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Meticulous Review: Cutting-Edge Cervix Cancer Stratification Using Image Processing And Machine Learning

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Abstract: Cervical cancer has under the top cancer found in women of developing countries since last many years. Classification of cervical cancer through a traditional microscopic approach is a monotonous and prolonged task. Most of the time hospital doctors cannot identify the cancer cells as sometimes the nucleus of a cell, which contains the genetic material (DNA), is typically very small and often not visible to the naked eye. Due to the different perspectives of doctors, cancer stages are classified falsely which leads to low recovery and late medication. The use of Image Processing and Machine Learning technologies can take off misclassification and inaccurate prediction. Although many deep learning techniques are available for cervical cancer cell detection and classification, the performance of such techniques for prediction and classification with real and sample datasets is the main challenge. In this paper, we did a thorough state-of-the-art review of the available current literature. The objective of this paper is to bring forth in-depth knowledge to novice researchers with a thorough understanding of the architecture of the computer-assisted classification process. The current literature is studied, analyzed, and discussed with their approaches, results, and methodologies.

Keywords: Image Processing, Machine Learning, Image Classification, Pattern Analysis, Feature evaluation, Feature selection

1. INTRODUCTION

Cancer remains the major leading cause for death among women across the globe [1], [2]. There is a significant prevalence of cervical cancer patients in developing nations such as India and China [3]. As per the World Health Organization (WHO), breast cancer and cervical cancer are more prevalent among women compared to other forms of cancer. Based on the Statistics derived from the WHO Global Health Estimates-2019 [4], [5], [6], out of 656 300 000 total population of females in India, 4 191 000 females died due to cervical cancer [7]. Even though cervical cancer falls into a category of cancers that can be readily prevented through vaccination [2] and has an extended pre-malignant phase [8], [9], [10] which can be utilized for detection and treatment of the disease, lack of awareness is the key reason for this mortality rate in developing countries [11], [9], [12], [13], [14]. Cervical cancer is developed in the cervix area of the vagina the entrance of the uterus in women [3]. HPV vaccination and prevention actions such as regular screening and detection of malignant cells in the cervix help to reduce the mortality ratio occurring due to cervical cancer [8], [15], [9], [16].

Primordial diagnosis and screening are effective key factors to prevent cervical cancer effectively [17], [13], [16], [6]. There are various detection and/or screening techniques used to detect precancerous changes that develop in the cervix area throughout 10 to 20 years [18], [6]. For a single patient, the cyto technicians have to examine plenty of the slides of smear under a microscope to conclude the accurate result [19]. The conventional approach of screening through visual examination is comparatively time-consuming and has a likelihood of errors. Moreover, a lack of trained cytologists and laboratory instruments may lead the whole screening process to cumbersome [11], [13], [19]. This diagnostic screening can be performed either at the cellular level or tissue-level [20]. HPV DNA testing, liquid-based cytology (LBC), Pap smear, and electromagnetic spectroscopies belong to the cellular-level screening approach whereas cervicography, colposcopy, hyperspectral diagnostic imaging (HSDI), and visual inspection after applying Lugol's iodine (VILI), or acetic acid (VIA) belong to tissue-based screening techniques [21], [18], [22], [23], [24], [20], [9], [25]. The Pap test stands out as the most frequently employed, straightforward, rapid, and painless screening technique for detecting cancer and pre-cancerous

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conditions of the uterine cervix [6]. Along with above mentioned issues, these techniques also have a lack of accuracy and information [13], [19]. Hence , computer assisted screening methods are being introduced to speed up and accurate the whole diagnostic process [26].

Technological advancement in medical image processing (IP) has proved to be an add-on blessing to the health-care sector [23]. Medical images captured through various technologies such as X-rays, CT scans, MRI, sonography, Ultrasound, etcetera provide an insight into the patient's body without cutting it open [23], [27], [28], [29]. Detection and identification of the actual problem, identifying the root cause of the disease, classification between benign and malignant cells within the human body, and suggesting immediate or primary care treatment have become effortless nowadays. Medical image analysis techniques like enhancement, denoising, segmentation, feature extraction, and morphological image processing provide detailed insights into the area of interest due to which doctors and medical teams can proceed with the treatment in no time [23], [3], [5], [6]. IP has a wide spectrum of medical applications viz. brain tumor detection, multiple stone detection, identifying fractures, identifying congenital heart defects, breast cancer detection, diagnosing heart valve diseases, tuberculosis detection, and identifying birth defects can be measured into different domains where images are used [27], [28], [29]. Specifically, the analysis of Pap smear images has become increasingly popular for the effective detection of carcinoma cervix cancer. In underdeveloped and developing countries, due to a lack of expertise, resources, awareness, and remote location, Machine learning has become very popular for medical diagnosis these days [30], [9]. Machine-generated results for identifying cervical cancer in the patient prove to be a boon to remote locations and/or low-income regions. However, it fails in accuracy sometimes due to unfit images having low resolution, noise, overlapping of cervix cells, and texture variation [13].

Machine learning [30], [12], [7], [31] is a branch of Artificial Intelligence, which is associated with identifying problems and solutions from the data sample available [19]. These algorithms implement various probabilistic, statistical and optimization techniques that allow the system to review/ learn from past records and to identify the complex patterns/solutions from the large, complex and noisy structured semi-structured or unstructured datasets [31], [19]. Augmenting machine learning with image processing techniques facilitates automization of pap-smear analysis and generates authentic and accurate results in a faster way [15], [19], [6], [32], [2]. Machine learning algorithms such as Artificial Neural Network (ANN) [33], [13], [5], [6], Neural Network (NN), Support Vector Machine (SVM) [17], [5], Linear Discriminant Analysis (LDA) [24], [20], K-nearest neighbor (KNN) [5], Decision Trees [34], [20], [13], Random Forest (RF) [18], [17], [6], Gray Level Co-occurrence Matrix (GLCM) [33], C5.0, Multivariate Adaptive Regression Splines (MARS), spatial fuzzy clustering algorithms [35], Probabilistic Neural Networks (PNNs), Classification and Regression Trees (CART), Genetic Algorithm, and Hierarchical clustering algorithm are being used at various stages of automatic cervical cancer detection [12], [36], [37], [5], [38], [32].

