DOI: http://dx.doi.org/10.26483/ijarcs.v15i6.7153

ISSN No. 0976-5697

Volume 15, No. 6, November-December 2024

International Journal of Advanced Research in Computer Science

REVIEW ARTICLE

Available Online at www.ijarcs.info

A CONCISE REVIEW FOR EXPLORING DEEP LEARNING'S POTENTIAL IN CERVICAL CANCER PREDICTION FROM MEDICAL IMAGES

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Abstract: Cervical cancer originates in the cervix situated between the vagina and the bottom end of the uterus. It evolves gradually which begins with the appearance of aberrant cells in the cervical tissue. These aberrant cells might develop into cancer cells and migrate more into the cervix and adjacent tissues if they are not treated. Therefore, a patient's survival depends on rapid identification of cervical cancer. Various imaging modalities are widely used to identify cervical nodules as pre-cancer or cancer cells. But limited results were determined and takes more time and needs many skilled radiologists. To solve this problem, many Deep Learning (DL) frameworks have emerged in these decades for automatic cervical cancer detection and categorization. These algorithms can detect suspicious nodules early, improving patient outcomes and aiding physicians in decision-making, thereby reducing fatality risk. This study provides an in-depth analysis of many DL frameworks developed to recognize and categorize cervical cancer from various imaging modalities. Initially, different cervical cancer categorization systems designed by many researchers based on DL algorithms are briefly examined. Comparison research is carried out to comprehend the shortcomings of those algorithms and recommend an alternative method for accurately classifying cervical cancer in order to regulate worldwide morality rates.

Keywords: Cervical Cancer, Imaging Modalities, Deep Learning, Patient Survival, Earlier Diagnosis

I. INTRODUCTION

Cervical cancer is particularly vulnerable to female reproductive system which is caused by uncontrolled and unregulated growth of cells in the cervical region. It is often caused by continued infection with specific varieties of Human Papilloma Virus (HPV) that induce alterations in the cells of the cervical membrane that may become cancerous if not treated [1]. Signs includes bleeding other than normal periods, discharge and abdominal pain become apparent as the cancer progresses from stage one where the tumor is confined to the cervix to stage three in which the cancer may have extended to the surrounding structures or organs [2,3]. However, cervical cancer persists in affecting women across the world, most prominently among women with poor access to utilize the preventive services like HPV vaccination or cervical cancer screening [4,5]. Early prediction is crucial for cervical cancer to be diagnosed at an early stage to minimize on the mortality rate and enhance on the treatment program. It reduces burden of cervical cancer.

Some of the common cervical cancer tests applied for cervical cancer such as Pap Test and HPV infection test, Colposcopy test and Biopsy test.

- Pap Tests - Collecting cells from the cervix to check for any indication of precancerous or cancerous abnormalities. It helps in early detection.
- HPV Tests - For detecting high-risk strains of HPV which is responsible for cervical cancer.
- Colposcopy Tests - For cervix, vagina, and vulva for abnormalities, if Pap test or HPV test results are positive.
- Biopsy Test – Last test to confirm the presence of cervical cancer cells if Colposcopy test results are abnormal.

All these tests are essential, yet they still pose challenges. False positives and false negatives lead to unnecessary anxiety, and delay necessary treatment by failing to detect existing abnormalities or early-stage cancer.

Various classical treatments, such as surgery, chemotherapy, and radiation, are tailored to different stages and severity levels of cancer [6].

- Surgery - standard cancer treatment in which doctors remove tumors and nearby tissue. It is used for localized cancer growths. Based on Size and location of the cells, Surgeries ranges from simple to complex operations.
- Conization - a piece of the cervix is removed in the form of a cone for the treatment of early cervical cancer [7].
- Radical hysterectomy - Excision of the uterus, cervix and adjacent tissues [8].
- Pelvic exenteration - Require the total removal of cervix, uterus, upper vagina and adjacent organs, such as bladder or rectum [9].
- Chemotherapy - Involves killing cancer cells throughout the body. It shrinks tumor, stops cancer cells from spreading and minimizes side effects.
- Radiation therapy - Targets and eliminates cancer cells using high-energy radiation. Either delivered externally or internally.

