specimens. Cervical cancer screening has seen a recent uptick in the use of computational methods. Handling smear variability, artefact segmentation of individual cells and clusters, and the nucleus and cytoplasm segmentation, in addition to the identification of abnormal cell morphology are all included in this process of automating computer vision.

Tobacco use, prescription medication, and weakened immune system cells are just a few of the dangers that come with using tobacco products. Because early

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symptoms of cervical cancer are difficult to detect, the PAP smear programme is used. Scans appear to be time-consuming, and the results are frequently inaccurate. Blood patterns that are uneven, disproportionate, or overlapped are all examples of representation. Smear test results may be tracked and analysed using screening images, one of their most amazing advantages. Cervical cancer is shown at various stages in Figure 1 (right).

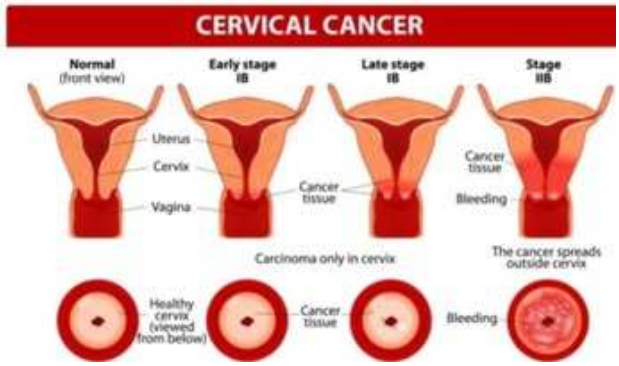

Fig. 1: Cervical cancer stages

Automation of cervical cancer screening systems is primarily aimed at addressing the third issue. In part, this is due to the fact that cytotechnologists routinely examine large numbers of samples, making them vulnerable to making mistakes as a result of boredom or fatigue. Numerous advantages of using a computer include the fact that it does not get tiring, is not prone to monotony-related errors, and will never make biased decisions. It is also possible that the number of trained cytotechnologists required to evaluate samples could be reduced with an automated cytology system. A large number of cytotechnologists are needed for mass screening programs, which can be difficult to train in countries with limited funds.

1.1 Classification

To find out if a sample includes malignant cells is the major objective of a cervical screening system / (or precancerous lesions). Different approaches to classification have been taken. One of the most common ways to classify cells is by analyzing them for features like those discussed. Finally, the system takes into account all of the data to arrive at a smear diagnosis. Rare event (RE) systems are systems that focus on identifying (the rare) occurrences of suspicious cells.

Classification can be improved by looking for variations in cell features that aren't readily apparent between healthy and diseased samples. Because the alterations are often so subtle, this phenomenon is also known as Malignancy-Associated Changes (MAC). Because of this, it cannot be studied on a cell-by-cell basis but instead must consider the entire cell population. Classifying a smear is based on the values of the population parameters (means and variances). Another approach to creating a classification system is to model it after the classification methods employed by cytotechnologists and pathologists. Instead of focusing on a single element, the sample is assessed in light of a number of variables, such as cell distribution patterns, cell density, the existence of degraded cells and cytoplasms, the frequency of naked nuclei, etc. It is impossible for them to achieve the same level of accuracy if they were forced to classify samples solely on the basis of single cells. A common term for systems that attempt to model this approach to classification is "contextual evaluation" (CE). Architectural features and relational features are two other terms that are frequently used in academic writing.

Cervical cancer is the second biggest cause of mortality among women, according to the American Cancer Society. In the previous few years, image-based disease detection has come a long way. In 2018, 7.5% of all female cancer fatalities were caused by cervical cancer, making it the world's fourth most prevalent cancer type [1].

Cervical cancer claims the lives of 31,000 women annually in developing and emerging economies. If caught early enough, this condition can be prevented. Cervical cancer in HIV-positive women may be connected to the virus in one out of five instances, according to the Centers for Disease Control and Prevention. Screening effectiveness has been redefined to include factors such as ease of use, consistency, and oversight, as well as the ability to detect and treat lesions early [2].

As a result, this disease is not completely reversible, especially in developing countries where it is most prevalent. Cervical cancer screening and prevention are, therefore, extremely important. This includes HPV tests, cytology or PAP tests, colposcopy, and biopsy for cervical cancer detection. The procedure was made more efficient, practical, and cost-effective by the creation of a range of tools. Most commonly used for cancer and non-cancer patients is the PAP smear imaging, but it is time-consuming and requires experienced specialists, which can lead to missed positive cases. PAP smears and HPV tests are not only expensive, but they also have lower accuracy rates. On the other hand, colonoscopies are routinely employed in poor nations. PAP smear and HPV tests fail, thus colposcopy is used. At this stage, the lack of symptoms makes it difficult to make an early diagnosis for cervical cancer, which is more treatable. Preventing deaths from cervical cancer and reducing

sickness and impermanence are both possible with effective screening programs [3].

Inadequate healthcare resources and a scarcity of skilled healthcare personnel have combined to substantially restrict access to screening facilities for cervical cancer [4].

It's not uncommon to perform a colposcopy in order to check for signs of cervical cancer prevention. There can be a significant impact on the patient's treatment and outcomes if this cancer is discovered earlier. In digital colposcopy, a variety of approaches have been taken to extracting information from images. They are designed to assist healthcare providers in conducting colposcopy examinations, regardless of their proficiency. It has long been known that computer-aided systems can improve and analyze the image quality, identify regions and patterns of instability (TZs), transition zone classifications (TZs), and categorize cancer risk [5].

Cervical colposcopy and areas of concern can be improved by using CAD instruments, which can identify abnormalities. These diagnostic aids can be used by clinicians, but only those with adequate training and experience should do so. Pathological regions may be a sign of these tumours, so spotting them during a colposcopy examination is crucial. Some of these anomalies include acetowhite, irregular vascularization and mosaic areas as well as punctures [6,7].

Table 1: Comparison between proposed architecture and various parameters run-time measurements; results are presented.

S.No.	Model Name	Number of Parameters	Execution Time (Per epoch)
1	DenseNet-121[8]	7978856	21 min 10 s
2	DenseNet-169[8]	28681000	24 min 59 s
3	Colponet [9]	6977000	16 min 27 s
4	Inception-Resnet-v2[10]	55843161	15 min 36 s
5	CYENET	8465376	3 min 32 s
6	VGG19 (TL)	123642856	5 min 24 s

The proposed model CYENET has a run time of 3 minutes and 32 seconds, while VGG19 has a run time of 5 minutes and 24 seconds, as shown in Table 1. For the CYENET, there are 8465376 parameters, and for VGG19, there are 123642856 parameters. This doesn't stop us from freezing the outermost levels in order to limit the number of programmable parameters. Due to its dense structure, the densenet architecture takes the longest to train of the three models. The soft computation based cervical tumor segmentation systems is expressed in Table 2.

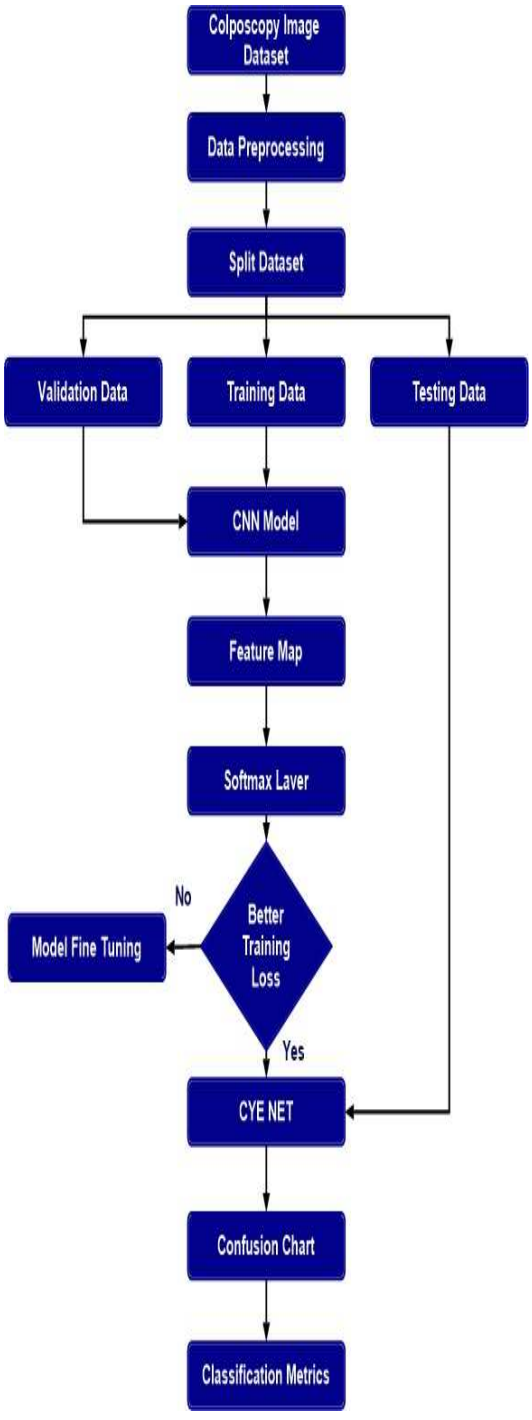

Fig. 2: Diagram of the CYENET cervical cancer detection technique presented

[] Since Jantzen et al. [16] released their dataset, it has become the gold standard for classification studies in the

