Deep Learning Techniques in Cervical Cancer Diagnosis

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Abstract

The second most frequent malignancy in women globally is cervical cancer, with a 60% fatality rate, which arises from the change of cells in the female cervix, and is one of the treatable malignancies when detected in its early stages. Thus, the goal of early detection of cervical cancer is to diminish the mortality rate. Unfortunately, the diagnosing procedure is inefficient and imprecise because it relies primarily on the pathologist's experience. Considering this issue, the researchers have started working on the automatic diagnosis of cervical cancer for preventing the misclassification of cancerous and non-cancerous cells. This review paper presents various deep learning approaches for the automatic diagnosis of cervical cancer which is more accurate than the traditional approach. Moreover, weaknesses, strengths, accuracy, other performance metrics, and dataset description have been highlighted for each respective technique. The paper also addresses the classification, segmentation, and feature extraction that will help pathologists with an efficient diagnosis process. The survey examines nine years' worth of articles, conference papers, and journals on deep learning in the automated diagnosis and categorization of cervical cancer. Moreover, the study examines 55 papers collected via electronic means from reputed scientific databases.

Keywords: ***Cancer, Deep Learning, Pre-Cancerous, Segmentation, Virus***

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1.Introduction

The transition of normal cells that cover the top section of the cervix into malignant tumors is known as cervical cancer, which is one of the chief reasons for women's death [1],[24]. It is one of the tumors that can be cured if caught early enough. The different signs of cervical cancer include longer and heavier menstrual periods than usual, painful sex, and Vaginal discharge being more frequent, followed by back pain. This malignancy is one of the world's most dangerous and frequent cancers in females. It is a sexually transmitted viral disease that primarily affects women and is caused by the human papillomavirus (HPV) [2],[37]. This type of cancer has an 89 percent survival rate if identified early, however it requires computer-aided diagnosis for proper analysis of false negative rate [3], [7]. As a result, effective early screening and treatment can significantly decrease cervical cancer mortality, unfortunately, proper screening methods are still unavailable in underdeveloped nations [4], [29]. The most common screening mechanism for cervical lesions is the Pap smear test to visualize the pre-cancerous and cancerous cells [5], [55]. The different screening methods involve Pap tests or HPV DNA tests. In a Pap test, the cervix is scraped and brushed for cells, which are subsequently checked in a lab for abnormalities. About 445,000 patients have been identified with cervical cancer disease [6],

[49]. HPV DNA test specifically looks for infection with any of the HPV strains that are most likely to cause cervical cancer in cells taken from the cervix. In both situations, the cells are finally analyzed by a pathologist which includes manual intervention.

Cervical cells are broadly categorized into seven distinct cells: superficial squamous epithelial (polygon shaped, centralized pyknotic nuclei and size range from 40-60 microns), intermediate squamous epithelial (same size as superficial squamous cells, with slightly bigger central vesicular nuclei, fine, uniform chromatin patterns), columnar epithelial (consists of columnar cells with a larger nucleus), mild dysplasia(pre-cancerous and only the bottom one-third of the cells in the cervix's top layer are abnormal), moderate dysplasia(abnormal cells can be found in up to two-thirds of the layer), severe dysplasia(entire upper layer of the cervix contains precancerous cells) and carcinoma-in-situ.

This hand-operated cell screening frequently results in a considerable difference in specimen quality, like unequal cellular material distribution, which creates thick clusters that light does not pass, while other portions of the specimen may contain numerous overlapped cells, making precise interpretation difficult. It takes a lot of mental effort to visually scan and classify hundreds of cervical cells and cell clusters. This procedure is time-consuming and has a lot of inaccuracy, even hundreds or thousands of cells can be incorrectly classified and analyzed [1, 7, 17]. Thus Computer-assisted cervical screening approaches are offered to assess the cervix and categorize the cells as either normal or abnormal [41]. The development of artificial intelligence has brought more productive alternatives to various medical imaging difficulties like skin cancer detection, lung cancer, and other types of cancer [3]. The CAD technology has been aided greatly in recent decades by deep learning technology, which is a strategy to minimize observational errors and, the rate of false negatives in medical images. Because it can produce high-level feature representations directly from raw images, deep learning is gradually displacing standard machine learning methods [10], [33]. Deep Learning is effective in a variety of real-world applications. Cervical cancer spread can be declined if powerful screening tools are properly used. Thus, this paper introduced a detailed description of various supervised and unsupervised deep learning algorithms for automatic and timely cervical cancer diagnosis. From a detailed study, it has been observed that Automatic cervical cancer screening focuses on three major issues: segmentation of cytoplasm and nucleus, extracting features from (cytoplasm, nucleus), and classification of (normal, abnormal) cells. The classification process is further categorized into 2 class classifications or 7 class classifications. As per the survey few authors have also worked on 4 or 5 class classification. Cell classification and public dataset description have been mentioned properly which will assist researchers to understand the deep learning trend in cervical cancer study for further research purposes. After a rigorous inspection, it was discovered that supervised deep learning algorithms are far more commonly implemented than unsupervised learning approaches.

1.2 Outline of Paper

Following is a breakdown of the paper's structure: Section 2 starts with different datasets, the total number of cells, and normal or abnormal classification. Various deep learning models along with strengths and main functions are introduced in section 3, followed by a literature review. Summary of the techniques, datasets, advantages of the proposed approach, performance metric implemented for model evaluation, and type of problem-focused (classification, segmentation, and feature extraction) are also presented in the same section. Section 4 is about the discussion and the last section 5 is based on the conclusion of the prepared survey.

2 Public datasets for cervical cancer research

The efficiency of the deep learning techniques relies on various factors like computational resources, availability of testing and training datasets, and many more. This section introduces the most popular datasets used by the authors; however, few have also worked on UCI, ISBI challenge database, and Guanacaste database.

2.1 Herlev dataset description

Herlev datasetis a publicly available benchmark dataset that is used by most authors. A total of 917 images (normal and abnormal) are present in this database which has been categorized into seven distinct classes depending upon the various characteristics of the cells. This dataset can be accessed through

http://mdelab.aegean.gr/index.php/downloads

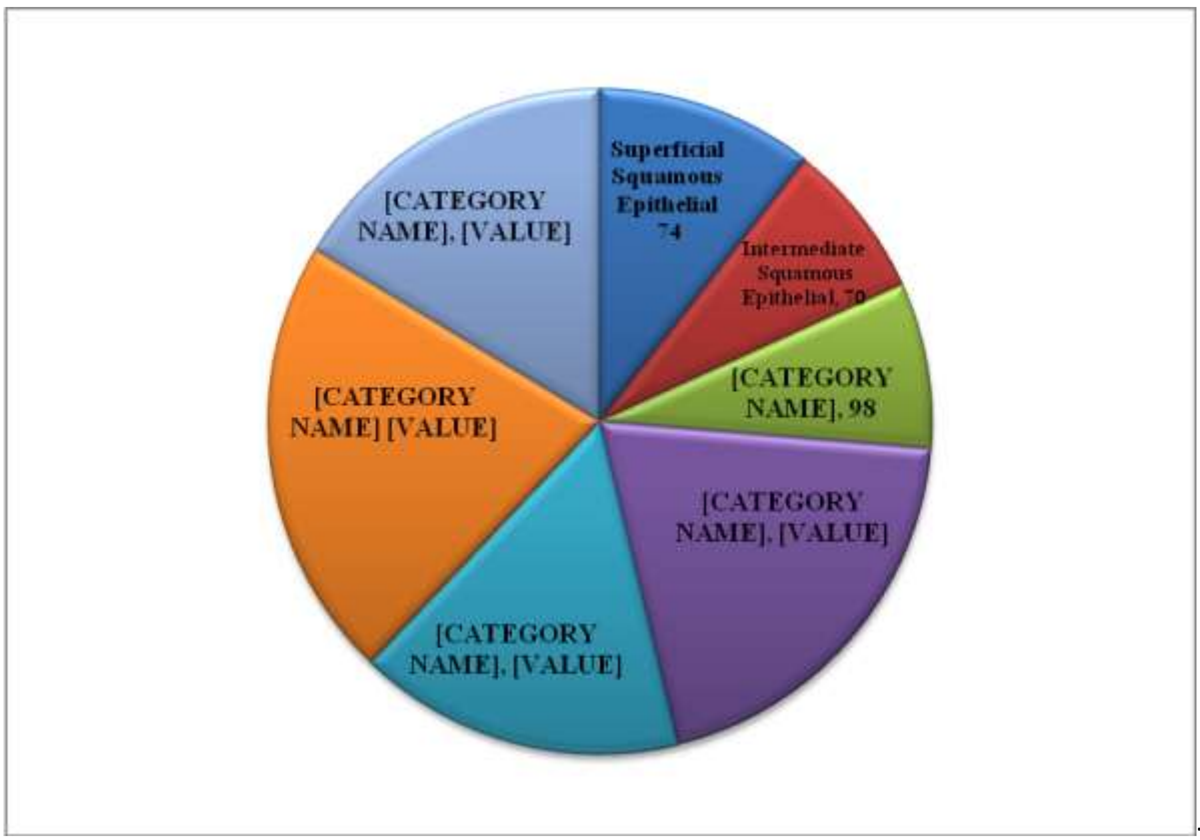

Figure 1: Cell distribution in Herlev Database

2.2 SpakMed dataset description

The SIPaKMeD Database includes 4049 images that are taken from a group of cells manually from pap smear images which are available at https://www.cs.uoi.gr/~marina/sipakmed.html. These images were captured with a digital camera and the dataset has been classified into 5 classes.