However, these conventional treatments have notable drawbacks.

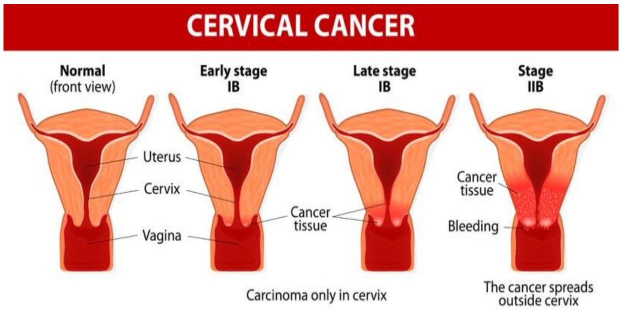

Figure 1. Stages of Cervical Cancer [1]

Figure 2. Colposcopy image of Cervix [10]

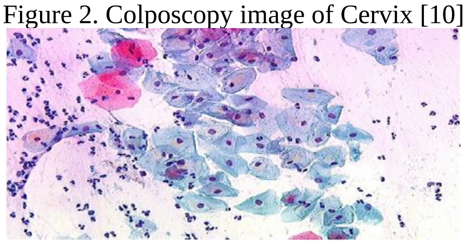

Figure 3. Microscopic view of a Pap smear [11]

They often involve invasive procedures that require large incisions, leading to prolonged hospital stays and increased post-operative discomfort, like sterility and possible infection, bleeding or injury to other organs that surround the cervix.

In an attempt to eliminate the aggressive procedures and possible adverse effects observed in surgical methods in cervical cancer treatment, current therapies embrace sophisticated imaging techniques including colposcopy, Pap smear, MRI and CT scans. These advanced technologies provide a better understanding of the morphology and characteristics of cervical cancer and provide better guidance in preoperative planning and therapy.

- Colposcopy imaging can help the clinicians to directly observe the areas of cervix that need be biopsied and virtually exclude healthy tissues from the biopsy, thereby minimizing unnecessary excision [10].
- Pap smear imaging involves screening for cervical cells which may be abnormal and treated before the progress to cancer [11].
- MRI scans are useful for detecting abnormalities in soft tissues and determining whether the disease spread to surrounding organs. It helps oncologists to examine the size, location and extent of tumors. [12].
- CT scans are useful in identifying metastasis to nearby organs and lymph nodes. Similar to MRI, it helps doctors to evaluate the extent, location, and size of the tumor [12].

Manual analysis has consistently proven to be a reliable method for detecting cervical cancer, yielding accurate results that are invaluable in the identification and examination of the cancer. However, this meticulous process is a laborious and time-intensive task, requiring a significant investment of time and resources.

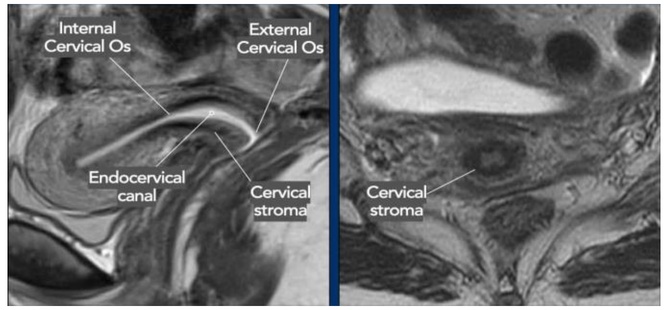

Figure 4. MRI scan labeled with key anatomical features of cervix [12]

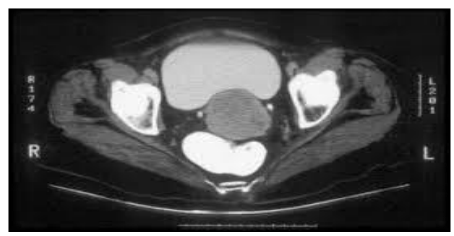

Figure 5. CT Imaging of cervical cancer [12]