Table 2: Cervical cancer screening: A review of relevant studies

METHODS	DATASETS	ADVANTAGES	DISADVANTAGES
Inception V3 Model [1]	Herley Dataset	✓Accuracy is a priority here. ✓Good generalizability complexity	Cervical cells need to be studied further in the deep network.
Transfer Learning, Pretrained Densnet [2]	Fujian Meternal and child health hospital Kaggle	More practicality and efficacy are gained	Limited data.
CNN- extreme learning machine (ELM) based system [6]	Herley Dataset	You can learn a lot in a short time. Convergence is a snap. The randomness is less.	More complexity Need more investigation
Gene-assistance module voting strategy [7]	Chinese hospital and Universitaro De Carcas, Venezuela	Scalability and practicality are improved	Limited data.
Random forest Adaboost [10]	Radiotherapy dataset	Improved treatment strategy	Requirements for feature extraction The pain is more intense.
ColpoNet [11]	Olposcopy images	Improved precision. The ability to classify information quickly and accurately.	By extracting relevant data, we can improve our accuracy.
CNN Model [12]	Papanicolaou-stained cervical smear dataset	For one thing, it's more accurate.	False negative images account for 1.8% of all images, according to the data.
Fourier transform and machine learning methods [13]	Mocroscopic images	Automated and hands-free system. The microscopist saves precious time.	Complexity is a lot more.
CNN-SVM Model [14]	Herley and one private dataset	Strongness and sturdiness High precision	Parameters must be improved. The need for handcrafted features.
Stacked auto encoder[15]	UCI database	a high degree of precision Minimize the amount of data that must be transmitted.	Due to the reduction in dimensions, training takes a long time.

literature. This set of data shows that ANNs and SVMs perform the best. That being said, it's been more than a decade since this was written, so their performance is clearly outdated. The performance of the seven-class classification problem was noticeably lower before more recent developments. Many people complain about their inability to tell the difference

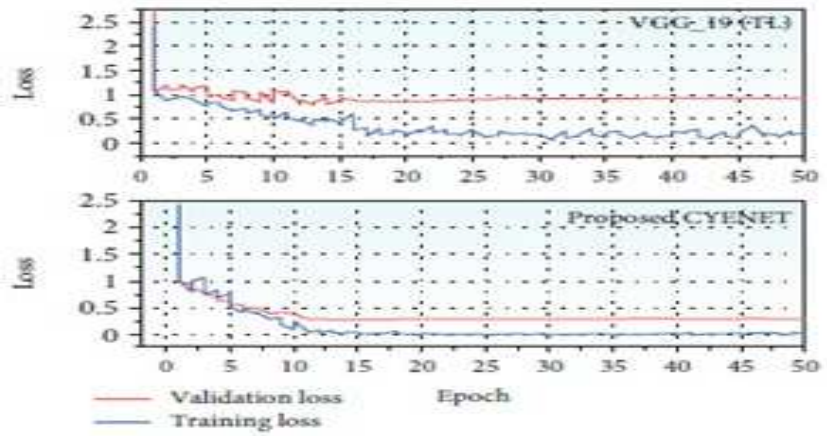

Fig. 3: Loss curves for CYENET and VGG 19 training and testing (TL), [17]

Compromising performance is possible when relying primarily on multiclass techniques that are overly sophisticated. There are many advantages to using finer-grained classification methods. There are a variety of methods that can be used for multiclass classification, while others are better suited for binary classification. That's why it's critical to consider the needs and goals of the CADx system being developed when making a design decision. Research on binary and multi-class problems has shown exceptional results in recent studies. Researchers Chankong and colleagues [17] conducted an extensive analysis of three datasets and compared their results to those of best-known algorithms in the field.

2 REVIEW OF LITERATURE

Pre-processing and segmentation are not required, allowing it to capture the most essential features of an object. To allow for a broader range of datasets, this method does not require any "hard-coding" in order to work. All these advantages notwithstanding, it takes almost three minutes and a half to process one picture patch using this method. Even better results were found in an alternative approach to the above-mentioned strategy, devised by Jith et al. [18]. Performance was only evaluated by accuracy, and a more thorough evaluation is needed in order to prove its efficiency.

False negative rates are higher in cytoplasm segmentation methods like those by Lu et al. [19], for example, which has a high true positive rate. As a result, the mentioned research examines the advantages and disadvantages of different segmentation approaches for cervical cells. When developing an intelligent automated system, several criteria such as computing complexity, sensitivity, and specificity must be taken into account, and this contribution might serve as a starting point by Kumar T S et al. [20]. Just looking at accuracy alone won't tell you much about a computer-aided design system's potential.

As a last check to guarantee that the Genctav dataset [21] is resistant to image variability, it is additionally tested on a more realistic private collection of samples. In spite of their pre-challenge release, many other authors later replicated and compared these methods, making them the standard by which other implementations were measured.

Retrieving visual elements that better complement clinical information using network learning can be achieved by using backpropagation. When various screening alternatives were available, Fernandes and his colleagues were able to forecast the patient's risk using a partial transfer paradigm, [22]. Both numerically and verbally expressed. In order to translate the contributions of each feature into a common linear model, researchers are looking into regularisation strategies.

Different tests have been proposed to automatically discover their relative weights by using information gain and gradient-based algorithms [23]. The final decision is reached by combining and comparing data from various sources with the training set. As a result of this, these methods tend to look at clinical variables on their own, without taking into account their correlations.

A major drawback of conventional approaches is the wide range of possible cell appearances. It is also possible that the abnormality detection process will overlook important or more complex discriminative information if only specific hand-crafted features are extracted and selected. Convolutional neural networks (CNNs) can automatically extract hierarchical features without the need for prior segmentation steps. Deep learning can refer to either an ANN with a high number of hidden layers or segmentation-free methods that use only the pixels in an image as input rather than previously extracted numerical data. Deep Belief Networks outperformed SVM-based feature extraction and segmentation in a range of classification tasks, according to Rasche et al. [24]. There were, however, some difficulties in distinguishing between minor structural differences between LSIL and healthy types.

For women who have not yet complained of any symptoms, a cervical cancer screening can look for both precancerous and cancerous tumours. More than half of cervical cancer cases may be prevented if precancerous tumours were discovered and treated early on. We'll focus on cervical cancer screening in this section because it's important to understand medical and biological principles thoroughly [25].

The Bethesda method specifies a minimum level of cellularity as a need for smear adequacy, however this is rarely referenced in automated solutions research. When it comes to cellularity, it is important to distinguish between squamous and glandular cells, as adequate cell density only takes into account the latter. In contrast, finding and classifying glandular cells is an extremely rare occurrence. For this sort of cell, commercially available technologies have shown substantial false-negative rates [26].

In medical applications, it is generally desirable to avoid false negatives, i.e., miss-classifying any abnormal condition. While this results in an increase in FP, it may not be a problem for cytology systems. Even a modest amount of FP can render the system almost worthless because a single slide can include tens of thousands of cells (depending on how it was prepared). With this in mind, a healthy sample of 20k cells with an error rate of one percent will yield 200 abnormal cells on a normal slide. An ASC-US-diagnosed test slide contains an average of 20 abnormal cells [27], and an FNA error rate of 20% results in 16 abnormalities when scanning the entire slide. When there are abnormal cells present, finding an abnormal cell is still difficult. As a result, sensitivity is an important consideration when searching for an abnormal cell on an abnormal slide.

Squamous abnormalities are 10 times more common in cervical cytology specimens than glandular atypia.