For this review, we have studied and covered 2016 onwards state-of-the-art covering 62 research and review papers from various journals and conferences from IEEE, Springer, Elsevier, ACM, Research Gate, Hindawi and many more renowned publications. Table I and II depicts the summary of review. Efficiency and accuracy of ML algorithms relies on Dataset. Most of the reviewed papers introduced a common procedure where image processing and machine learning approach is experimented [11]. Image acquisition, pre-processing, image segmentation, feature extraction, feature selection, and classification [6], [20], [19], [38]. In the first phase image/data acquisition, two dataset were most popular which are Herlev dataset with single cell images and SIPaKMed with multi cell Pap-smear images. Apart from these, TCT images from collaborating hospitals [4], images captured through android devices with particular resolution and microscope are being used for the processing [25]. The second phase is the pre-processing phase. The digital images collected through various modes might contain a plethora of unnecessary objects such as noise, low resolution, blurriness, etc. Hence, various image processing techniques are implemented either to correct the data or to extract adequate information. In the third phase, Image Segmentation, cervical cell images' nuclei or cytoplasm are segmented from either isolated cells, touching cells or overlapping cells [13], [6]. However, in some applications of machine learning, the segmentation phase is optional for example implementation of basic CNN [39]. The subsequent phase focuses on extracting and selecting essential attributes like shape, size, color intensity, textures, and so forth from segmented regions that are helpful in detection of abnormal cells from the cervix images [19]. In the last phase, classification of the images into different classes such as superficial cell, intermediate cell, columnar cells, dysplastic cells, carcinoma in situ, etc. to differentiate between normal and abnormal cells are achieved [3], [14].

In the current state-of-an-art, most of the researchers emphasize single cell cervical images which are easy to work with and provide successful results. Quite a few researchers focused on using multi-cell images and generating successful detection of abnormal cells [39]. The difficulty level of identifying the malignant cells and classifying them according to their degree of infection is immense. However, many expert research analysts have achieved success in delivering results using multi-cell cervix images with high accuracy and efficiency [36].

This article's contributions can be outlined as follows:

- An exhaustive exploration of cutting-edge techniques for meticulous examination of Pap Smear images, focusing on cervical cancer detection, segmentation, and stratification through the integration of image processing and machine learning methodologies is done.

A comprehensive overview of reputable journals' articles is covered. Additionally, background theory is comprised to elucidate the significance of technological advancements in cervix cancer detection and classification.

To the best of our knowledge, it offers a comparative analysis of different techniques across each stage of the classification process.

Furthermore, It provides an extensive discussion of various methods and technologies to explicate the workings of the different phases involved.

This publication is fashioned as follows: Section 2 provides an overview of image processing techniques and machine learning concepts in healthcare, along with their applications. Section 3 discussed related work from the research and survey papers collected from Google Scholar, science direct, and Research Gate. The primary terms employed to gather papers include machine learning, image processing, Pap-smear image analysis, medical image processing, cervical cell detection, automated cervix cell detection, and classification. Followed by section 4, which covers a comparative study and discusses various approaches with pros and cons. Lastly, section 5 concludes the whole study and discusses future direction.

2. Background

A. Image Processing Techniques For Healthcare

Image Processing (IP) is a computer technology that processes images to analyze and extricate fruitful information from them. Due to technological advancement, IP techniques have become widely popular all over the world. Among all other application sectors of IP, the medical sector gained a lot of popularity due to its wide range of imaging tools and technologies for the internal diagnosis of body parts [23]. Figure 1 depicts the working process of IP. It is a sequential process from lower level to higher level processing. It is divided into three categories according to their outcomes and applications viz. low-level, mid-level, and high-level processing [27]. Low-level image processing techniques take images for the input and produce updated, enhanced, denoised, and improved appearance images for the output. In most cases, low-level processing is used for pre-processing and image enhancement. In mid-level image processing, input is images and output will be attributes extracted which can be used for various applications such as image segmentation, object recognition, and description of images as mentioned [23]. Lastly, high-level image processing is used to extract important information from images and later use them as knowledge for making sense of it. Input for high-level processing is images and the outcome can be a better understanding of the images for various applications such as object detection and identification, autonomous navigation systems, intrusion detection systems, theft identification, and scene recognition. [40].

Figure 1. Image Processing Levels

Biomedical images are an integral part of medical science that demonstrates the human biological system to understand the nature of the human body [18], [27], [41], [28], [37]. Plenty of tools and techniques are being developed to inspect the human body and identify and analyze the diseases for medical diagnosis [36]. X-rays [28], CT-Scan (computerized tomography scan) [28], Mammography [42], MRI (magnetic resonance imaging), ECG (electrocardiogram) [43], Ultrasound sonography [28], [44], MRA (magnetic resonance angiography) [45], stereo endoscopy, PET (positron emission tomography) [46], doppler techniques, photoacoustic imaging [47] are some of the example of it [23], [27], [28].Some of the applications of various medical image processing techniques [28], covering X-Ray to MRI demonstrated in figure 2 [14].

B. Medical Diagnosis In Image Processing- A General Approach

Conventional medical imaging techniques provide prospective and guaranteed advancement in science and healthcare [27], [31]. Imaging technologies in medicine help doctors to see the internal body parts for quick and easy diagnosis, and keyhole surgeries for unreachable body parts without cutting them open. The digital image processing involves steps mentioned in the figure 3 below which provides general insight into how medical diagnosis can be performed by degrees [27].