To overcome this limitation and unlock the full potential of cervical cancer screening, the integration of Artificial Intelligence (AI) technology is essential for streamlining the process, improving overall efficiency, and enhancing the quality of care provided to patients [13]. Deep learning (DL) and Machine Learning (ML) are two AI fields that concern with the teaching of computers on improving the capability of making decision through data. ML involves the use of algorithms and models in the interpretation of medical information like images and past records of patients that contains cervical cancer or precancerous characteristics. The algorithms can improve the effectiveness of screening techniques by reducing instances of false negatives and false positives. Some of the problems associated with these models are that they require big and varied data sets to be trained before they can be used, and could rely on bad data to make their decision [14].

DL has been used effectively for prediction and diagnosis of cervical cancer based on its capability to process large medical data. DL algorithms, especially Convolutional Neural Network (CNN), are adopted to analyze and explain medical images like Colposcopy [15], Pap Smear [16] and Whole slide images (WSIs) [17]. These algorithms can identify patterns and anomalies that may not be perceived when observed manually which increases the chances of early detection. For cervical cancer prediction, DL models can be used through feeding a large number of labeled medical images of precancerous and cancerous tissues [18]. These models, once trained, can help pathologists in evaluating new images faster and more accurately and thereby help in reducing time spent in diagnosis of the images and enhance reliability.

1.1 Cervical Cancer Prediction using Deep Learning Techniques

Recent developments in image processing methods have tremendously raised the capacity of cervical cancer diagnosis. Using many imaging modalities, cervical cancer detection proceeds in several phases like image acquisition, pre-processing, feature extraction and classification.

Image Acquisition: The initial process is to collect images from the various image database, internet source or from the hospitals. Images were demonstrated as a gray-scale image and kept in format such as JPEG and PNG image standards [19].

Image pre-processing: The collected images are pre-processed to improve image quality, suppress distortions and enhance features for further processing. This process minimizes distortion effects in image equipment including blueness and light fluctuation. Pre-processing also removes unwanted areas and enhances features like lines, boundaries and textures. Some of the pre-processing techniques include filtering techniques like Median Filtering, Gaussian Smoothing, Wavelet Transform [20]. Enhancements techniques like Histogram Equalization, Contrast Stretching, Adaptive Histogram Equalization (AHE), Unsharp Masking, Contrast Limited Adaptive Histogram Equalization (CLAHE) are also used to enhance image pixel quality.

Image Segmentation: Segmentation is the process of dividing an image into segments to identify and differentiate between them. It involves processing input images into distinct pieces and using specific segments for each object. This process creates a pixel-by-pixel mask for each object. Cervical nodule segmentation is crucial for learning image characteristics in several images and distinguishing benign and malignant tumors [21,22]. The ROI (wanted part) in cervical cancer diagnosis identifies the tumor, while the unwanted area is the unwanted part. This method includes edge-based, gradient methods, region-based and Thresholding.