Some 9 percent to 38 percent of the observed findings were later diagnosed with substantial lesions or aggressive carcinomas in follow-up examinations [28]. Even though it isn't one of the top goals for CADxsystems, some attention should be paid to the detection of glandular cellular abnormalities, not only because it can indicate more significant issues, but also because it can help assess whether or not a slide is suitable or not. In terms of deep learning, we'd like to point out two examples. The first significant CNN-based technique was proposed by Zhang et al. [29], with findings that are similar to but marginally inferior to those of Chankong et al. [30]. Features-based techniques, on the other hand, necessitate extensive pre-processing or segmentation, which is not necessary with this method. As a result, it is more tolerant of noise and can be applied to different datasets because it is not "hard-coded." Even with these improvements, the approach is still too slow for clinical application, taking 3.5 seconds for each picture patch.

In terms of classification, a research by Jantzen et al. [31], which used the Herlev dataset as a baseline, is the gold standard. SVMs and ANNs are the most popular models in this dataset. That being said, it's been more than a decade since this was written, so their performance is clearly outdated. The performance of the 7-class multi-class classification issue was much lower before the more recent improvements. It's widely accepted that it's difficult to tell the difference between social classes. "Normal Columnar Epithelial" is also a common source of incorrect classifications due to the cell type and shape of Herlev's class. Senthil Kumar T et al. improved accuracy by extracting performance assessment measures using an image thickening and background thinning technique [32]. Table 3 shows the performance analysis of different segmentation techniques and datasets based cervical cancer classification methods. This is the most important studies on cervicalcell segmentation.

Table 3: Performance analysis of various segmentation techniques based cervical cancer classification methods.

Authors/ Year	Segmentation Technique	Cells Overlap	Datasets	Performance
Tareef et al. 2018 [33]	Multi-pass watershed + Ellipse fitting	Yes	ISBI 2014, ISBI 2015	0.925; Rec: 95.0%; Prec: 90.6%. (ISBI 2015) Cyt DSC: 0.851
Nosrati and Hamarneh 2015 [34]	Random forest (RF) classifier + Level Set with elliptical, 2014, and/or star shape prior, 2015, and Voronoi energy based, 2015	Yes	ISBI 2014	Rec:91.6%; DSC: 0.900. Cyt DSC: 0.871
Ushizima et al. 2015 [35]	Graph-based region growing + Voronoi Diagram	Yes	ISBI 2014, ISBI 2015	(ISBI 2014): Nuc Rec: 87.1%; Prec: 96.8%; DSC: 0.914. Cyt DSC:0.872. (ISBI 2015): Cyt DSC: 0.875
Phoulady et al. (2017) [36]	Iterative thresholding + GMM Expectation-Maximization (EM) + Grid approach with distance metric from multi-focal images	Yes	ISBI 2014, ISBI 2015	(ISBI 2014): NucPrec: 96.1%; Rec: 93.3%. Cyt DSC: 0.901. (ISBI 2015): Cyt DSC: 0.869
Tareef et al. 2017 [37]	SVM classification + Shape based-guided Level Set based on Sparse Coding for overlapping cytoplasm	Yes	ISBI 2014	Nuc Prec: 95%; Rec: 93%; DSC: 0.93. Cyt DSC: 0.89
Song et al. (2014, 2017) [38]	Multi-scale CNN feature extraction with spatial pyramids + neural network (NN). Refinement: Graph partitioning + Unsupervised	Only touching nuclei (2015).	Private, ISBI 2015	(ISBI 2015): Nuc DSC: 0.93. Cyt DSC: 0.91
Gautam et al. (2018, 2018) [39]	CNN with selective pre-processing based on nucleus size and chromatin pattern + post-processing morphological filtering.	No	Herlev	Prec: 89%; Rec: 91%; DSC:0.90
Tareef et al. 2017 [40]	CNN patch-based for cellular components classification. Cytoplasm estimation by Voronoi Diagram + Level Set with Shape prior.	Yes	ISBI 2014	DSC:0.94. Cyt DSC:0.897

Table 4 summarises the cervical cell classification. When comparing results from multiple datasets, only publicly available datasets were used. Image datasets for the analysis of breast cancer images are shown in Table 5.

Table 4: Performance analysis of various cervical cell Classification techniques

Authors/ Year	Segmentation Technique	Cells Overlap	Datasets	Performance
Zhao et al. 2016 [41]	Image segmentation and partitioning. Classification using a radial basis function-SVM after feature extraction from non-background blocks.	Private	2-class	Acc 98.98%; Rec 95.0%; Sp 99.33%
Bora et al. 2017 [42]	Combination of LSSVM, MLP, and RF, each with a different weighting scheme. Classification at the single cell and smear level	Herlev, Private	2, 3 class	(Herlev) 2-class: Acc 96.51%; Rec 98.96%; Sp 89.67%. 3-class: Acc 91.71%; Rec 89.41%; Sp 94.84%;
Gómez et al. 2017 [43]	Various algorithms are put up against one another for comparison. Bagging + MultilayerPerceptron and AdaBoostM1 + LMT are the best.	Herlev	2-class	Acc 95.74%
Zhang et al. 2017 [44]	Using Transfer Learning, a nuclei-centered patch-based CNN	Herlev, HEMLBC (Private)	2-class:	Acc 98.3%; Rec 98.2%; Sp 98.3%; H-mean 98.3%;
Jith et al. 2018 [45]	CNN based on fine tunedAlexNet	Herlev, Aindra (Private)	2-class:	Acc 99.6%
Gautam et al. 2018 [46]	Decision trees with CNNs on each leaf, or CNNs created from AlexNet-trained patches.	Herlev, Aindra (Private)	2, 7-class	2-class Acc: 99.3%. 7-class Acc: 93.75%
Lin et al. 2019 [47]	Combine RGB images with cytoplasm and nucleus masks as a five-channel input to a number of pre-trained CNNs.	Herlev	2,7-class	2-class: Acc 94.5%; Rec 97.4%; Sp 90.4%. 7-class: Acc 64.5%
Elayaraja et al. 2022 [48]	GA based CNN classification method	Guanacaste dataset	2-class	Sen: 99.37% Sp: 98.9% Acc: 99.21%

Table 6 shows the estimating of the combined influence of African HIV-infected women's knowledge, attitude, and practice toward cervical cancer.

2.1 Predictions of cervical cancer identification by photonic method

Cervical cancer is the most frequent cancer in the world, according to estimates [62,63]. Every year, approximately 2,500 Polish women are diagnosed with cervical cancer, which is part of a global total of 500,000, [64]. Cervical cancer mortality and incidence have been drastically reduced thanks to screening programmes, [65]. There is still a great need for solutions that can back up the doctor's subjective diagnosis in many cases, [66].

Table 5: Image datasets for breast cancer image analysis

Dataset	Size	Classes/Targets	Format	Type	Author/Repository, Year
MIAS	322	2	pgm	Mammography	Suckling, J. et al. [49]
DDSM	55,890	410	Npy	Mammography	Scuccimarra [50]
InBreast			XML	Mammography	
InBreast			XML	Mammography	
Breast Cancer Wisconsin	568	3	csv	Mammography	Dua, D. and Graff, C. [51]
BreakHis	7909	2	png	Histology	Bukun [52]
BACH/ICIAR2018	400	4	tiff	Histology	G.Aresta [53]

Table 6 shows the estimating the combined influence of African HIV-infected women's knowledge, attitude, and practice toward cervical cancer.

Table 6: Study characteristics include: estimating the combined influence of African HIV-infected women's knowledge, attitude, and practice toward cervical cancer.

First Author	Year	Study setting	Study location	Study design	Sample size	Knowledge	Attitude	Practice	Age range /Mean age in years
Solomon et al [54]	2019	Health facility	Ethiopia	Cross-sectional	475			119	36
Shiferaw et al [55]	2018	Health facility	Ethiopia	Cross-sectional	581	136			35
Mitchell et al [56]	2017	Health facility	Uganda	Cross-sectional	87		1		30-–69
Stuart et al [57]	2019	Health facility	Ghana	Qual-Quant of parent cohort	60	48			≥ 18
Adibe & Aluh [58]	2017	Health facility	Nigeria	Cross-sectional	447	45	194		≥ 9
Belglaiaa et al [59]		Health facility	Morocco	Cross-sectional	115	24		15	34.9
Rosser et al [60]	2015	Health facility	Kenya	Cross-sectional	106	69	72	89	34.9
Maree & Moitse [61]	2014	Health facility	South Africa	Cross-sectional	315	198			38.9

Patients may be subjected to unnecessary procedures, increased treatment costs, and even death as a result of the lack of precision in the classification of a patient's neoplastic lesion. Cervical premalignant alterations are most often caused by the human papilloma virus, or HPV [67]. Only a handful of HPV strains pose a significant risk to women.