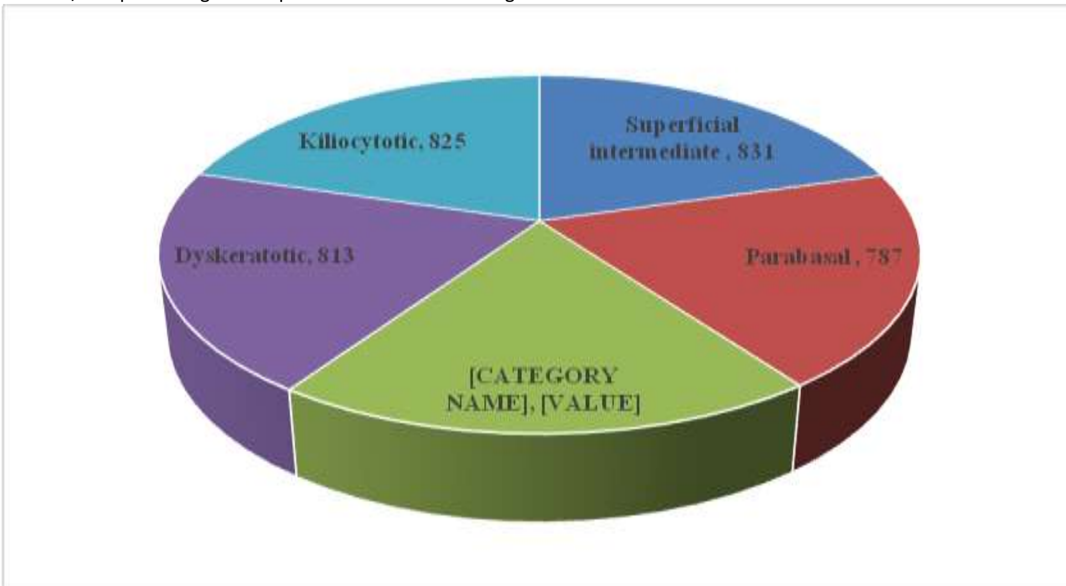

Figure 2: SpaKMed cell distribution

2.3 Intel and Mobile ODT dataset description

This Dataset is in partnership between Intel and MobileODT which is available at Kaggle's website https://www.kaggle.com/c/intel-mobileodt-cervical-cancer-screening. included 1481 training samples, 512 test images, and 4633 extra images for training. A few sample images taken from the dataset are given below. This dataset is entirely different from the previous two datasets where different cell classification is given, whereas we can seethe samples taken from the dataset do not categorize the dataset based on changes in respective cells.

Figure 3: Sample pictures from Intel & Mobile ODT dataset

2.4 Frequency of the datasets used from the past nine years in the field of cervical cancer study

It is clear from the survey that the majority of the researchers have worked on the primary datasets which were collected from various hospitals. A few years ago, the Herlev dataset being the benchmark dataset was used frequently. However, after doing the detailed analysis from the previous work most of the authors train and test the models on real datasets which require the help of pathologists for proper cell classification. The second most dataset implemented is the Herlev dataset which could be used for segmentation, classification, and feature extraction. Cytoplasm and nucleus are an area of interest for 99% of authors for automatic cervical cancer diagnosis.

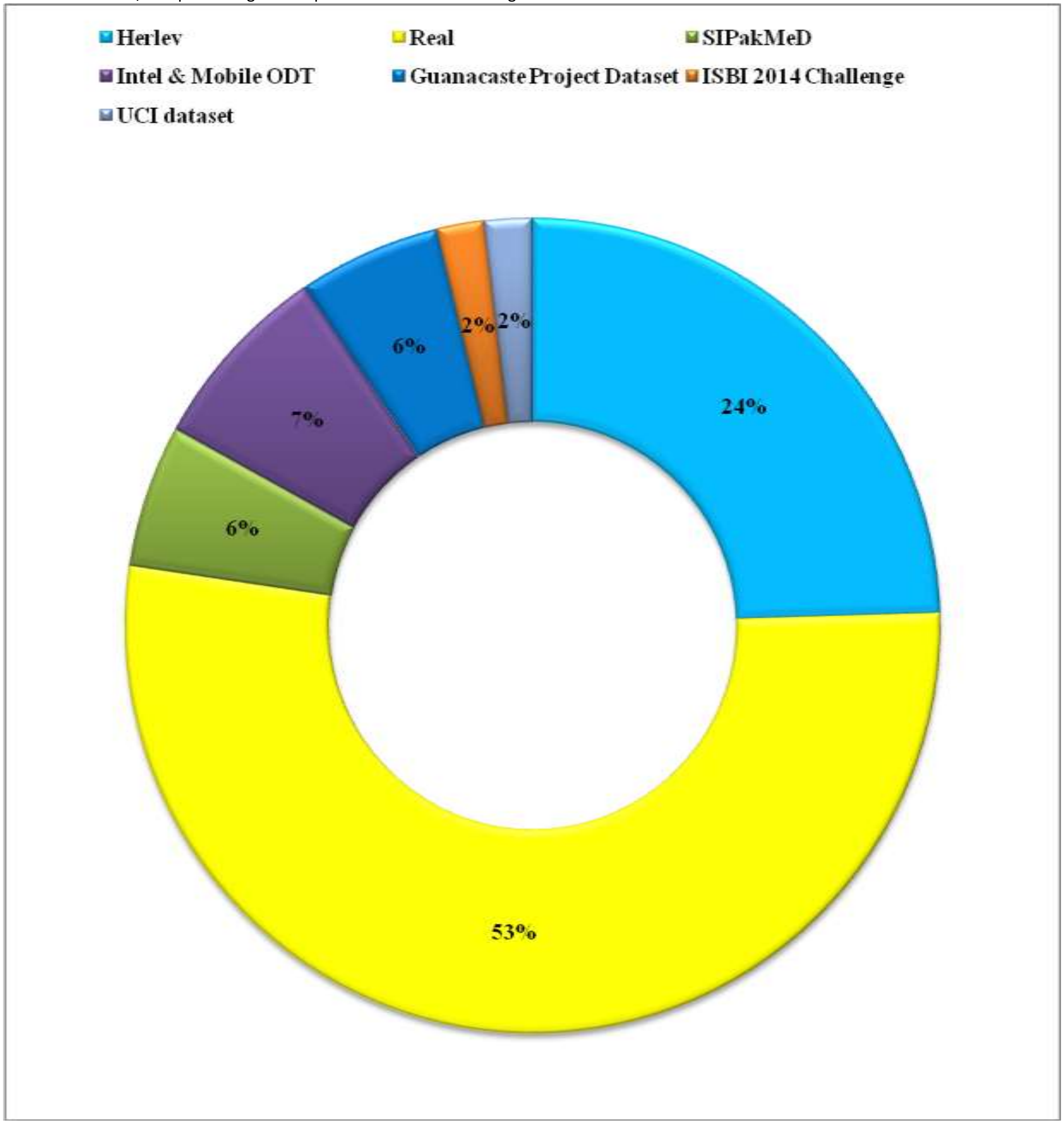

Figure 4: Comparisonof trained and tested datasets from the past 9 years in cervical cancer especially using deep learning approaches

2.5 Performance evaluation metric

The various deep learning models have been evaluated on the following metrics. As per the survey report prepared accuracy, sensitivity and specificity are used by most of the researchers for comparing the performance of the models.

- **Accuracy**

  It is defined as correctly classified values that can be calculated by below mentioned formula.

Accuracy= precise predictions/ Total number of predictions

- **Specificity**

The fraction of real negatives that were estimated as negatives is known as specificity.

- **Sensitivity or Recall**

The fraction of actual positive cases that were projected as positive is known as sensitivity.

