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# A systematic review of effective data augmentation in cervical cancer detection

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***Abstract*—The rapid progress of AI has made computer-assisted systems essential in medical fields like cervical cytology analysis. Deep learning requires large datasets, but data scarcity and privacy concerns pose challenges. Data augmentation addresses this by generating additional images and improving model accuracy and generalizability. This review examines effective augmentation techniques and top-performing deep-learning models for segmentation and classification in cervical cancer detection. Analyzing 57 articles, we found that hybrid deep feature fusion with augmentation (rotation, flipping, shifting, brightness adjustments) achieved 99.8% accuracy in binary and 99.1% in multiclass classification. Augmentation is vital for enhancing model performance in limited data scenarios.**

***Keywords*—cervical cancer; data augmentation; deep learning; artificially generated images**

## I. Introduction

As artificial intelligence advances rapidly, computer-assisted systems have turned into crucial tools for medical professionals across various fields, including cervical cytology analysis [1][2]. Deep learning (DL) techniques have greatly improved the screening process for cervical cancer, especially in the analysis of Pap smears [3]. Among these methods, convolutional neural networks (CNNs) are especially prominent due to their capability to automatically learn and identify hierarchical patterns and features. This makes CNNs highly effective for extracting intricate information from images [4]. CNNs are commonly used for image classification, object detection, and segmentation tasks.

Deep learning techniques typically require large datasets to train models effectively [5], [6]. However, in medical imaging, obtaining sufficient data can be challenging due to concerns over patient privacy and data scarcity [7]. A common issue in such scenarios is class imbalance, where certain classes are overrepresented in the training data. This imbalance can lead to biased models that perform poorly on underrepresented classes, affecting the overall model performance. Another challenge is overfitting, where the model excels on the training data but struggles to generalize to new, unseen data, diminishing its real-world effectiveness. To mitigate these issues, data augmentation is often employed. This technique artificially increases the size of the training dataset by applying transformations such as rotations, flips, or color changes to existing images [8]. By diversifying the training data, data augmentation enhances model performance, reduces overfitting, and improves the model's ability to generalize, especially in scenarios with limited data [9].

Several studies have been conducted using data augmentation to improve performance in segmentation and classification tasks for cervical cells. In paper [10] a comprehensive review of various data augmentation strategies specifically for brain tumor segmentation is presented, focusing on techniques that improve segmentation outcomes. Paper [11] emphasizes augmentation techniques aimed at medical image classification. Meanwhile, [12] offers a systematic review of cervical cancer diagnosis, addressing both detection and classification methodologies. Additionally, [13], provides a broader review of data pre-processing and augmentation methods, covering general applications. Furthermore, study [14] explores the use of generative adversarial networks (GANs) in medical image segmentation and classification. Each of these review papers addresses distinct aspects, from segmentation and classification to GAN-based augmentation in medical imaging. Finally, the paper [15] identifies data augmentation techniques specifically for the segmentation and classification of cervical cancer using deep learning. The paper highlights the techniques employed in both tasks and recommends future work, such as comparing model performance in cervical cancer detection. Therefore, in this study, we reviewed a data augmentation technique for the segmentation and classification of cervical cells to compare the performance of DL models. We formulate the following research questions:

RQ1: Which data augmentation techniques are used for segmentation tasks, and which algorithm performs best?

RQ2: Which data augmentation techniques are used for classification tasks, and which algorithm performs best?

The remainder of the paper is structured as follows: Section 2 outlines the methods used in the review. Section 3 presents the results and discussion of the findings. Lastly, Section 4 provides the conclusion, followed by the references.

## II. Materials and Methods

The materials and the methods used in the study are presented in this section. The analysis follows the PRISMA protocol, a framework commonly used to guide the reporting of items in systematic reviews and meta-analyses [16]. This protocol is widely favored in the majority of review papers [17].

### *A. Search Term*

In this review, we conducted a search for relevant studies published from January 2017 to September 2024 using the keywords "data augmentation," "cervical cancer," and "deep learning." This search yielded a total of 614 articles, retrieved from databases such as Scopus, Web of Science, PubMed,

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IEEEXplore, and ScienceDirect, along with manual searches on Google Scholar.