Because early detection of cervical cancer is so critical, several approaches aimed at improving it have been proposed and are currently being developed. The most common methods include a biopsy, imaging, and a doctor's examination. When it comes to analysing data, imaging provides a wide range of options, and these results can help clinicians at the diagnosis stage of treatment. [68].

Deep learning-based convolutional neural networks can detect and categorise malignant cells with an accuracy of 99.7 percent [69]. Cervical cancer can now be detected and classified automatically from cervigram images using a specialised pipeline [70]. Deep learning models and CNNs are used in the solution, which guarantees fast and accurate results. Fuzzy C-means (FCM) clustering was found to have an accuracy of 93.78 percent for issues with two classes and 99.27 percent for problems with seven classes [71]. The stacked autoencoder—softmax model deep learning method can reduce dataset dimensions and achieve classification accuracy of 97%, [72]. Using the Support Vector Machine (SVM), up to 90% accuracy, nearly 100% sensitivity, and 83% specificity can be attained [73]. SVM-RFE (recursive feature elimination) and SVM-PCA (recursive feature elimination) can benefit from limiting the number of components to eight (principal component analysis). SVM, on the other hand, struggles with large datasets, and training takes a long time. The majority of the techniques and algorithms presented show satisfactory performance in accomplishing their tasks [74]. Kumarganesh et.al. (2018) recommended an ANFIS classifier method for the classification of tumours from the source images. They achieved 96.6% of classification accuracy [75].

A large database is required to train CNNs, which may be a problem when dealing with medical data. In terms of time efficiency, it is also worse than the conventional algorithms. There can be over 98 percent classification accuracy utilising random algorithmic methods like random tree or random forest or instance-based K-nearest neighbour [76]. The neuro-Fuzzy algorithm provides high accuracy and less computation time compared to the Fuzzy C means algorithm by Senthilkumar T et al. [77].

For the sake of speed, we present a simpler solution for data collection, processing, and data size reduction [78,79]. Optical sensing and machine learning are two of the most quickly developing domains, and we propose integrating their application in this study. Using a fast, reliable, and non-destructive optical approach [80,81] and specialised software to analyse the recorded data [82,83], surgeons may now promptly diagnose neoplastic lesions in the cervical spine. The refractive index values of tissues will be used to identify them.

The refractive index of a substance is one of the most critical physical qualities for identifying it. Cell density and the nuclear-cytoplasm ratio, two morphological characteristics of biological tissues, are significantly linked to it [84]. T S Kumar et al. proposed morphological operations over the RNFL that provide better results in obtaining the layer thickness compared to the other existing enhancement approaches [85]. Normal and malignant cells in the cervix have varying refractive indices, making it possible to distinguish between the two with considerable ease [86].

Three stages of CIN have been defined by histological findings: CIN1, CIN2, and CIN3 [87]. The percentage of cervical epithelial alterations determines the severity of cervical dysplasia. CIN1 has a modest level of carcinogenicity. CIN1 resides in the basal one-third of the epithelium. The nuclear abnormalities in CIN2 are more severe compared to those in CIN1. When looking at the epithelium, we notice abnormal cell proliferation in its lower two-thirds. With the presence of aberrant cells throughout the epithelium, the CIN3 syndrome can be correctly identified. Low cancer risk and high relapse risk are two of its distinguishing characteristics. The L-SIL and CIN1 are histologically identical when examined under a microscope. In terms of progression and regression, the H-SIL (High-Grade Squamous Intraepithelial Lesion, CIN2 and CIN3) is more common.

Samples with known refractive index values [88,89] could be categorized as either healthy or malignant based on their results. This classification model's predictive power was tested using a variety of supervised machine learning algorithms. Additionally, a new test dataset was needed to evaluate the suggested approach's performance. Cancer has been discovered if the basal membrane is penetrated. In addition, the determination of the refractive index must be accompanied by a determination of the basal layer. Consequently, the Fabry–Perot interferometer length sensitivity of the developed method is essential. The depth of the cervical epithelium, which determines the degree of dysplasia, is measured by this parameter.

A Fabry–Perot interferometer was used to measure the refractive indices of the liquids under study. Fiber-optic technology was used to build the reflective measurement setup. FiberLabs Inc. in Japan provided the optical spectrum analyzer (Ando AQ6319) and optical coupler (SLD-1550-13-) (Lightel from Renton in Washington, USA). Central wavelength of the light source was 1550 nm with a 35-nm wide spectral range. A silver mirror and a polished fibre end-face formed the Fabry–Perot resonance cavity, [90,91].

Thiyaneswaran B et al.(2020) used k-mean clutsering approach for the detection and segmentation of cancer regions in skin images. The authors have attained 90.0% of average accuracy with respect to open access dataset, [92]. Microscopy diagnostics are not widely available in low-resource countries, preventing many common and treatable ailments from being detected and treated [93]. Implementation in clinical practise has been slow, despite significant advancements in point-of-care digital microscopy diagnostic technology (POC), [94]. A deep learning AI model is used to analyse microscopy slides that have been digitised at the POC and transferred through local data networks. Cervical cancer is still a common and deadly disease in places where there are no screening programmes in place [95]. Sub-Saharan Africa will bear the brunt of the disease load in the coming decade, with prevalence and mortality rates likely to grow sharply, [96].

Kumarganesh et.al. (2016) suggested an Adaptive Neuro Fuzzy Inference System (ANFIS) classifier technique for the classification of tumors from the source images. They achieved 93.07% of sensitivity, 98.79% of specificity, and 97.63% of cancer segmentation accuracy [97].Although vaccines against HPV, [98] have the potential to significantly reduce disease occurrence, vaccine programmes can take decades to reach their maximum potential, leaving millions of women vulnerable despite the best efforts [99]. Thiyaneswaran B et. al projected the deep learning Alex network system categorizes the iris with an accuracy of 99.1%, [100]. New POC diagnostics and screening tests are still needed [101,102]. It is possible to employ cytology screening (Papanicolaou test analysis) in resource-constrained countries, but it is labor-intensive and vulnerable to fluctuations in sensitivity or reproducibility so that medical experts must analyse the samples [103,104]. This can be done utilising polymerase chain reaction techniques that have a high level of sensitivity and repeatability [105]. Precancerous lesions, on the other hand, have a low specificity due to the fact that most HPV infections are temporary, [106,107,108,109].

3 METHODOLOGICAL METHODS FOR DIAGNOSIS OF CERVICAL CANCER

3.1 HPV Testing: Methodologies and Implementation

Pap tests and other cytology-based methods can detect varying degrees of cellular degeneration by morphologic analysis of cells taken from a woman's cervix. Although there are certain limitations to cytology-based testing, it has been the norm for cervical cancer screenings since the Pap test's inception owing to its high specificity. Imperfect fixation, non-uniform cell distribution, blood and mucus obscuration, and low repeatability are some of the issues that can arise. These problems can make it even more difficult to interpret the results, hence experts in the field are needed. In addition, there have been attempts to enhance cytology-based methods and alternatives, such as the UltraFast staining technique, liquid-based cytology (LBC) with the ThinPrep® Pap test (Hologic, Inc., Marlborough, MA, USA) and SurePathTM (SP; BD Diagnostics, Burlington, NC, USA) [110], and visual inspection using acetic acid or Lugol's iodine. However, the sensitivity of these methods is not ideal, leading to uncertain results, such as Atypical squamous cells of undetermined significance (ASCUS, or ASC-US after the 2001 Bethesda Workshop).

3.2 Reasoning of HPV Testing Implementation in Screening Programs

HPV testing eliminates the need for morphologic interpretation of data, which can be influenced by inter-observer variability in cytology, and instead relies on an objective molecular technique to screen for cervical cancer. In order to identify high-grade cervical dysplasia, HPV testing depends on detecting the virus or its consequences [111]. One advantage of HPV testing is that it permits longer screening intervals. This is because hrHPV takes longer to progress to cancer than pre-cancer cells. To be more specific, initial HPV testing according to European criteria can be done every five years, with the possibility of extensions to every ten years depending on the woman's age and medical history. As an added bonus, HPV testing is quite accurate, has a high negative predictive value (NPV), requires little in the way of training, is very reproducible, and can handle a large volume of patients with ease. A more economical choice was to conduct primary HPV testing every five years using cytology as a triage in conjunction with HPV vaccination. Nevertheless, when determining the starting age for screening, it is crucial to consider the virus's biology in connection to its host.