- **Matthew's correlation coefficient**

It is the variation between actual and expected values. The value ranges between 1 and -1.

kappa score

Cohen's kappa is a common metric for determining how well two raters agree. It can also be used to evaluate a classification model's performance. It is used to assess the degree of agreement between two raters who classify items into mutually exclusive groups

- **Dice similarity coefficient or Dice coefficient**

It is a quantitative metric for determining how similar two sets of data are. This index is likely the most often used metric for validating the segmented images.

- **Hausdorff distance**

The average Hausdorff distance is a popular performance metric for computing the difference between two sets of points. In medical imaging, this metric is used to compare the ground images with the segmented ones.

- **F1 score**

The F-score, also known as the F1-score, is a metric for how accurate a model is on a given dataset. It is used for binary classification.

3 Popular deep learning architectures

This section is presenting the deep learning models which have been used for the past nine years in the field of automatic cervical cancer. Before deep learning got evolved cervical cytology detection was done with either basic image processing techniques or machine learning approaches. Now the trend has changed from basic learning to advanced learning in the form of deep learning approaches for precise segmentation, classification, and feature extraction, especially from the cytoplasm, nucleus, or cervix region. The following mentioned chart enlists the architectures that are used for automatic cervical cancer diagnosis.

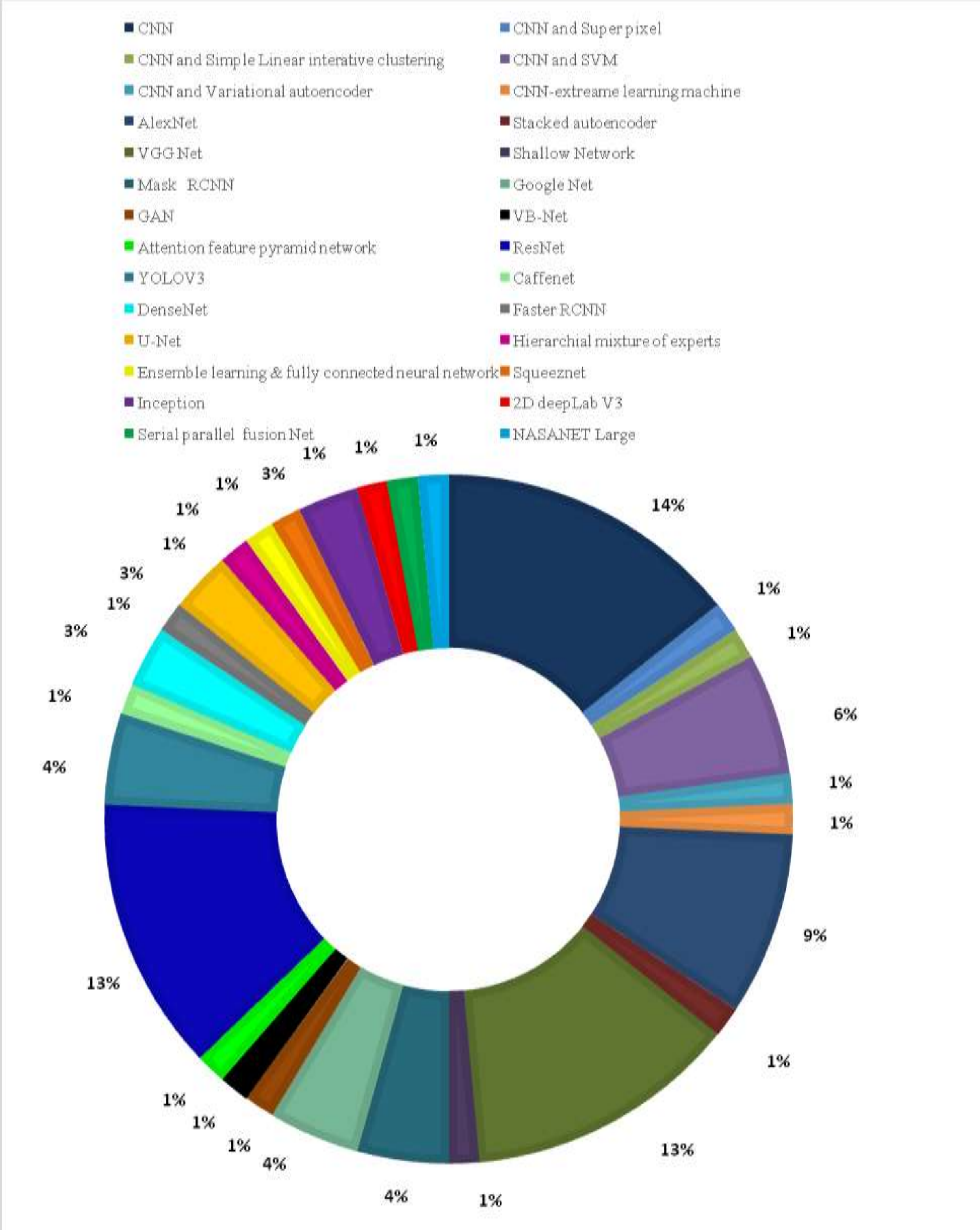

Figure 5: Frequency of techniques used in cervical cancer study

This donut chart describes the frequency of techniques used in past nine years in cervical cancer. From the diagram it is clear that 14% of techniques are CNN based, which is predominantly used, followed by VGGNet (13%), ResNet (13%), AlexNet (9%), CNN-SVM (6%), YOLOV3 (4%), GoogleNet (4%), Mask RCNN(4%), UNET (3%), DenseNet (3%), Inception (3%), and other 17 approaches (CNN and Superpixel, CNN and Simple Linear interactive clustering, CNN and Variational autoencoder, CNN-extreme learning machine, Stacked autoencoder, Shallow Network, GAN, VB-Net, Attention feature pyramid network, Caffenet, Faster RCNN, Hierarchical mixture of experts, Ensemble learning & fully connected neural network, Squeeznet,2D deepLab V3, Serial parallel fusion Net, NASA NET Large) are used 1% of the total technique's.

3.1 Segmentation Techniques

Segmentation is the process of separating an image into various sub-parts. These sub-parts generated belong to different classes. The segmentation is broadly categorized into two groups a) instance segmentation b) semantic segmentation. In instance segmentation, related items acquire their unique labels, however, in semantic segmentation, all elements belonging to the same type are labeled using a single class label. Segmentation achieved with deep learning approaches is far better than traditional image segmentation and machine learning approaches. Thus, this section focuses on the various deep learning-based segmentation approaches in cervical cancer. The two major techniques implemented on the cervical are Mask R-CNN, UNET, and modified UNET. Both approaches follow the instance segmentation scheme. However, one of the major advantages of UNET over Mask-RCNN is that UNET requires fewer training labeled samples.

- **Mask RCNN**

A CNN technique that provides a solution for instance segmentation. The model architecture is the same as that of the Faster R-CNN. This algorithm is easy to train and is one of the simple approaches in deep learning. It is based on the instance segmentation approach. One of the major pitfalls of MASK RCNN is that it does not perform accurate segmentation.

- **UNET**

UNET model is a deep convolutional neural network that is made up of a total of eight blocks (four encoders and four decoders). Like MASKRCNN UNET architecture also rely on instance segmentation. However, precisesegmentation is achieved with the UNET model in comparison to MASK RCNN.Learning may slow down in deep architectures, which is a disadvantage of the model. Below mentioned authors have worked on the segmentation problem of cervical cancer. These approaches differ in accuracy, performance metric, and dataset used.

Song et al. (2014) investigated a superpixel and convolution neural network for automatic segmentation of cervical cancerous cells. Nucleus area detection has a precision of 0.91430.0202 and a recall of 0.87260.0008. According to authors, CNN outperforms other methods (Backpropagation neural network, support vector machine, and so on), demonstrating that deep learning is particularly successful at detecting nuclei and cytoplasm. The process begins with pre-processing of the images which are corrupted by Gaussian and impulse noise. The images are denoised with the help of a median filter. Then a coarse cytoplasmic mask is created using a global threshold value. The next step involves fine segmentation with the superpixel-based algorithm. Finally, the CNN is implemented to extract the various features from cervix cells. The dataset for the model training has been collected from the Sixth People's Hospital of Shenzhen. Another author Sompawong et al. (2019) implemented Mask Regional convolutional neural network for cervical cancer diagnosis. Herlev dataset has been used for model training. The technique has achieved an accuracy of 89.8%, sensitivity of 72.5%, specificity 94.3%.Araújo et al. (2019) highlighted a CNN approach to segment abnormal cervical cells. The average area of segmented sections is used to rank the images based on the likelihood of aberrant cells in that image field. With high overlapping, the suggested technique segments both free-floating and clusters of aberrant cells. Furthermore, this approach uses a CNN and a post-processing step to remove these regions. It is resistant to noise and artifacts that are frequent in conventional pap smear images. When compared to existing approaches, it works faster because it does not require prior segmentation. It also assigns a ranking to the results based on the likelihood that the images will be used. Wang et al. (2020) investigated a new network for classifying the images of pap smears which is complex to address. Proper segmentation and extraction of features from pap smear continue to be a difficult task because of overlapped cells, dust, and contaminants. Deep learning is becoming an essential alternative to address the problems of feature-based techniques. An adaptive pruning deep transfer learning model (PsiNet-TAP) is designed with ten convolution layers and followed by three fully connected layers. A convolution kernel is a filter that may extract edge information comparable to a filter. The image can be abstracted layer-wise to get better feature extraction, which discriminates and significantly impacts classification accuracy.The dataset used for training the network model is based on 389 pap smear images (primary dataset). This approach has achieved more than 98% accuracy and could prove an excellent tool for cervical cancer categorization in clinical settings.

