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A SURVEY OF DIFFERENT METHODS FOR AUTOMATED DIAGNOSIS OF CERVICAL CANCER IN PAP-SMEAR IMAGE

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Abstract: A cancer type's early diagnosis as well as classification can facilitate the patient's subsequent clinical management. Cervical cancer (CC) grades as the 4th most existent cancer universally affecting women and also its timely discovery offers the chance to protect lives. The CC's automated diagnosis and also its classification as of the Pap-Smear (PS) images has developed as a requirement since it facilitates reliable, accurate and also well-timed examination of the condition's growth. Diverse algorithms and methodologies are utilized aimed at CC's automated screening via segmenting and categorizing the CC cells into diverse categories. This work explicates the survey on the CC's diagnosis in the PS image. This study highlights the latest studies regarding cervical cancer diagnosis, like PS image enhancement (IE), the PS image's automated segmentation, cervical cells' features in PS image examination, and automated PS analysis. Lastly, the diverse diagnosis technique's performances are analogized centred on the accuracy metric. For both the single-cell and multi-cell images, the comparison examination is

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1. INTRODUCTION

The most primary reason for cancer mortality amongst women is CC which ranks second globally, with about 530,000 recent cases of fast-growing cervical carcinoma along with around 280,000 associated demises reported every year. In least-developed countries, around 95% of the cases take place [1]. Cancer that occurs in the cervix is called CC, which is normally caused by a virus called Human Papillomavirus (HPV). Squamous cells and also glandular cells are the cells in the cervix that might be damaged by the virus that may develop into carcinoma of the squamous cell (squamous cells' cancer) and adenocarcinoma (glandular cells' cancer), correspondingly [2]. HPV will augment and also the existence of this cancer on account of the augmented smoking, drug abuse, and hookah amongst the younger generation, lifestyle changes along with increased dangerous behaviors [3]. Using 3 types of tests that are presently available, CC is examined, and are extensively employed for the CC's screening. These comprise tests for HPV, unaided visual inspection with acetic acid, along with cytology-centered Papanicolaou test (Pap test). The PS test is the suitable method in the latest diagnosis of CC, as it will identify the existence of precancerous and cancerous cells [4]. Hence, Cervical Tumor can well be averted by efficient interventions on the HPV infections' prevention [5]. Identifying and removing important precancerous lesions along with preventing mortality from invasive cancer is the cervical screening's goal [6]. Through the appropriate treatment of pre-invasive lesions, CC is avoidable [7].

1.1 Pap Smear Screening Test

Aimed at the CC's early detection, Pap test screening is basically the solution. For preparing Pap test slides, there are '2' methods: (i) conventional smears, along with (ii) utilizing liquid-centered

cytology (LBC) preparation [8]. Samples are smeared directly on a microscope slide after collection in conventional PS. Utilizing a cytobrush, liquid-centered PS was executed to wipe cells as of the cervix. Smears were stained via hematoxylin and also eosin stain along with examined by a pathologist [9]. The top technique of screening aimed at carcinoma cervix is a PS. For detecting the precancerous lesions in a woman, it is basically a dependable, simple, non-invasive, low-cost, and also easy screening tool. But, detection could only be executed with a pathologist's facility [10].

1.2 CAD-Based Diagnosis of Cervical Cancer

For assisting pathologists in the segmentation as well as identification of cervical cells in a PS image, a Computer-aided diagnosis (CAD) system is required. The workload of pathologists is decreased by applying CAD permitting them to concentrate on the diagnosis along with detection of abnormal cervical cells. Therefore, PAP's accuracy is enhanced, and also the CC's mortality is decreased [11]. Centered upon signals, numerical data, or in the form of images, CAD systems are utilized to identify things [12]. The probable cancerous cells as of the images (input) of CC cells are automatically detected by the CAD system and then provides to the qualified cytologists for judgment. The detection results can frequently attain adequate accuracy [13]. Figure 1 exhibits the CAD-centered general flow diagram for the CC diagnosis,