According to the European guidelines, main HPV testing should begin after the age of 30 and continue up to 35. This is to prevent women who are likely to have temporary infections from being overtreated or subjected to needless follow-up due to the test's relatively low specificity. Although primary HPV testing is mandated for anyone over the age of 30, the European standards permit primary cytology programmes to remain in place for those aged 20 to 30 in regions or countries where such programmes are prevalent and effective. However, women who have not had an HPV infection since they were 55 years old are not at high risk for a persistent HPV infection that could lead to cervical cancer, even though the recommended age to begin a screening programme is 60–65 years old [112]. There have been reports that cytology testing is not ideal for postmenopausal women and women in this age range because the cervical canal has fewer accessible transformation zones and epithelial atrophy [113]. The age at which HPV testing should no longer be performed is an ongoing topic of discussion and is subject to revision in light of new scientific data, nevertheless, this is necessary because the risk remains for that cohort, [113].

3.3 Machine learning methods in cervical cancer detection

Brain tumours, cervical cancer, breast cancer, COVID, physical activity, thermal sensation, and cognitive health evaluation of dementia patients are some of the areas that are now benefiting from the application of machine learning and deep learning. It outperforms more conventional methods of diagnosis thanks to developments in the healthcare sector [114]. There has been an increase of 493,000 cervical cancer patients annually, with 15% of those patients being female, according to medical records released by Global Cancer Statistics. With an 83% fatality rate, this illness is most common in underdeveloped nations. Particularly common in African nations, such as Uganda (with 65% of confirmed cases), which has the fourteenth-highest prevalence of cervical cancers.

Cervical cancer is the leading cause of human papillomavirus (HPV) infection. HPV infection can be spread through sexual contact. The higher risk of HPV acquisition is associated with sexual behaviour that is related to age at first sexual contact and the sexual activity of the accomplice. Important to realising risk expectations, cervical cancer is more easily avoided than other types of cancer thanks to widely available screening and diagnosis methods. A tumour that is malignant is the malignant cervical development. Uncontrolled cell division and aberrant cell proliferation characterise cervical cancer. In the worst case scenario, early detection can save lives by preventing the spread of infection to other parts of the body caused by cancer cells that metastasize from the tumour. A decrease in cervical cancer-related deaths is possible with the help of efficient screening programmes, [115]. A number of screening and

diagnostic approaches rely on computer-aided design (CAD) frameworks due to the rapid development of current clinical innovation and computer technological innovation.

To enhance the quality of the training dataset, our research used the random forest (RF) to discover crucial features. Every tree in the RF forest grows on a bootstrap sample of data, and the attributes of each other node are chosen at random from a subset of all characteristics. The entity's final level is determined by the total number of votes cast across all forest trees. An RF approach is ideal for analysing specific biological data in pharmacogenomics studies because of its many advantages. Finally, it accepts a large variety of vectors as inputs, both quantitative and qualitative. Additionally, it provides a standard for feature selection by testing the attribute's importance in estimating the type. Third, as the forest expands, RF creates a reliable classifier for doing impartial, internal generalised analysis, [116].

4 CONCLUSION

The World Health Organization (WHO) says that cancer of the cervix is the utmost frequent cancer among women. In 2018, a predictable 570 000 women were detected with cervical cancer worldwide and about 311000 women pass away from the illness. Effective primary (HPV immunization) and secondary (precancerous lesion screening and treatment) impediment methods will avoid most cases of cervical cancer. Cervical cancer is one of the furthermost effectively curable types of cancer when detected early and managed properly. Late-stage cancers can also be managed with suitable medication and remedial care. Cervical cancer as a public well-being complication can be eradicated within a generation with an extensive method for prevention, screening, and treatment.

Cervical screening procedures and relevant computational methods for cervical cell analysis are examined in this review, which provides a context for current screening practices. As a whole, numerous segmentation and classification methodologies were examined and contrasted for their various advantages and disadvantages. Some of the issues that will define the next generation of computer-aided diagnosis systems and the goals of future cervical screening research are discussed in this article. Among the many topics, we'll cover are how to assess the appropriateness of a solution, data segmentation, and data classification.

4.1 Future work

The future of cervical cancer detection and therapy holds great promise, especially with the discovery of key risk factors and the application of diverse segmentation pre-processing approaches. Future categorization algorithms can potentially benefit from larger and more evenly distributed data. Ultimately, there are now a number of options for cervical cancer screening, each with its own set of pros and cons. Though older procedures like Pap smears are still used most often, newer ones like HPV testing, VIA, and VILI are gaining ground. When it comes to diagnostics and follow-up, a colposcopy is a valuable tool. In order to diagnose cervical cancer early and treat it effectively, screenings should be conducted regularly. Cervical cancer screening recommendations should be followed, and women should talk to their doctors about their screening alternatives.

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References

[1] N. Dong, L. Zhao, C. H. Wu, and J. F. Chang, "Inception v3 based cervical cell classification combined with artificially extracted features," Applied Soft Computing, vol. 93, p. 106311, (2020)

[2] L. Zhao, C. H. Wu, and J. F. Chang, "Inception v3 based cervical cell classification combined with artificially extracted features," Applied Soft Computing, vol. 93, p. 106311, (2020).

[3] T. Zhang, Y. M. Luo, P. Li et al., "Cervical precancerous lesions classification using pre-trained densely connected convolutional networks with colposcopy images," Biomedical Signal Processing and Control, vol. 55, p. 101566, (2020).

[4] W. Hua, T. Xiao, X. Jiang et al., "Lymph-vascular space invasion prediction in cervical cancer: exploring radiomics and deep learning multilevel features of tumour and peritumor tissue on multiparametric MRI," Biomedical Signal Processing and Control, vol. 58, p. 101869, (2020).

[5] T. I. Yusufaly, K. Kallis, A. Simon et al., "A knowledge-based organ dose prediction tool for brachytherapy treatment planning of patients with cervical cancer," Brachytherapy, vol. 19, no. 5, pp. 624–634, (2020).

[6] J. Shao, Z. Zhang, H. Liu et al., "DCE-MRI pharmacokinetic parameter maps for cervical carcinoma prediction," Computers in Biology and Medicine, vol. 118, article 103634, (2020).

[7] Ghoneim, G. Muhammad, and M. S. Hossain, "Cervical cancer classification using convolutional neural networks and extreme learning machines," Future Generation Computer Systems, vol. 102, pp. 643–649, (2020).

[8] J. Lu, E. Song, A. Ghoneim, and M. Alrashoud, "Machine learning for assisting cervical cancer diagnosis: an ensemble approach," Future Generation Computer Systems, vol. 106, pp. 199–205, 2020.

[9] F. B. M. Suah, "Preparation and characterization of a novel co(II) optode based on polymer inclusion membrane," Analytical Chemistry Research, vol. 12, pp. 40–46, 2017.

[10] S. K. Saini, V. Bansal, R. Kaur, and M. Juneja, "ColpoNet for automated cervical cancer screening using colposcopy images," Machine Vision and Applications, vol. 31, no. 3, pp. 1–15, 2020.

[11] B. J. Cho, Y. J. Choi, M. J. Lee et al., "Classification of cervical neoplasms on colposcopic photography using deep learning," Scientific Reports, vol. 10, no. 1, p. 13652, 2020.

[12] Q. Meng, "Machine learning to predict local recurrence and distant metastasis of cervical cancer after definitive radiotherapy," International Journal of Radiation Oncology • Biology • Physics, vol. 108, no. 3, article e767, 2020.

[13] S. K. Saini, V. Bansal, R. Kaur, and M. Juneja, "ColpoNet for automated cervical cancer screening using colposcopy images," Machine Vision and Applications, vol. 31, no. 3, pp. 1–15, 2020.

[14] P. Sanyal, P. Ganguli, and S. Barui, "Performance characteristics of an artificial intelligence based on convolutional neural network for screening conventional Papanicolaou-stained cervical smears," Medical Journal, Armed Forces India, vol. 76, no. 4, pp. 418–424, 2020.

[15] B. R. Jany, A. Janas, and F. Krok, "Automatic microscopic image analysis by moving window local Fourier transform and machine learning," Micron, vol. 130, article 102800, 2020.

[16] Dongyao Jia, B. Zhengyi Li, and C. Chuanwang Zhang, "Detection of cervical cancer cells based on strong feature CNN-SVM network," Neurocomputing, vol. 411, pp. 112–127, 2020

[17] Jantzen, J.; Norup, J.; Dounias, G.; Beth, B. Pap-smear Benchmark Data for Pattern Classification. Nat. Inspir. Smart Inf. Syst. (NiSIS 2005) 2005, 1–9.

