

Advancements and Challenges in Deep Learning-Based Medical Image Segmentation for Cervical Cancer Detection

Saranya. A1, S. Ravi1*, Harsha Latha. P2, T.Kalaichelvi2
 1,2 Department of Computer Science
 School of Engineering and Technology
 Pondicherry University, Puducherry,
 605014, India

ABSTRACT

Cervical cancer remains a leading cause of cancer-related mortality for women, particularly in low-income areas where access to routine screening programs is sometimes limited. Early disease detection through precise diagnosis reduces mortality and enhances patient outcomes. Deep learning has emerged as a valuable tool in recent years for improving the accuracy and reliability of cervical cancer detection. Medical image segmentation is one of the most significant fields that has an impact and supports computer-aided diagnosis. The ability to accurately detect characteristics in cervical cytology and tissue images has shown considerable promise because of technologies like convolutional neural networks (CNNs) and other deep learning models. This study examines the most recent developments in the segmentation of medical images using deep learning to detect cervical cancer. It covers frequently utilized datasets, well-liked model architectures, and standard assessment techniques. The review also examines contemporary obstacles such as the scarcity of data, unequal class distribution, and issues with model transparency and model performance across populations. The work highlights the need for continued research to develop deep learning models that are dependable, understandable, and easily incorporated into clinical practice for early cervical cancer diagnosis by examining both developments and difficulties.

Keywords: Cervical cancer, Medical image segmentation, Deep Learning, Convolutional Neural network.

I. INTRODUCTION

Cervical cancer is common among women worldwide, particularly in underdeveloped nations. Cervical cancer is prevalent in women and has a high incidence and fatality rate. Usually, cervical cancer progresses gradually over time. Cervical cells undergo a metamorphosis when cervical cancer develops in the cervix. Dysplasia refers to changes in the cervical tissue that cause abnormal cells to appear. As the condition proceeds, cancer cells multiply and invade the cervix and its surroundings more deeply. Active screening and detection measures are the main ways to prevent cervical cancer. Earlier detection of cervical cancer reduces the premature cancer death rate. The areas with the highest recorded death rates correlate with this scarcity. Currently, cervical cancer screening techniques are used, and it has its advantages and disadvantages. Testing for the HPV, Pap smear cytology, colposcopy, and acetic acid cervix examination (VIA) are some screening tests for cervical cancer. Screening techniques for cervical cancer are as follows:

Bimanual pelvic examination: The physician will do a visual and physical examination in a Bimanual pelvic examination. It includes visual examinations with a speculum tool and tactile examinations with the hands.

Cervical cytopathology: The Pap test, which is additionally known as a Pap smear or liquid-based cervical cytology, gathers cervical cells to examine them for HPV-related anomalies that, if ignored, might grow into cervical cancer. Precancerous cells and cervical carcinoma can be found. Gently scraping cervical cells and examining them under a microscope is known as a Papanicolaou smear (Pap smear) or liquid-based cytology.

HPV typing test: Utilizing an HPV test, one can determine whether one is exposed to HPV strains linked to cervical cancer. Fourteen distinct HPV kinds were present throughout the trial. Most closely related to cervical cancer are HPV types 16 and 18, respectively. It is typically carried out concurrently with a Pap test or after it reveals abnormal alterations to the cervix. Human Papilloma Virus does not necessarily indicate malignancy.

Colposcopy: It examines the cervical tissues using a tool with a specific lens. Cervical biopsies detect cancer or precancer cells on the cervix. Precancerous cells are those that appear abnormal but are not yet cancerous. The tool magnifies the cervix region examined in the microscope. Pregnant women can make use of it.

Visual inspection with acetic acid (VIA): VIA is simple and helps identify cervical precancerous lesions and early invasive carcinoma that involves inspecting the uterine cervix with the eye after applying 5% acetic acid and reviewing the findings after one minute.[1].

Figure 1: Screening Methods of Cervical Cancer

Medical image analysis obtains relevant information from medical photographs, frequently accomplished through computer algorithms. Figure 1 explains the screening methods for cervical cancer. Significant issues in medical image analysis are in 2D visualization and exploration and the case of 3D classification and volumes, image segmentation, registration, and so on. For analyzing the medical image, techniques are used, namely x-ray (2D & 3D), Ultrasound, Computerized tomography (CT), MRI, and the microscope can obtain images for this analysis, and nuclear imaging (PET and SPECT). Medical segmentation of images is challenging

because of the many constraints imposed by the medical image collection technique, pathology kind, and biological variances. Professionals can analyze medical images, and there is a need for more medical imaging professionals.