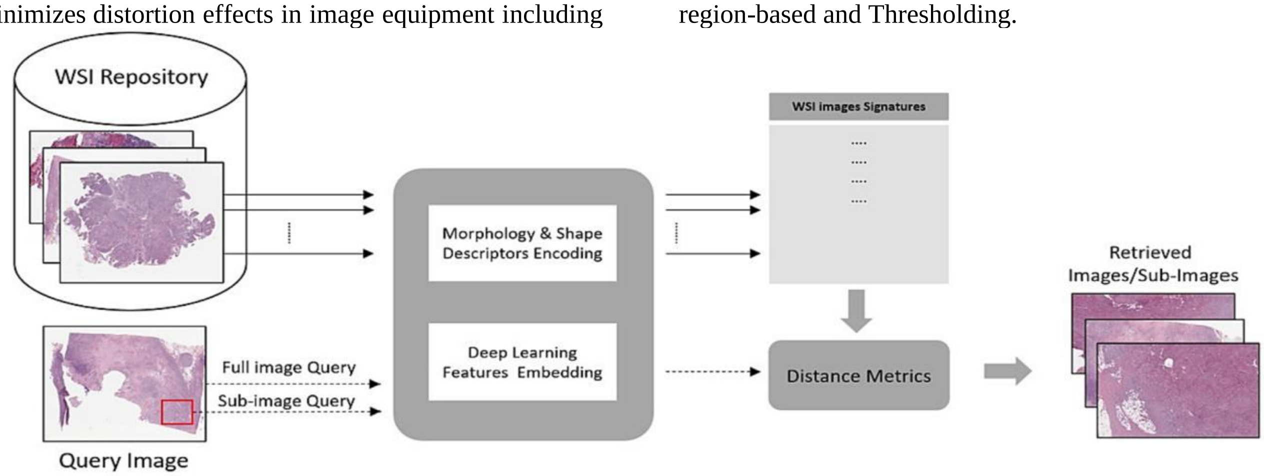

Figure 6. Typical workflow of WSI images retrieval applications. [17]

Feature Extraction: Feature extraction is a crucial step in image processing, identifying and separating preferred image slices. It helps in segmenting the cervical area, allowing for the calculation of analysis rules to identify malignancy nodules. This process extracts quantitative measurements from different images, recording nodule form, texture, and intensity characteristics.

These characteristics act as discriminative indicators to help identify benign from malignant nodules. Three types of features are used in image processing structural, texture and spectral which are extracted from the collected images [17]. The well-known models are Gray Level Co-occurrence Matrix (GLCM), Local Binary Patterns (LBP), Histogram of Oriented Gradients (HOG), Principal Component Analysis (PCA) etc. In contrast, CNN can automatically learn and capture characteristics, neglecting the necessity for manual feature extraction.

Classification: The general process in image processing is classification. Once the attributes are derived from the images, the cancer stages (pre-cancer/cancer) or levels can be detected. Once the cancer stage is detected, the doctors or radiologists make a proper decision to provide appropriate treatments based on their malignancy [22].