Step 1 starts with image acquisition which includes capturing digital images through imaging technologies such as x-rays, MRI, CT-scan etcetera. In step 2 image pre-processing and noise reduction are performed to enhance the appearance of the images and make it more readable for further processing [36]. In the next step image segmentation, various operations such as edge detection are performed which is an essential operation for medical image analysis systems and used to recognize human anatomy such as vessels, liver, brain, cervix, and breasts. In step 4, various algorithms are performed to successfully detect the bones, organs, and nodules in lungs, tissues, and cells so that detailed analysis can be performed on the selected areas in step 5 to identify the problems in the areas of interest in the human body and making sure that the

TABLE I. Details of state-of-an-art Journals-Year wise

Year	2023	2022	2021	2020	2019	2018	2017	older
Papers	9	22	5	7	5	5	2	6

TABLE II. Details of state-of-an-art Journal wise

Year	IEEE	Springer	Elsevier	ACM	Research Gate	MDPI	Others
Papers	5	4	6	3	5	6	33

Figure 2. Image Processing For Healthcare

organs are working normally. The analyzing algorithm of digital image processing systems focuses on measurement in terms of volume, growth, functioning of the organs, cardiac functions, checking for stroke-related problems, and many more. The last step consists of image classification and diagnosis-related techniques which help in determining the existence of cancer, differentiating between normal and abnormal cells, identifying the actual cause and problem, and suggesting primary cure treatment on an early basis.

C. Machine Learning For Healthcare

Machine Learning (ML) and Deep learning is a subset of Artificial Intelligence (AI) that can analyze extensive, intricate datasets from the past, learn from them through training, and use this knowledge to forecast future outcomes for specific problems [30], [12], [19], [48].

The ML approach for medical diagnosis applications has gained momentum in recent years [30], [49]. The applications of using machine learning algorithms for healthcare

Figure 3. Medical Diagnosis in Image Processing- A general Flow

Figure 4. Machine Learning for Healthcare

include providing personalized medications with precision, detailed analysis, and examination of radiology images and data, computer-assisted prognosis, clinical workflow monitoring including patients, etc. Various important aspects of applying machine learning techniques for the healthcare field are portrayed [50] in figure 4. Managing the patients' records and medical histories, suggesting primary care treatments of chronic diseases, cancer screening, surveillance, tumor characterization, and drug discovery are the key line areas where machine learning deep learning techniques provide satisfactory outcomes in terms of prediction and detection [31], [26].

3. Related Work

Loe Zhe Wei et al [5] presented a review article for detection and classification methods for cervical cells in automated systems. They discussed the pros and cons of each method. They concluded that the identification of the overlapping cells of the nucleus is one of the most significant findings during the whole screening process. A comparative study is provided that can help to figure out difficulty levels associated with each technique and simultaneously provides basic knowledge of generating and using their algorithms as per the requirement.

Yessi jusman et al [20] presented a comparative study for the screening of cervical carcinoma and divided the whole process into two approaches which are cellular level and tissue level. They proposed that automation could be applied to either images or spectra. During the feature extraction process, morphology operations are applied to texture, the intensity of cell or tissue images, and/or shape, while for spectra primary features include intensity height, wave number or shift and area under peaks. Feature selection techniques include sequential backward, forward, and floating search methods, discriminant analysis, and principal component analysis (PCA). The classification process involves using support vector machines (SVM), neural networks (NN), linear discriminant analysis (LDA), k-nearest neighbors (KNN), and decision trees. It was recommended that six various types of cervix precancerous data, such as FISH, cytology, colposcopy, electromagnetic spectrum, cervicography, and HSDI, could be utilized [21], [18], [23], [24], [20], [9]. They have shown that cellular-level data, namely, cytology, FISH, and electromagnetic spectrum can achieve better outcomes when compared with tissue-level data such as cervicography and colposcopy.

S. PradeepKumar Kenny et al [3] represented a comparative study between single and multiple features extraction methodologies. Segmentation applying a multiscale watershed technique is explained for the feature extraction process. Data mining techniques to identify suitable features to figure out different stages of cancer are used with a 100 percent successful detection ratio. Later, the conclusion was derived that rather than a single feature, the combination feature set technique is significantly better.

Wan Azani Mustafa et al [13] presented a thorough review of cervix cancer detection based on nucleus segmentation and classification techniques. For nucleus detection, many approaches are being used to identify signs of human papillomavirus using various tools such as Matlab 2009a. The data processing includes picture collection, thresholding, noise reduction, filtration, and many more methods used to identify cells as either normal or abnormal. For the classification, according to the authors, the results are controversial. The disadvantages of pap smear tests led the researchers towards automated classification for abnormal cells in the cervix area. The proposed system includes feature extraction, feature selection, and classification techniques such as SVM, and neural networks (ANN,DNN). fuzzy logic, bayesian network, KNN, decision tree, etc. The pros and cons of all the algorithms are discussed. One of the more important conclusions is that it's a challenging task to detect overlapping cells.

Wasswa William et al [19] represented a detailed review on automated cervical cancer detection. All the papers reviewed are gathered through 4 scientific databases using a set of keywords. CHAMPS software is used to perform segmentation by using algorithms KNN and SVM which are reportedly excellent classifiers for the cervical cancer detection with accuracy over 95% when they are applied for more than one class classification.

Yash Singh et al [37] provided an ordered review of cervical cancer screening algorithms. Different algorithms of segmentation and classification of cervical cancer screening are explained considering various parameters such as size of the datasets used, accuracy, drawbacks etcetera. Various ML algorithms are performed for early detection and classification of malignant cells/tissues in the cervix area. SVM, GLCM, RF Trees, CART, Hierarchical clustering, c5.0, MARS, K-,eans clustering algorithms, genetic algorithms, probabilistic neural networks are such ML algorithms that are used for feature extraction, segmentation and classification operations.

Sarah L. Bedell et al [18] presented a review on new screening technologies for cervical cancer detection which have more potential to reduce the mortality ratio occurring due to cervical cancer incidents in the underdeveloped countries. description on how cancer gets generated along with what are the screening methods conventional and modern.

B. Chitra, S. S. Kumar [11] presented a review on automated screening of cervical cancer happening all around recently along with their pros and cons and their effectiveness. The emphasis is being put on recent soft computing techniques for detection of cervical cancer cells. An insight has also been provided on how soft computing techniques can be helpful in segmentation as well as classification of cervical cancer diagnosis.