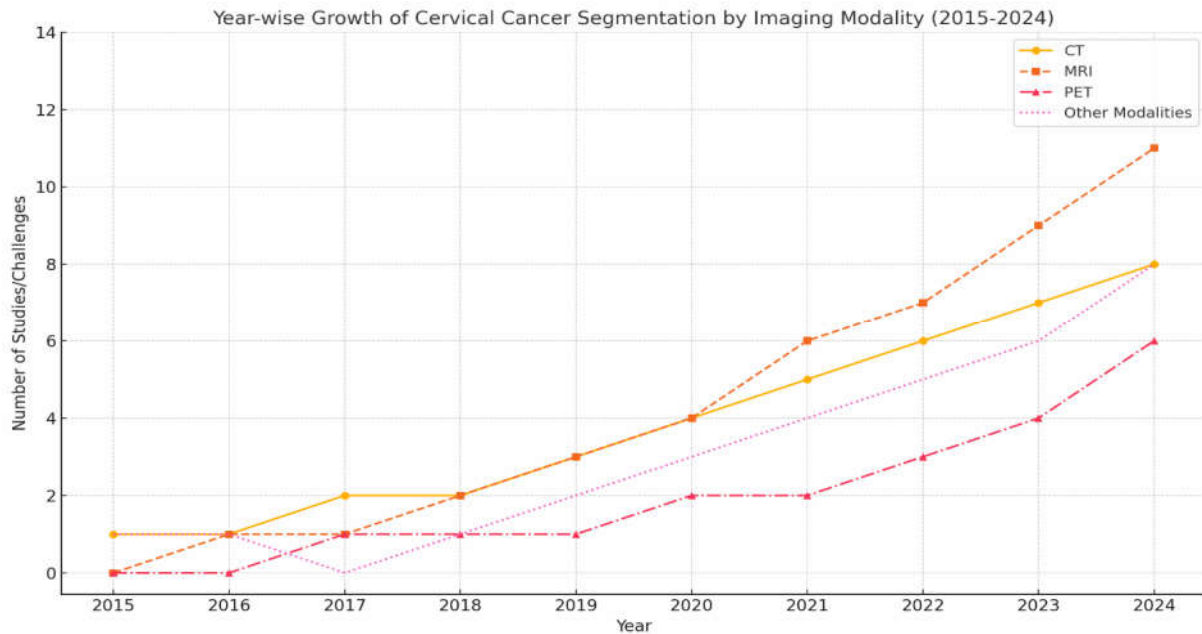


Figure 2: Grand Challenges in Diagnosis of Medical Modalities about Number of Segmentation Challenges [2]

The above figure 2 briefly explains the Number of segmentation challenges that took part in the diagnosis of CAD year-wise deviations when compared to earlier stages. They only focused on the CT scanner, but now many CAD systems have been implemented. Through that, it is easy to analyze the detection of medical images because it is much easier. Nowadays, instead of moving towards CT, we can use EM, Histology, MRI, and RGB for early diagnosis of the diseases[2].

II. MOTIVATION OF COMPUTER-AIDED DIAGNOSIS

The pap smear test helps to minimize the mortality rate from cervical cancer over the past 60 years. Usually, cells are taken from the cervix with a brush or spatula and spread on the glass slides; then, the test is performed. By utilizing a light microscope, cytotechnologists can assess whether the cells on the glass slides are malignant; by doing so, we can predict the cancer in the earlier stage. Depending on how challenging it is to align the cells, the screening procedures typically take 5 to 10 minutes. No more than 70 samples may be examined per day by a cytotechnologist. This procedure also necessitates complete attention at all times to detect any cancerous cells. We developed an automated computerized system to rapidly and accurately analyze the pap slides because it is always a top priority to have a qualified cytotechnologist screening and diagnosing them. For clinical follow-up, personalized treatment, Comparative research, and extensive imaging data must also be handled, and an autonomous system is needed.

Digital pathology and microscopes, as opposed to human examination, are crucial in early disease detection because they provide information for computer-aided diagnosis. (CAD).

Figure 3: Analysis of Medical Image Processing

In recent decades, extensive research has created computer-aided diagnosis systems to assist doctors in tracking cervical cancer. Figure 3. Explains the analysis of medical image processing. Cytology specimens can be automatically classified and identified with this system. Segmenting cells (cytoplasm and nuclei), extracting characteristics, and organizing them are the three processes of a conventional automated system. Before pre-processing, filtering techniques are used in traditional CAD systems to enhance image quality. The segmentation technique (k-means, clustering, superpixel, and so on) is used for cell nuclei extraction and correcting the segmented nucleus postprocessing work. After extracting each nucleus's features (morphological, color metric, and texture) selection, feature selection is performed with the highest discriminant ability.

Contrarily, In this article, we mainly focus on the raw data (RGB images) using the deep learning approaches and collect the data related to cancer. Deep learning approaches have significantly benefited from artificial intelligence, medical imaging, computational biology, natural language processing, image understanding, and computer vision.[3]

III. HISTORY OF DEEP LEARNING IN MEDICAL IMAGING

Deep learning plays a substantial role in medical imaging or medical image segmentation. The diagram below briefly explains the timeline of deep learning networks from the 20th and 21st centuries. In 1965, the first work of DL was initiated, and then in 1979, visual pattern recognition using ANN was used for the pattern recognition. Moving towards the Hopfield network, RNN came into the picture. Some neural networks were introduced in the 90s: LeNet, DBNs, ImageNet, AlexNet, and ZFNet. Since 2014 Inception, GAN VGGNet has been trained to

identify the segmentation of the images in medical image diagnosis.[4] Figure 4 explains the timeline of DL models in medical learning.

Figure 4: Timeline of Deep Learning Models in Medical Learning[2]

IV. SURVEY ON CERVICAL CANCER

A. Deep Learning in Segmentation and Classification Tasks

Segmentation is a crucial first stage in detecting cervical cancer using deep learning algorithms. Segmentation is separating the areas of interest (ROI) from the surrounding areas of a picture and locating the areas with cancerous tissue or abnormal cell growth. Various classification methods can be used when detecting cervical cancer with deep learning. Utilizing the Fully Convolutional Network(FCN) deep learning method is one popular strategy. Since they were created especially for image segmentation tasks, FCNs can be trained to map an input image to an output segmentation mask—some of the deep learning used in the previous work to enhance the ideal requirement.