Rigaud et al. (2021) examined the deep learning models that were able to auto-segment the cervix anatomy with equivalent results on two different datasets, paving the path for automatic online dose optimization for advanced adaptive radiation therapy techniques. The 2-dimensional (2D) DeepLabV3 (Google) and 3-dimensional (3D). Unet in RayStation models were explored. The 2D architecture was designed for single-pass inference, with every pixel given to either the background or one of the 12 anatomic regions. The 3D architecture works on the classification of various body organs. The performance of the model was evaluated with Hausdorff distance, dice similarity coefficient, and distance-to-agreement. Both models achieved the same performance for cervical cancer therapy. Ma et al. (2022) since radiotherapy is required to treat cervical cancer, it is crucial to outline the radiation targets precisely and effectively. For autonomous contouring of clinical target volumes in cervical malignancies, deep learning auto-segmentation systems have been explored. A new variety of networks called VB-Net is offered as a better alternative to V-Net. B in VB-Net, replaces the convolution, normalization, and activation layers in V-Net. The number of model parameters may be greatly minimized because the spatial convolution is done on the lower dimension feature image, which may lead to enhanced efficiency. The dataset training is conducted on computer tomography images, the total samples are 535. The auto-segmentation approach suggested in this research is better than manual contouring segmentation procedures. As a result, this technique could be a viable way for increasing the therapeutic effects of radiation in the treatment of cervical cancer.

3.2 Classification approaches

Classification is a technique of categorizing the data based on input given to it. In this approach, the algorithm gains knowledge from the input data and later learns to categorize into different groups. The classification is broadly categorized into two different classes. Binary class classification and multiclass classification. Binary class classification comes with only two values either positive or negative. However, multi-class

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classification generates more than two classes. In cervical cancer, diagnosis authors have explored both classification approaches, but the majority of the research has been done on binary classification. Thus, this section highlights 2 class, 3 class, 4 class, and 7 class classifications for cervical cancer diagnosis. The techniques that are predominantly used for classification purposes are

- **AlexNet**

AlextNet is a Convolutional Neural Networktechnique that is composed of eight convolutional layers and 80 million parameters. The strengths of the architecture are high accuracy, shows good performance for colored images. AlexNetSuffers in learning features from the images and requires high time to generate accuracy in comparison to other models.

- **Convolutional Neural Network (CNN)**

A CNN is a deep learning technique that learns the different features using Multi-Layer Perceptron. CNN architecture is composed of three layers; convolutional layer, pooling layer, and fully connected layer, each of which performs a different function. CNN does not require extensive pre-processing in comparison to other classification approaches.

- **VGGNet**

A CNN neural network developed in 2014 has VGG19 and VGG16 variants. The first one is having 19 convolutional layers whereas the latter one supports 16 convolutional layers;however, this network is not preferable to GoogleNet.

- **DenseNet**

DenseNet is densely connected CNN which is very identical to ResNet, although there are a few key distinctions. ResNet is based on additive operation whereas, DenseNet uses a concatenation operator. This architecture is small in size in comparison to ResNet and enhances feature propagation.

- **ResNet**

A residual network CNN approach that supports only 5 convolutional layers was developed in 2015. The architecture easily handles the vanishing gradient issue. One of the major application areas of ResNet is classification. ResNet is based on a complex architecture which makes it fit to solve highly complicated problems.

Bora et al. (2016) developed a robust system for efficiently and accurately identifying dysplasia from pap smears. The architecture chosen for the model design is ALexNet.The feature extraction has been done with deep CNN, Moreover, two classifiers have been investigated least square Support Vector Machine and softmax regression. The experiments were conducted on both public (Herlev dataset) and private datasets. The private database is composed of 1611 samples which have been categorized into various classes. This type of computerized system can aid in the diagnosis of cervical cancer in its early stages. The designed model works in four major steps. The first step is based on creating a private dataset that consists of class1, class2, and class 3 images. The system is validated with the Herlev dataset also. After the database is ready the features are extracted with the help of AlexNet. The next phase works on minimizing the various features (extracts subset features), finally, the cell classification is carried out with the help of mentioned classifiers. Moreover, accuracy could be increased to 90-95 percent after using the feature selection technique.Zhang et al (2017) presented a CNN-based cervical cell classification. Unlike prior systems that relied on segmenting cytoplasm from the nucleus and hand-crafted characteristics, the suggested technique extracted the deep features without the segmentation. The ConvNet is first pre-trained on a real-world image dataset. It is then fine-tuned using a cervical cell dataset made up of coarsely centered image patches that have been adaptively re-sampled. The model training is completed on the Herlev dataset, and results reveal that it beats earlier algorithms in terms of classification with 98.3% accuracy, 0.99 as the area under the curve, and 98.3% as specificity (compared to prior methods).The proposed method achieves the best results on the Herlev dataset and the liquid-based cytology datasets. One of the major limitations of this research is that it requires 3.5 seconds for a single patch classification, which is far too long in a clinical environment.Rohmatillah et al. (2018) presented an automatic cervical cancer classification. The research work is conducted in three different steps: the first phase is extracting different features using a convolutional neural network, the second phase is reducing the number of features with the help of Principal Component Analysis and Linear Discriminant Analysis, and followed by classification. The last phase is to classify the cells based on the features extracted from the previous phases. The two classifiers that have been taken into consideration for classification are Support Vector Machine and the other one is softmax classifier. The experimental results revealed that the suggested approach performs better than other existing techniques.Harinarayanan et al. (2018) introduced a deep neural network (VGG16) for cervical cancer diagnosis. The authors presented a segmentation-free deep learning algorithm for classifying PAP smear images. The proposed approach generates a map of important regions for the pathologist to investigate using the network's inherent knowledge. This map was created using subtraction. This segmentation-free classification will result in a significant decrease in the time and effort required to collect training and testing data. The extracellular information will help in classifying the data. The intrinsic information in the neural network offers the doctor a map of significant images and regions within an image, which is in line with the needs of assisted screening. This map not only increases the interpretability of results but also speeds up the doctor's evaluation process.Promworn et al. (2019) explored five deep learning models to recognize abnormal cells from cervical cells. Model training is achieved with Herlev dataset. Densnet 161 has achieved best results in comparisons to other four deep learning techniques.

Guo et al. (2019) developed and finetuned numerous deep learning approaches, including RetinaNet, fined-tuned VGG, and Inception-based models for cervical cancer screening. A deep learning approach for screening cervical imaging demonstrated the potential to locate precancer cells faster than human specialists, particularly in women aged 25 to 49. To give bounding box annotation of the observed cervix regions, the authors performed automatic cervix detection using a pre-trained deep learning model. The image might be cropped to this region if necessary for additional processing. Then, a leading object identification model (RetinaNet) and VGG16 as base networks forpicture sharpness, and classification are used. RetinaNet with ResNet50 has outperformed other state-of-art techniques.Hussain et al. (2020) explored six distinct deep convolutional neural networks to detect cervical cancer's precancerous and cancerous lesions The benchmark Herlev dataset and real pap smear images were obtained using conventional and liquid-based cytology procedures. The hospital-based dataset consists of 1670 (liquid cytology-based) and 1320 (pap smear test) collected from different hospitals. Unlike many conventional methods, this technique resolves inaccurate prognosis and does not need segmentation or manual feature extraction processes. The experimental results revealed that this ensemble method is beneficial since it focuses on all stages of dysplasia and it could be useful for early-stage illness diagnosis. Googlenet achieved the maximum accuracy and minimum log-loss, while Alexnet achieved the lowest accuracy and largest log-loss. Three classifiers Resnet-50, Resnet-101, and Googlenet – showed accuracy greater than 90% for liquid-