[18] Chankong, T.; Theera-Umpon, N.; Auephanwiriyakul, S. Automatic cervical cell segmentation and classification in Pap smears. Comput. Methods Progr. Biomed. 2014, 113, 539–556. [CrossRef]

[19] Jith, O.U.N.; Harinarayanan, K.K.; Gautam, S.; Bhavsar, A.; Sao, A.K. DeepCerv: Deep Neural Network for Segmentation Free Robust Cervical Cell Classification. In Computational Pathology and Ophthalmic Medical Image Analysis; Lecture Notes in Computer Science; Springer: Berlin, Germany, 2018; pp. 86–94

[20] Kumar, T. S., and Helenprabha, K. (2017). Top-Hat transform based retinal nerve fiber layer thickness measurement for Alzheimer detection using OCT images. J. Computat. Theor. Nanosci. 14, 1499–1505. [CrossRef]

[21] Gençtav, A.; Aksoy, S.; Önder, S. Unsupervised segmentation and classification of cervical cell images. Pattern Recognit. 2012, 45, 4151–4168. [CrossRef]

[22] Lu, Z.; Carneiro, G.; Bradley, A.P. An Improved Joint Optimization of Multiple Level Set Functions for the Segmentation of Overlapping Cervical Cells. IEEE Trans. Image Process. 2015, 24, 1261–1272. [CrossRef]

[23] Fernandes, K.; Cardoso, J.S.; Fernandes, J. Transfer Learning with Partial Observability Applied to Cervical Cancer Screening; Pattern Recognition and Image Analysis; Lecture Notes in Computer Science; Springer International Publishing: Berlin, Germany, 2017; pp. 243–250.

[24] Song, D.; Kim, E.; Huang, X.; Patruno, J.; Muñoz-Avila, H.; Heflin, J.; Long, L.R.; Antani, S. Multimodal Entity Coreference for Cervical Dysplasia Diagnosis. IEEE Trans. Med. Imaging 2015, 34, 229–245. [CrossRef]

[25] Rasche, C.; ¸Tig ane¸steanu, C.; Neghina, M.; Sultana, A. Cervical Nuclei Classification: Feature Engineering Versus Deep Belief Network. In Medical Image Understanding and Analysis; Communications in Computer and Information Science; Springer: Berlin, Germany, 2017; pp. 874–885.

[26] WHO, World Health Organization Human Papillomavirus (HPV) and Cervical Cancer, Fact Sheet. [(accessed on 17 September 2019)]; Available online: https://www.who.int/news-room/fact-sheets/detail/human-papillomavirus-(hpv)-and-cervical-cancer.

[27] Zhao C., Li Z. Automated cell block system for atypical glandular cells of cervical cytology. Cancer Cytopathol. 2014;122:5–7. doi: 10.1002/cncy.21368. [PubMed] [CrossRef] [Google Scholar]

[28] Bigras G., de Marval F. The probability for a Pap test to be abnormal is directly proportional to HPV viral load: Results from a Swiss study comparing HPV testing and liquid-based cytology to detect cervical cancer precursors in 13,842 women. Br. J. Cancer. 2005;93:575–581. doi: 10.1038/sj.bjc.6602728. [PMC free article] [PubMed] [CrossRef] [Google Scholar]

[29] Marques J.P.d.H., Costa L.B., de Souza e Pinto A.P., de Lima A.F., Leite Duarte M.E., Fernandes Barbosa A.P., de Medeiros P.L. Atypical glandular cells and cervical cancer: systematic review. Revis. Assoc. Médica Bras. (Engl. Ed.) 2011;57:229–233. doi: 10.1016/S0104-4230(11)70049-5. [CrossRef] [Google Scholar]

[30] Zhang L., Lu L., Nogues I., Summers R.M., Liu S., Yao J. DeepPap: Deep Convolutional Networks for Cervical Cell Classification. IEEE J. Biomed. Health Inf. 2017;21:1633–1643. doi: 10.1109/JBHI.2017.2705583. [PubMed] [CrossRef] [Google Scholar].

[31] Chankong T., Theera-Umpon N., Auephanwiriyakul S. Automatic cervical cell segmentation and classification in Pap smears. Comput. Methods Progr. Biomed. 2014;113:539–556.doi: 10.1016/j.cmpb.2013.12.012.

[32] Senthilkumar T, Kumarganesh S, Sivakumar P and Periyarselvam K, "Primitive detection of Alzheimer's disease using neuroimaging: A progression model for Alzheimer's disease: Their applications, benefits, and drawbacks" Journal of Intelligent & Fuzzy Systems, Vol. 43(4), pp. 4431– 4444, 2022. DOI: 10.3233/JIFS-220628.

[33] Jantzen J., Norup J., Dounias G., Beth B. Pap-smear Benchmark Data for Pattern Classification. [(accessed on 15 October 2019)].

[34] Tareef, A.; Song, Y.; Huang, H.; Feng, D.; Chen, M.; Wang, Y.; Cai, W. Multi-pass fast watershed for accurate segmentation of overlapping cervical cells. IEEE Trans. Med. Imaging 2018, 37, 2044–2059. [CrossRef] [PubMed].

[35] Nosrati, M.S.; Hamarneh, G. Segmentation of overlapping cervical cells: A variational method with star-shape prior. In Proceedings of the 2015 IEEE 12th International Symposium on Biomedical Imaging (ISBI), New York, NY, USA, 16–19 April 2015; pp. 186–189.

[36] Ushizima, D.M.; Bianchi, A.G.; Carneiro, C.M. Segmentation of Subcellular Compartments Combining Superpixel Representation with Voronoi Diagrams; Technical