### B. Eligible Criteria

The inclusion and exclusion criteria for the papers are described in Table I.

TABLE I
THE INCLUSION AND EXCLUSION CRITERIA TO INCLUDE THE PAPER

| No | Inclusion criteria | Exclusion criteria |
|---|---|---|
| 1 | Publication year between 2017 and 2024 | Articles published before or after the specified date range |
| 2 | Papers published in the English language | Papers published in a language other than English |
| 3 | The article type is either a journal or conference | Article types are categorized out of the specified type |
| 4 | Research papers related to data augmentation techniques for the segmentation and classification tasks in the diagnosis of cervical cancer | Papers lack information about data augmentation techniques for segmentation and classification tasks in the diagnosis of cervical cancer |

### C. Selection Process

In this section, we explain the paper selection process. Initially, 614 articles were gathered from five databases and manual searches. After removing 73 duplicates, 541 unique papers remained. Applying inclusion and exclusion criteria led to the exclusion of 445 papers, leaving 96. Of these, 16 were inaccessible, and 80 required further analysis. Following a detailed review, 57 articles were finalized for inclusion. The selection process is shown in Fig. 1.

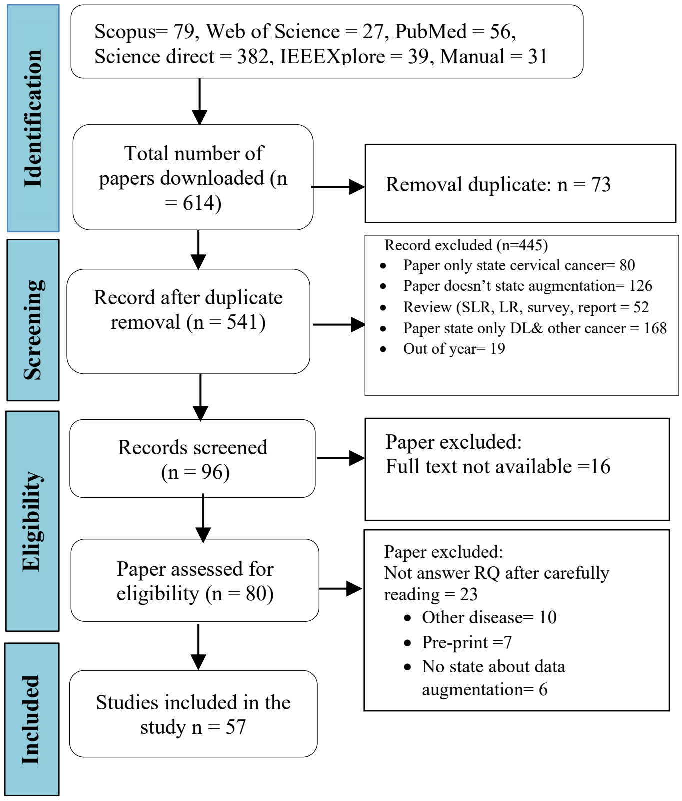


Fig. 1. Selection process of the studies

### D. Data Extraction

We selected papers to address the research questions by categorizing data augmentation techniques into two groups: basic and artificial data generation methods. We identified whether these techniques were applied to segmentation or classification tasks with the DL algorithm, considering the publication year of each study. Additionally, we detailed the augmentation methods, the segmentation and classification algorithms, their performance, and the metrics used in each study.

## III. RESULTS AND DISCUSSIONS

This section addresses the research questions by identifying the data augmentation techniques used for segmentation and classification tasks, the algorithms applied, and their performance in cervical cancer detection. The studies employed basic augmentation techniques such as rotation, flipping, cropping, translation, and zooming to segment cervical cells. In contrast, basic augmentation techniques and artificially generated images were used for classification tasks to improve the diversity of training data.