Elmer Diaz et al [15] have reviewed a plethora of researches and provided a system research flow for the analysis of cervical cancer. According to their analysis there are mainly 3 things to focus on : risk factors that cause cervical cancer, precautionary measures, and techniques to detect the cancer successfully. Considerable risk factors includeHPV infection, behavior sexual, psychosocial, economic, cultural , health and reproduction . A preventive measure is Vaccine for HPV and detection techniques deep learning techniques provide improved accuracy for various operations.

Xiangu Tan et al [4] proposed a deep convolutional neural network based TCT (thin prep cytologic test) cervical screening model in order to help pathologists for the whole diagnosing process. automated deep learning algorithms attain high precision fast cancer screening.collected TCT images from the collaborating hospitals were divided into three datasets: training, validation and testing of faster R-CNN system. The proposed model was able to differentiate positive and negative cells and focused on sensitivity and specificity parameters. A very small computational cost based proposed model is likely to be a part of the foundation of preliminary medical services.

Yao Xiang et al [39] implemented an efficient automated cervical screening system using CNNbased object detection detection method using YOLOv3 as a baseline omitting segmentation phase unlike other researches carried out these days. Their model demonstrates a sensitivity of 97.5% and a specificity of 67.8% in squamous cell image-level screening. The system is also able to provide location of the malignant cell along with the cell classification.

Kyi Pyar Win et al [6] proposed a four step cervical screening structure. Cell segmentation is able to detect cancer cell nuclei using shape based approach inorder to segment overlapping cytoplasm using marker-based watersheds technique. Next, the feature extraction process helps in focusing three important features such as texture, shape and color from cytoplasms and nuclei using the GLCM. For feature selection, RF (random forest) algorithms are employed to simplify the proposed model and decrease the training time of machine learning algorithms. Finally, in the classification phase, a bagging ensemble classifier is utilized by amalgamating the results from five distinct classifiers: Boosted trees, LD, bagged trees, SVM, and KNN . The proposed system's outcomes focus on two-class and five-class classification with accuracy level 98.27% and 94.09% respectively. Benefit of the proposed system is it helps identify normal and abnormal cells and it also provides better classification results compared to individual five classifiers.

Dr. S. Athinarayanam et al [33] presented an automated cervical cancer cells classification system in order to overcome the detection errors considering thickness, overlapping of cells and other unwanted substances identified by the cytologists during pap-smear analysis. The whole proposed system consists of segmentation followed by feature extraction with SVM classification and at last results of classification components are compared with KNN and ANN techniques.

Wassawa Willian et al [51] presented that A tool has been created for diagnosing and classifying Pap-smear images. The process begins with scene segmentation, which is accomplished using a trainable Weka segmentation classifier and a sequential elimination technique for noise reduction. Subsequently, feature selection is carried out using simulated annealing in conjunction with a wrapper filter, followed by fuzzy c-means classification. This entire procedure is applied to three diverse datasets comprising single-cell and multiple-cell Pap-smear slide images. 3 parameters accuracy, sensitivity and specificity are considered for the classification results on each individual datasets. The results obtained from their study indicate that the proposed method surpasses numerous existing algorithms in terms of accuracy (98.88%), specificity (97.47%), and sensitivity (99.28%) when tested on the Herlev benchmark Pap-smear dataset.

Vidya Kudva et al [25] have elaborated on whether classifying image patches as normal or abnormal using shallow layer CNN and its feasibility. The input datasets consist of cervical images obtained after applying acetic acid on 102 women using an Android device. Image patches extracted through various techniques are subjected to classification using a shallow layer CNN comprising convolution layers, rectified linear unit pooling, and two fully connected layers, resulting in a 100% accuracy rate.

Shrishti Gautam et al [34] suggested patch-based approach for nuclei in single-cell segmentation by using CNN. A CNN-based transfer learning approach for classification has been suggested along with a decision tree-based approach. According to the results, decision tree-based classification outperforms multi-class classification with transfer learning. Their ultimate finding demonstrates that precise segmentation is unnecessary for classification with deep learning.

Jiayi Lu et al [52] introduced a combined approach to effectively predict risk of vaginal cancer. To tackle the challenges linked with cervical malignant cells, they proposed employing a voting strategy alongside data correction mechanisms, which enhance performance and bolster the robustness of predictions. They demonstrated that their proposed system is more feasible and scalable compared to others.

Shanthi P B1 et al [14] proposed CNN based system for the detection of malignant cells and classification of the cells into appropriate stage categories of malignancy of the cell. A huge dataset was being prepared by combining the Herlev Dataset carefully and feature extraction operation was being performed by using preprocessing and segmentation techniques in the sequential manner. The CNN model used here not only generates results of feature extraction successfully and extracting features that includes shape, edges, size, colors in classification stage but also differentiates the cervical cell images into various grades (normal, mild, moderate, severe, and carcinoma) according to their degree of malignancy. Outcome of their classification process provides the result into 3 sets that include single-cell enhanced images, contour-extracted images, and binary images sequentially. The result has shown accountable accuracy in classification of various degrees of cervical cell images.

4. Comparative Study of Different Techniques at Each Level

The overall understanding of how the computer-assisted cervical cancer screening process works is summarized in this section. The table III covers a set of techniques and algorithms for various stages of screening process including stages such as image acquisition, pre-processing, feature extraction followed by selection, segmentation followed by classification along with the additional information such as possible outcomes, limitations and future work, set of parameters, tools and technologies used by the researchers in the current research.

From the comparative study shown in table III, it is quite evident that some techniques, approaches and algorithms are more frequently in use. The study reflects that an open source dataset Herlev dataset (single cell) [33], [34], [3], [14], [53], [19], [51], [6], [54] and SIPaKMeD (multicell) of Pap-Smear images are most widely used. However, other possible approaches to get the desired dataset are collaborating with hospitals and/or laboratories to get TCT [4] or Pap-Smear images, and capturing Cervix images after applying 3%-5% acetic acid using android device with specified resolution or converting the slide data into digital form by means of some digital medium such as camera [25].

