A REVIEW OF DEEP LEARNING APPLICATIONS IN CERVICAL CANCER CELL DIAGNOSIS AND SCREENING

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ARTICLE INFO

Received: 09/5/2025
Revised: 27/6/2025
Published: 28/6/2025

KEYWORDS

Deep learning
Cervical cancer
Computer-aided diagnosis
Image segmentation
Cervical screening techniques

ABSTRACT

Cervical cancer ranks as the second leading cause of cancer-related mortality among women globally, claiming over 700 lives daily, with projections of 400,000 annual deaths by 2030. Early detection of cervical cancer and precancerous stages can lead to a full cure, but current screening methods like Pap smears and colposcopy suffer from high error rates due to human interpretation. Deep learning has become widely adopted as an effective tool in healthcare, capable of addressing complexities beyond the traditional artificial intelligence. To overcome manual screening limitations, computer-aided diagnosis systems using deep learning and machine learning are gaining traction, particularly for cervical cancer screening in underdeveloped regions where mortality rates are highest. This article reviews advanced deep learning techniques for analyzing cervical cytology and colposcopic images, focusing on classification and segmentation methods. It evaluates current deep learning algorithms in cervical cancer screening, discussing their potential to enhance diagnostic accuracy and accessibility. Additionally, the paper highlights ongoing research, challenges, and future directions, emphasizing deep learning's role in reducing the global cervical cancer burden through improved screening solutions.

TỔNG QUAN VỀ ỨNG DỤNG HỌC SÂU TRONG CHẨN ĐOÁN VÀ SÀNG LỌC TẾ BÀO UNG THƯ CỔ TỬ CUNG

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THÔNG TIN BÀI BÁO

Ngày nhận bài: 09/5/2025
Ngày hoàn thiện: 27/6/2025
Ngày đăng: 28/6/2025

TỪ KHÓA

Học sâu
Ung thư cổ tử cung
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Phân vùng ảnh
Kỹ thuật sàng lọc cổ tử cung

TÓM TẮT

Ung thư cổ tử cung được xếp hạng là nguyên nhân gây tử vong do ung thư đứng thứ hai ở phụ nữ trên toàn cầu, cướp đi hơn 700 sinh mạng mỗi ngày và được dự báo sẽ gây ra khoảng 400.000 ca tử vong mỗi năm vào năm 2030. Việc phát hiện sớm ung thư cổ tử cung và các giai đoạn tiền ung thư có thể dẫn đến khả năng chữa khỏi hoàn toàn; tuy nhiên, các phương pháp sàng lọc hiện tại như xét nghiệm Pap và soi cổ tử cung vẫn còn tồn tại tỷ lệ sai sót cao do phụ thuộc vào đánh giá chủ quan của con người. Học sâu đang được ứng dụng rộng rãi như một công cụ hiệu quả trong y học, với khả năng xử lý các vấn đề phức tạp vượt xa trí tuệ nhân tạo truyền thống. Để khắc phục các hạn chế của phương pháp sàng lọc thủ công, các hệ thống chẩn đoán hỗ trợ bằng máy tính dựa trên học sâu và học máy đang dần được chú ý, đặc biệt trong sàng lọc ung thư cổ tử cung tại các khu vực kém phát triển ở nơi có tỷ lệ tử vong cao nhất. Bài báo này tổng quan các kỹ thuật học sâu tiên tiến trong phân tích tế bào học cổ tử cung và hình ảnh soi cổ tử cung, tập trung vào các phương pháp phân loại và phân đoạn. Bài viết đánh giá các thuật toán học sâu hiện tại được ứng dụng trong sàng lọc ung thư cổ tử cung, thảo luận tiềm năng của chúng trong việc nâng cao độ chính xác chẩn đoán và khả năng tiếp cận y tế. Ngoài ra, bài báo cũng đề cập đến các nghiên cứu đang triển khai, những thách thức hiện hữu và định hướng phát triển trong tương lai, nhấn mạnh vai trò của học sâu trong việc giảm gánh nặng ung thư cổ tử cung toàn cầu thông qua các giải pháp sàng lọc hiệu quả hơn.