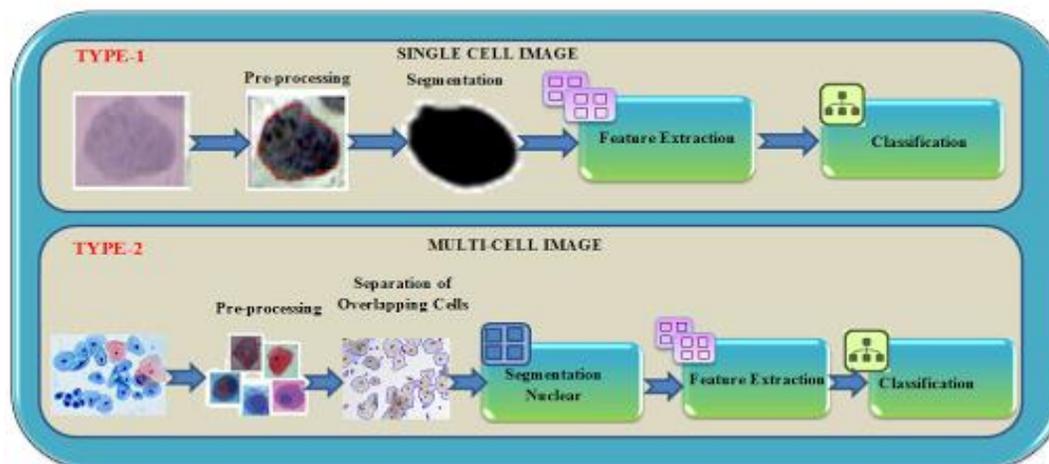


Figure 1: General flow diagram

Pre-processing: Usually, through unnecessary noise like impulse noise, poisonous noise, etc, PS images are affected. For removing that noise, disparate kinds of filters like Median Filter (MF), Weiner Filter, along with Gaussian Filter (GF) are employed by the existing method. For detecting the image's clear outlier, the contrast enhancement technique was employed [14]. This sort of pre-processing was useful for lessening the classification error.

Segmentation: The resultant pre-processed image was offered to the segmentation process after pre-processing of single along with multi-cell images. For segmenting the nuclei, numerous algorithms namely mean shift clustering, K-Means, Fuzzy-C means, level set, etc., are utilized in the prevailing method. By identifying the fine edges of nuclei, multi-cell cytoplasm is split from the overlapped cell [15]. The fine nuclei are attained from the segmented cytoplasm [16].

Feature Extraction: The images are prepared aimed at feature extraction (FE) after the segmentation method. Next, the feature can be specified as a piece of information that is pertinent for resolving the computational task associated with the PS image analysis. The general features are, (a) size and shape, (b) intensity, (c) texture, along with (d) structure. Morphometric features are possessed by the size along with shape feature that expresses a cell's overall size and shape. The absolute intensity values are utilized by the intensity features in the image aimed at single-cell and multi-cell images. The texture features assist to acquire quantifiable measures of the total local density variability in an object of interest. Every chromatin particle in the cell is deemed as an object in structural features [17]. Visual Geometry Group-19, Visual Geometry Group-16, InceptionV3, and Residual neural network (ResNet50) are utilized as features extractor for the PS image classification. It provides higher accuracy centered on Training, Validation, along with Test values [18].

Classification: Lastly, for automated diagnosis, the features (extracted) are proffered to the classifier. Many classifiers are employed namely Deep Convolutional Neural Network (DCNN),

Convolutional Neural Network (CNN), K-Nearest Neighbors (KNN), etc, worked very effectively to choose specific features for obtaining the precise result [19]. For augmenting the final classification's efficiency along with performance, classifiers are functioning on seeking the maximum classifiers' decisions along with weighing their decisions [20]. The decision shall provide if the cells are normal or abnormal cells.

This paper is categorized as. Section 2 proffers the top-notch techniques for CC diagnosis together with the performance is examined. Section 3 completes the paper.

2. RELATED WORK

The existent research techniques of the PS image enhancement (IE), automated segmentation, cell's features and automated diagnosis are explained in this section, and also their advantage and drawbacks are interpreted.

2.1 Pap-Smear Image Enhancement

Srishti Gautam et al. [21] stated a PS image analysis for CC screening for both single along with multi-cell images. Detection of nuclei, nuclei segmentation, as well as the categorization of segmented or detected nuclei through deep-learning approaches were the '3' steps of the framework. The image's quality was augmented by removal of noise from the image by utilizing median filtering in the detection phase. Afterward, aimed at the enhancement of contrast and accentuating the differences amongst the nucleus along with background, CLAHE was implemented. Finally, a global threshold was employed which localized the nuclei. '2' steps were deemed for the nuclei segmentation: cell separation along with patch-centered CNN. In classification, the classifier classified the cell as normal along with abnormal cell. The algorithms' effectiveness was separately displayed by the investigational outcomes, and concurrently proved the sufficiency of cell-nuclei detection for classification. It only focused on a restricted number

of features required for training the model using several features, which was the approach's drawback.