Proposed DL-based approach for segmenting individual cells in Pap smear images with robust shape priors, enabling autonomous monitoring of cell changes; this technique solves the overlap problem. We divided the issue into discrete labeling tasks with suitable cost functions for many cells. A comparison between two different datasets shows how superior our suggested strategy is. Generally speaking, separating cervical cells from overlap aggregates in Pap smear images is challenging. Peng Liang 2019 et al. proposed the Depth learning algorithm to optimize the accuracy of cervical cancer. The method will be used to calculate the calculation results accurately after being optimized to match the requirements fully. Our modification significantly

boosts and improves the capability of cervical cancer MRI image segmentation technology for data processing. [5]. P. Guo 2020 et al. proposed an automatic segmentation method using deep learning in the cervix region. This work uses two cutting-edge DL segmentation methods: Mask R- (CNN) and MaskX R-CNN. Here, single-dataset and multi-dataset evaluation of large cervical imaging datasets is performed [6]. Yu-Chun Lin 2020 et al. suggested a deep-learning technique for automatically segmenting tumors. According to the research being done now, completely automated localization and segmentation of cervical cancer can aid in planning radiation therapy and lessen changes in gross tumor volume [7]. A. Baydoun 2021 et al. proposed technique mimics the human thinking paradigm by combining anatomical and imaging properties with a new, shallow U-net architecture to improve semantic segmentation efficacy U-Net has fewer parameters that need to be optimized than U-Net, making it better suitable for tasks [8]. X. Wang 2021 et al. This study's objective is to create a DL model for automatically delineating cervical cancer adjuvant radiotherapy using the CTV. Using 263 postoperative (CT) scans for radiation planning in patients who underwent radical hysterectomy at our clinic, the automatic contouring models were assessed [9]. Hua Chen 2021 et al. proposed that Instead of the complex yet ineffective methods of cell segmentation, there is a straightforward cell extraction method based on the nucleus that can successfully extricate all cell images from a WSI. It would be necessary to look further into how overlapping nuclei and cell clumps affect CompactVGG's detection precision to enhance the classification of such objects [10].

R. Mohammadi 2021 et al. proposed a strategy for quick and repeatable auto-contouring of OARs in HDR-BT based on deep convolutional neural networks. When using hand contouring as the standard, auto-segmentation for OAR delineation is possible using a deep learning approach—the major drawback of this method. An expert radiation oncologist's hand-drawn manual contours were the benchmark for measuring the DCNN's performance[11]. In an upcoming study, S. Adhikary 2021 et al. proposed the segmentation technique to investigate overlapping cells. The last two classes are combined into a single anomalous category, changing the situation into a two-class problem. Deep learning plays a vital role in this work to analyze screening features through cell images of DIC[12].

X. Jiang 2021 et al. proposed deep learning-based radiomic algorithms. These results show that deep neural network-based radionics techniques can predict vascular invasion in early-stage cervical cancer before surgery without time-consuming human tasks like feature development or selection or hand-crafted segmentation. The flexible and extendible models of the proposed prediction models make it simple to adapt them to new datasets by parameter fine-tuning, suggesting that this strategy could be utilized to support future clinical applications[13].

Y. Fan 2022 et al. proposed an object detection method whereby the U-net structure can be made to adapt to ambiguous borders. In addition, they employ the loss function for object detection to achieve better results and tackle the issue with the small dataset size.[14]. G. Liu 2022 et al. proposed cervical cytology images called Cx22. This dataset is built on open-source photos that our institute previously provided and comprises fully annotated labels for all cellular instances.

We discovered that false-negative effects still have a sizable negative influence on the network performance even when cell nuclei are segmented, where there are fewer positive pixels [15]. Krishna Prasad Battula 2022 et al. proposed classification efficiency, and even more pre-processing was done. Here, data enhancement methods are applied, images can be scaled, and to increase the image's quality, we use CLAHE. By including the image processing tools, there will be a much greater increase in improvement [16].

J. Park 2022 et al. ROI can be unsupervisedly extracted from colposcopy images using the proposed autonomous cervix region segmentation method based on DL. The performance in cervical ROI segmentation is improved due to this work, which is a significant benefit. The disadvantage of this approach is that when analyzing colposcopy, cervix division impacts the diagnostic precision [17].

J. Wang., 2022 et al. proposed structures obtained by Deep Learning-based auto-segmentation to that conventional human delineation. Our auto-segmentation satisfactorily segmented most EBRT planning structures. However, using CTV could lead to clinical acceptance. The cervical cancer workflow required DL-based auto-segmentation to produce proper contouring. The approach for cervical cancer will depend heavily on automatic delineation to deliver precise contouring[18]. S. R, 2022 et al. proposed classified and distinguished cervical cytopathology images using DL and ML methods. According to the review, processing images from cervical cytopathology is an increasing problem. It is, therefore, simple to determine which algorithm is better. Future models could be more intricate to increase accuracy. In this paper, they have briefly explained the machine learning and deep learning technologies used in artificial intelligence[19]. D. Brenes 2022 et al. proposed deep learning, high-resolution in vivo optical images that can identify cervical precancers. The network is drawn to nuclear features by multi-task atomic segmentation. Even with less training data, the method outperformed cutting-edge benchmarks. Independent validation set performance was consistent with expert clinical perception. Combining optical image data with HPV test results increased the capacity to identify cervical precancers. In the case of low- and middle-income countries, DL-based CAD solutions help to detect cervical cancer [20].