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based cytology, conventional, and Herlev pap smear datasets with significantly reduced log loss at epoch 30. Deeper networks, such as Google net, perform better. Alexnetnetworkshave a 37% reduction in the number of trainable parameters. This shows that finetuned Googlenet, Resnet-50, and Resnet-101 models can readily converge and learn considerably more visual deep characteristics of pap smear images.Yilmaz et al. (2020) explored KNN, SVM, decision tree, random forest, extreme gradient boosting and deep learning approaches. CNN has outperformed other traditional machine learning techniques for cervical cancer classification. All these approaches have been trained on a publicly available Herlev dataset. CNN has achieved 93% of accuracy, whereas traditional approaches have achieved the highest accuracy, up to 85% only. Martínez-Más et al. (2020) introduced a cell merger and convolutional neural network to perform classification for proper cervical cancer analysis. Early diagnosis of cervicalcancer is essential to lessen the death rate. However, there is no automated classification for accurate cervical screen analysis. Most of the algorithms proceed with pre-processing (segregating the cells); this research has directly used the folded cells for building the CNN model for developing a perfect and reliable cervical analysis system. The model has been validated on specific parameters like accuracy, specificity, and standard deviation. The proposed approach has achieved an excellent accuracy of 88.8%, which could be used for clinical screening. The dataset has been collected from ten patients. The cells have been categorized into four distinct classes: normal squamous, ASC-US, L-SIL, and H-SIL. After this, cells are labeled into "review not needed" and "review needed." Squamous cells are labeled with no review needed, whereas ASC-US, L-SIL, and H-SIL are labeled with "review needed" for proper cervical cancer classification.Mohammed et al. (2021) presented convolutional neural network for cervical cancer diagnosis. Models like ResNet 101, ResNet 152, DenseNet 169, and so on are examined for the classifying the cancerous cells from pap smear images. DenseNet169 has outshined than other existing deepCNN techniques. Tripathi et al. (2021) introduced learning approaches for cervical cancer diagnosis. The three models used were RESNET-50, VGG 16, RESNET-152, VGG 19 RESNET-50. ResNet-50 has achieved best accuracy in comparison to other techniques. Chandran et al. 2021 investigated VGG19 and CYNET for cervical cancer study. CYNET has performed better than VGG19.

Tan et al. (2021) introduced an efficient deep convolutional neural network (DCNN) approach to aid doctors in cervical cancer screening. A retrospective investigation of multicentre ThinPrep cytologic test (TCT) images was used to develop an automatic screening model. This methodology improves the speed and precision of cervical cancer screening. In just three minutes, this model could identify the images and provide a test report. As a result, the system can relieve pathologists' workload and free up time for them to investigate more complex cases. The proposed cervical cancer screening system had a sensitivity and specificity of 99.4% and 34.8%, respectively, with an area under the curve of 0.67. The designed approach easily classifies the positive and negative cells. Dhawan et al. (2021) presented multiple deep learning methods to solve the problem of cervix classification. Cervix images are taken as input to the architecture like VGG19, Inception V3, and ResNet50. The first two algorithms are used for classification, whereas, the last one takes the advantage of transfer learning. The classification problem is divided into different classes type I, type II, and type III. The convolution layer's last layer is a completely connected layer that employs the SoftMax activation layer. Authors have also taken the advantage of transfer learning approach. The images for the network training have been collected from Kaggle, which comprises 5287 labeled images. Pre-processing of the dataset is achieved with an inbuilt function in python. Thus, by fine-tuning the values of numerous parameters, the model's performance improves with time and achieved 97.3% of accuracy. The experimental results revealed that Inception V3 outperformed VGG19 and ResNet 50. Jia et al. (2020) designed a robust strong-feature CNN-SVM model for cervical cancer cell classification.Jia et al. (2020) introduced CNN-SVM architecture for diagnosis of cervical cancer.LeNet-5 architecture has been used for feature extraction which performed better than other existing techniques.Park et al. (2021) performed a comparison between machine learning and deep learning algorithms for cervical cancer screening. The authors worked on 4119 Cervicography samples including both cancerous and non-cancerous cells. The famous architecture ResNet-50 has been taken into consideration for comparing it with machine learning techniques (Extreme Gradient Boost, Support Vector Machine, and Random Forest). The major pre-processing step followed is image crop to maintain uniformity. From the machine learning classifier SVM has achieved an accuracy of 0.84 which is far better than Extreme Gradient Boost and Random Forest. However, ResNet-50 has defeated the mentioned three classifiers in performance and has achieved an accuracy of 0.97. Experimental findings reveal that the ResNet-50 architecture could outperform current machine learning models from cervicography images. Cao et al. (2021) presented a deep learning approach called attention feature pyramid network (AttFPN) for cervical cancer. There are two essential components to the proposed technique. The first module mimics how pathologists read a cervical cytology image. Second, to fuse the refined features for detecting aberrant cervical cells at multiple scales. Finally, a multi-scale region-based feature fusion network guided by clinical information was developed. The multi-scale network's region proposals are based on clinical information on the size and shape distribution of real aberrant cervical cells. The suggested algorithm's average diagnosing time is 0.04s per image, which is significantly faster than the pathologists' average time (14.83s per image).

Adweb et al. (2021) designed deep residual learning-based networks (ResNet) for cervical cancer detection. Furthermore, the authors emphasized the significance of activation functions on the performance of a residual network (ResNet). As a result, three residual networks with distinct activation functions of the same structure are formed. The models were trained and tested on a cervical image dataset, and the findings revealed that presented residual networks with leaky and parametric rectified linear unit activation functions bring off nearly the same in terms of accuracy, with 90.2% and 100% accuracy, respectively. Moreover, it was demonstrated that both activation functions may be used as a performance enhancer for a developed residual learning-based network.Elakkiya et al. (2022) majority of the techniques require manual labeling, including image-level spatial localization of cervical cells. Due to cell clusters, proper segmentation of cervical cells has remained a problem despite sixty years of research. To solve such drawbacks, a blended method using Small-Object Detection Generative Adversarial Networks and Fine-tuned Stacked Autoencoder is designed to overcome the issues. The whole detection procedure is divided into three steps: 1) data fine-tuning and normalization, 2) cervical lesion identification and classification 3) stage identification and cervical cancer prognosis. The encoders identified the pertinent prominent features from the images using normalized dimensionality and dominating features. The object detection method has been used to locate the area of interest for further process. Apart from this, Bayesian Optimization (BO) is used to balance the network parameters. The dataset for the model training has been collected from multiple resources including public repositories and real datasets. The presented deep learning architecture was created using heterogeneous data to diagnose and predict cervical abnormalities.

3.3 Feature extraction and classification techniques

Feature extraction is a technique of reducing dimensions, and dividing a large amount of raw data into smaller, easier-to-process groups.Feature extraction attempts to decrease the number of attributes in a dataset. This section focuses on feature extraction and classification of cervical cancer datasets. The techniques that have been used for classification or feature extraction are as AlexNet, ResNet50, VGG, InceptionV3, Variational autoencoder, GoogleNet, YOLOV3, and Faster RCNN. Apart from this, the various classifiers used are MLP and SVM. However, the SVM classifier is predominantly used in comparison to MLP.

- **YOLOV3**

  A deep learning approach that stands for you only look once and is used to detect different objects. YOLO has another variant called YOLOV3. It generates fast and precise results. Since YOLOV3 is especially meant for object detection for complex objects. However, it is difficult to implement object detection for small-sized objects.

- **Faster RCNN**

  Faster RCNN is a deep CNN to detect the various objects, R stands for region based convolutional neural network. This CNN method is based on a selective search algorithm which makes it slow. The major tasks are object detectionand classification.

- **Stacked Autoencoder**

  A stacked autoencoder is a deep learning architecture that takes the advantage of a backpropagation algorithm to produce the output. This network reduces the dimensionality of the data, thus helpful in extracting the essential features. It has application areas both in classification and feature extraction.