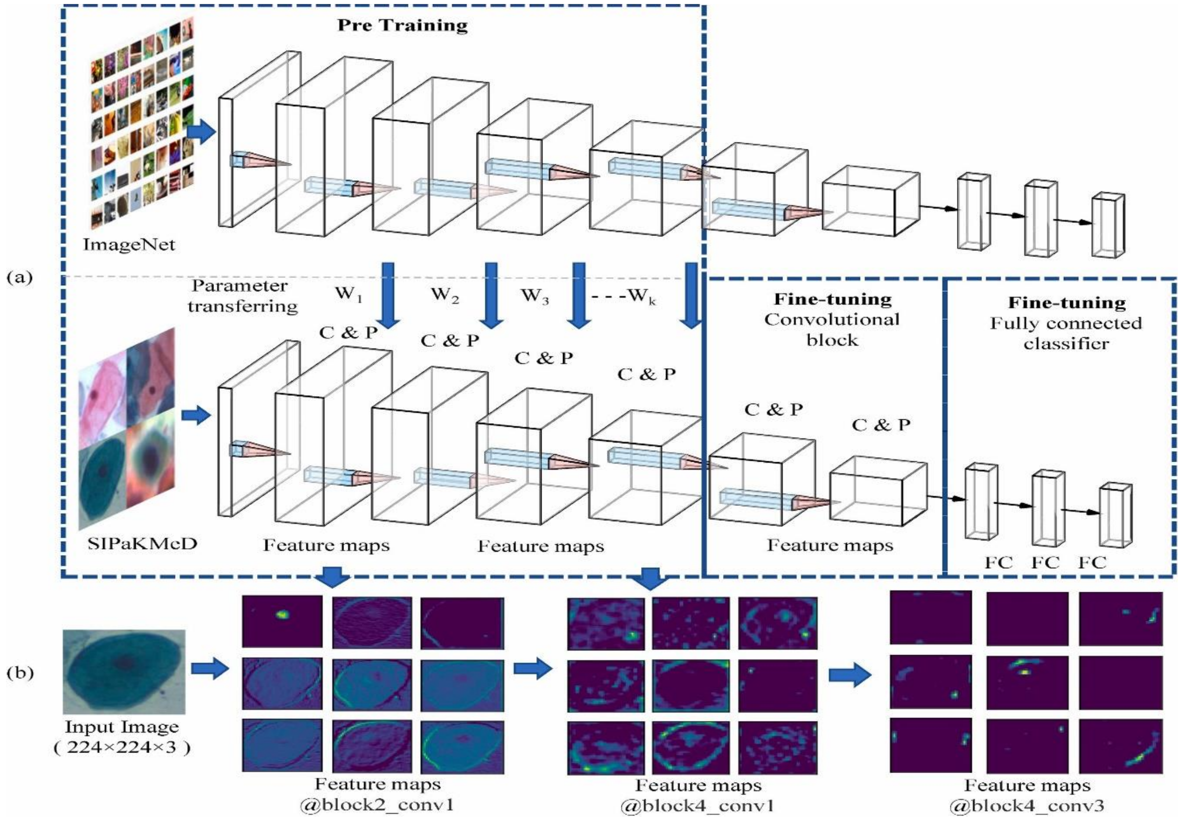

Figure 7. (a) Visualization of TL process, (b) Visualization of the feature maps [22]

This paper aims primarily to provide a thorough review of several detection and classification frameworks for cervical cancer using different imaging models images. In addition, a comparative study is provided to examine the strengths and weaknesses of these frameworks and provide potential areas for future development. The remaining parts are organized in the following manner: Section II explores several DL frameworks specifically developed for the prediction and classification of cervical cancer using scan images. Section III presents a comparative examination of the systems. Section IV provides a comprehensive overview of the whole survey and suggests the future direction.

II. Survey On Deep Learning Models For Cervical Cancer Detection

Chandran et al. [23] proposed VGG19 (TL) and Colposcopy Ensemble Network (CYENET) models to detect cervical cancer. The images were pre-processed and augmented to enhance the efficiency of the training data. The VGG 19 model was employed to for classifying different kinds of cervical cancer. This was done by keeping the top layers fixed and evaluating the model's performance on a cervical image dataset. The CYENET architecture enhanced the extraction of cervical cancer features from colposcopy images using depth and parallel convolutional filters. Occlusion sensitivity maps identified the features of images which are significant for CYENET classification.

Chen et al. [24] developed the CytoBrain model for automatic cervical cancer screening using the CompactVGG model. The images were extracted from WSI and labeled by separate cytopathologists. Data was augmented by randomly flipping, rotating, translating, changing brightness and adding Gaussian Blur and Gaussian noise. CompactVGG adopt one dropout operation along with the first fully connection layer and L2-norms regularization to avert overfitting. Finally, the CompactVGG model was trained by a 5-fold cross-validation strategy for the screening of cervical cancer.

Huang et al. [25] developed a DL-CNN model for categorizing cervical cancer. The colposcopy images were pre-processed to reduce its size. Different features were extracted from the datasets. The softmax layer acted as the classification layer and was used to classify cervical cancer using the patient’s colposcopy images.

Alsalatie et al. [26] developed Ant-Lion and Particle Swam Optimization (AL-PSO) in order to develop a reliable method for the automated detection of cervical cancer using pap-smear images. At first, the image dataset was augmented by rotating and scaling the images. AlexNet, DarkNet-19, and NasNet were utilized to extract the features. Feature weighting was done using AL-PSO to establish the relative importance of each feature about providing appropriate weight for classification. The extracted features were fed into SVM and RF for cervical cancer classification.

Alsubai et al. [27] developed a CNN-based cervical cell classification using Pap Smear Slide images. The images were pre-processed and segmented using pre-defined nuclei. The images were augmented to expand the dataset. Four different layers were employed to classify the data.

The convolution layer was used for feature extraction. The pooling layer was used to minimize the derived feature map. The flattened layer converted the 3D image output to 1D image output. Fully connected layer (FCL) acted as a transition layer to transform the output into the required form. The combination of these layers was used to classify cervical cancer.