Yuliana Jiménez Gaona., 2022 et al. The proposed work presents a different approach to colposcopy-based cervical examination, and the colposcopy diagnosis is contrasted with CAD colposcopy—computer-aided Images of a diagnostic tool flowchart for the cervix. Regions of interest (ROIs) manually cropped were first extracted. Then, artificial pictures were created using data augmentation from the colposcopy ROIs. Finally, if our model holds up, it has a wide range of applications, particularly in low-resource areas with a shortage of skilled medical workers [21]. Peng Guo., 2022 et al. proposed a work that explains the robust segmentation network assessing the registration of cervical images. We developed an independent channel, an unsupervised registration network comprised of CNN, and a spatial transform module. We outperformed the initial unregistered time sequences on the recognized time sequences regarding the average Dice score. Over time, precise alignment of cervical areas can aid in automated longitudinal analysis for AVE and landmark tracking[22]. C . W. 2022 et al. suggested locating the SCJ, the area of aceto-whitening, and other clinically significant information for visual assessment in a dynamic routine. We tested the registration results using the expected segmentation masks because the segmentation network behaved well on the time sequence

dataset. In a subsequent investigation, we intend to refine the algorithm to achieve more reliable registration performance [23]. Table 1 describes the segmentation and classification of cervical cancer.

Table 1. Deep Learning Models for Segmentation&Classification, highlighting the techniques and key features

Model	Type	Key Features	Applications in Medical Image Segmentation	Applications in Medical Image Classification
CNN	Segmentation & Classification	Hierarchical feature extraction- Local spatial features- End-to-end training	Tumor/lesion segmentation- Lesion detection in MRI, CT scans	- Tumor classification (benign vs. malignant)- Pap smear image classification
U-Net	Segmentation	Encoder-decoder architecture- Skip connections for fine spatial details	Pap smear segmentation- Tumor or organ segmentation in MRI/CT	Not commonly used for classification; focused on segmentation
FCN	Segmentation	Pixel-wise predictions- Replaces fully connected layers with convolutions	Lesion/organ segmentation- MRI/CT scan segmentation	Not commonly used for classification; focused on segmentation
Mask R-CNN	Segmentation	Instance segmentation- Detects and segments multiple objects- Adds pixel-wise masks.	Tumor or abnormal cell segmentation- Cervical lesion detection	Not typically used for classification; more focused on segmentation
DeepLab (v3, v3+)	Segmentation	Dilated convolutions- Atrous convolutions for multi-scale feature extraction	Tumor/organ segmentation- Detailed segmentation of regions of interest in CT/MRI	It is not typically used for classification; it is more focused on segmentation.
Vision Transformers (ViTs)	Segmentation & Classification	Divides image into patches- Self-attention mechanism- Captures global dependencies.	Segmenting complex patterns in high-resolution images- Cervical cytology image segmentation	Classifying complex medical images (e.g., cancerous vs. non-cancerous)

Pre-trained Models (Transfer Learning: ResNet, VGG16)	Classification	Fine-tuned on smaller medical datasets- Leverages knowledge from large datasets like ImageNet	Not typically used for segmentation	Cervical cancer classification- Histopathology image classification
Hybrid CNN-Transformer Models	Segmentation & Classification	Combines CNN feature extraction with Transformer global context- Improved performance	Tumor/lesion segmentation- Organ segmentation in high-res images	Classifying complex patterns in images (e.g., cancer stage classification)
Support Vector Machines (SVMs) with Deep Features	Classification	Uses deep features extracted from CNNs- Robust Classification for small datasets	Not typically used for segmentation	Tumor classification (benign vs. malignant) based on extracted CNN features

B. Deep Learning in Classification Task

Cervical cancer classification can be done using deep learning techniques. Typically, it forms in the lower portion of the uterus. Stages in cancer and the most effective treatments are usually determined when classifying cervical cancer. Large datasets of medical images, such as scans for cervical cancer, can be used to teach deep-learning algorithms to find patterns and features connected to various stages of the illness. These algorithms can divide cervical cancer into multiple stages based on how the cancer cells appear in the images. CNN is one type of deep learning method applied to classify cervical cancer. In the survey below, we took some classification tasks done using deep learning in cervical cancer.

N. Dong 2020 et al. The author briefly explains the techniques used in classification, which integrates Inception v3 and artificial characteristics, improving the accuracy of cervical cell detection. The algorithm aims to overcome the shortcomings of the two classification methods previously discussed. The article also carries over the significant capacity for learning from transfer learning. This approach yields more than 98% accuracy, offering a valuable framework for computer-aided cervical cancer diagnosis [24]. Aditya Khamparia 2020 et al. DL system for the Internet of Health Things (IoHT) is being created using Pap smear images to identify and categorize cervical cancer. Transfer learning plays a significant role in the Internet of Health Things. This information was then used to classify healthy and diseased cervical cells in a dense, flattened layer [25].

Elima Hussain 2020 et al. reduced observer biases or even decreased the workload of manual pathologists, which has been suggested as a benefit of the deep learning-based technique. Utilizing the majority vote method, with an attempt to include, based on the analysis of images in Pap smear, six different CNN models that were used to identify the classification [26]. José Martínez-Más 2020 et al. proposed the cell merge approach, which has been designed and

implemented a classification model that improves the efficiency of the PAP smears. They allow the overlapping and folding of various cells for feasibility, reliability, and accuracy of cervical smears Classification. They also designed and implemented a CNN for Pap-smear image classification to give realistic cell fusion [27].

N. Diniz et al. 2021 et al. proposed the classification of actual images in cervical cells. We use cutting-edge convolutional neural network architectures and collect from traditional Pap smears to increase the test findings' dependability and make them more reproducible in the real world. Introduction of the recurrent neural network (rnn) architecture. The most recent findings for the CRIC [28]. O. E. Aina 2021 et al. proposed the challenge for medical professionals to categorize the cervix based on the degree of cervical intraepithelial neoplasia (CIN). Indiscriminative fine-tuning and an optimal learning rate are utilized to increase the performance level of the models. In that way, actual treatments are given to the patients, and accurate diagnoses can be made [29].