### A. Data Augmentation in the Segmentation Task

For Research Question 1 (RQ1), we present the data augmentation techniques used in the segmentation task and the deep learning algorithms employed. Various studies utilize different datasets, and the results of segmentation using basic data augmentation techniques are summarized in Table II.

In Tables II-VI, Acc is accuracy, Pre is precision, Rec is recall, F1 is the F1-score, dice is the dice coefficient, IoU is the intersection over union, SN is sensitivity, SP is specificity, AR is average recall, AP is average precision, mAP is mean average precision, AUC is the area under the curve, Ref for reference, and Qty indicates the amount of the data used in the study. Comparing model performance can be difficult when the data is collected from different sources. Additionally, even when using the same dataset, variations in segmentation algorithms for detecting cervical cancer make it challenging to compare studies, especially when different augmentation techniques are applied. Moreover, various studies use different performance metrics to evaluate their models, and we present each study's performance metrics where they differ. However, in this study, we considered this issue during our comparisons.

As shown in Table II, the best model for the Herlev dataset achieved a 96.1% recall using augmentation techniques such as rotation, cropping, flipping, contrast adjustment, and elasticity with the Lightweight Feature Attention Network (LFANet) algorithm [18]. The dice coefficient is predominantly used in other datasets, and we compared studies based on this metric. For example, in the HU-UFSC dataset, using U-Net as a baseline with ResNet50 as a backbone, the augmentation techniques of flipping, rotation, zooming in, increasing contrast, and symmetric warping achieved a dice coefficient of 99% [19]. In [20], the two numbers in the results section represent values for different datasets: the first value is for the PEG dataset, and the second is for the Mobile Eva dataset.

TABLE II
DATA AUGMENTATION TECHNIQUES USED IN THE SEGMENTATION TASK, ALONG WITH THE ALGORITHMS AND MODEL PERFORMANCE

| Ref | Dataset | Qty | Class | Augmentation | Segmentation | Performance metrics |
|---|---|---|---|---|---|---|
| [19] | HU-UFSC (University Hospital Professor Polydoro Ernani de Sao Thiago of Federal University of Santa Catarina) | 2540 | - | flip, rotation, zoom up, contrast up, symmetric wrap | U-Net and ResNet18 as a backbone | **Dice= 99**<br>IoU=87 |
| [21] | Thammasat University (TU) Hospital | 178 | - | rotation, translation, cropping | Mask-RCNN | Acc= 89.8<br>SN=72.5<br>SP= 94.3 |
| [22] | Division of Cancer Epidemiology and Genetics of the National Cancer Institute (DCEG-NCI) | 256 | - | rotation, flipping | CNN (Inception V3 | AUC= 98 |
| [23] | PatchSeg,<br>ClusterSeg,<br>DomainSeg TargetA,<br>DomainSeg TargetB | 3487,<br>2362,<br>381,<br>332 | | transformation. Flip, random crop | AL-Net | Dice=83.01<br>81.65<br>73.59<br>71.42 |
| [24] | Tertiary referral center with a dedicated interdisciplinary gynecological oncology MRI | 169 | - | Rotation, shift, crop | U-Net | SN= 89<br>Dice=82 |
| [25] | University of Oklahoma Medical Center | 453 | 3 | Flip, rotation, blur contrast, noise | DeepCIN, | Acc=88.5<br>Pre=88.6<br>Rec=88.5 |
| [20] | PEG &<br>Mobile EVA system dataset | 978,<br>1342 | 2 | Rotation, translation, shear | Faster-RCNN | Acc=78.1, 66<br>Pre=68.9, 63.3<br>Rec=83.3, 44.1 |
| [26] | High-resolution micro-endoscope in Brazil (HRME) | 1600 | 5 | Rotation, flipping, and random cropping | Multi-Task Network | SN=94<br>SP=58<br>AUC=87 |
| [27] | Gland datasets | 213 | - | flip, brightness, contrast | NuClick (multiscale conv block) | Dice= 95.6 |
| [28] | Herlev | 917 | 7 | Horizontal inversion, | RFN, RCNN with SPFNet | AP=78.4 |
| [18] | Herlev | 917 | 7 | Rotation, crop flipping, contrast elasticity, | LFANet (lightweight feature attention network) | Pre=93.01<br>**Rec=96.1**<br>Dice=94.1 |
| [29] | Herlev | 917 | 7 | Rotation, translation | Pyramid Scene Parsing | Acc=Pre=Rec=96<br>IoU=74 |
| [30] | Herlev | 917 | 7 | Translation, reflection, rotation | Mask R-CNN<br>& ResNet10 as backbone | Pre=92<br>Rec=91 |
| [31] | CX22,<br>Herlev,<br>SIPaKMeD | 1320,<br>917,<br>4049 | -<br>7<br>5 | Rotation, flip, color transform | CerviSegNet-DistillPlus | Acc= 94, 93.65, 92.5<br>SP=92.2, 91, 89.9<br>SN=96.2, 96.2, 93.7 |
| [32] | ISBI, and<br>Herlev | -<br>917 | -<br>7 | Rescaling, flipping, and rotation | CNAC-Seg | Dice= 92.39 and 94.92 |
| [33] | ISBI, and<br>Herlev | -<br>917 | -<br>7 | Flipping, rotation, and cropping | PATrans | Dice= 94.06, 94<br>IoU= 88.8, 89.7 |
| [34] | Pomeranian | 419 | 3 | Rotation, flipping, and scaling | U-Net & DenseNet121 as a backbone | Acc= 99.86,<br>Pre=97.7, Rec=98.1,<br>IoU=99.8 |