DOI: https://doi.org/10.34238/tnu-jst.12764

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1. Introduction

Cervical cancer (CC) originates in the cervix, often due to abnormal cell growth that can spread to other parts of the body. The primary cause of CC is human papillomavirus (HPV) infection, responsible for over 90% of cases, with HPV strains 16 and 18 causing nearly 50% of high-grade precancers [1] - [4]. In 2012, cervical cancer was responsible for an estimated 528,000 new cases and 266,000 deaths, representing about 8% of the global cancer burden in terms of both incidence and mortality [5], [6]. Developing countries are disproportionately affected, with about 70% of cases and 90% of deaths occurring in these regions. CC still poses a significant public health challenge in low-income countries, where it affects approximately 47.3 out of every 100,000 women and remains a primary cause of cancer-related mortality [7], [8]. By 2030, CC is expected to cause around 400,000 deaths annually, with 90% in developing countries. In 2018, over 311,000 deaths among women aged 20-39 were reported [9], [10]. In Europe, more than 60,000 cases and 25,000 deaths occur annually [11]. In developed countries, cervical screening programs have significantly reduced CC rates [12], [13]. According to the report of the HPV information centre (Spain), Vietnam has 39.1 million women aged 15 and above are at risk of developing CC. Each year, approximately 4,132 new cases and 2,223 deaths are reported. CC ranks as the eighth most prevalent cancer among women overall and the fifth among those aged 15 to 44. Infections with HPV types 16 and 18 affect about 2.1% of women and 82.8% CC cases must use invasive cure solutions [14].

For older women who are sexually active, Pap smear screening is the recommended method for CC screening [15] - [18]. Complementing traditional diagnostic techniques, cutting-edge medical imaging and computational image analysis now play a pivotal role in cervical cancer detection, characterization, and clinical management. By enhancing diagnostic accuracy for premalignant and malignant conditions, these technologies help optimize CC screening and therapeutic interventions. These techniques enable healthcare providers to visualize and analyze the progression of cervical cancer, known as cancer staging [19]. Computer-aided diagnosis (CAD) systems are essential in this context [20], [21]. These systems greatly improve the reliability and efficiency of analyzing medical images, aiding in early detection and detailed staging of CC. By streamlining and optimizing image assessment, CAD tools help medical professionals deliver more precise diagnoses, resulting in better clinical outcomes.

Deep learning (DL) represents a subset of artificial intelligence (AI) and machine learning (ML) that has demonstrated remarkable success across diverse sectors, including healthcare, business, education, and government [22] - [26]. DL operates through multi-layered computational models that enable learning through progressively abstract representations of input data. This approach has revolutionized fields such as medical image analysis, where DL techniques are pivotal in detecting and diagnosing various types of cancer [27], [28]. DL's capacity to analyze complex medical images with high accuracy in healthcare has transformed diagnostic capabilities. Practical applications show DL algorithms effectively interpreting X-rays, MRIs, and microscopic tissue images to catch cancer indicators in initial phases [29]. Early recognition through these means directly enables life-saving interventions. Additionally, deep learning supports clinical decisions by projecting illness advancement, facilitating personalized therapy designs, and innovating medication research via large-scale data-driven target identification [30], [31]. Integrating DL into medical practice enhances precision and efficiency, bolstering healthcare systems globally. Ongoing research continues to refine DL models, further addressing challenges such as interpretability and robustness to enhance their applicability in clinical settings [32], [33]. DL's medical image analysis and cancer detection advancements underscore its transformative potential in improving public health outcomes and combating one of humanity's most pressing health challenges [34]. As technology evolves, DL stands poised to drive further cancer research and treatment innovations.

Diagnosing CC using AI involves training supervised learning algorithms (ML or DL) with expert-labeled images [35] - [37]. The training procedure equips the system with the diagnostic acumen to identify subtle deviations from normal physiology in medical images, optimizing model parameters to enhance accuracy. After training, the algorithms are evaluated using validation images, measuring recognition and generalization capabilities through accuracy (A number of correct predictions in total), sensitivity (True positive rate, model's ability for identifying the correctly positive cases comparing to total actual positives), specificity (True negative rate, model's ability for identifying the correctly negative cases comparing to total actual negatives), AUC (Area under the curve, model's performance with certain thresholds), and F1 score (Harmoniously averaged value of precision and recall) metrics [38]. Specifically, convolutional neural networks (CNNs) break down images using convolutional filters that detect patterns ranging from simple (lines, shapes) to complex (edges, textures) [39] - [41]. These unique features are extracted to differentiate between normal and pathological images. AI identifies distinguishing features in images, aiding in more accurate diagnoses. The goal of integrating AI is not to replace specialists but to develop reliable, rapid, automated diagnostic support systems that enhance overall diagnostic performance [42] - [44]. AI reduces the workload for doctors, enables early detection of pathological signs, and improves diagnostic accuracy and patient outcomes.