Pin Wang et al. [22] explained a CAD for quantitative analysis aimed at cervical PS images. ROI extraction, Pre-processing, along with overlapped nuclei isolation were the '3' steps. The contrast was improved between the nuclei and also other regions in the pre-processing phase. The approach utilized the top-bottom hat transform. After that, centered on density information, a mean-shift clustering was chosen for extracting ROI; then, the overlapping cells were divided. Next, the texture, shape, together with Gabor features was extracted as of the cells. Then, the important features were chosen from the features (extracted). The cell was categorized by the Chain-like Agent Genetic Algorithm – Support Vector Machine (CAGA-SVM) classifier as normal along with abnormal. The image enhancement, Gabor features, along with feature selection centered on CAGA were apparently useful aimed at the enhancement of classification's performance, which was understood as of the experimental results. For further evaluating the method's robustness, the methods must be tested in disparate data sets by various classification methods.

Debashree Kashyap et al. [23] introduced an automatic technique for detecting along with categorizing the CC's grade by both geometric as well as texture features of PS images and categorized by multi SVM. The images were first changed into a grayscale image in the IE stage. For reducing noise and enhancing images before segmenting them, Gaussian and Wiener filters were implemented. Then, the image's contrast was improved. Using independent level sets, the nucleus along with cytoplasm were segmented. Via segmenting the nucleus along with cytoplasm, the geometric features were attained. The images were classified with 95% accuracy by the extraction of distinct GLCM texture features as well as via an amalgamation of Principal Component Analysis (PCA) in addition to the top class of multi SVM. The image details and also

the edges of the CC images would be degraded by a GF in a pre-processing step. Further, the segmentation was affected.

Sarabpreet Kaur and Sahambi [24] recommended a technique aimed at extracting the cell nuclei (CN) and also the cell boundaries of touching cells in low contrast (LC) images. Initially, utilizing an amalgamation of multiple scale top hat filters together with h-maxima, the LC cell image's contrast was enhanced. After that, for identifying the CN along with the boundaries, a curvelet initialized level set technique was utilized. The IE result was verified through Peak Signal to Noise Ratio (PSNR), sensitivity, accuracy, along with precision metrics, the segmentation outcomes were verified. The performance metrics' improved values with the technique were exhibited by the outcomes. For finding the true cell pixels, more contrast improvement was needed for such sort of very LC cell images whilst evading false cell pixels. Thus, segmentation results could be enhanced.

K. Hemalatha and K. Usha Rani [25] presented an enhanced method for edge detection with the Fuzzy approach. It aimed at segmenting cervical PS images within the nucleus along with cytoplasm. The pre-processing phase involved color space conversion, salt and also pepper noise removal through MF and also Histogram Equalization was utilized for adjusting the image's uneven intensity distribution. Then, the nucleus along with cytoplasm was segmented by the fuzzy approach. Next, using the edge detection, '4' major features of cervical PS Images were extracted. The extracted feature's accuracy by a method was examined and weighted against other well-liked image segmentation techniques. The method had performed better analogized to the prevailing methods. The MF could not work effectively while the spatial noise was higher, which was the method's drawback.

Table 1: Analysis of different Pap smear image enhancement techniques

Author	Approach used	Purpose	Outcome	Limitation
Lili Zhao <i>et al.</i> [26]	Non-local means	The image is denoised without affecting the image's details.	Devoid of affecting the information of nuclei images, the noise is efficiently eliminated. Therefore, for proper segmentation, the noise removal technique was useful. 0.93 ± 0.03 ZSI values in nuclei and 0.82 ± 0.11 values in the cytoplasm were attained by the technique.	This method's robustness was not effective.
Paridhi Agarwal <i>et al.</i> [27]	De-correlation stretching	The Covariance matrix was computed by enhancing the image's contrast. Next, the approach improved the contrast.	Better precision along with recall value that is 0.9357 and 0.8275 was possessed by the resulting image. By deeming the de-correlation stretching, a superior result was attained.	Aimed at edge detection of PS images, the method was inappropriate as it was extremely appropriate for color separation only.
Mithlesh Arya <i>et al.</i> [28]	Median filter	The edges are enhanced by removing the noise and edge sharpening function.	The image was efficiently segmented without damaging the edges of cervical cell images. CC detection system's accuracy was 99.50%.	When the impulse noise ratio >0.4 , the image details were eliminated.
Kaaviya S <i>et al.</i> [29]	Median filter	Utilized for cleaning up the images. The edges of the cervical cell image were conserved.	The salt and pepper noise was effectively removed.	The nuclei were not completely detected from highly stained cells.
Meenakshi Sharma <i>et al.</i> [30]	GF and Histogram equalization	For eliminating the unwanted noise, GF was utilized. Aimed at improving the image's quality of cervical CN, Histogram Equalization was employed.	As a result of the pixel-centered Technique, the method's robustness was higher. Hence, for improving the accuracy with 84.3% of highest performance with no validation, the method was useful	The cervical CN's edges were not conserved by GF. For GF, salt and pepper noise was more difficult.