Xu et al. (2016) propose a deep multimodal network for diagnosing cervical dysplasia. Feature learning is based on AlexNet. The network consists of five convolutional layers, two fully connected layers, and a 1000-way softmax layer. The transfer learning approach is implemented to train the model. The CNN feature vector from the fc7 layer has a substantially larger dimension than the non-image feature. If high dimensional image features are fused directly with the low dimensional non-image feature, then the high dimensional image feature can overpower the low dimensional non-image feature. The dataset for the model training has been collected from National Cancer Institute (NCI). Through backpropagation, the suggested framework may learn improved complimentary features for image and non-image modalities. With 87.83 percent sensitivity and 90 percent specificity, a big dataset automatically offers the proper diagnosis for cervical dysplasia, exceeding techniques that employ only one source of information and prior multimodal frameworks. Plissiti et al. (2018) introduced annotated image dataset cell for cervical cancer analysis. 26 features were explored on SPaKMeD dataset using convolutional neural network. CNN has achieved the best performance in comparison to MLP and SVM. Hu et al. (2019) presented a faster region-based convolutional neural network to find cancerous cells. In most low-resource areas, where more than 500000 cancer cases occur annually, HPV vaccination and cervical screening are not affordable. Thus, the authors designed a visual evaluation technique based on "deep learning" to detect cervical precancer and cancer automatically. Different cervical examination procedures and histopathologic confirmation of precancers were used to follow a population-based longitudinal cohort of 9406 females in Guanacaste, for seven years. The proposed system has two basic functions: it detects (locates) the cervix in the input image and predicts the likelihood that the image is a CIN2 case. Object (cervix) identification, feature extraction (calculating object features), and classification (predicting case probability score) are all performed by the Faster R-CNN algorithm. The deep learning-based method was trained and validated using digitized cervical pictures from screenings obtained with a fixed-focus camera ("cervicography"). The R-CNN method, which was faster, gave the optimum balance of speed and accuracy.

Mousser et al. (2019) explored four CNN models for extracting deep features from Pap Smear images for cervical cancer analysis. Cervical cancer is one of the world's most serious public health issues. Even though it is one of the most preventable malignancies, early detection with an excellent Pap-smear test has become a primary concern for researchers. Cytopathologists use hand-crafted features to determine whether the structures are healthy or unhealthy. However, deep learning provides more accurate results in terms of classification. The authors extracted features from Pap Smear images with the help of deep neural networks, and these features are fed as input to the multi-layer perceptron classifier. The experimental results have been carried out on DTU/HERLEV Database, revealing that ResNet50 had outperformed VGG and InceptionV3 by achieving 89% accuracy.Xiang et al. (2020) presented an automatic cervical screening technique using an object detection method. The proposed approach provides an effective and segmentation-free solution for automatic cervical cell analysis. IT relies on a contemporary object detector to recognize individuals or groups of cells without the need for a hand-crafted feature. YOLOv3 is divided into two components: a unique deep architecture Darknet53 that extracts features using a 53-layer network trained on ImageNet, and multi-scale feature fusion layers that serve as feature maps and predictors. Unlike multi-stage standard approaches that rely on segmentation accuracy and hand-crafted features to detect cervical cells, this method extracts high-level features instantaneously and detects cervical cells immediately. The model achieved 97.5% of accuracy, mean average precision of 63.8%, and a specificity of 67.8%.

Xia et al. (2020) introduced the Series-parallel fusion network as a new network topology for detecting cervical cancer cells (SPFNet). Authors applied multiple combination tactics in the series module and build five distinct head components to discover the best-suited architecture for the detection task, as opposed to standard architectures that implement classification models as the backbone for image feature extraction. The entire work is composed of three major steps such as feeding the processed image as an input to the network, extracting the proper features from the image, and getting the different feature maps. The feature maps with various resolutions are then transmitted via the Regional Proposal Network (RPN). The second step obtains 9 anchors and produces 256 regions of interest. The 256 RoI obtained in the second step are then sent to the R-CNN head.SPFNet extracts high-semantics information and spatial information. For end-to-end training, the methodology implemented back-propagation and stochastic gradient descent (SGD). Except for the head component, the feature extraction network (SPFNet) employed in the experiment was pre-trained on the large-scale ImageNet dataset. The dataset for the model training has been collected from the Herlev database. The framework achieved a 78.4% average precision in identifying cancerous cells, which is much superior to other traditional detection methods.Alyafeai et al. (2020) highlighted an automatic deep learning approach to diagnose the cervical cancer. techniques like RCNN, YOLO, and GoogleNet have been explored. The proposed approach is 1000 times more efficient than other existing models and has achieved 0.68 intersection of the union, and the AUC score is 0.82, which is 20 times faster than other techniques. Lee et al. (2021) introduced a deep learning method for automatic cervical cancer detection. Yolo V3, a deep learning-based object recognition algorithm is used. The algorithm is especially light, allowing it to function easily on low-performance devices while maintaining a high level of accuracy. As a result, Yolo V3 is employed to create a model that identifies abnormal cells from normal cells in cervical cancer pictures by utilizing bounding boxes to mark the cells. The average precision value corresponding to the recall value was calculated from the precision and recall values for all test images and used as an indicator to measure the algorithm's performance. The model's average precision in this study was 73.34 percent, and it might be utilized as an auxiliary tool for pathologists.

Khamparia et al. (2021) combined a convolutional neural network with a variational autoencoder (VA) for cervical cancer analysis. Convolution serves as the model's encoding phase, while Autoencoders manages the decoding phase, which recreates damaged cells. The VA generates unique output in a variety of specific directions using data augmentation for training data. High-dimensional feature vectors are produced at the encoding end using a convolutional architecture with aggregated features, and they are reconstructed at the decoding end using VA. The pre-processing steps involved are enhancement in the resolution, rotation, resizing, and so on. According to the results of the experiments, VA provides spatial image features for convolutional networks and provides the best classification for cervical cells. Due to the resemblance between abnormal classes of malignant cells, the accuracy of classifying the normal class for the 3*3 filter is substantially greater than the 2*2 filter. Training time was long for experimental work due to the increase in period sizes and low hardware availability. The designed architecture obtained variational accuracy of 99.2 percent with a 2*2 filter size and 99.4 percent with a 3*3 filter size. Herlev dataset has been used for model training. For the first time, the proposed hybrid variational convolutional autoencoder technique was used for cervical cancer analysis, outperforming other state-of-art machine learning algorithms.Jia et al. (2022) used the YOLO method to detect aberrant cervical cells in a novel way, ensuring that the detection is quick and accurate. To boost the model's generalization ability to cell features, the dense block and Stochastic-pooling (S3Pool) algorithms based on the feature extraction network Darknet-53 have been introduced. DenseNet is responsible for connecting the lower layer's feature map to the higher layer's feature map, bringing the network layer's structure closer together. S3Pool is responsible for improving the network's ability to generalize. As a result, better features are extracted, enhancing the network's overall performance. The model has been trained on two separate datasets, one is the Herlev dataset and another is the primary dataset. From 70.65 percent to 78.87 percent, the average detection accuracy rate increased. Furthermore, the Focal Loss and balanced cross-entropy functions are used to increase the model's diagnosis ability against the complicated background, dense clusters of cells, and an irregular cell.

3.4 Segmentation and Classification

Authors in this section have worked on segmentation and classification approaches for early diagnosis of cervical cancer. The deep learning approaches that have been used by the researchers are CNN, VGGNet, 2D UNET, 3D UNET, and MASK RCNN.

Harangi et al. (2019) presented a robust screening method to detect and segment each cervical cell in a high resolution with a high degree of sensitivity and specificity. The work is conducted in two phases segmentation and implementation of deep learning techniques for cervical cancer classification. Thus, an ensemble approach for precise cell segmentation is designed, to incorporate it into an automatic system for the early screening of cervical cancer. When correlated to techniques with traditional algorithms, deep learning-based methods usually outperforms. Higher and more balanced performance in terms of sensitivity and specificity could be achieved by combining the outputs of the fully convolutional neural network (FCN-8, FCN-16), and superpixel-based segmentation algorithms.As a result, these models can more precisely estimate the output class for each pixel. The dataset has been prepared from 6 digitized slides, which consist of 10,000 images to be fed as input to the network. The model evaluation has been done on sensitivity, specificity, Matthew's correlation coefficient, and intersection over the union. From the experimental results, it is confirmed that integrating deep learning segmentation approaches with image processing approaches generate better segmentation performance as well as more balanced behavior.Lin et al. (2019) introduced a robust approach for diagnosis of cervical cancer. Authors have used GoogleNet, and achieved a good accuracy both in 2 and 7 class classification in comparison to other architectures. Experimental studies have been conducted on the Herlev dataset.Gorantla et al. (2019) presented the CervixNettechnique for Cervical Cancer diagnosis. The Hierarchical Convolutional Mixture of Experts (HCME)appraoch has achieved an accuracy of 96.77% and a kappa score of 0.951. Harangi et al. (2019) introduced screening method to detect and segment each cervical cell for cervical cancer diagnosis. From the experimental study, it is confirmed that incorporating deep learning segmentation approaches with image processing approaches generate better segmentation results as well as more balanced behavior.Allehaibi et al. (2019) presented a mask regional convolutional neural network for cervical cell segmentation, followed by classification using Visual Geometry Group-like Network. There are two steps in the proposed method. The first stage uses Mask R-CNN segmentation to divide the cell areas. By identifying the segments from the first stage, the second phase specifies the entire cell region. ResNet10 is used as the backbone of the Mask R-CNN to exploit spatial information and prior knowledge, fully Mask R-CNN's objective is to segment and construct pixel masks for each image component automatically. For further classification of the segmentation findings, a smaller VGG-like Net is used. The pre-processing followed for segmentation and classification is different in both approaches. The dataset used for the model training is the Herlev dataset. VGGNet improves recognition performance. Only one fully connected layer is employed before the softmax layer instead of three fully connected layers in the original VGGNet. For 250 epochs, the suggested method for two classifications gives high performance with low standard deviation for all metrics, i.e., 96.5 percent F1 score, 98.1 percent accuracy, 96.7 percent sensitivity, 98.6 percent specificity, and 97.7 percent hmean, moreover classification performance for the 7-class problem achieved accuracy of 95.9 percent, sensitivity of 96.2 percent, and specificity of 99.3 percent. The main strength of the technique is that it does not require extensive pre-processing as compared to other existing techniques; however, this also has a drawback of high computational cost.