Attallah [28] proposed a Computer-Aided Design (CAD) model, which improves cervical cancer detection diagnostic accuracy by extracting information from many fields. Pap-smear images were primarily augmented using flipping, rotating, scaling, and shearing. Discrete Wavelet Transform (DWT) and Gabor Wavelets (GW) were used for feature extraction. This model employed Principal Component Analysis (PCA) to combine all the DL features with various handcrafted descriptors. The detection step is enacted in several configurations. Instead of utilizing a single feature from a specific domain, a CAD system was erected with several CNNs that retrieved numerous descriptors to detect cervical cancer.

de Lima et al. [29] employed a deep learning architecture based on Mask Region-based CNN (RCNN) to detect cervical cancer & segmentation using tissue images. Pap-smear samples were collected in the private data set. The images were cropped to reduce its size. The three different datasets were combined forming a merge dataset. This dataset was pre-processed and augmented to increase the size of the dataset. Finally, the data was fed into a modified Mask RCNN to detect cervical cancer.

Devi et al. [30] devised an Improved Boykov's Graph Cut-based Conditional Random Fields and Superpixel imposed Semantic Segmentation Technique (IBGC-CRF-SPSST) to detect cervical cancer using Pap Smear images. Initially, Bias Correction-based pre-processing were done to prevent intensity inhomogeneity. VGG-based FCL was employed for feature extraction. Boundary Optimization was estimated by Boykov's Graph Cut. Finally, IBGC and Conditional Random Fields (CRF) were utilized to detect boundaries for the cervical cancer detection.

Kanimozhi et al. [31] developed a DL based Deeply Supervised Shuffle Attention Modified CNN (DSSAMCNN) to classify vessel and non-vessel invasion in cervical cancer using MRI images. Bilateral filtering was used in pre-processing to eliminate noise from the images. Modified U-Net model was used for segmentation. Residual blocks were used to extract the features. Tightly coupled convolution was used for feature recycling and propagation. Finally, the segmented images were fed into the DSSAMCNN model to categorize the cervical cancer.

Sahoo et al. [32] presented a novel ensemble architecture for categorizing cervical cancer. The Pap Smear images were categorized into Squeeze-and-Excitation (SE) Inception V4, ResNet-152 V2, DenseNet 169. A rank-based fuzzy ensemble technique combined with the pre-trained models for the prediction of accuracy. Moreover, Advanced techniques like MixUp, CutMix, and CutOut were employed for the data augmentation. Finally, the pre-trained models were adjusted to categorize the images of cervical cancer.

Tian et al. [33] developed Silva's pattern-based Classification system (SPBC) to detect Endocervical Adenocarcinoma (EAC) using WSI. The data was augmented to prevent overfitting. The tiles were extracted by WSI to reduce the spatial dimensions for input. DLS served as a pre-screening tool in the classification procedure of endocervical carcinoma.

Mathivanan et al. [34] developed an integrated model that combines DL and ML for the prediction of cervical cancer. The Pap Smear images were categorized into normal and abnormal using ML techniques. The feature extraction was done by several DL models like ResNet-101, ResNet-152, Inceptionv3, and AlexNet. ML techniques like Simple Logistic Regression (SLR), Decision Tree, Random Forest, Naive Bayes (NB), and PCA were implemented for the categorization of Cervical cancer.

Muksimova et al. [35] proposed a Reinforcement Learning Cancer Network (RL-CancerNet) model to detect cervical cancer using pap smear images. The image datasets were augmented using horizontal & vertical flipping, and random zooming in & out to effectively increase the variability of the training data. The model integrated revised EfficientNetV2 with r-by-object supporter blocks inside its architecture. The Supporter block used a convolutional and a Bidirectional Long Short-Term Memory (BiLSTM) layer, which functioned together as a one-shot attention mechanism. Finally, a meta-learning ensemble method-based CNN was used to classify cervical cancer.

Nour et al. [36] devised a Computer-Aided Cervical Cancer Diagnosis using the Gazelle Optimizer Algorithm with DL (CACCD-GOADL) to classify cervical cancer. The improved MobileNetV3 model was used to extract feature vectors. To optimize the hyperparameter values of this model Gazelle Optimizer Algorithm (GOA) was used. Finally, the Stacked Extreme Learning Machine (SELM) method was used for classifying cervical cancer.