The analyses of IE methods of PS images are exhibited in Table 1. For eliminating the image's noise and improving the contrast, disparate techniques are utilized. The result along with drawbacks of various techniques is elucidated in this table.

2.2 Automated Segmentation of the Pap-Smear Image

Youyi Song et al. [31] suggested a learning-centered technique with robust shape aspects. It was generated to deem the cells (individual ones) segmentation on PS images that would monitor the automatic changes on cells. It was an imperative requirement of early CC detection. I) Cell element segmentation, ii) manifold cell labeling, iii) cell boundary refinement were the main processes for the individual cervical cell segmentation. To study the disparate cell appearance aspects, multiple-scale deep convolutional networks were taken. Two disparate datasets were taken for the estimation. This method was better contrasted with the top level ones concerning segmentation accuracy. Additionally, the approach was effectual for images that encompassed a large quantity of overlapped cells together with higher degrees of overlapping. Splitting the overlapped objects was more challenging as it was centered upon the pixel.

Sajeena T A and Jereesh A S [32] rendered a technique for automatic CC detection via cervical cell segmentation in addition to classification. Radiating Gradient Vector Flow (RGVF) segmented a solo cervical cell image as the cytoplasm, nucleus, together with backdrop. Pre-processing, FE, segmentation, along with classification were the steps involved in this approach. Initially, the image color space was transformed, in conjunction with that, the unnecessary noises were lessened. Then, RGVF segmented the cell. Subsequently, six nuclei-centered in conjunction with three cytoplasm-centered aspects were extracted. Therefore, the features were inputted to the classifier, and it classified the cell as i) normal and ii) abnormal cells. The Artificial Neural Network (ANN), SVM, together with Euclidean Distance (ED) was joined to form the classifier. The RGVF centered segmentation was not concerned with inherent

shape restraints aimed at the segmented boundary. Therefore, it might bring about an irregular nucleus boundary.

William Wasswa et al. [33] generated a potent method aimed at cervical cell segmentation as of a PS image as the nucleus, cytoplasm, together with background through pixel-level information. Several pixels as of these were extracted for generating a feature vector. To generate a pixel-level classifier, it was trained via noise diminution, edge detection, along with texture filters. Nucleus, longest diameter, perimeter together with cytoplasm, roundness, longest diameter, along with perimeter was the parameter. The pixel-level segmentation was capable of extracting the nucleus along with cytoplasm regions accurately, albeit there was no noteworthy contrast betwixt the elements on the image. An appropriate pre-processing step was needed to eliminate noise as well as enhance the contrast among cytoplasm in addition to nucleus. The false-positive together with false-negative rates might be lessened, which in-turn improves the precision, recall, along with DC.

Jie Zhao et al. [34] posited a technique of automated cervical nuclei segmentation via the Deformable Multi-path Ensemble Model (D-MEM). U-shaped convolutional network was adopted as a fundamental one. In this, dense blocks were employed for transferring feature information more efficiently. An aspect convolution was employed for dealing with disparate nuclei irregular shapes together with sizes to augment the model's flexibility. Manifold networks with disparate settings were built as an ensemble model to diminish the predictive bias. The segmentation structure attained top-notch accuracy in the dataset (Herlev) with 0.933 ± 0.14 Zijdenbos similarity index (ZSI). The noise ought to be eradicated through disparate filters, which in-turn augmented the segmentation's performance.

Ling Zhang et al. [35] generated an approach that joined the Fully Convolutional Networks (FCN) with Graph-centered method aimed at the cervical nuclei's segmentation. Two stages were

encompassed by the segmentation framework. The initial stage was that the FCN, which segmented the complete-cell image as the cytoplasm, backdrop, together with nuclei. The second stages the graph-centered fine segmentation. In respect to edge and region-information, nucleus shape constraint, along with nucleus context prior, optimal segmentation was assured. The technique's better performance was established with the dataset (Herlev). The work has considered only fewer features. Thus, to ameliorate the segmentation along with detection's performance, more features ought to be regarded. Furthermore, the classification task could as well be extensive as of '2'-class to '7' classes.

Meng Zhao et al. [36] suggested a Selective Edge Enhancement centered Nuclei Segmentation (SEENS). For segmenting entire slide cervical images whilst automatically evading the recurring segmentation together with eradicating non-nuclei regions, selective searches in tandem with mathematical operators were integrated. Furthermore, for extracting the edge information to ameliorate the nucleus' edge, an edge amelioration technique centered upon the canny operator together with mathematical morphology was rendered. The Chan-Vese segmented the ameliorated ROI with elevated accuracy. The SEENS attained higher accuracy. Compared to baselines, the method functioned better on lower-contrast cases. The ROI extraction's accuracy can well be ameliorated, and the SEENS can be implemented as an end-to-end structure.