### *B. Data Augmentation in the Classification Task*

In RQ2, we examine the data augmentation techniques used for the classification task. The class refers to the number of categories used in the study or the type of cervical cells. The results from using the Herlev dataset with basic augmentation techniques are presented in Table III

TABLE III
BASIC DATA AUGMENTATION TECHNIQUES USED IN THE CLASSIFICATION TASK, ALONG WITH THE ALGORITHMS AND MODEL PERFORMANCE ON THE HERLEV DATASET

| Ref | Dataset | Quantity | Class | Augmentation | Classification | Performance metrics |
|---|---|---|---|---|---|---|
| [30] | Herlev | 917 | 7, 2 | Rotation, translation, reflection | VGG Net | Rec=95, 96 |
| [35] | Herlev | 917 | 7, 2 | Rotation, flip, shift, brightness | Hybrid deep feature fusion (HDFF) | Acc=90.3, 98.3 |
| [36] | Herlev | 917 | 4 | flip, zooming, rotation, shearing, shift, feature-wise center & standard deviation, brightness increase, full mode, and normalization | MASO-optimized DenseNet 121 (Mutation-based Atom Search Optimization) | Acc=98.38<br>Pre=98.6<br>Rec=99.3<br>F1=98.3 |
| [37] | Herlev | 917 | 2 | Zooming, shifting, flipping, and rotation | MobileNetV2 InceptionResNetV2, (ensemble) | Acc=98.97<br>Pre=98.7<br>Rec=98.5 |
| [38] | Herlev | 917 | 2 | Rotation, mirroring, flipping | Ensemble TL (Inception-V3, Xception, VGG-16, and Resnet-50) | Acc=98.37<br>Pre=98.5<br>Rec=99.3<br>F1=98.9 |
| [29] | Herlev | 917 | 2 | Rotation, translation | Ensemble of NB, J48, RF, SVM and ANN | **Acc=99.7** |
| [39] | Herlev | 917 | 2 | Rotation, mean filter, salt and pepper noise | IFDL GoogleNet (Improved Fuzzy DL) | Acc=99.2<br>Rec=99.3<br>SP=99.75 |

The number '2' represents a binary classification, while numbers other than 2 represent a multi-class classification. For example, the widely used Herlev dataset contains seven classes: squamous cell carcinoma in situ, intermediate squamous non-keratinizing dysplasia, severe squamous non-keratinizing dysplasia, moderate squamous non-keratinizing dysplasia, mild squamous non-keratinizing dysplasia, normal columnar epithelial, intermediate squamous epithelial, and superficial squamous epithelial, with 150, 197, 146, 182, 98, 70, and 74 images, respectively. The first four are classified as abnormal, while the last three are normal in binary classification.