J. Li 2022 et al. proposed a DL-based classification algorithm for cancer cells (L-PCNN), which can automate the classification of cervical cells, diagnose cervical precancerous lesions quickly, improve cervical cancer diagnosis efficiency, and reduce cervical cancer screening costs. They are aiming to prevent cervical cancer and improve screening cure rates.[30]. H. Alquran 2022 et al. proposed a novel automatic segmentation in cervical cancer using the DL method to detect or analyze data. For the detection of cancer, they use a six-step process, which is used to detect the cells that have the cancer. PCA and CCA help to reduce the significant features and to produce the features in pap smear images [31]. R. Yakkundimath 2022 et al. proposed an ensemble classifier created by (ANN), (RF), and (SVM)—to classify images. An ensemble classifier was created using the co-occurrence histogram combined with the base classifiers. The classification workflow used in the ensemble classifier helps to integrate the previously mentioned basic classifiers, which were assessed after the segmented image dataset using the k-means clustering technique. [32].

Key findings from the literature review on deep learning-based cervical cancer diagnosis reveal great segmentation accuracy, with models reaching 99.5% accuracy. Nonetheless, there are still issues with computing efficiency, data quality, and dataset constraints. Although models show versatility, they must be further optimized, particularly for handling overlapping cells and enhancing image quality. More sophisticated methods, like label cropping based on Region of Interest, can improve performance. Even with excellent accuracy rates, practical applications still need to be integrated with clinical supervision, and additional study is required to overcome current constraints.

V. DEEP LEARNING APPLICATION OF CERVICAL CANCER

Deep learning plays a significant role in the medical field and in analyzing or detecting lesions over the CAD system.

SEGMENTATION is further classified into two different types. Segmentation is one of the methods that helps to split the digital images into various subgroups, reducing the image's complexity.

CLASSIFICATION works based on the visual features of automatically categorizing medical images into different classes and identifying them. A classification of medical images helps doctors to determine the results accurately. In the case of deep learning, CNN algorithms split the patterns and features from the images and then categorize them based on the features of the image.

DETECTION Regarding medical imaging, detection is the method of autonomously locating and identifying abnormalities or other features of interest utilizing DL algorithms. Medical image detection aims to assist clinicians and physicians in precisely and swiftly identifying potential illnesses or ailments, which will help them plan their subsequent diagnoses and treatments.

REGISTRATION In medicine, registration is a method of lining up two or more images of the same patient that were acquired at different intervals or by employing various imaging modalities. Registration is crucial in several medical applications, such as treatment planning, image-guided therapies, and illness monitoring. DL-based medical image registration techniques provide enormous results in image modalities.

CHARACTERIZATION Possible benefits of DL-based medical picture categorization include increased diagnostic precision, decreased diagnostic turnaround time, and more individualized therapy planning.

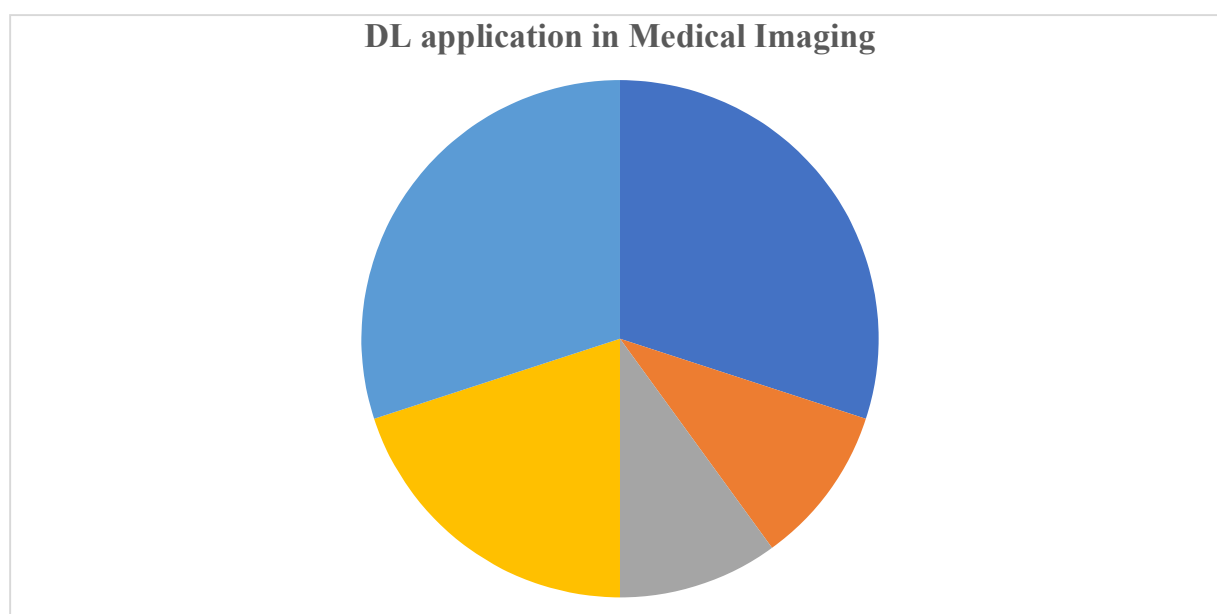


Figure 5: Deep Learning Application in Medical Imaging[2]

Frameworks used in detecting cervical cancer

Several DL frameworks have been used to detect cervical cancer. Here are some commonly used frameworks:

TensorFlow: TensorFlow is an open source that may be used for various tasks, including medical image analysis. TensorFlow can analyze medical imagery, such as Pap smear or cervical biopsy images, to find aberrant cells or lesions that could signal cervical cancer diagnosis.