The present work provides a comprehensive critical analysis of contemporary literature concerning DL techniques and automated methods for diagnosing CC cells, with a specific focus on solutions utilizing algorithms and DL computations applied to digital colposcopy images. The review examines existing DL-based approaches for CC detection, highlighting their methodologies and efficacy. Furthermore, this study identifies current research gaps and potential challenges within the field, aiming to provide insights into the advancements and limitations of ML methods in CC detection.

2. Materials and Methods

The literature reviewed was sourced from peer-reviewed databases, including PubMed, Scopus, and IEEE Xplore, using keywords such as "cervical cancer screening," "HPV testing," "Pap smear," "CIN classification," "medical image denoising," and "deep learning in cervical cancer diagnosis." Articles published between 2012 and 2025 were prioritized to ensure relevance to current diagnostic advancements. These studies included addressing clinical protocols, imaging techniques, or computational methods for the detection of CC.

Detecting CC cell involves several screening methods aimed at identifying precancerous or cancerous changes in cervical cells. Primary CC screening modalities comprise cytological examination (Pap test/Papanicolaou smear), HPV DNA testing, co-testing (combined cytology-HPV testing), visual inspection with acetic acid (VIA), colposcopy with biopsy confirmation [14], [16], [45]. The conventional Pap smear involves cervical cell collection and microscopic evaluation for dysplastic changes, recommended triennially for women aged 21-65 years. For enhanced sensitivity, women aged 30-65 may opt for co-testing with extended 5-year intervals. Other methods, like VIA, colposcopy, and biopsy, are employed for further evaluation when abnormalities are suspected. HPV testing focuses on detecting high-risk HPV strains, often combined with Pap smears to enhance detection rates. It is recommended every five years for women aged 30 and older. Co-testing involves performing both a Pap smear and HPV test during the same pelvic exam to improve detection. It is recommended every five years for women aged 30-65. Colposcopy uses a magnifying device (colposcope) to closely inspect abnormal areas of the cervix and may involve taking a biopsy for further examination. These methods aim to detect cervical cell changes early, facilitating effective treatment and management of the disease. Adherence to recommended screening schedules is crucial for maximizing the benefits of early detection and intervention.

The pathogenesis of cervical intraepithelial neoplasia (CIN), the direct precursor to invasive cervical cancer, is fundamentally linked to persistent oncogenic HPV infection [46]. Despite an 80% lifetime prevalence of HPV exposure in women, only sustained infections with high-risk types (most notably HPV 16/18) confer significant risk for CIN development and subsequent malignant transformation, underscoring the importance of persistent infection rather than mere HPV exposure [47]. Pathologists assess CIN lesions through the careful examination of histological samples. Histopathological assessment of cervical biopsies through light microscopy identifies architectural and cytological abnormalities, allowing grading of cervical intraepithelial neoplasia: normal epithelium (no CIN), CIN1 (low-grade squamous intraepithelial lesion), CIN2 (high-grade squamous intraepithelial lesion), and CIN3 (high-grade lesion with severe dysplasia/carcinoma in situ). This classification reflects both disease severity and progression risk [48]. Visual representations of these grades play a crucial role in diagnosing and stratifying the severity of lesions. Analyzing malignant cells often requires advanced imaging systems and medical image processing techniques, which combine computational methods with healthcare diagnostic models [40]. This synergistic integration yields unprecedented insights into cellular anomalies, enriching diagnostic strategies. As CC diagnostics evolve, new methods will emerge with dual attributes of resource efficiency and time effectiveness.