Rahaman et al. (2020) presented a detailed review of deep learning approaches for cervical cancer diagnosis. It is one of the deadliest diseases that affect females. The Pap smear test is widely followed for screening and early detection of cancer. However, this hand-operated screening method has a significant false-positive rate because of human error. Computer-aided diagnosis approaches based on deep learning have been widely used to automatically segment and classify cervical cytology pictures to increase accuracy and manual screening procedure. This work focused on deep learning approaches to segment and classify cervical cytopathology images. MASK-RCNN combined with LFCCRF gives superior performance for the segmentation of overlapping and nonoverlapping cells and provides better performance. However, for classification CNN(AlexNet) and decision-based tree performs better in contrast to other algorithms. Dharani et al. (2020) introduced a new approach for cervical cancer diagnosis which considers both single and overlapped cells. The work has been conducted in three phases such as detection, segmentation, and classification. Mask-RCNN a deep learning technique has been used for cell nuclei segmentation. The classification is carried out with the decision trees which categorize the cells into two types normal and abnormal cells. The dataset for model training has been collected from the Guanacaste dataset. The research work is conducted in two phases; the first phase is implementing the Mask-RCNN to segment the cells. The second phase is based on calculating the area of the cytoplasm and nucleus to classify the segmented images. The authors examined conv5T, conv3T, and conv1T, for multiclass classification using transfer learning. Experimentation indicates that successful segmentation is not required for deep learning classification. 2-class classification achieved 99.3% accuracy and 7-class classification achieved 93.7% accuracy.Chen et al. (2021) designed a deep learning technique (CytoBrain), an autonomous cervical cancer detection system. There are three key components in CytoBrain: segmentation of cervical cancer, classification of segmented cells, and visualized human-aided diagnosis component.The architecture is made up of ten convolution layers, four max-pooling layers, and two fully-connected layers in the image. To build feature maps, the convolutional layers take up various features from the input images. By combining semantically comparable features into one, the max-pooling layers lower the output dimensionality of the feature maps. These features are combined in the fully-connected layers, which provide prediction probabilities for various classes. CompactVGG is thinner (with a maximum of 64 convolution filter channels) and shallower (with three fewer convolution layers and one fewer full connection layer) than VGG16, which lessens the computational cost. As per the experimental results, CompactVGG diminishes training and testing time more than VGG11, which is the most efficient VGG network in the family. Kano et al. (2021) presented the automatic contour segmentation for cervical cancer diagnosis. The modelis composed of 2D UNet and 3D UNet. This approach would lessen the burden on oncologists which has been rarely used in clinical practices.

Desiani et al. (2021) presented the segmentation and classification of pap smear images for cervical cancer screening. The manual screening method for classifying cells is a laborious task, that is vulnerable to inaccuracy, thus authors have worked on automatic analysis of cervical cancer cells. The image quality has been enhanced with Normalization, CLAHE, and Adaptive Gamma Correction which act as the pre-processing steps. Multi-class classification has been carried out with the help of the softmax function. Artificial neural networks and K Nearest Neighbour was used to perform the classification task. The dataset has been collected from the Herlev database which is publicly available. UNET architecture (consists of two paths contracting and expanding path), which is based on semantic segmentation has been used to segment the cytoplasm, nucleus, and background. The segmentation findings with CNN were not pleasing, but they had a significant impact on the classification process using ANN or KNN. The dataset for the model training has been taken from the benchmark dataset (Herlev dataset). From the experimental study, it can be concluded that the proposed architecture technique is robust enough to be utilized to classify which Pap-smear images are normal and do not have cervical cancer and which are abnormal and may have cervical cancer.

3.5 Three addressed approaches (segmentation, classification, and feature extraction)

Since it has been already stated in the introduction that the cervical cancer problem is always addressed in three distinct ways like segmentation, classification, and feature extraction. From the detailed analysis, it is quite clear that the majority of the work has been done on classification problems in comparison to the other two. However, few authors have worked on three approaches as well. The mentioned authors highlighted the three issues and the techniques used are CNN and RetinaNet.

Kuko et al. (2020) presented the cervical cancer classification based on machine learning techniques. The research has addressed four approaches such as data collection, cell extraction, cell segmentation, and classification of abnormal cells in pap smear images. A total of 104 Pap smear images were collected from the University of Southern California Medical Center. Cell extraction converts the input image into grayscale; after that, thresholding is used to convert the grayscale image into black and white for more readability and even discards debris from the area of interest. During the segmentation and feature extraction, the cells are broken down into three distinct vector pixels to categorize the pixels into four different clusters. K-means algorithm is taken into consideration for clusters. A total of 33 morphological features like the size of (the nucleus and cytoplasm), and nuclei channel color mean (red, green, and blue) were used. The architecture consists of 5 separate convolutional neural network that trains five pre-defined clusters individually to highlight the irregularity among cell clusters. Each convolutional layer is composed of a ReLU activation function and a dropout. The authors used ensemble learning with multiple random forests and have shown promising results by achieving 90.37% accuracy, whereas Convolutional neural networks have achieved 91.63% accuracy. Hence manual examination by pathologists is time-consuming; this automatic cell screening has the potential to automatically analyze the majority of the cells using ensemble learning and deep learning techniques. Whereas, deep learning has outperformed than ensemble learning approach. The ensemble technique reduced sensitivity and specificity variation by 95.47 percent and 95.47 percent, respectively.

Da et al. (2021) combined machine learning and deep learning approaches for cervical cancer diagnosis. The main idea behind combining both approaches is to overcome the disadvantages of the respective techniques. The hybrid model starts with pre-processing of input images, then these images are fed as an input to the RetinaNet with a ResNet50. The deep learning approach is used for analyzing the area of interest from the images, followed by feature extraction then a basic machine learning approach like SVM is used for classification purposes. Two primary datasets have been used for model training. These are then loaded into a RetinaNet with a ResNet50 backbone to detect anomalous regions and classify them as low- or high-grade lesions. The nuclei inside each anomalous region with a detection score greater than 50% are then segmented using an iterative thresholding approach. The feature extraction module uses the segmentation findings to locate 29 geometrical, color, and texture features from the nucleus structures, as well as 840 additional features from the entire aberrant area. The results are then used by two SVMs to generate a final classified result. Precision, recall, and F1 scores of 0.20, 0.40, and 0.27, respectively, were achieved by the system.

3.6 Comparison with existing review papers

To our best knowledge, it is the first time in the past 10 decades that a survey paper on deep learning approaches has been presented. Not only this dataset distribution, accuracy metric, supervised, unsupervised and frequency of deep learning techniques used have been properly summarized. The below-mentioned author has also worked on cervical cancer but it highlights a basic machine learning approach to cervical cancer diagnosis.

Chitra et al. (2021) presented an extensive review of various soft computing-based approaches for cervical cancer segmentation and classification. Cervical cancer detection using soft computing has been successfully investigated. A total of 60 publications are used in this study, all of which were chosen from the previous year. This study examines the majority of research papers published between January 2010 and December 2020. This paper gives a graphical and organized overview of recent research findings. The study looked into the potential for more research into soft computing methods for segmenting and classifying cervical cancer. Table 1 summarizes the techniques in cervical cancer diagnosis year wise, dataset used, features highlighted and advantages of existing approaches.