In contrast, the SIPaKMeD dataset includes five classes of cervical cells: superficial-intermediate cells, parabasal cells, meta-plastic cells, dyskeratotic cells, and koilocytotic cells, with 831, 787, 793, 825, and 813 images, respectively. In binary classification, the first two classes are considered normal, while the last three are classified as abnormal.

In the Herlev dataset, almost all of the models perform well which is more than 90% accuracy. In [29], using the rotation and translation basic augmentation, the model achieves an accuracy of 99.7% using the ensemble of Naïve Bayes, J48 decision tree, random forest, support vector machine, and artificial neural network in binary classification. On the other hand, in a multiclass classification, the model scores a recall value of 96% using the rotation, translation, reflection basic augmentation and VGG Net is a classifier algorithm. In [30] and [35], the two numbers in the results section represent values for multiclass and binary classification. The results for the SIPaKMeD dataset, using basic augmentation techniques, are presented in Table IV.

TABLE IV
BASIC DATA AUGMENTATION TECHNIQUES USED IN THE CLASSIFICATION TASK, ALONG WITH THE ALGORITHMS AND MODEL PERFORMANCE ON THE HERLEV DATASET

| Ref | Dataset | Qty | Class | Augmentation | Classification | Performance metrics |
|---|---|---|---|---|---|---|
| [40] | SIPaKMeD | 4049 | 5 | crop, flip, rotate, copy paste | Voting (ensemble 12), ViT (vision transformer) | Acc=91.8, 92.9, Pre=92.6, 93.9<br>Rec=91.9, 92.7, F1=92.3, 93.3 |
| [37] | SIPaKMeD | 4049 | 5 | Zooming, shifting, flipping, rotation | MobileNetV2 InceptionResNetV2, (ensemble) | Acc=96.96 |
| [41] | SIPaKMeD | 4049 | 5 | Flip, rotation, shift | ViT-CNN ensemble | Acc=97.65, Pre=99.5, Rec=97.7, F1=98.6 |
| [35] | SIPaKMeD | 4049 | 5, 2 | Rotation, flip, shift, brightness | Hybrid deep feature fusion (HDFF) | Acc=**99.1, 99.8** |
| [42] | SIPaKMeD | 4049 | 5, 2 | Rotation, flipping | VGG16, ResNet152, DenseNet169 (feature concatenate) | Acc=97.5, 99.3, Pre=97.9, 98.9<br>Rec=98, 100, F1=98, 99.5 |

| | | | | | | |
|---|---|---|---|---|---|---|
| [43] | SIPaKMeD | 4049 | 5 | Rotation, resize, flipping, | FL CNN (federated learning) | Acc=94.36 |
| [44] | SIPaKMeD | 4049 | 5 | Fliping | Dual-stream self-attention (DSA) | Acc= 99.01, Pre=99.02, Rec= 99. 02, F1=99.01 |
| [45] | SIPaKMeD | 4049 | 5 | Rotation, zooming | ViT & SeNet with ResNet and DenseNet | Acc= 95.88, Pre= 95.37, Rec= 96.25, F1= 95.79 |
| [46] | SIPaKMeD | 4049 | 5 | Cropping, flipping, rotating, copy-pasting, and scaling. | ConvNextTv2-based Multi-Axis Vision Transformer model (MaxCerVixT) | Acc= 99.02, Pre= 99.03, Rec= 99.04, F1= 99.02 |

In the SIPaKMeD dataset of [35], the hybrid deep feature fusion achieves an accuracy of 99.1% for multiclass classification and 99.8% for binary classification using rotation, flip, shift, and brightness as basic augmentation techniques. The fused feature algorithms are VGG16, VGG19, ReseNet50, and Xception. The results for the other datasets, using basic augmentation techniques, are presented in Table V.