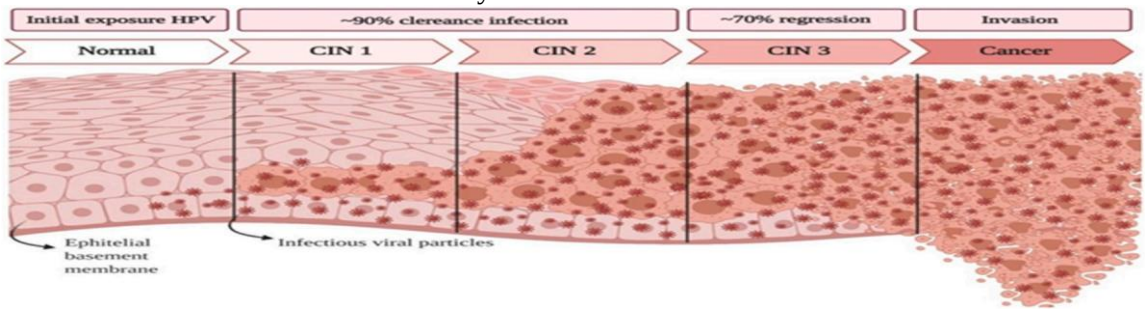

Figure 1. *Histological classification of CIN grades based on epithelial involvement* [49]

Furthermore, the World Health Organization (WHO) recommends four principal diagnostic modalities for cervical cancer screening: (1) conventional Papanicolaou (Pap) smear cytology, (2) liquid-based cytology (LBC) preparations, (3) molecular detection of high-risk HPV DNA, and (4) visual inspection with acetic acid (VIA), which may be conducted through either traditional manual examination or digital cervicography techniques [50], [51]. In Figure 1, both CIN2 and CIN3 are clinically categorized as high-grade squamous intraepithelial lesions (HSIL) due to their significant malignant potential. The subsequent discussion focuses on deep learning (DL) architectures implemented in cervical cancer detection systems, emphasizing their capacity to improve both the sensitivity and throughput of diagnostic processes. These computational approaches demonstrate particular promise in automating the analysis of cytological and histopathological features, potentially reducing inter-observer variability in CIN grading.

In recent decades, diagnostic techniques and medical imaging have rapidly advanced, becoming crucial tools in disease diagnosis [28]. Medical imaging provides detailed information about the heart, brain, nerves, and other body parts, offering insights into internal conditions. Mathematical applications in medical imaging can help determine if healthy tissue is infected. However, missing any specific area during imaging can have severe consequences, including death. A significant challenge is obtaining comprehensive images without losing critical information due to noise or artifacts during collection and processing. Therefore, denoising medical images is an essential preprocessing step. Common medical imaging modalities, such as Ultrasound (US), Magnetic Resonance Imaging (MRI), Computed Tomography (CT), and Positron Emission Tomography (PET), often exhibit signal-dependent noise, which poses

challenges for standard denoising techniques typically used for natural images. A graphical illustration summarizing the role of image processing in medical diagnosis is shown in Figure 2.

Previous discussions have emphasized the importance of image-denoising techniques in the post-processing stage, supporting subsequent medical image-processing steps [28], [52], [53]. This section briefly overviews various denoising techniques, categorized into pre- and post-acquisition methods. Pre-acquisition involves integrating special processing modules into the imaging system to denoise and enhance information content. Post-acquisition techniques, such as Gaussian, mean, median, Lee, and diffusion filters, reduce noise and improve image quality [54]. However, these methods can blur small details and low-contrast areas. Although prone to blurring, adaptive filters like median and bilateral filters offer better performance when their behavior is finely tuned. Non-local means filters deliver good denoising capabilities but face challenges due to their high computational complexity, particularly in real-time US imaging.