Report; Lawrence Berkeley National Lab. (LBNL): Berkeley, CA, USA, 2015; 3p.
[37] Phoulady, H.A.; Goldgof, D.; Hall, L.O.; Mouton, P.R. A framework for nucleus and overlapping cytoplasm segmentation in cervical cytology extended depth of field and volume images. Comput. Med. Imaging Gr. 2017, 59, 38–49.
[38] areef, A.; Song, Y.; Cai, W.; Huang, H.; Chang, H.; Wang, Y.; Fulham, M.; Feng, D.; Chen, M. Automatic segmentation of overlapping cervical smear cells based on local distinctive features and guided shape deformation. Neurocomputing 2017, 221, 94–107
[39] Song, Y.; Tan, E.L.; Jiang, X.; Cheng, J.Z.; Ni, D.; Chen, S.; Lei, B.; Wang, T. Accurate cervical cell segmentation from overlapping clumps in pap smear images. IEEE Trans. Med. Imaging 2017, 36, 288–300.
[40] Gautam, S.; K., H.K.; Jith, N.; Sao, A.K.; Bhavsar, A.; Natarajan, A. Considerations for a PAP Smear Image Analysis System with CNN Features. arXiv 2018, arXiv:1806.09025.
[41] Zhao, M.; Wu, A.; Song, J.; Sun, X.; Dong, N. Automatic screening of cervical cells using block image processing. Biomed. Eng. Online 2016, 15, 14.
[42] Bora, K.; Chowdhury, M.; Mahanta, L.B.; Kundu, M.K.; Das, A.K. Automated classification of Pap smear images to detect cervical dysplasia. Comput. Methods Progr. Biomed. 2017, 138, 31–47.
[43] Gómez, O.H.; Sánchez-DelaCruz, E.; Mata, A.P.d.l. Classification of Cervical Cancer Using Assembled Algorithms in Microscopic Images of Papanicolaou. Res. Comput. Sci. 2017, 139, 125–134.
[44] Zhang, L.; Lu, L.; Nogues, I.; Summers, R.M.; Liu, S.; Yao, J. DeepPap: Deep Convolutional Networks for Cervical Cell Classification. IEEE J. Biomed. Health Inf. 2017, 21, 1633–1643.
[45] Jith, O.U.N.; Harinarayanan, K.K.; Gautam, S.; Bhavsar, A.; Sao, A.K. DeepCerv: Deep Neural Network for Segmentation Free Robust Cervical Cell Classification. In Computational Pathology and Ophthalmic Medical Image Analysis; Lecture Notes in Computer Science; Springer: Berlin, Germany, 2018; pp. 86–94.
[46] Gautam, S.; Bhavsar, A.; Sao, A.K.; Harinarayan, K.K. CNN based segmentation of nuclei in PAP-smear images with selective pre-processing. Medical Imaging 2018: Digital Pathology. Int. Soc. Opt. Photon. 2018, 10581, 105810X.
[47] Lin, H.; Hu, Y.; Chen, S.; Yao, J.; Zhang, L. Fine-Grained Classification of Cervical Cells Using Morphological and Appearance Based Convolutional Neural Networks. IEEE Access 2019, 7, 71541–71549.
[48] Elayaraja P, Kumarganesh S, Martin Sagayam K, Dang Hien, Marc Pomplun "An efficient approach for detection and classification of cancer regions in cervical images using optimization based CNN classification approach" Journal of Intelligent & Fuzzy Systems, 2022, DOI: 10.3233/JIFS-212871.
[49] Suckling, J.; Parker, J.; Dance, D.; Astley, S.; Hutt, I.; Boggis, C.; Ricketts, I. Mammographic Image Analysis Society (MIAS) Database v1.21 [Dataset]; Dataset; Digital Mammogram Database Exerpta Medica: Dordrecht, The Netherland, 2015.
[50] Scuccimarra, E.A. DDSM Mammography [Dataset]; Dataset; Digital Mammogram Database Exerpta Medica: Dordrecht, The Netherland, 2018.
[51] Dua, D.; Graff, C. UCI Machine Learning Repository; University of California, Irvine, School of Information and Computer Sciences: Newport Beach, CA, USA, 2017.
[52] Bukun. Breast Cancer Histopathological Database (BreakHis); Dataset; P and D Laboratory—Pathological Anatomy and Cytopathology: Parana, Brazil, 2019.
[53] Aresta, G.; Araújo, T.; Kwok, S.; Chennamsetty, S.S.; Safwan, M.; Alex, V.; Marami, B.; Prastawa, M.; Chan, M.; Donovan, M.; et al. BACH: Grand challenge on breast cancer histology images. Med. Image Anal. 2019, 56, 122–139.
[54] Solomon K, Tamire M, and Kaba M, "Predictors of cervical cancer screening practice among HIV positive women attending adult anti-retroviral treatment clinics in Bishoftu town, Ethiopia: the application of a health belief model," BMC Cancer (2019) 19:989 https://doi.org/10.1186/s12885-019-6171-6 PMID: 31646975.
[55] Shiferaw S, Addissie A, Gizaw M, Hirpa S, W. Ayele W, Getachew S, et al., Knowledge about cervical cancer and barriers toward cervical cancer screening among HIV-positive women attending public health centers in Addis Ababa city, Ethiopia; Cancer Medicine 2018; 7(3):903–912 https://doi.org/10. 1002/cam4.1334 PMID: 29441700
[56] Mitchell SM, Pedersen HN, Stime EE, Sekikubo M, Moses E, Mwesigwa D, et al., "Self-collection based HPV testing for cervical cancer screening among women living with HIV in Uganda: a descriptive analysis of knowledge, intentions to screen and factors associated with HPV positivity," BMC Womens. Health, (2017) 17:4 pp. 1–10.
[57] Stuart A, Obiri-yeboah D, Adu-sarkodie Y, Hayfron-benjamin A, Akorsu AD, and Mayaud P, "Knowledge and experience of a cohort of HIV-positive and HIV-negative Ghanaian women after undergoing human papillomavirus and cervical cancer screening," BMC Women's Health (2019) 19:123; pp. 1–11 https:// doi.org/10.1186/s12905-019-0818-y
[58] Adibe MO, and Aluh DO, "Awareness, Knowledge and Attitudes Towards Cervical Cancer Amongst HIV-Positive Women Receiving Care in a Tertiary Hospital in Nigeria," J Canc Educ (2018) 33:1189– 1194.
[59] Belglaiaa E, Souho T, Badaoui L, et al. Awareness of cervical cancer among women attending an HIV treatment centre: a cross-sectional study from Morocco. BMJ Open 2018; 8:e020343. https://doi.org/ 10.1136/bmjopen-2017-020343 PMID: 30139893.
[60] Rosser JI, Njoroge B, and Huchko MJ, "Cervical Cancer Screening Knowledge and Behavior among Women Attending an Urban HIV Clinic in Western Kenya," J Canc Educ (2015) 30:567–572 https://doi. org/10.1007/s13187-014-0787-7 PMID: 25595965
[61] Maree J.E. & Moitse K.A., 'Exploration of knowledge of cervical cancer and cervical cancer screening amongst HIV-positive women', Curationis 2014; 37(1), Art.#1209, 7 pages. http://dx.doi.org/10.4102/ curationis.v37i1.1209.
[62] Zhang, X., Zeng, Q., Cai, W. & Ruan, W. Trends of cervical cancer at global, regional, and national level: data from the Global Burden of Disease study 2019. BMC Public Health 21, 894 (2021).
[63] Zhang, S., Xu, H., Zhang, L. & Qiao, Y. Cervical cancer: Epidemiology, risk factors and screening. Chin. J. Cancer Res. 32, 720–728 (2020).

[64] Pikala, M., Burzyńska, M. & Maniecka-Bryła, I. Years of life lost due to cervical cancer in Poland in 2000 to 2015. Int. J. Environ. Res. Public Health 16, 1545 (2019).
[65] Nowakowski, A. et al. The implementation of an organised cervical screening programme in Poland: An analysis of the adherence to European guidelines. BMC Cancer 15, 279 (2015).
[66] Conceição, T., Braga, C., Rosado, L. & Vasconcelos, M. J. M. A review of computational methods for cervical cells segmentation and abnormality classification. Int. J. Mol. Sci. 20, 5114 (2019).
[67] Zhang, J., Cheng, K. & Wang, Z. Prevalence and distribution of human papillomavirus genotypes in cervical intraepithelial neoplasia in China: A meta-analysis. Arch. Gynecol. Obstet. 302, 1329–1337 (2020).
[68] William, W., Ware, A., Basaza-Ejiri, A. H. & Obungoloch, J. A review of image analysis and machine learning techniques for automated cervical cancer screening from pap-smear images. Comput. Methods Progr. Biomed. 164, 15–22 (2018).
[69] Ghoneim, A., Muhammad, G. & Hossain, M. S. Cervical cancer classification using convolutional neural networks and extreme learning machines. Futur. Gener. Comput. Syst. 102, 643–649 (2020). Return to ref 10 in article
[70] Alyafeai, Z. & Ghouti, L. A fully-automated deep learning pipeline for cervical cancer classification. Exp. Syst. Appl. 141, 112951 (2020).
[71] Chankong, T., Theera-Umpon, N. & Auephanwiriyakul, S. Automatic cervical cell segmentation and classification in Pap smears. Comput. Methods Programs Biomed. 113, 539–556 (2014).
[72] Adem, K., Kiliçarslan, S. & Cömert, O. Classification and diagnosis of cervical cancer with stacked autoencoder and softmax classification. Exp. Syst. Appl. 115, 557–564 (2019).
[73] Wu, W. & Zhou, H. Data-driven diagnosis of cervical cancer with support vector machine-based approaches. IEEE Access 5, 25189–25195 (2017).
[74] Senthil kumar, T et al. Comparative Analysis of Fuzzy c-means and Neuro Fuzzy for the Detection of Retinal Disease. Circuits, Systems, and Signal Processing (CSSP) - Springer nature. 698-720(2019).
[75] Nithya, B. & Ilango, V. Evaluation of machine learning based optimized feature selection approaches and classification methods for cervical cancer prediction. SN Appl. Sci. 1, 641 (2019).
[76] S.Kumarganesh, M.Suganthi, An Enhanced Medical Diagnosis Sustainable System for Brain Tumor Detection and Segmentation using ANFIS Classifier, Current Medical Imaging Reviews 2018,14,2, 271-279.
[77] Ali, M. M. et al. Machine learning-based statistical analysis for early stage detection of cervical cancer. Comput. Biol. Med. 139, 104985 (2021).
[78] Decaro, C., Montanari, G. B., Bianconi, M. & Bellanca, G. Prediction of hematocrit through imbalanced dataset of blood spectra. Healthc. Technol. Lett. 8, 37–44 (2021).
[79] Venkat, S. et al. Machine learning based SpO2 computation using reflectance pulse oximetry. Annu. Int. Conf. IEEE Eng. Med. Biol. Soc. 2019, 482–485 (2019).
[80] Hornung, R. et al. Quantitative near-infrared spectroscopy of cervical dysplasia in vivo. Hum. Reprod. 14, 2908–2916 (1999).
[81] Krawczyk, B. Learning from imbalanced data: Open challenges and future directions. Prog. Artif. Intell. 5, 221–232 (2016).
[82] Gulshan, V. et al. Development and validation of a deep learning algorithm for detection of diabetic retinopathy in retinal fundus photographs. JAMA 316, 2402–2410 (2016).
[83] T Senthil Kumar et al. Geometric mean filter with grayscale morphological method to enhance the RNFL thickness in the OCT images: Multimedia Tools and Applications- Springer, 77(8), 10285–10301. (2018).
[84] Chang, W. et al. A Machine-learning-based prediction method for hypertension outcomes based on medical data. Diagnostics 9, 178 (2019).
[85] Mustafa, N. & Li, J.-P. Medical data classification scheme based on hybridized SMOTE technique (HST) and Rough Set technique (RST). in 2017 IEEE 2nd International Conference on Cloud Computing and Big Data Analysis (ICCCBDA) 49–55 (2017). doi:https://doi.org/10.1109/ICCCBDA.2017.7951883.
[86] Giannios, P. et al. Visible to near-infrared refractive properties of freshly-excised human-liver tissues: marking hepatic malignancies. Sci. Rep. 6, 27910 (2016).
[87] Sharma, V. & Kalyani, V. L. Nano-cavity coupled waveguide photonic crystal based biosensor detection of cervical cancer using nucleus and cytoplasm. in 2017 International Conference on Information, Communication, Instrumentation and Control (ICICIC) 1–5 (2017). doi:https://doi.org/10.1109/ICOMICON.2017.8279111.
[88] Bruno, M. T., Cassaro, N., Bica, F. & Boemi, S. Progression of CIN1/LSIL HPV persistent of the cervix: Actual progression or CIN3 coexistence. Infect. Dis. Obstetr. Gynecol. 2021, e6627531 (2021).
[89] Panda, A. & Puspa Devi, P. Photonic crystal biosensor for refractive index based cancerous cell detection. Opt. Fiber Technol. 54, 102123 (2020).
[90] Parvin, T., Ahmed, K., Alatwi, A. M. & Rashed, A. N. Z. Differential optical absorption spectroscopy-based refractive index sensor for cancer cell detection. Opt. Rev. 28, 134–143 (2021). Return to ref 28 in article.
[91] Kosowska, M. et al. Microscale diamond protection for a ZnO coated fiber optic sensor. Sci. Rep. 10, 19141 (2020).
[92] B. Thiyaneswaran, K. Anguraj, S. Kumarganesh, K. Thangaraj, Early detection of melanoma images using gray level co-occurrence matrix features and machine learning techniques for effective clinical diagnosis, International Journal of Imaging System Technology. 2020;1–13.
[93] Kosowska, M. et al. Incorporation of nitrogen in diamond films—A new way of tuning parameters for optical passive elements. Diamond Relat. Mater. 111, 108221 (2021).
[94] Fleming KA, Naidoo M, Wilson M, et al. An essential pathology package for low- and middle-income countries. Am J Clin Pathol. 2017;147(1):15-32.
[95] Bogoch II, Lundin J, Lo NC, Andrews JR. Mobile phone and handheld microscopes for public health applications. Lancet Public Health. 2017;2(8):e355. doi:10.1016/S2468-2667(17)30120-2
[96] Arbyn M, Weiderpass E, Bruni L, et al. Estimates of incidence and mortality of cervical cancer in 2018: a worldwide analysis. Lancet Glob Health. 2020;8(2):e191-e203. doi:10.1016/S2214-109X(19)30482-6.