In other datasets, such as the Mendeley dataset, the model achieves an accuracy of 99.68% using an ensemble of MobileNetV2 and InceptionResNetV2 algorithms, combined with zooming, shifting, flipping, and rotation as basic augmentation techniques [37]. The second augmentation method generates artificial images to classify cervical cells, as shown in Table VI. This data augmentation technique focuses on creating artificial images based on the original ones, producing synthetic images that closely resemble the real ones.

In Table VI of [47], using the generative adversarial network (GAN) augmentation technique with the Herlev and SIPaKMeD dataset, which includes 8 different classes, the VGG16 model achieves an accuracy of 99.81%. In the

TABLE V
BASIC DATA AUGMENTATION TECHNIQUES USED IN THE CLASSIFICATION TASK, ALONG WITH THE ALGORITHMS AND MODEL PERFORMANCE ON THE OTHER DATASET

| Ref | Dataset | Qty | Class | Augmentation | Classification | Performance metrics |
|---|---|---|---|---|---|---|
| [48] | Intel&MobileODT | 1500 | 3 | Rotation, cropping, flipping | DCNN | AUC=82 |
| [49] | Intel&MobileODT | 8215 | 3 | flips, translations, shears, and zooms | ResNet | Acc=69.93 |
| [50] | Intel&MobileODT | 9378 | 3 | Rotating, brightness, cropping | VGG19, Colposcopy Ensemble Network (CYENET) | Acc=73.3, 92.3 Rec=33, 92.4 SP=79, 96.2 |
| [51] | Mendeley LBC | 2376 | 4 | Rotation, shift, shear, zoom, flip | ResNet50V2 | Acc=Pre=Rec=F1 = 97 |
| [37] | Mendeley LBC | 963 | 4 | Zooming, shifting, flipping, and rotation | MobileNetV2 InceptionResNetV2, (ensemble) | **Acc=99.68** Pre=99.34 Rec=99.87 |
| [45] | Mendeley LBC | 963 | 4 | Rotation, zooming | ViT & SeNet with ResNet and DenseNet | Acc= 98.44, Pre= 97.34, Rec= 97.99, F1= 97.66 |
| [46] | Mendeley LBC | 963 | 4 | Cropping, flipping, rotating, copy-pasting, and scaling. | ConvNextTv2-based Multi-Axis Vision Transformer model (MaxCerVixT) | Acc= 99.48, Pre= 99.26, Rec= 99.8, F1= 99.52 |
| [25] | University of Oklahoma Medical Center | 453 | 3 | flip, rotation, blur contrast, noise | DenseNet | Acc=88.5 Pre=88.6 Rec=88.5 |
| [20] | PEG & Mobile EVA system dataset | 978, 1342 | 2 | Rotation, translation, shear | VGG16 | Acc=72.6, 67.5 Pre=66.5, 63.5 Rec=69.6, 45.9 |
| [52] | HMCHH (Heilongjiang maternal & child & Harbin Medical University Cancer hospital) | 335 | 2 | Flip, rotation, brightness change, Gaussian blur (Affine transform) | AttFPN (Attention FPN) DenseNet-169 backbone | Acc=90.91 Rec= 91.3 SP=90.62 |
| [53] | JA Shizuoka Kohseiren Enshu Hospital | - | - | Flip, Rotate, RandomGrid Shuffle, Brightness Contrast, and random Gamma | EfficientNet | Acc=87.3, F1=83.3, AUC=90.8 |