Keras: Keras is another popular DL framework that is simple and accessible. It builds and trains DL models for various applications, including cervical cancer detection.

PyTorch: PyTorch is a DL framework developed by Facebook, and also it is open source. PyTorch is used to build and train neural networks for various tasks, including medical image analysis. The following steps can be taken to detect cervical cancer using PyTorch: Collect and pre-process the dataset, Define the model architecture, Train the model, and Validate& test the model.

Caffe: Caffe is also one of the frameworks used in DL. It is particularly well-suited for image classification tasks and can be used to identify cervical cancer. Caffe should be used to detect cervical cancer by training a (CNN) on datasets of cervical cell images to classify them as normal or abnormal (indicative of cervical cancer or other abnormalities).

Figure 6: Framework of Deep Learning for Cervical Cancer

MXNet: MXNet is a deep learning framework that Apache develops designed for large-scale image analysis tasks and comes up with some features like scalability efficiency. It has many libraries to build and train the DL models. It is a much more accurate and efficient method for

researchers and medical professionals for detecting and diagnosing cervical cancer, ultimately improving patient outcomes.

VI. COMPARISON BETWEEN DEEP LEARNING SEGMENTATION AND CLASSIFICATION

Table 2 Comparison between Deep Learning Segmentation and Classification

Author & Year	Merits	Demerits	Dataset	Accuracy (%)
Y. Song, 2020 [4]	It helps to address the overlapping issues.	Low color contrast among cells	ISBI dataset, SZU dataset	
Peng Liang, 2020 [5]	Feasibility, Accuracy, Reliability	Need to handle particular difficulties		98
P. Guo, 2020 [6]	More reliable and robust	Suggests employing sparsely labeled picture data	CVT, ASCUS/LSIL, ALTS, NCI, Kaggle Dataset, Intel & MobileODT	94.7
Yu-Chun Lin, 2020 [7]	Accurate and reliable	Needs work on performance and accuracy levels		92.3
A. Baydoun, 2021 [8]	Effectiveness	Needs work on volumes and GTV		
X. Wang, 2021 [9]	Reduces time and cost	Needs work on performance and accuracy level		92.16
Hua Chen, 2021 [10]	Accuracy, Reliability	Needs work on overlapping and accuracy	SIPaKMeD, Herlev datasets	92
R. Mohammadi, 2021 [11]	High accuracy	The location of needles differs between patients		92
S. Adhikary, 2021 [12]	Less complex, Accurate results	Needs work on reliable data	Herlev dataset, DIC dataset, SMOTE	97
X. Jiang, 2021 [13]	Flexible, Extendible models	Drawbacks in early-stage cervical cancer prediction	DCE-T1 and T2WI MRI dataset	91.1
Y. Fan, 2022 [14]	Good performance	With a limited dataset size, object detection relies on a loss function	CT images from the database	90.3
Q. Liu, 2022 [15]	Better performance	Needs work on accuracy and reliability	SIPAKMED, Cx22 dataset,	93.5

			CEDD-514-FNO dataset	
Krishna Prasad Battula, 2022 [16]	Improved classifier performance, segmentation	Needs to improve efficiency and lower computational complexity	Herlev dataset	97.42
J. Park, 2022 [17]	Increased segmentation performance	Needs to enhance accuracy while diagnosing in colposcopy	Intel and MobileODT database	97.8
J. Wang, 2022 [18]	High-level tasks efficiently	Needs to improve segmentation accuracy	Clinical dataset	95
S. R, 2022 [19]	Increased accuracy	Needs to increase the accuracy level	Herlev dataset	99.5
D. Brenes, 2022 [20]	Accuracy, Efficiency	HRME requires colposcopic impressions for guidance		95
Yuliana Jiménez Gaona, 2022 [21]	Performance, Accuracy	Needs to enhance the training classification using CNN models	Public and private datasets from ODT	95.8
Peng Guo, 2022 [22]	Robust, Accurate	Needs to optimize the algorithm for robustness and image quality	--	--
C.-W. Wang, 2022 [23]	Increases diagnostic accuracy	Needs to increase performance level	--	94.6
N. Dong, 2022 [24]	Accuracy, Efficiency in computer-assisted cervical cancer diagnosis	It needs work on efficiency, low complexity, and good universality	Herlev dataset	98
Aditya Khamparia, 2022 [25]	Effective and reliable detection and classification	Knowledgebased on specific hardware is much more important	Pap smear, Herlev dataset	97.86

VII. PERFORMANCE METRICS

Performance metrics help to evaluate the accuracy and effectiveness of medical image processing techniques. Some of the commonly used performance metrics in medical image processing include:

Sensitivity: In medical image processing, sensitivity measures the ability of a system to correctly identify regions of interest (such as tumors) in medical images.

Sensitivity =

(1)

Specificity:In medical image processing, it helps to measure a system's ability to accurately exclude regions that are not of interest (such as normal tissue) in medical images.

$$\text{Specificity} = \quad (2)$$

Accuracy:In medical image processing, accuracy measures how well a system's output matches the ground truth.

$$\text{Accuracy} = \quad (3)$$

Precision: In medical image processing, precision helps to measure the degree to which a system's result is consistent across multiple runs.

$$\text{Precision} = \quad (4)$$

Recall: Recall is a metric used in medical image processing to gauge how consistently a system's output holds across various images.

$$\text{Recall} = \quad (5)$$

F1 score: In medical image processing, the F1 score is frequently employed in evaluating the overall accuracy of a system's output. Assessing the precision and recall average, with a maximum value of 1.

$$\text{F1 score} = \quad (6)$$

Dice coefficient: The maximum value describing the overlap between two data sets is 1. The Dice coefficient measures how closely a system's output matches reality in medical image processing.

$$\text{Dice coefficient} = \quad (7)$$

Performance metrics play a significant role in evaluating the effectiveness of medical image processing techniques, such as segmentation and classification algorithms, and guiding clinical decision-making in diagnosing and treating medical conditions.