Table 2: Comparative analysis of various segmentation methods on PS images

Author	Approach used	Purpose	Outcome	Limitation
Marina E. Plissiti <i>et al.</i> [37]	CircFH	In the CircFH algorithm, a weighted shape before employing the nuclei's circularity. The nuclei region's boundaries would be detected.	The nuclei regions of PS images were exactly detected. The final Euclidean along with Housdorff outcome was 2.29 ± 0.71 as well as 7.69 ± 1.89 . Both values were extremely near to the real cell boundaries.	This was not suitable for overlapping the cells as the nuclei might present under the overlapped cytoplasm.
Ratna Saha <i>et al.</i> [38]	Spatial Shaped FCM	Segmented cell nucleus as of overlapping PS cell images.	The robustness was high. Concerning Zijdenbos similarity index, pixel-level precision, together with recall, it had better segmentation outcomes.	It was prone to noise. The segmentation was affected by means of the intensity in homogeneity together with other imaging artifacts.
MithleshArya <i>et al.</i> [39]	Modified Moving k-means	The center redundancy issue together with dead center of clusters was lessened.	In the debris presence, it rendered favourable outcomes on dysplasia detection. For the abnormal class, it had 160.20 mean values and 14.40- standard deviation.	The inflammatory cells extraction was hard.
Ratna Saha <i>et al.</i> [40]	Fuzzy C-means	A clustering algorithm was utilized to segment the cervical cells' single-cell images into the nucleus, cytoplasm, in addition to backdrop.	It accurately detects the nuclei. It attained 0.918 precision and 0.915 recall value.	It could not extract the nuclei as of overlapping PS cell images. It only partitions the nucleus, cytoplasm, in tandem with background classes.

Table 2 exhibits the analyses of disparate segmentation methods along with the restriction of every method. Many limitations are rendered in the prevailing research methodologies specifically in the instance of cytoplasm overlapping.

2.3 Features of Cervical Cells in Pap-Smear Image Analysis

Abhinaav R and D. Brindha [41] planned to effectively categorize the affected cells as of normal cells through supervised classification techniques and further the affected cells' Logistic Regression (LR) were grouped. Initially, from the PS input image, the area, brightness, ratio, elongation, diameter, roundness, along with perimeter were extracted by the method. Two-Class Boosted Decision Tree, along with Two-Class LR, was the classifiers to which the image features were inputted. Therefore, the cell was categorized as i) normal and ii) abnormal cells by means of the classifier. After that, to a multiple class logistic regression classification, the abnormal cells were presented, which classified it into '4' classes with augmented accuracy. Centered on accuracy along with total error metrics, the system's performance was examined. The approach wasn't efficient as only the shape-related features were deemed and the other features were not deemed.

Kangkana Bora et al. [42] introduced an intellectual method aimed at the automatic classification of PS images for identifying cervical dysplasia. The work had '5' phases at a cell in addition to smear levels. The database (image) was set in phase 1. For experiments, both cells and smear level database was created. The region of interest (ROI) was extracted in phase 2 for segmentation. 121 low-level ones were extracted in phase 3 aimed at feature extraction, which was utilized for the smear's shape, texture, along with color. Phase 4 aimed at final aspects set design as well as phase 5 aimed at classification wherein ensemble classification was utilized for last decision. The same methods were utilized on cells as well as smear level. The dysplasia degree offered in an image was reflected by the system's final output classes. PS images were successfully categorized by the system which executed considerably superior when analogized to other prevailing methods as revealed by the extended experiments.

Lili Zhao *et al.* [43] introduced a '3' phase boosting framework aimed at the recognition of abnormal cells. Initially, concerning every cervical cell from '3' aspects by deeming chromatin pathology, cytology morphology, along with region intensity, 160-dimensional features were extracted. Especially, for describing the nucleus textural transformation, 106-dimensional chromatin pathology aspects were recently taken. Secondly, for choosing the optimum feature patterns, an adaptive feature combination method was proffered, which merged every feature by a reinforced margin-centered technique with the heuristic information. Lastly, for lessening the erroneous classification of abnormal cells by 2 disparate classifiers, a '2' stage classification strategy was introduced. A top-notch performance was attained by the experimental outcomes. The framework surpassed the '16' contrasted detection techniques.