Omodunbi et al. [37] developed the EfficientNet B7 model for the prediction of cervical cancer. The pap smear slide images were pre-processed to reduce image interference, and then, normalized using the Min-max normalization technique. Transfer Learning trained by the EfficientNet model was used for cervical cancer detection.

Tan et al. [38] established a CNN model using a transfer learning approach to detect cervical carcinomas by using Pap-smear images. The data was pre-processed and normalized by scaling the inputs. Deep CNN models accurately classify images from Class 2 and Class 5 that exhibit significant similarity. DenseNet-201 outperformed with satisfactory accuracy in cervical cancer prediction.

Wang et al. [39] developed Attention Gated (AG) 3D Unet – CNN model for automatic needle digitization to improve HDR brachytherapy. Initially, patients with different stages of cancer were selected. The images of Manual digitized needles were pre-processed and then augmented using rotation, horizontal flip, vertical flip & scaling. Spatial attention gates (SAGs) were used to extract needle features. Geometric and Dosimetric analysis were used for the comparison of manual and automatic digitization of needles in HDR brachytherapy for cervical cancer.

Youneszade et al. [40] developed a CNN model to predict cervical cancer using digital Colposcopy Images. In this method, the dataset was collected and pre-processed using the scaling method. The pre-processed images were augmented using. the augmented images were fed into the

VGG-19 model for feature extraction. Finally, the softmax layer in VGG-19 was used for cervical cancer classification.

III. COMPARATIVE ANALYSIS

Table 1 below presents a comparative analysis based on the advantages and disadvantages of the aforementioned models developed for cervical cancer detection utilizing various images.

Table I. Comparison of various Cervical Cancer classification models for different images

Ref No.	Techniques	Merits	Demerits	Datasets	Performance Evaluation
[23]	VGG19, CYENET	It removes segmentation and feature engineering steps.	Models may collapse due to distractors	Intel ODT dataset	Accuracy = (VGG19) 73.3%, (CYENET) 92.3%
[24]	CompactVGG, drop-out technology, L2-norm regularization	Faster running speed, better classification performance	Discarding inconsistently labeled cell images may lead to losing crucial information	WSI dataset	Accuracy = 88.30% Precision = 82.26% F1-score = 87.04
[25]	DL	Overcame the problem of misrecognized due to high similarity		Colposcopy images dataset	Accuracy = 95.19%
[26]	AL-PSO, AlexNet, DarkNet-19 Nasnet SVM and RF	Does not require any pre-processing steps	Lacks in nucleus segmentation and the nucleus region delineating	Herlev Pap smear dataset	Accuracy = 99.5%
[27]	CNN	Does not require much time to train, low misclassification rate	Failed to adapt to larger datasets	SIPaKMeD dataset	Accuracy = 91.1%
[28]	CAD, CNN, DL, TL,	Does not need pre-segmentation, therefore simpler.	Maintain default hyperparameters and no correlation analysis were performed	Mendeley LBC dataset	Accuracy = 100%
[29]	Mask RCNN	Applied to any data set without adding new layers	Pre-cancer cells were difficult to predict	Private, SipaKMeD Mendeley dataset	Accuracy = (5-class) 76.51%, (3-class) 84.31%
[30]	IBGC-CRF-SPSST, VGG-based FCL	False positive rate is highly reduced	Accuracy will reduce if a cell has a double nucleus	Pap Smear images datset	Accuracy = 99.78%
[31]	DSSAMCNN	Efficient in providing nuclear segmentation	Convergence time is considerably longer	MRI image dataset	Accuracy = 94%
[32]	Ensemble model, SE Inception V4, ResNet-152 V2, DenseNet 169, MixUp, CutMix, CutOut	Employed for other disease detection too	Ensemble model's complexity is high	SIPaKMeD Mendeley LBC Pap smear images dataset	Accuracy = 97.18%
[33]	SPBC, ResNet50, DLS	Minimizes surgical complications	A single tissue slice might not accurately represent the entire sample	WSI datasets	Accuracy = 74.36%,
[34]	SLR, DT, RF, NB, ResNet-101, PCA, ResNet-152, Inceptionv3, AlexNet	Flexible and more accurate	Poor generalization due to overfitting	SIPaKMeD dataset	Accuracy = (AlexNet) 99.12%
[35]	EfficientNetV2, RL-CancerNet	Rapid adaptation to the dataset resulted in accuracy gain	Unknown datasets may require adjustments to maintain their accuracy	SipaKMeD, Herlev Pap Smear dataset	Accuracy = 99.85%
[36]	CACCD-GOADL, GOA, SELM	Potential to reduce human error		Herlev dataset	Accuracy = 99.38%
[37]	EfficientNet B7, CNN	No overfitting or underfitting problem	Failed to adapt to larger datasets	SIPaKMeD dataset, Pap smear slides image dataset	Accuracy = 87% Precision = 87%, F1score = 87%
[38]	CNN	Does not need feature extraction and segmentation steps	Lack of performance thresholds for detection	Pap smear images	Accuracy = 87.02%
[39]	3DUnet CNN	Faster Convergence due to Low loss, highest DSC	Potential uncertainty in manual contour may affectthe accuracy of needle	CT images	Dice similarity coefficient (DSC) = 93.7%, Jaccard index (JI) = 88.2%
[40]	CNN, CYENET, VGG19	Detect early stages of cancer	Number of images are high	Colposcopy images dataset	Accuracy = 98.17% (VGG19)