| | | | | | | |
|---|---|---|---|---|---|---|
| [54] | Gynecological oncology database | 485 | 3 | rotation, zoom, flipping | CNN | Acc=50 |
| [55] | Fujian Maternal and Child Health Hospital | 8839 | 4 | Light change, blur, crop, rotate | DenseNet121 | Acc=73.08<br>AUC=75 |
| [56] | CRIC | 400 | 2 | rotation, scaling, shear, blur, flip, noise | YOLOv5 | mAP= 83 |
| [57] | National Cancer Institute, Bethesda, USA | 2120 | 5 | Rotation, zoom, translation, flip, warp, gaussian blurring | DenseNet121 | Acc=96.3<br>SN=94.97<br>SP=98.86 |
| [58] | Obafemi Awolowo University Teaching Hospitals Complex (OAUTHC) | 1331 | 2 | Flip | sparse attention-based multiple-instance learning | Acc=84.55 |
| [59] | Provincial Hospital of Shandong First Medical University Central | 90 | 3 | rotation, flip, shift | ResNet50 | Acc=74.36 |
| [60] | Affiliated Hospital of WanNan Medical College at Wuhu | 3294 | - | Rotation, translation | EfficientNet | Acc=90.0<br>Rec=87.1<br>F1=89.1 |
| [61] | Obstetrics and Gynecology Hospital of Fudan University | 9562 | 4 | Rotation, translation, and scaling | Improved EfficientNet-B3 | Acc=90.5, Pre=76.5, Rec=83.6, SP=93.2 |
| [62] | ComparisonDetector, DST | 7410& 3807 | 4, 4 | Scaling, rotation, and flipping | DETRwith Improved deNoising anchOr boxes (DINO) | AP=24.6 & 15.4<br>AR=46.6 & 45.1 |
| [63] | CRIC, CLBC | 340 & 50 | | Cropping, Flipping | Dual-path Proposal Discriminative detection Network (DPD-Net) | AR=55.32 & 36.47<br>mAP=35.2& 13.3 |
| [64] | Pap Smear | 4800 | 4 | Rotation, brightness, contrast, and zoom | ResNet50 | Acc=91 |

Cervix93 dataset, the model reaches 100% in accuracy, precision, recall, and F1 score using the Self-Attention Generative Adversarial Network (SAGAN) augmentation technique and a multi-scale transformer-based ensemble learning classifier (CervixFormer) [65].

This systematic review highlights the data augmentation techniques applied in cervical cancer detection, a critical area in medical imaging. The findings indicate that basic augmentation methods such as rotation, flipping, translation, cropping, and zooming are utilized in both segmentation and classification tasks, to improve model performance. In contrast, artificially generated techniques, such as those using generative adversarial networks (GANs), are exclusively employed for classification tasks, reflecting a more advanced approach to enriching the dataset. In the classification task, binary classification performs better than multiclass classification across different datasets. The data proportions are described in Fig. 2. Of the 57 selected studies, 13 papers (23%) used basic augmentation for the segmentation tasks, 29 papers (51%) used basic augmentation for the classification task, 4 papers (7%) used basic augmentation for both tasks, and 11 papers (19%) employed artificially generated augmentation for the classification task.

By synthesizing results from existing studies, this review aims to deepen the understanding of how data augmentation impacts model performance when paired with deep learning algorithms. The incorporation of these techniques not only increases the training size but also enhances the models' performance and generalizability, making them more robust note that the test set was not utilized for image generation; instead, it served solely for evaluating model performance, ensuring that the assessment reflects true predictive capabilities. Our future research will explore additional data augmentation techniques that were not covered in this review. This could include more sophisticated GAN architectures that can generate diverse and representative synthetic images. Expanding the variety of augmentation techniques will be crucial in further improving the robustness of cervical cancer detection systems, ultimately leading to better diagnostic accuracy and patient outcomes.

## IV. CONCLUSIONS

In this systematic review, we examined 57 studies focused on data augmentation techniques for segmentation and classification tasks in cervical cancer detection. In the medical field, where image availability is often limited, data augmentation proves to be a valuable approach to improving model performance. Throughout the review, we encountered the challenge of identifying the best segmentation and classification algorithms, as different studies utilized diverse datasets, deep learning algorithms, and performance metrics. We took this variability into account in our comparisons to pinpoint the most effective models. Most of the reviewed papers emphasize the use of basic data augmentation-