VIII. CONCLUSION

Cervical cancer is one of the life-threatening diseases millions of women are affected worldwide. While developing effective prevention and treatment strategies has improved patient outcomes, much work remains to fight against cervical cancer. DL applications in cervical cancer detection and diagnosis are an emerging study area with significant promise to enhance patient outcomes. Although deep learning techniques for cervical cancer diagnosis are still in their infancy, the early results are pretty promising. Through medical image segmentation and other advanced

technologies, researchers can achieve highly accurate results that can assist medical professionals in making informed decisions about patient care. While further research and validation are needed to establish the efficacy of these techniques fully, the evidence at the premises points to their potential to completely change cervical cancer detection and therapy.

REFERENCES

- [1] T. G. Debelee, S. R. Kebede, F. Schwenker, and Z. M. Shewarega, "Deep Learning in Selected Cancers' Image Analysis—A Survey," *J. Imaging*, vol. 6, no. 11, pp. 1–40, 2020, doi: 10.3390/jimaging6110121.
- [2] I. Rizwan I Haque and J. Neubert, "Deep learning approaches to biomedical image segmentation," *Informatics Med. Unlocked*, vol. 18, p. 100297, 2020, doi: 10.1016/j.imu.2020.100297.
- [3] M. M. Rahaman *et al.*, "A survey for cervical cytopathology image analysis using deep learning," *IEEE Access*, vol. 8, pp. 61687–61710, 2020, doi: 10.1109/ACCESS.2020.2983186.
- [4] R. Yousef, G. Gupta, N. Yousef, and M. Khari, *A holistic overview of deep learning approach in medical imaging*, vol. 28, no. 3. Springer Berlin Heidelberg, 2022. doi: 10.1007/s00530-021-00884-5.
- [5] P. Liang, G. Sun, and S. Wei, "Application of Deep Learning Algorithm in Cervical Cancer MRI Image Segmentation Based on Wireless Sensor," *J. Med. Syst.*, vol. 43, no. 6, Jun. 2019, doi: 10.1007/s10916-019-1284-7.
- [6] P. Guo, Z. Xue, L. Rodney Long, and S. Antani, "Cross-dataset evaluation of deep learning networks for uterine cervix segmentation," *Diagnostics*, vol. 10, no. 1, 2020, doi: 10.3390/diagnostics10010044.
- [7] Y. C. Lin *et al.*, "Deep learning for fully automated tumor segmentation and extraction of magnetic resonance radiomics features in cervical cancer," *Eur. Radiol.*, vol. 30, no. 3, pp. 1297–1305, Mar. 2020, doi: 10.1007/s00330-019-06467-3.
- [8] A. Baydoun *et al.*, "Auto-contouring FDG-PET/MR images for cervical cancer radiation therapy: An intelligent sequential approach using focally trained, shallow U-Nets," *Intell. Med.*, vol. 5, no. September 2020, p. 100026, 2021, doi: 10.1016/j.ibmed.2021.100026.
- [9] X. Wang, G. Ouyang, Z. Chen, L. Fu, Y. Shen, and Y. Yao, "Automatic Contouring of the Clinical Target Volume (CTV) for Cervical Cancer Adjuvant Radiotherapy Using Deep Learning Algorithm," *Int. J. Radiat. Oncol.*, vol. 111, no. 3, p. e99, 2021, doi: 10.1016/j.ijrobp.2021.07.491.
- [10] H. Chen *et al.*, "CytoBrain: Cervical Cancer Screening System Based on Deep Learning Technology," *J. Comput. Sci. Technol.*, vol. 36, no. 2, pp. 347–360, 2021, doi: 10.1007/s11390-021-0849-3.
- [11] R. Mohammadi, I. Shokatian, M. Salehi, H. Arabi, I. Shiri, and H. Zaidi, "Deep learning-based auto-segmentation of organs at risk in high-dose rate brachytherapy of cervical cancer," *Radiother. Oncol.*, vol. 159, pp. 231–240, 2021, doi: 10.1016/j.radonc.2021.03.030.
- [12] S. Adhikary, S. Seth, S. Das, T. K. Naskar, A. Barui, and S. P. Maity, "Feature assisted cervical cancer screening through DIC cell images," *Biocybern. Biomed. Eng.*, vol. 41, no. 3, pp. 1162–1181, 2021, doi: 10.1016/j.bbe.2021.07.005.
- [13] X. Jiang *et al.*, "MRI Based Radiomics Approach with Deep Learning for Prediction of Vessel Invasion in Early-Stage Cervical Cancer," *IEEE/ACM Trans. Comput. Biol. Bioinforma.*, vol. 18, no. 3, pp. 995–1002, 2021, doi: 10.1109/TCBB.2019.2963867.
- [14] Y. Fan, Z. Tao, J. Lin, and H. Chen, "An Encoder-Decoder Network for Automatic Clinical Target Volume Target Segmentation of Cervical Cancer in CT Images," *Int. J. Crowd Sci.*, vol. 6, no. 3, pp. 111–116, 2022, doi: 10.26599/IJCS.2022.9100014.
- [15] Q. Liu and P. Hu, "Extendable and explainable deep learning for pan-cancer radiogenomics research," *Curr. Opin. Chem. Biol.*, vol. 66, p. 102111, 2022, doi: 10.1016/j.cbpa.2021.102111.