IV. RESULT AND DISCUSSION

The performance evaluation of the existing DL techniques presented in Table 1 illustrates the precision of overall prediction and classification of cervical cancer detection.

Most of the studies employed the SIPaKMeD and Herlev datasets. Other models used various benchmark datasets for predicting cervical cancer from various images. This section assesses the accuracy of different DL-based cervical cancer prediction models utilizing these and other benchmark datasets. The graphical representation demonstrates the accuracy of these models in identifying and categorizing cervical cancer based on different images.

Figure 8 represents DL based cervical cancer detection using various datasets. From this analysis, it is evident that CAD [28] and RL-CancerNet [35] delivers both superior efficiency and satisfactory outcomes in cervical cancer detection compared to other models.

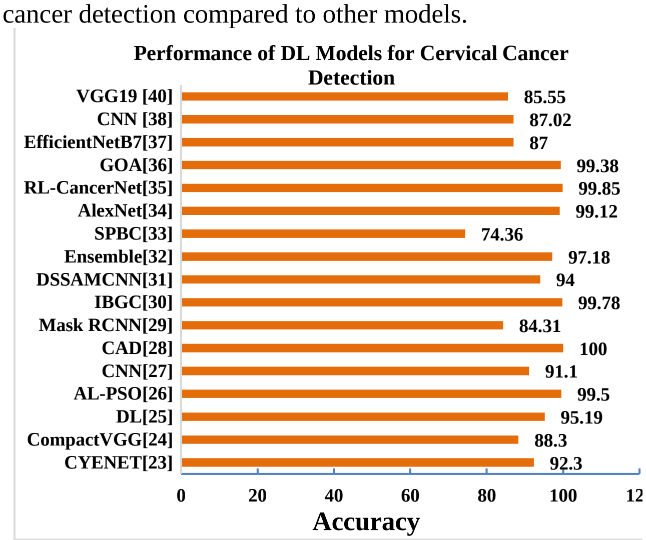

Figure 8. Comparison of DL models for cervical cancer prediction in terms of accuracy

V. CONCLUSION

Cervical cancer is a dangerous and challenging disease, necessitating immediate and accurate examination of nodules. It is important to detect the cancer at the initial stage to control the death rate. Recently, DL techniques have been widely used to detect cervical cancer in its early stages. In this research work, various DL approaches are examined for forecasting the cervical cancer figuring out their advantages, disadvantages and performance efficiency. The identified problems enable the researchers to create functional models for cervical cancer diagnosis and prevention, aiding decision-making and accurate output prediction. Future study will concentrate on advanced models for training various sorts of cervical cancer datasets and recognizing cervical cancer nodule characteristics for efficient cervical cancer treatments.

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