For preprocessing and image enhancement most used approaches are noise removal techniques that includes various filters [49] such as median filter [34], [19], gaussian filters [19], sobel vertical-horizontal filter [19], [14], and some smoothing filters, contrast enhancement- CLAHE (contrast limited adaptive histogram equalization) technique [11], [24], [20], [31], [6]. For feature extraction , techniques used are ANN [33], [13], [31], [5], [6], [51], CNN [37], [4], [5], GLCM [33], [37], [6], for the extraction of visual features, texture features, shape features etc [51]. Feature selection can be implemented using faster R-CNN [4] for the features such as cytoplasm, nuclear shape, fluid color, Random Forest algorithm [18], [17], [6], SVM [33], [17], [20], [13], [37], [19], [6], LBP [25], DNN [31], [14], [55].

Many of the researchers have incorporated segmentation phase while others have simply omitted it by claiming that after the feature selection process, classification algorithms can be applied directly to achieve more accurate results. Segmentation techniques used are shape-based iterative methods, marker-controlled watershed approach to segment overlapping cytoplasm [6], Modified Otsu Thresholding Algorithm [33], [51], Hessian matrix, Sobel filtered edge detection, Gabor filter for boundary detection(canny edge detection), texture based filtering using mean, variance, median, maximum, minimum and entropy masks [3], Random Subset feature selection (RSFS) [17], [25], and Patch-based CNN based approach [34], [4]. The classification is implemented using machine learning algorithms that includes Bagging ensemble classifier (LD, SVM, KNN, BOOSTED TREES, BAGGED TREES) [9], [6], [38], SVM [33], [17], [12], [52], [5], ANN [33], [13], [5], [6], KNN [33], [17], [20], [13], [19], [6], [5], Fuzzy c- means algorithm [5], [51], [35], Deep learning methods using transfer learning [22], [36], [56], [57] on Alexnet on both segmented and non-segmented single [34], Logistic regression [52], MLP (multilayer perceptron) [52], Decision Tree classifier [17],

[12], [52], and Convolutional Neural Network (CNN) [4], [5], [39], [1], [58], [59], [60].

The automated cervical cancer screening system can classify between normal and abnormal cells from both single-cell and multicell datasets according to the classification algorithms. The outcomes are mainly measured using parameters which are accuracy, sensitivity and specificity and generate outcomes in multi-class classification. From the results shown in the summary table III on existing literature, Bagging ensemble classifier is able to provide accuracy in two class and 5-class classification [6] 98.27% and 94.09% sequentially, SVM provides 86% accuracy [33], Fuzzy c-means classifiers single cell gives accuracy 98.88%, sensitivity-99.28%, specificity-97.47%, Multi-cell provides accuracy-97.64%, sensitivity-98.08%, specificity-97.16%. Pap-smear data generates accuracy-95%, sensitivity-100%, specificity-90% [51], 100% accuracy is achieved using shallow CNN [25], Deep learning methods using transfer learning on Alexnet are able to provide accuracy (2-class:99.3%, 7-class: 93.75%) [34].

5. State-of-the art: Cervix cancer detection and classification

A. Automated Cervical Cancer Detection Workflow

Figure 5. Cervical Cancer Detection Workflow

From the current literature, it is observed that cervical cancer detection and classification follows six main steps as shown in figure 5. It provides a general approach for the whole screening process which consists of process steps mentioned here. Every stage is equally important. Hence, their detailed study is essential and so been explained in detail in the following subsections.

B. Invasive Cervical Cancer Diagnosis- Available Screening Methods

Squamous cell carcinoma is a leading contributor to cancer-related fatalities among women in developing regions. Almost every day new technologies are being developed, implemented, and tested for fast, efficient, and cost-effective cervical cancer screening and medical treatment [18], [50]. Screening a woman for HPV (human papillomavirus) and cervical Dysplasia can considerably reduce the risk of cervical cancer deaths [9]. The figure 6 showcases available cervical cancer screening imaging technologies. The Papanicolaou test is a manual cervical screening process and is used for detecting precancerous changes in cervix cells using shape and color-like features of the cervix cell nuclei and cytoplasm regions [6]. Samples collected through pap-smear tests are observed under a microscope to find out the atypical development of cells which leads to precancerous changes. However, this is a very time-consuming, and laborious analysis technique. The cervical cancer diagnostic screening methods have two approaches, cell-level and tissue-level [11], [20]. The cellular-level approach includes pap-smear, Human papillomaviruses- Deoxyribonucleic acid (HPV-DNA) testing, liquid based cytology (LBC) [9], [53], and electromagnetic spectroscopies [11]. The tissue-level screening technique includes VILI, or VIA [22], [24], hyperspectral diagnostic imaging (HSDI) [18], [20], [9], [25], colposcopy [26], cervicography, digital cervigrams, mobile phone images, pocket colposcopes. However, each of the techniques has its advantages and disadvantages, and all the techniques mentioned highly skilled experts for the judgment or prediction of the results. There are various advanced technologies available for automated screening such as AutoPap 300, Focal Point, and ThinPrep imaging systems (TIS) approved by the United States Food and Drug Administration (USFDA) [30], [20].

Figure 6. Invasive Cervical Cancer Diagnosis- Available Screening Methods

C. Image Acquisition

Image acquisition in IP is a process of acquiring images from verified sources/techniques which can be further processed. Many researchers are using available open-source datasets for cervical cancer cells called Herlev (Single Cell) and SIPaKMed (Multi Cell). Also, other dataset sources such as AINDRA [34], HEMLBC [9], TCT images from collaborating hospitals and laboratories [4], [6], National Cancer Institute (NCI) dataset can be acquired for primary research.

D. Image Preprocessing and Enhancement

Being an utmost important step in computer-assisted cervical cancer screening procedure, Image Enhancement provides fruitful outcomes for preprocessing and further process [8]. In the preprocessing, various operations such as increasing and/or decreasing contrast, smoothening, sharpening, removal of noise, and filtering are applied to improve the images and make them suitable for the next

Figure 7. Image Pre-Processing And Enhancement

operation/procedure [24], [11]. Various noise removal filters such as mean, median, sum of squares, Gaussian filter etc. are being used for preprocessing, and histogram or contrast stretching algorithms such as CLAHE is widely used for image enhancement [11], [24], [20], [31], [6]. Figure 7 depicts the procedure covering various techniques to identify features like gradient, shape and pixel intensity, and radius which can be identified using techniques such as mathematical morphology (dilation, erosion, opening, closing) [11], filtering and thresholding methods [13] and making them suitable.