TABLE VI
ARTIFICIALLY GENERATED AUGMENTATION TECHNIQUES USED IN THE CLASSIFICATION TASK, ALONG WITH THE ALGORITHMS AND MODEL PERFORMANCE

| Ref | Dataset | Qty | Class | Augmentation | Classification | Performance metrics |
|---|---|---|---|---|---|---|
| [66] | Herlev | 917 | 7 | GAN | VGG16 | Acc=82.8, Pre=59.5, Rec=52.4, F1=51.7, SP=90.5 |
| [47] | Herlev & SIPaKMeD | 4807 | 8 | GAN | VGG16 | **Acc=99.81** |
| [67] | Fourth central hospital of Baoding city, China | 124 | 2 | GAN | CNN | Acc=93.8, Pre=47.8, F1=63.8, SP=93.6, AUC= 98.4 |
| [68] | Liquid based-cytology Pap smear | 963 | 4 | GAN | EfficientNet | Acc=99.1, Pre=99.2, Rec=99.4 |
| [69] | Pap smear image | 3400 | 2 | DCGAN | | Acc=79.5, Pre=74, Rec=91, F1=81.6 |
| [70] | Herlev | 917 | 2 | RCGAN | CNN | Acc=88.87 |
| [71] | Herlev<br>Mendeley<br>SIPaKMeD | 917<br>963<br>4049 | 7<br>4<br>5 | VGGAN | T2T ViT (token to token | **Acc=SN=99.9**, SP=99.64<br>Acc=98.8, SN=98.6, SP=97.54<br>Acc=99.6, SN=98.3, SP=98.6 |
| [65] | SIPaKMeD<br>CRIC<br>Mendeley<br>Cervix93 | 4049<br>400<br>963<br>93 | 5<br>6<br>4<br>3 | SAGAN | CervixFormer | Acc=Pre=Rec=F1=98.3<br>Acc=95, Pre=97, Rec=95, F1=95<br>Acc= Pre=Rec=F1= 99.4<br>**Acc= Pre= Rec=F1=100** |
| [72] | Health center | 5000 | 4 | cGAN (DCGAN) | ResNet18 | Acc=71.7, SN=60.2, SP=88.2, AUC=81.1 |
| [73] | SIPaKMeD | 4049 | 5 | denoising diffusion probabilistic model (DDPM) | FusedDLAM (DL Arch with Attention Mechanisms | Acc=99.29, Pre=99.3, Rec=99.3, F1=99.3 |
| [74] | Pomeranian, SIPaKMeD | 2219, 8000 | 3, 2 | Residual DCGAN (RES_DCGAN) | Xception, & DenseNet121 with self-attention | Acc=Pre=Rec=F1= 98 & Acc=Pre=Rec=F1= 95 |

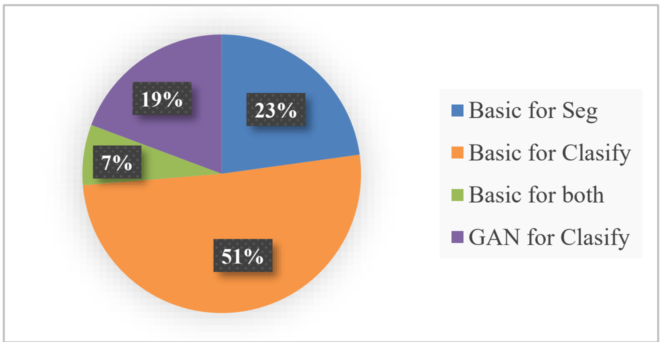


Fig. 2. Selection process of the studies

techniques, particularly for classification tasks. Furthermore, GAN-based augmentation techniques were exclusively employed for classification, further underscoring their potential to enhance model performance in this area. Overall, data augmentation has played a significant role in improving both the performance and generalizability of deep learning models. This review provides a comprehensive analysis of numerous studies to identify the best models for cervical cancer detection, offering valuable insights that may contribute to the advancement of future detection methods. By synthesizing findings from a wide range of research, this work highlights key areas for further exploration, such as the comparison of more advanced augmentation techniques and their impact on both segmentation and classification tasks. This may ultimately lead to more accurate and reliable cervical cancer detection models.

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