Ashmita Bhargava *et al.* [44] introduced identification along with categorization of cancer by Histogram of the gradient (HOG) FE and also classified it using SVM, KNN, along with ANN. The database was gathered as of Air Force Command Hospital. '25' normal PS images along with '41' abnormal PS images were present in a total '66' PS images which were gathered. The ROI's features within the image were extracted by HOG since it transformed pixel-centered representation into gradient-centered representation. Utilizing a multi-classifier, the classification abnormal along with normal cells was performed. The method's performance had outshined the top-notch methods.

A. Dongyao Jia *et al.* [45] recommended a framework centered upon a stronger feature CNN-SVM aimed at precisely classifying the cervical cells. The strong feature that was extracted via Gray-Level Co-occurrence Matrix (GLCM) as well as Gabor was merged with abstract ones as of the CNN's hidden layers. For classification, the joined ones were inputted to the SVM. Aimed at improving the model's robustness, an efficient dataset amplification technique was designed. In '2' independent datasets, the technique was assessed with sensitivity, accuracy, along with specificity metrics. The top-notch models were outshined by the system.

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Table 3: Analysis of feature extraction method on PS images

Author	Features / Approach used	Purpose	Outcome	Advantages
Jonghwan Hyeon <i>et al.</i> [46]	CNN	Separated the image into numerous pieces, extraction of feature vectors of every piece, and computing the average of them.	Utilizing a pre-trained CNN, the feature vectors of the microscopic images were effectively extracted. Via the extracted features, 78% precision, recall, along with F-score were attained by the classifier.	Learned to resolve ImageNet Large Scale Visual Recognition problems.
Mingzhu Zhao <i>et al.</i> [47]	Size, Shape, Hyperkeratosis along with Deeply Stained.	Size-The ratio betwixt the size of the abnormal and the normal nucleus was found. The nucleus' heteromorphic features were explained. The shape of the normal cells' nucleus was in a regular circle, boat shape, or shuttle shape. After dyeing, cervical squamous epithelial cells turn to jacinth was named Hyperkeratosis.	The abnormal nucleus was effectively detected from squamous epithelial cells. The abnormal cell's accuracy was 76.47%.	For lesion detection of stained cells, this feature was vital.
Siti Noraini Sulaiman <i>et al.</i> [48]	Pseudo Colour Feature Extraction (PCFE) Semi-Automatic PCFE	PCFE-The nucleus size, cytoplasm, in conjunction with the grey level aimed at both parts were extracted. Semi-Automatic PCFE- The overlapping cell image's features were extracted.	The pre-CC stage of nuclei was efficiently diagnosed. Moreover, for improving the classification, the features (extracted) were helpful. The approach's classification performance was 76.35% accuracy.	The nucleus along with cytoplasm size of the cervical cells was successfully identified and retained.

Moh. Faturrahman <i>et al.</i> [49]	Local Binary Pattern (LBP) GLCM Shape Feature	LBP-The nucleus was extracted as of the multiple resolution <i>cervical images</i> . GLCM-Calculated statistical properties namely Correlation, Contrast, Energy, along with Homogeneity	Good results were attained by the amalgamation of LBP and GLCM. The framework's outcome was 97.35%.	The cervical cell image's edges were effortlessly detected because of pixel-centered computation.
Meng Zhao <i>et al.</i> [50]	GLCM '3' color models (Intensity color model, R-channel, along with gray image)	Colour Model-The contrast level would be augmented in nuclei together with cytoplasm utilizing the color models. GLCM- The pixel in the nuclei region was identified.	The nuclei (Abnormal and also normal) were effectually extracted. The method's accuracy was 98.98%, sensitivity, and also specificity was 95.0%, along with 99.33%.	Using GLCM, boundaries of nuclei were extracted grounded upon the intensity of pixels.

The features of the nucleus together with cytoplasm of PS images were examined in table 3. Therefore, the table stated that superior results were attained by the diagnosis system if more features were deemed.

2.4 Automated Pap-Smear Analysis

Elima Hussain *et al.* [51] recommended a shape context fully CNN aimed at the cervical nuclei's segmentation as well as classification in the PS images. The protocol was partitioned as '3' steps: in step-1, a Shape Representation Model's (SRM's) pre-training was implemented by the nuclear pixel mask. In Step-2, a fully CNN by SRM output image was trained and compiled with the pre-trained SRM design by pondering the network parameters. In step-3, the SRM's output was compiled with the nuclear pixel mask together with a nuclear type prediction mask aimed at acquiring the instance segmentation as well as classification output image. The design outshined '2' to-notch deep learning designs regarding the average Zijdenbos similarity index linked to segmentation together with binary categorization centred on accuracy. The methodology was efficient and more advanced analogized to the other prevalent techniques.