E. Image Segmentation

Figure 8. Image Segmentaion

In step 3 of the automated screening process, the outcomes of step 2 i.e. enhanced and preprocessed images are further processed to segment the regions of interest (ROI) of cells [24], [53] and is shown in figure 8. The ROI can be segmented using a variation of techniques which can be features like contour, shape, color or texture based, edge detection based, clustering-based, or region to be extracted based [11]. Cell segmentation aims at nuclei or cytoplasm of the cells out of which segmenting the nuclei is easier as compared to later. Both nuclei and cytoplasms are used for overlapping cell segmentation [38], [6]. Isolated cells, overlapping cells, and touching cells segmentation are performed where shape-based iteration methods considering features such as area, intensity value, solidity, major and minor axis length for nuclei and watershed transform approach for cytoplasm where smoothening of boundaries is performed using edge smoothing methods [6].

F. Feature Extraction

After the image segmentation, its output passes to the features extraction process. In this stage, various image features such as texture (rough texture for abnormal nucleus), shape (smooth, circular and oval boundary specifies normal nucleus), ratio, color intensity, chromaticity (cancerous nuclei are darker in shade), size (radius, area, perimeter of the cell) etcetera are extracted. Various factors as shown in the figure 9 are considered for both cell and tissue feature extraction process [11]. Many algorithms are available to extract features. For example, texture features can be extracted by applying a co-occurrence matrix, wavelet technique, mathematical morphological operations, clustering techniques, thresholding approach and many more [11], [13], [38]. Differentiation between normal and abnormal cells is performed using color and shape features for which various color models such as RGB, HSV, gray-level histogram, watershed technique etc are used [11], [20], [6].

Figure 9. Feature Extraction

G. Feature Selection

In the process of automated cervical screening, the next step is Feature Selection used for enhancing the performance of the classifiers. The selection of appropriate features plays a vital role as it helps reduce size of the dataset and at the same time transforms high-dimensional input to the low-dimension input form. From the thorough review [11], Principal Component Analysis (PCA), and Discriminant Analysis (DA) are identified as popular selection and extraction algorithms [17]. The PCA technique [8] utilizes orthogonal linear transformation principles to convert data into a new coordinate system. It serves as a linear classifier frequently employed for classifying Pap-Smear images. Conversely, the Discriminant Analysis (DA) technique generates a new value referred to as the discriminant function score. DA method resembles the computation of Eigenvalues. The figure 10 the basic idea is depicted. Both PCA and DA techniques are utilized for feature selection, encompassing Texture, Shape, and Ripplet Description. Texture features can encompass attributes like energy, mean, variance, skewness, contrast, average, entropy, sum of homogeneous features, cluster, sum of squares, and energy, among others [3]. Shape Features are further classified into eccentricity, compactness, circularity, area and perimeter. Ripplet Description can be classified into color and texture which are used to identify ripplet descriptors [11].

H. Cervical Cell Screening Algorithms

Figure 11 showcases the summary of algorithms used so far for an automated cervical cancer screening system [50]. The algorithms and techniques summarizes the methods of

Figure 10. Feature Selection

various research survey papers reviewed based on database size, accuracy, drawbacks, etc. [61], [37] Various machine learning algorithms [8], [11], [62], [37], [38] widely used are Decision Trees [17], [34], [20], [13], Support Vector Machines (SVM) [17], [5], [26], C5.0 classification model, Random Forest Trees (RF Trees) [18], [17], [41], [6], Gray Level Co-Occurrence Matrix (GLCM), Multivariate Adaptive Regression Splines (MARS), Hierarchical Clustering, Classification And Regression Trees (CART), K-means Clustering Algorithm [6], Probabilistic Neural Networks (PNN), Genetic Algorithms, Convolutional Neural Networks (CNN) [62], [4], [5], [26], Artificial Neural Networks (ANN) [33], [13], [5], [6], Deep Neural Networks (DNN) [55], [26], K-Nearest Neighbors (KNN) [33], [17], [20], [13], [19], [5], Bayesian Network [41].

Figure 11. Cervical Cancer Screening Algorithms

I. Cervical Cell Image Object Categories

Cervical cell/ nuclei can be categorized into various categories mentioned in the figure 12 i.e either normal /and or abnormal (cancerous benign and/or malignant) cell/nuclei [24], [6], [39]. There are typically 10 different object categories for cervical cells which are normal, Atypical Squamous cells-Undetermined Significance (ASC-US), Atypical Squamous Cells- cannot exclude HSIL (ASC-H), Low-Grade Squamous Intraepithelial Lesion (LSIL), High-Grade Squamous Intraepithelial Lesion (HSIL), Atypical Glandular Cells (AGC), Adenocarcinoma (ADE), Vaginalis Trichomoniasis (VAG), Monilia (MON) and Dysbacteriosis (DYS) [24], [4], [39]. As per the current literature, cervical cell images can be categorized into two categories Normal (Immediate, Columnar, Superficial) and abnormal (Moderate Dysplasia, Light Dysplasia, Severe Dysplasia, Carcinoma in Situ) for single cell images and three categories like Normal (Superficial-Intermediate, Parabasal), benign (Metaplastic) and abnormal (Dyskeratotic, Koilocytotic) for multi-cells images [19], [6].