- [16] K. P. Battula and B. S. Chandana, "Deep Learning based Cervical Cancer Classification and Segmentation from Pap Smears Images using an EfficientNet,"*Int. J. Adv. Comput. Sci. Appl.*, vol. 13, no. 9, pp. 899–908, 2022, doi: 10.14569/IJACSA.2022.01309104.
- [17] J. Park, H. Yang, H. J. Roh, W. Jung, and G. J. Jang, "Encoder-Weighted W-Net for Unsupervised Segmentation of Cervix Region in Colposcopy Images,"*Cancers (Basel)*, vol. 14, no. 14, 2022, doi: 10.3390/cancers14143400.
- [18] J. Wang, Y. Chen, H. Xie, L. Luo, and Q. Tang, "Evaluation of auto-segmentation for EBRT planning structures using deep learning-based workflow on cervical cancer,"*Sci. Rep.*, vol. 12, no. 1, pp. 1–12, 2022, doi: 10.1038/s41598-022-18084-0.
- [19] R. Surendiran, M. Thangamani, S. Monisha, and P. Rajesh, "Exploring the Cervical Cancer Prediction by Machine Learning and Deep Learning with Artificial Intelligence Approaches,"*Int. J. Eng. Trends Technol.*, vol. 70, no. 7, pp. 94–107, 2022, doi: 10.14445/22315381/IJETT-V70I7P211.
- [20] D. Brenes *et al.*, "Multi-task network for automated analysis of high-resolution endomicroscopy images to detect cervical precancer and cancer,"*Comput. Med. Imaging Graph.*, vol. 97, no. February, 2022, doi: 10.1016/j.compmedimag.2022.102052.
- [21] Y. Jiménez Gaona *et al.*, "Radiomics Diagnostic Tool Based on Deep Learning for Colposcopy Image Classification,"*Diagnostics*, vol. 12, no. 7, 2022, doi: 10.3390/diagnostics12071694.
- [22] P. Guo, Z. Xue, S. Angara, and S. K. Antani, "Unsupervised Deep Learning Registration of Uterine Cervix Sequence Images,"*Cancers (Basel)*, vol. 14, no. 10, 2022, doi: 10.3390/cancers14102401.
- [23] C. W. Wang *et al.*, "Weakly supervised deep learning for prediction of treatment effectiveness on ovarian cancer from histopathology images,"*Comput. Med. Imaging Graph.*, vol. 99, no. November 2021, p. 102093, 2022, doi: 10.1016/j.compmedimag.2022.102093.
- [24] N. Dong, L. Zhao, C. H. Wu, and J. F. Chang, "Inception v3 based cervical cell classification combined with artificially extracted features,"*Appl. Soft Comput.*, vol. 93, p. 106311, 2020, doi: 10.1016/j.asoc.2020.106311.
- [25] A. Khamparia, D. Gupta, V. H. C. de Albuquerque, A. K. Sangaiah, and R. H. Jhaveri, "Internet of health things-driven deep learning system for detection and classification of cervical cells using transfer learning,"*J. Supercomput.*, vol. 76, no. 11, pp. 8590–8608, Nov. 2020, doi: 10.1007/s11227-020-03159-4.
- [26] E. Hussain, L. B. Mahanta, C. R. Das, and R. K. Talukdar, "A comprehensive study on the multi-class cervical cancer diagnostic prediction on pap smear images using a fusion-based decision from ensemble deep convolutional neural network,"*Tissue Cell*, vol. 65, no. November 2019, p. 101347, 2020, doi: 10.1016/j.tice.2020.101347.
- [27] J. Martínez-Más *et al.*, "Classifying Papanicolaou cervical smears through a cell merger approach by deep learning technique,"*Expert Syst. Appl.*, vol. 160, 2020, doi: 10.1016/j.eswa.2020.113707.
- [28] D. N. Diniz *et al.*, "A deep learning ensemble method to assist cytopathologists in pap test image classification,"*J. Imaging*, vol. 7, no. 7, 2021, doi: 10.3390/jimaging7070111.
- [29] O. E. Aina, S. A. Adeshina, A. P. Adedigba, and A. M. Aibinu, "Classification of Cervical Intraepithelial Neoplasia (CIN) using fine-tuned Convolutional Neural Networks,"*Intell. Med.*, vol. 5, no. April, p. 100031, 2021, doi: 10.1016/j.ibmed.2021.100031.
- [30] J. Li *et al.*, "Cervical cell multi-classification algorithm using global context information and attention mechanism,"*Tissue Cell*, vol. 74, no. August 2021, pp. 1–7, 2022, doi: 10.1016/j.tice.2021.101677.
- [31] H. Alquran, M. Alsalatie, W. A. Mustafa, R. Al Abdi, and A. R. Ismail, "Cervical Net: A Novel Cervical Cancer Classification Using Feature Fusion,"*Bioengineering*, vol. 9, no. 10, 2022, doi: 10.3390/bioengineering9100578.
- [32] R. Yakkundimath, V. Jadhav, B. Anami, and N. Malvade, "Co-occurrence histogram based ensemble of classifiers for classification of cervical cancer cells,"*J. Electron. Sci. Technol.*, vol. 20, no. 3, pp. 1–10, 2022,

doi: 10.1016/J.JNLEST.2022.100170.

- [33] Y. Song *et al.*, "Accurate cervical cell segmentation from overlapping clumps in pap smear images,"*IEEE Trans. Med. Imaging*, vol. 36, no. 1, pp. 288–300, 2017, doi: 10.1109/TMI.2016.2606380.