Table 1: Summary of techniques, dataset used, area explored, and advantages

Technique	**Year**	**Dataset**	**Features Highlighted**	**Advantages of the proposed approach**
CNN [1]	2014	Real dataset of 1400 images	Cytoplasm and nucleus of cervix cell	Better segmentation even for abnormal nucleus
CNN [2]	2016	A public dataset of 10,000 cases from the Guanacaste project	Cervix cells	Automatic diagnosis
CNN [3]	2016	Real 1611 images	Cervix cells	Efficient classification
CNN [4]	2017	Herlev benchmark and one real dataset	Cervical cells	Better performance
SVM, MLP, and CNN [5]	2018	SPaKMeD	Nucleus and cytoplasm 26 features extracted	Best performance is given in comparison to handcrafted features
Stacked autoencoder [6]	2018	UCI which consists of 858 samples	-	Reduces the data dimensionality
Faster R-CNN [7]	2019	Real dataset	Cervix cells	Automatic recognition of pre-cancerous cells
CNN [9]	2018	NA	NA	Better classification
VGG16 [10]	2018	Real pap smear images 14301	Cervical cells	Can reduce the pathologist's burden of analyzing the slides
CNN and simple linear iterative clustering [11]	2018	ISBI 2014 challenge dataset	Cervix cells	low computational cost

Mask RCNN [12]	2019	Real-time dataset	Nucleus	Minimizes the average time taken during cell analysis
Shallow network, CaffeNet and VGG16 [13]	2020	Herlev dataset	Cytoplasm and nucleus	Perform better even if the dataset is small
AlexNet, GoogLeNet, ResNet, and DenseNet [14]	2019	Herlev dataset	Cytoplasm and nucleus	Provides better performance in fine-grained classification of cells
DenseNet161,AlexNet,ResNet101,VGG19 and SqueezNet [15]	2019	Herlev dataset	Cervix cells	Better efficiency and classification
CNN(Hierarchialconvolutional mixture of experts) [16]	2019	Intel and Mobile-ODT	Cervix	The minimum cost for screening
Mask RCNN and VGGNet [17]	2019	Herlev dataset		Does not require intensive pre-processing
Ensemble learning and Fully connected neural network[18]	2019	Real pap smear 1082		Enhanced segmentation process
RetinaNet, Inception V3, VGG[19]	2019	4525 Real dataset		Better classification
VGG, ResNet50 and inception V3 [20]	2019	DTU/HERLEV D	Cervix cells	Better feature extraction
YOLOv3 [21]	2019	Real dataset	Cervical cells	Efficient and robust object detection
CNN [22]	2019	Real pap smear images	Cervix cells	Robust
Ensemble learning and CNN [23]	2020	Real dataset (pap smear and liquid-based cytology) 104 pap smear	Nucleus, cytoplasm, nuclear membrane	Random feature selection is possible

CNN and SVM [24]	2020	Herlev and private (2000 cell images) liquid-based cell slides	Nucleus and cytoplasm	Good robustness
CNN [25]	2020	Intel&MobileODT Dataset NCI Guanacaste Project Dataset	Cervix	Cancer detection is 20 times faster
AlexNet, VGGNet, ResNet, GoogleNet [26]	2020	Herlev dataset and private dataset	Cervical cells	Does not require extensive segmentation and extraction of features
CNN((PSINet-TAP) [27]	2020	Primary 389 cervical Pap smear	Cervical cells	Better classification
CNN and basic machine learning approaches [28]	2020	Herlev dataset		Better results in contrast to machine learning
Deep learning 2020[30]	2020	Real and public dataset	Cervical cells	CNN achieved better classification and segmentation
CNN, Variational autoencoder [31]	2020	Herlev dataset	Cervical cells	Best classification
CNN [32]	2020	Real dataset		Feasible and reliable
CNN(Series-parallel fusion network) [33]	2020	Herlev dataset, Real dataset	Cervix cells	Better classification
CNN-extreme learning machine[34]	2020	Herlev dataset	Cervix cells	Better accuracy
CNN [35]	2020	Guanacaste dataset	Cervical cells	Better screening for single and multiclass cells
(2D) DeepLabV3+Google and (3D) Unet [36]	2020	Real dataset (408 CT scans)	Cervical region	Automatic segmentation
10 Deep CNN [37]	2021	SPaKMeD(pap smear)	Nucleus and cytoplasm	Reduced size and easier deployment
2D U-Net and 3D	2021	Primary dataset 98 cases	-	High accuracy for automatic

U-Net [38]				segmentation
ResNet-152 [39]	2021	Pap smear Spakmed	Cervical cells	Better classification
VGG19 and CYNET [40]	2021	Real Colposcopy images	-	Better classification and enhanced efficiency
CNN [41]	2021	2504 Real dataset	Nucleus, cytoplasm, and their boundary	The final results achieved were consistent with medical experts' understanding
UNET [42]	2021	Herlev dataset	Cervix cells	Better segmentation
Faster R-CNN[43]	2021	Real dataset	Cervix cells	Highest performance in identifying cancerous cells
InceptionV3, ResNet50, and VGG19 [44]	2021	Intel & Mobile ODT Kaggle	Cervix	Better accuracy
YOLO V3 [45]	2021	Real dataset 987 samples	Cervical cells	Low cost
RetinaNet and SVM [46]	2021	2 real datasets	Cervical cells	Better performance
YOLOv3 [47]	2021	Real dataset and Herlev dataset	Cervical cells	Enhances the detection of cervical cancer cells
VGGNet [48]	2021	Real dataset 198 952 cells	Cervical cells	Can provide better screening for cervical cancer
ResNet50 [50]	2021	Real 4119 Cervicography images	Cervix cells	Simpler approach
CNN(Attention feature pyramid network) [51]	2021	Real 3970 cervical cytology images	Cervix cells	Efficient screening technique
ResNet[52]	2021	Intel and MobileODT, Real dataset	Cervical cells	High accuracy
Soft computing techniques [53]	2021	Multiple datasets	Cervical cells	Better classification achieved by various approaches
VB-Net [54]	2021	Real CT images of cervical cancer	Cervix region	
GAN [55]	2022	Public (colposcopy	Cervix cells	Proper identification of

		images) and real dataset		cancerous stage

4 Discussion and challenges

Cervical cancer can be declined if successful screening systems are designed. The Pap smear is the most standard technique for precancerous diagnosis. The human analysis of pap smears, on the other hand, is prone to errors because the process is difficult and time-consuming due to human error. As a result, it would be advantageous to create a computer-assisted diagnosis tool that is more precise for the diagnosis and classification process. Thus, this paper examines a couple of recent deep learning techniques for the diagnosis and categorization of cervical cancer, which not only minimizes human errors but makes the diagnostic process fast. According to the research, certain issues need to be addressed a) Lack of the latest public dataset b) High computation cost required c) Huge training time required. d) ground truth images for supervised approaches. This paper has not only highlighted classification but segmentation and feature extraction approaches have also been given the same importance. The classification problem can be multiclass depending on the Bethesda system of classification. 99 percent of algorithms have achieved an accuracy of above 90 percent for classifying normal and abnormal cells. However, none of the approaches have achieved 100 percent results. The explored techniques differ in the total number of parameters, size of the model, the complexity of the architecture, quantity of the dataset, labeled images, and total time required for training and testing the model. Techniques like CNN, VGGNet, ResNet, GoogleNet, AlexNet, GAN, and other approaches above mentioned in the chart are used for classification and feature extraction purposes. However, CNN, ResNet, and VGGNet have been used by most researchers. Another standalone CNN (YOLO V3) has shown promising results in object detection even in the cluster of cells. For segmenting the nucleus and cytoplasm authors have implemented Mask-RCNN and UNET, which have been used equally by the researchers. One of the major highlights from the review is that, even though the deep learning approaches have surpassed the basic AI techniques in performance but SVM is still used more frequently as a classifier with CNN, followed by other classifiers MLP, decision tree, and Random Forest. To our knowledge, this is the first survey that addressed the major area of interest in cervical cancer, dataset description, percentage of a particular dataset used in the past nine years, and performance metrics. Thus, this survey will guide other authors to understand the current trend in automatic cervical cancer analysis, on which dataset to work, and which technique to implement for three respective problems.

5 Conclusion

This research paper describes various deep learning approaches for detecting and classifying cervical cancer in the cervix region. Approximately 55 papers are used in this study, with dates ranging from 2014 to 2022. Each work was compiled from a variety of sources, including IEEE, Springer, and others. According to the review Cervical cytopathology image analysis in deep learning is a growing area of interest. The majority of the techniques have been explored on the Herlev, SIpakMed, Mobile ODT dataset, and real dataset.This survey can assist researchers in this field in recognizing the problem that needs to be addressed as well as current state-of-the-art methodologies, allowing them to gain a head start on fixing it. The current trends indicate that majority of the authors used CNN for segmentation, extracting important features, and classification of cervical cancer. Few authors have combined CNN with SVM to get an outstanding accuracy. Since there are various deep learning techniques but CNN has been used by most of the authors in comparison to other techniques.

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Conflict of interest

This research work does not have any conflict of interest with anyone.

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