Figure 12. Cervical Cell Image Object Categories

6. Conclusion and Future work

For this literature survey, various machine-learning papers and articles have been reviewed. In this review, around 50 papers from various journals and conferences are analyzed which are carefully selected through decorated publications which include IEEE, Springer, Elsevier, Sage, Acm and others from the year 2016 to 2022. Most of the papers have mentioned the usage of Herlev Pap-smear Dataset available open-source for single cell multi-class classification. This review should help novice researchers the primary assistance in developing different approaches to improve the existing outcomes or generate new algorithms. The Neural network-based approaches are widely popular for cervical cell image classification. Most widely used are SVM, CNN and KNN. Various Network models such as VGG-16, Alexnet, and ImageNet can be incorporated to improve the efficiency of the output. As the available open-source datasets are limited in terms of size, more data is required to improve the accuracy of the results from the collaborating hospitals, laboratories and private organizations. Also, image augmentation techniques can be experimented to increase the size of the training datasets which results in improved accuracy in the test datasets. Applying appropriate preprocessing techniques can help in improving the results of segmentation and classification algorithms.

TABLE III. A Comparative Study Of Di erent Techniques At Each Level

PAPER	IMAGE ACQUISITION	TOTAL NO. OF IMAGES	DATA PREPROCESSING	FEATURES EXRACTION	FEATURES SELECTION	SEGMENTATION	CLASSIFICATION	OUTCOMES	LIMITATIONS / FUTURE WORK	PARAMETERS	TOOLS AND TECHNOLO-GIES
Xi-angu Tan et al. (2021) [4]	TCT images from collaborating hospitals	Training data set(13775), validation dataset(2301), test dataset (408030 from 290 scanned copies)	Seamless slider technology, lesion labelling	ANN, CNN	Faster R-CNN to extract Cytoplasm, nuclear shape, uid base color	-	-	Separated normal and abnormal images, minimize the rate of missed diagnosis, improved speed and accuracy,	Di cult to di erentiate between malignant and normal cells due to high no. of overlapping cells.hard to nd characteristics of cells,dataset does not have enough samples of TCT images	Sensitivity, Speci city considering TN,TP,FN,FP,PPV,NPV	The labelling software: LabelImg(Version 1.5.0),
Kyi Pyar Win et al (2020) [6]	Pap smear im-ages. SIPaKMeD and Herlev	Herlev dataset (917 images), SIPaKMeD dataset (966 images, 4049 cells)	Image enhance-ment(noise removal- median lter, CLAHE (contrast limited adaptive histogram equalization))	3 features extracted-shape, size,texture and color features using GLCM (gray level co-occurrence matrix)	Random forest algo-rithm	Segmentation of nuclei regions and cytoplasm regions Nuclei detection-shape based iterative method, overlapping cytoplasm separation-marker-controlled watershed approach	Bagging ensemble classi er (LD, SVM, KNN, BOOSTED TREES, BAGGED TREES)	98.27% accuracy in two class classi cation, 94.09% accuracy in 5-class classi cation using SIPaKMed dataset	Use of other classi-ers can further en-hance the result	Accuracy, sensitivity/recall, speci city, precision and F_Measure	-NA-
Dr. S. Athi-narayanam et al.(2017) [33]	Pap smear images: captured with resolution of 0.201 m/pixel from public database of cervical cancer,Herlev university hospital	Normal (40 images), abnormal (60)	Gray scale conversion,Adaptive Path Smooth Filter to remove small noise and preserve sharp edges	Texture feature extraction-GLCM	energy, correlation, entropy, contrast and homogeneity using GLCM	Modi ed Otsu Thresholding Algorithm (background removal,cytoplasm and nucleus detection)	SVM, ANN, KNN	The proposed method is eective for the classi cation of Pap Smear Cell image into normal and abnormal compared the output of SVM with ANN and KNN and achieved 86% accuracy.	-NA-	Sensitivity, accuracy, speci city	-NA-
Was-sawa Willian et al.(2019) [19]	Pap-smear images: Herlev dataset	Dataset1: 917 single cell Dataset 2:497 full-slide images Dataset 3: 60 images from Mbarara Regional Referral hospital (MRRH)	Three phase elimination scheme :debris removal with image enhancement: CLAHE	Dataset divided into 7 class considering area, size, brightness and shape of cytoplasm and nucleus. 3 geometric features (eccentricity, solidity, compactness) and 6 texture features (variance, mean, energy, standard deviation, smoothness, and entropy)	Simulated annealing with wrapper lter. K-fold cross valida-tion.	Noise reduction, edge detection: sobel lter, Hessian matrix, Gabor lter (canny edge detection), mean, variance, median, maximum, minimum and entropy lters for texture ltering.	Fuzzy c- means algo-rithm	Developed their own tool PAT. single cell :speci city : 97.47%, accuracy : 98.88%, sensitivity-99.28% . Multi-cell: speci city : 97.16%, accuracy : 97.64%, sensitivity : 98.08%. pap-smear : speci city : 90%, ac-curacy : 95%, sen-sitivity : 100%. FN, FP, classi cation er-ror rate are 0.00%, 10.00%, 5.00% se-quentially.	Haven't included cer-vical cancer risk fac-tors assessment into the tool.	Accuracy, sensitivity, speci city for sin-gle cell and multi cell,and pap smear images.	Trainable Weka segmentation tool , MATLAB, Java Graphical user interface(GUI)
Vidya Kudva et. al. (2018) [25]	Cervix images after applying 3%-5% acetic acid using Android Device with 13MP camera	Total 102 out of which 42 (VIA-positive-pathologic) 60 (VIA-negative-healthy controls)	684 image patches of 15*15 pixels manually extracted (275-extracted from expert annotated AW regions-positie examples)(409-from non-AW regions-negative examples)	Randomly select weights for lter, pass training set through the fw, update lter weights,compute cross entropy error function, repeat the same	Traditional approach for comparison: SVM- extract features such as color, haralick, local binary pattern(LBP)	Traditional approach for comparison: Ran-dom subset feature selection (RSFS)	CNN	100% accuracy is achieved using shallow CNN	Training CNN requires complex computations.	Accuracy, training loss,	Intel processor Celeron and 4GB RAM, MATLAB R2017a. Python programming

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TABLE III. A Comparative Study Of Di erent Techniques At Each Level (cont.).