[97] S.Kumarganesh, M. Suganthi, An Efficient Approach for Brain Image (Tissue) Compression Based on the Position of the Brain Tumor, International Journal of Imaging Systems and Technology,2016,26,4,237-242.

[98] Mboumba Bouassa RS, Prazuck T, Lethu T, Meye JF, Bélec L. Cervical cancer in sub-Saharan Africa: an emerging and preventable disease associated with oncogenic human papillomavirus. Med Sante Trop. 2017;27(1):16-22. doi:10.1684/mst.2017.0648

[99] Bosch FX, Lorincz A, Muñoz N, Meijer CJ, Shah KV. The causal relation between human papillomavirus and cervical cancer. J Clin Pathol. 2002;55(4):244-265. doi:10.1136/jcp.55.4.244.

[100] Thiyaneswaran B, Kumarganesh.S, MartinSagayam K, Hien Dang, "An effective model for the iris regional characteristics and classification using deep learning alex network" IET Image Processing, Vol. 17(1) pp. 227-238, 2023, DOI: 10.1049/ipr2.12630,

[101] Randall TC, Ghebre R. Challenges in prevention and care delivery for women with cervical cancer in sub-Saharan Africa. Front Oncol. 2016;6:160. doi:10.3389/fonc.2016.00160.

[102] El-Zein M, Richardson L, Franco EL. Cervical cancer screening of HPV vaccinated populations: cytology, molecular testing, both or none. J Clin Virol. 2016;76(suppl1):S62-S68. doi:10.1016/j.jcv.2015.11.020PubMedGoogle ScholarCrossref

[103] Sayed S, Chung M, Temmermans M. Point-of-care HPV molecular diagnostics for a test-and-treat model in high-risk HIV populations. Lancet Glob Health. 2020;8(2):e171-e172.doi:10.1016/S2214-109X(19)30559-5

[104] Elsheikh TM, Austin RM, Chhieng DF, Miller FS, Moriarty AT, Renshaw AA; American Society of Cytopathology. American Society of Cytopathology workload recommendations for automated Pap test screening: developed by the productivity and quality assurance in the era of automated screening task force. Diagn Cytopathol. 2013;41(2):174-178. doi:10.1002/dc.22817

[105] Stoler MH, Schiffman M; Atypical Squamous Cells of Undetermined Significance-Low-grade Squamous Intraepithelial Lesion Triage Study (ALTS) Group. Interobserver reproducibility of cervical cytologic and histologic interpretations: realistic estimates from the ASCUS-LSIL Triage Study. JAMA. 2001;285(11):1500-1505.doi:10.1001/jama.285.11.1500

[106] Wright TC Jr, Stoler MH, Behrens CM, Sharma A, Sharma K, Apple R. Interlaboratory variation in the performance of liquid-based cytology: insights from the ATHENA trial. Int J Cancer. 2014;134(8):1835-1843. doi:10.1002/ijc.28514

[107] Wilson ML, Fleming KA, Kuti MA, Looi LM, Lago N, Ru K. Access to pathology and laboratory medicine services: a crucial gap. Lancet. 2018;391(10133):1927-1938.doi:10.1016/S0140-6736(18)30458-6

[108] Mapanga W, Girdler-Brown B, Feresu SA, Chipato T, Singh E. Prevention of cervical cancer in HIV-seropositive women from developing countries through cervical cancer screening: a systematic review. Syst Rev. 2018;7(1):198. doi:10.1186/s13643-018-0874-7

[109] Kuhn L, Saidu R, Boa R, et al. Clinical evaluation of modifications to a human papillomavirus assay to optimise its utility for cervical cancer screening in low-resource settings: a diagnostic accuracy study. Lancet Glob Health. 2020;8(2):e296-e304. doi:10.1016/S2214-109X(19)30527-3.

[110] Norimatsu, Y.; Yanoh, K.; Hirai, Y.; Kurokawa, T.; Kobayashi, T.K.; Fulciniti, F. A Diagnostic Approach to Endometrial Cytology by Means of Liquid-Based Preparations. Acta Cytol. 2020, 64, 195–207

[111] Bhatla, N.; Singhal, S. Primary HPV screening for cervical cancer. Best Pract. Res. Clin. Obstet. Gynaecol. 2020, 65, 98–108.

[112] Malagón, T.; Kulasingam, S.; Mayrand, M.-H.; Ogilvie, G.; Smith, L.; Bouchard, C.; Gotlieb, W.; Franco, E.L. Age at last screening and remaining lifetime risk of cervical cancer in older, unvaccinated women: A modelling study. Lancet Oncol. 2018, 19, 1569–1578. [Google Scholar] [CrossRef]

[113] Hermansson, R.S.; Olovsson, M.; Hoxell, E.; Lindström, A.K. HPV prevalence and HPV-related dysplasia in elderly women. PLoS ONE 2018, 13, e0189300

[114] Khamparia A, Gupta D, Rodrigues JJ, de Albuquerque VHC. DCAVN: cervical cancer prediction and classification using deep convolutional and variational autoencoder network. Multimedia Tools Appl. (2021) 80:30399–415. doi: 10.1007/s11042-020-09607-w

[115] 2. Abbas S, Jalil Z, Javed AR, Batool I, Khan MZ, Noorwali A, et al. BCD-WERT: a novel approach for breast cancer detection using whale optimization based efficient features and extremely randomized tree algorithm. PeerJ Comput. Sci.. (2021) 7:e390. doi: 10.7717/peerj-cs.390

[116] 3. Ayoub A, Mahboob K, Javed AR, Rizwan M, Gadekallu TR, Abidi MH, et al. Classification and categorization of COVID-19 outbreak in Pakistan. Comput Mater Continua. (2021) 69:1253–69. doi: 10.32604/cmc.2021.015655