Pin Wang *et al.* [52] proffered an automatic CAD cervical smear image categorization system centred on adaptive pruning deep transfer learning PsiNet-TAP. The technique adapted transfer learning aimed at attaining the pre-trained design for the reason of a restricted number of images. After that, it was optimized by the modified convolution layer and trimming a few convolution kernels, which can interfere with the targetted categorization task. The methodology PsiNet-TAP was verified on 389 cervical PS images. The methodology had attained incredible performance that explicates the method's strength aimed at providing an effectual tool aimed at CC's classification in the clinical settings.

Payel Rudra Paul *et al.* [53] established an automated CC's detection technique. The methodology covered primarily '4' steps: bi-group enhancement, segmentation, FE, and then classification. In the enhancement stage, the technique implemented an adaptive median filter for eradicating the impulse noises as of the PS images, and then, employed a bi-group enhancer for discriminating the nuclei pixels as of other object pixels. Next, the morphological operation was utilized aimed at segmenting the nucleus areas as of the cervical smear images. Next, the nucleus features were taken out. Hence, the features extracted were inputted to the '2' clustering-centred classifiers, minimal distance and K-nearest neighbour classifiers that categorized the normal as well as abnormal cervical cells. Next, the methodology's performance was analogized with the top-notch techniques. The design utilized technique yielded excellent accuracy analogized to the prevalent techniques.

N. Sompawong *et al.* [54] intended to employ Mask Regional CNN (Mask R-CNN) for CC screening by PS histological slides. Images as of the PS slides that were pre-processed before were utilized in the design. The images had been resized whilst retaining the horizontal and vertical resolution ratio via altering the horizontal resolution to 1,024 pixels and padding the vertical resolution with black aimed at obtaining 1,024 pixels. Next, the Mask R-CNN design was utilized aimed at performing instance segmentation and discovering the diverse objects prevalent inside an image. The technique was analogized with the top-notch methodologies regarding the mean average precision (mAP), accuracy, specificity, and also sensitivity. The technique yielded efficient outcomes analogized to the existent techniques.

Wasswa William *et al.* [55] intended to ease a mistake's risk by automating the CC classification process as of the PS images. The framework comprises '5' steps: pre-processing, segmentation, FE, feature selection, and then classification. In the pre-processing phase, the image's contrast was boosted by Contrast Limited Adaptive Histogram Equalization (CLAHE). Next, cell

segmentation was attained via the Trainable Weka Segmentation classifier, and a sequential elimination technique was employed aimed at debris rejection. After that, as of the segmented cell, the features were taken out, and the essential features were attained by simulated annealing compiled with a wrapper filter, whilst classification was attained by a fuzzy c-means technique. Outcomes exhibited that the technique outshined diverse prevalent algorithms regarding the false-negative rate, false-positive rate, and also classification error.

Mithlesh Arya *et al.* [56] established a Fuzzy-centred Classification aimed at Cervical Dysplasia utilizing the Smear Images. Initially, the RGB image was changed to the L * a * b * format. Next, the K-means clustering methodology segmented the background and also the cytoplasm. Thresholding and morphological procedures were utilized aimed at segmenting the nucleus just as of the 2nd cluster. The nucleus's shape-centred features were extracted. During the classification stage, fuzzy C-mean (FCM) was utilized aimed at clustering. PCA was employed to discover the supreme prominent features. The PS image's classification was centred on the Bethesda system. The methodology was executed on a dataset acquired as of a pathologic laboratory. Via Rand index (RI), the performance evaluation was executed. The outcome exhibited the PCA factors' efficient results.

Table 4: Comparative analysis of different classifiers on Pap smear images

Author	Approach used	Purpose	Outcome	Limitation
Ling Zhang <i>et al.</i> [57]	CNN	Extracted the intricate features as of the cervical cell image automatically and classified CC's diverse stages, like normal, mild, moderate, severe, and also carcinoma	This technique offered higher accuracy. The classification's accuracy was 98.3%, specificity was 98.3%, and also the Area Under Curve's (AUC's) value was 0.99.	CNN had numerous layers, therefore, the training procedure consumed more time.
Kangkana Bora1 <i>et al.</i> [58]	LSSVM MLP	Detected the malignancy's highest degree presented in the PS image and categorized the samples.	Regarding this, the classifier attained a high F-score. The system yielded 98.38%, and 98.71% accuracy utilizing the LSSVM MLP algorithm.	Should boost the performance centred on the '7' class issues.
Yumi Novita Dewi <i>et al.</i> [59]	Naïve Bayes Weighted -PCA	It could also manage the rectified attribute values by overwhelming training data in the design development and prediction procedure.	Compilation of Naïve Bayes algorithm together with Weighted -PCA exhibited the finest accuracy value; the accuracy value was 87.24%.	A combined technique aimed at sample Bootstrapping and Weighted PCA to categorize single-image PS to '7' classes such that excellent accuracy might be attained.
Mohammed Kuko and Mohammad Pourhomayoun [60]	Ensemble learning and Deep learning	This protocol together with multiple Random forests is trained with the same image's separate rotations and gathered promising outcomes. This classification technique is for augmenting the cell data by rotating each cell sample prevalent within the training data-set.	The deep learning yielded higher accuracy and specificity values that were, 91.63%, and 87.43%; the ensemble learning technique attained higher sensitivity that was, 96.33% and least accuracy and specificity that were, 90.37%, and 83.59% correspondingly.	The approach should focus on cell's extraction and segmentation and to gather more data to acquire higher accuracy.