PAPER	IMAGE ACQUISITION	TOTAL NO. OF IMAGES	DATA PREPROCESSING	FEATURES EXRACTION	FEATURES SELECTION	SEGMENTATION	CLASSIFICATION	OUTCOMES	LIMITATIONS / FUTURE WORK	PARAMETERS	TOOLS AND TECHNOLOGIES
Shrishti Gautam et al. (2018) [34]	Pap-smear (single cell and multi-cell) dataset.Herlev and Aindra dataset	Herlev (917-single nuclei)Aindra dataset (80 multicell),from Bangalore, India	Median lter- noise removal.	Detection of nuclei CLAHE + thresholding	Feature based cell separation method	Patch based CNN based approach.	Deep learning methods using transfer learning on Alexnet on both segmented and non-segmented single cell images. Combination of decision-tree based classi cation with transfer learning which then applied to multi-cell images.	Accurate segmentation is not necessary for classi cation with deep learning.herlev dataset state-of-art accuracy (2-class:99.3%, 7-class: 93.75%)	-NA-	accuracy	AlexNet
Azian Azamini Abdullah et al. (2019) [21]	13 from HUSM Kubang Kerian , 102 from pap-smear	115 images	Blue channel extraction template: unwanted background is ltered out. Contrast enhancement: nucleus appears in simulated images	Initial size, boundary condition, pixel value, control template, feedback template, threshold value	-NA-	-NA-	-NA-	Proposed CNN algo. Can detect the cervix cancer cells automatically with accuracy ¿80%	More images to be simulated for more accurate and precise results.	accuracy	Matlab based CNN simulator.CANDY software (vismouse). Few templates such as blue channel extraction template, contrast enhancement, median lter , binary edge detection, hollow-concave.
J. Lu, E. Song, A.Ghoneim et al. (2020) [52]	Gene sequencing dataset (3000 genetic loci, belonging to 23 pairs of chromosomes)	Private dataset: 472 questionnaires (50 attributes) obtained from a chinese hospital, UCI dataset: 858 samples (32 attributes)	Data correction: Random Forest algorithm. Fill missing data :correction mechanism carefully designed using logic	History of drinking, age of rst pregnancy, cervical surgery, etc.	-NA-	-NA-	Logistic regression, SVM, KNN, MLP (multilayer perceptron), Decision Tree classi er	As compared to existing methods, the proposed system is more implementable and scalable.	It doesn't have enough experimental support. Also further investigations can focus on more distinctive data that includes colposcopy images.	Accuracy, recall, precision, F1 score	-NA-
Shanthi P B, Faraz Faruqi et al.(2019) [31]	Pap Smear database developed by Herlev University Hospital collected using a digital camera and microscope under a resolution of 0.201 m/pixel	917 images distributed unequally on 7 di erent classes. Proposed system: 749 images with 5 classes,	Data augmentation to expand the dataset for training., 5 di erent algorithms for Image Enhancement (Bi-Histogram Equalization with adaptive sigmoidal function combined with Sobel lter-vertical and horizontal, dynamic Fuzzy Histogram Equalization, color image processing using YCbCr color space, Fuzzy image Mapping, Genetic algorithm	Extraction of visual features such as edges, size, shape, and colors out of nucleus and cytoplasm.	Shape and size of the nucleus and cytoplasm of the binarized images using deep neural network architecture	Canny edge detector to extract edge information from single-cell images	Deep prediction model using CNN network to classify grades of cancer and extracting features to do so.	Cancer grade classi cation: normal, mild, moderate, severe, carcinoma. The outcome for 3 di erent sets: single-cell, contour extracted, binary images sequentially with noticeable accuracy for various class problems.	Increase in no. of classes in binarized images leads to increasing the complexity of classi cation, hence model requires more features for improving the accuracy	Accuracy	Used own CNN model

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TABLE III. A Comparative Study Of Di erent Techniques At Each Level (cont.).

PAPER	IMAGE ACQUISITION	TOTAL NO. OF IMAGES	DATA PREPROCESSING	FEATURES EXRACTION	FEATURES SELECTION	SEGMENTATION	CLASSIFICATION	OUTCOMES	LIMITATIONS / FUTURE WORK	PARAMETERS	TOOLS AND TECHNOLOGIES
Yao Xiang et al. (2021) [11]	own dataset captured by digital camera Ximea MC124CG-SY-UB with 12 million pixels situated on the microscope Olympus BX40 with 20 objective. Each pixel has a size of 3.45 mm2	12,909 cervical images with 58,995 ground truth boxes and contains 10 categories objects from cervical cell images. 1014 cervical cell images with size of 4000 3000, which are consisted of 728 abnormal cell images (positive samples) and 286 normal cell images (negative samples).	-NA-	method extract high-level features automatically and detect cervical cells directly using CNN model-based YOLOv3	-NA-	-NA-	YOLOv3 as a base model to detect 10 categories and then cascade a further hard example classi er to re ne the 4 categories: ASC-US, ASC- H, LSIL, HSIL.	automatically detect cervical cells directly on multi-cell images. more e cient as we can extract features automatically without manual intervention and careful design for all stages. cervical cell image-level classi cation along with detailed location and category information of abnormal cells	-NA-	evaluation metrics used by the PASCAL VOC object detection challenge, which are average precision (AP) and mean average precision (mAP).accuracy (Acc), sensitivity (Sens) and speci city (Spec)	Darknet-53, YOLOv3, Imagenet, NVIDIA GTX 1080 Ti GPU.
Sudhir Sornapudi, et al. (2019) [53]	cytology slide data. two datasets. rst set comprises 25 cervical liquid-based cytology slides provided by Becton-Dickinson (BD) Corporation using their Sure Path technique. Hamamatsu NanoZoomer 2.0-HT whole-slide scanner, Herlev Pap Smear datase	BD Corp. Data, 0.228x0.228, NDPI le type, 25 images. Herlev Data, Single cervical cell BMP le type, 917	detecting ROI bounding box coordinates.	image registration through feature-based image alignment.	-NA-	-NA-	CNN models for successful classi cation of cytology image data, graph-based cell detection technique	Proposed approach considers realistic conditions of overlapping cells and automatically generated cleaner labeled patch image data for training and testing convolution	-NA-	Accuracy, precision, recall, f1 score, MCC	CNN models-Resnet-50, VGG-19, Densenet-121, Inception_v3

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