Table-4 examines the diverse classifiers centred on PS images with diverse metrics. The classifiers in this automated diagnosis are much time consuming and comprise fewer accuracy issues.

2.5 Comparative Analysis of Different Methods

The different classifiers' performance utilized for the CC diagnosis is examined in this section.

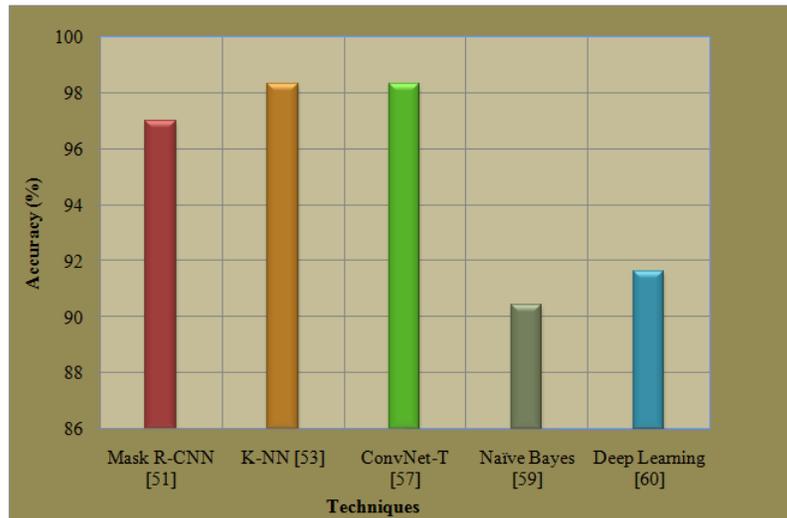


Figure 2: Accuracy analysis based on single-cell image

The performance of prevailing Mask R-CNN, ConvNet, KNN, Naive Bayes, along with deep learning approach centered upon an accuracy metric is analogized in figure 2. Herein, 98% accuracy is attained by the K-NN and also Convnet approaches, 97% accuracy is acquired by Mask R-CNN, remaining deep learning together with naive Bayes techniques attain 91.63% and 90.42% accuracy. Therefore, it is affirmed that a superior result is attained by the neural network-centered approaches when weighted against the other algorithms.

Table 5: Accuracy analysis based on multi-cell image

Methods	Accuracy
MLP [58]	98.71%
SVM [50]	77%
DBN [49]	97.35%
NN-RVM [61]	89%

The performance of disparate methods namely Multi-Layer Perceptron (MLP), SVM, Deep Belief Network [DBN], along with Neural Network- Relevance Vector Machine (NN-RVM) for CC diagnosis using the multi-cell PS image is examined in Table 5. Herein, higher accuracy like 98.71% and 97.35% is acquired by the MLP and DBN. Low accuracy analogized to the MLP and DBN was presented by the SVM along with NN-RVM like 77% and 89%.

3. CONCLUSION

One amidst the most general and deadliest cancers amidst women is CC. Regardless of that this cancer is completely curable if it is discovered at the precancerous phase. PS test is the most extensively executed screening protocol aimed at CC's early detection. Nevertheless, this hand-functioned screening technique suffers as of a high false-positive outcome owing to human errors. For incrementing the accuracy together with the manual screening mechanism, CAD techniques centred on deep learning is extensively established to automatically segment and then categorize the cervical image. This study explicates the survey of diverse methodologies in CC's automated diagnosis in the PS image. This study highlights the general flow of the CC diagnosis, such as, pre-processing, nucleus segmentation, the nucleus cell's features, and classification, utilizing diverse classifiers. The top-notch research pondered both the single-cell and multi-cell image. This survey examines the performance of both the single cell-centred and multi-cell centred diagnosis utilizing diverse classifiers centred on the accuracy metrics. For future work, this study recommends electing a neural network utilizing a deep analysis that boosts the performance of CC's diagnosis, as this will yield excellent accuracy in diagnosis.

CONFLICT OF INTERESTS

The authors declare that there is no conflict of interests.

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