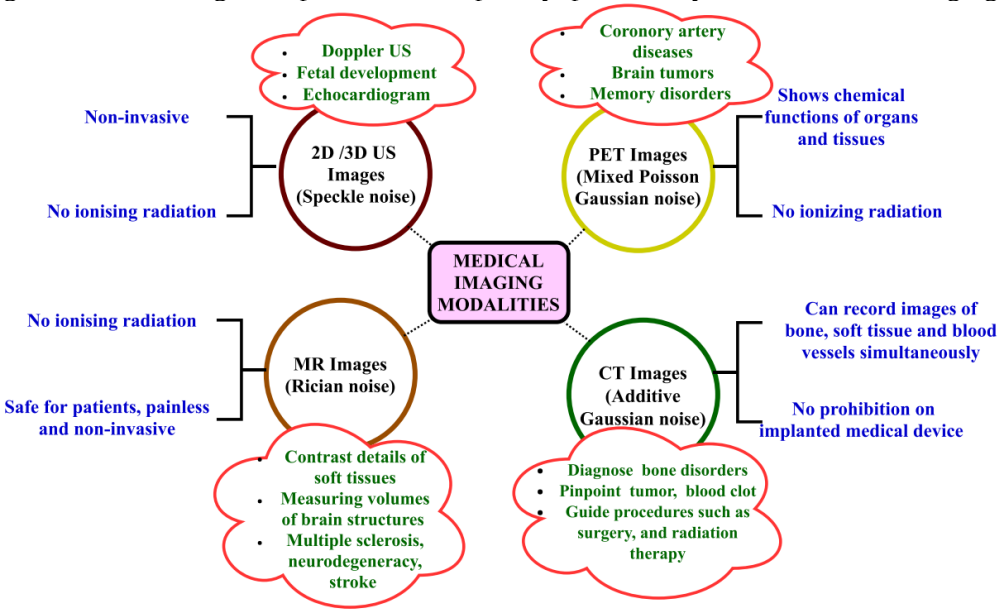

Figure 2. *Image processing enhances medical diagnosis [28]*

Traditional feature extraction techniques in image processing face certain limitations, prompting the advancement towards DL. DL addresses these issues and enhances performance by automating feature extraction from raw, unprocessed images, leveraging powerful GPU parallel computing. Models like CNNs have notably excelled in cancer detection, showcasing significant strides in healthcare and other fields. This transition from traditional methods to DL underscores clear benefits in automation, performance enhancement, and widespread applicability in modern image processing.

3. Results and Discussion

To evaluate DL models for both identification and classification of the CC disease, five key performance metrics including accuracy, sensitivity, specificity, F1 score, and AUC are utilized. It is noteworthy that while many studies report high accuracy (up to 98.9%), few provide a comprehensive set of metrics, limiting clinical relevance. Sensitivity and specificity are particularly critical in medical diagnostics to reduce false negatives and false positives. Recent models combining DL architectures like LeNet-5, Inception v3, and DarkNet with manual features have shown improved diagnostic performance. However, many still lack full metric reporting. Incorporating all five performance indicators is essential for fair comparison, robust evaluation, and ensuring real-world applicability in CC screening.

3.1. Deep learning

DL has revolutionized the detection of CC cells by leveraging CNNs to analyze digital images from Pap smears and other procedures [31], [55], [56]. These models excel at automatically identifying and categorizing abnormal cell patterns, enhancing the accuracy of diagnostics. Semantic segmentation capabilities allow DL to precisely delineate ROI within cervical cell images, aiding in the detection and classification of abnormalities such as precancerous or cancerous cells. By automating these processes, DL reduces reliance on subjective manual interpretation, thereby improving efficiency in screening programs. The implementation of DL in CC diagnostics faces several key challenges: (1) the requirement for large-scale, meticulously annotated datasets to ensure model generalizability; (2) variability in imaging protocols and quality across clinical settings; and (3) the need for rigorous multicenter validation to establish clinical utility. Additionally, ethical considerations regarding data privacy and algorithmic bias must be addressed to ensure equitable deployment.

This work focuses on evaluating the performance of DL algorithms in medical image recognition compared to healthcare professionals. The Food and Drug Administration (FDA) has approved several AI applications in this field, underscoring its recognition and advancement in healthcare technology. The research aims to realistically assess DL's capability in diagnosis, including reviewing result reporting, clinical value, and study design suitable for clinical settings. Synthesis analysis is employed to compare DL's diagnostic accuracy with healthcare experts. The study's findings are crucial for understanding AI's potential in enhancing medical diagnostics and reducing errors, offering new prospects in medical and healthcare information technology.

3.2. Deep learning in medical diagnosis

DL has significantly impacted the field of medicine, particularly through its applications in medical imaging, diagnostic support, personalized treatment, healthcare operations, genomics, telemedicine, and robotics [57], [58]. DL has emerged as a powerful tool for automated analysis of medical imaging modalities, including radiographs (X-rays), computed tomography (CT) scans, and magnetic resonance imaging (MRI) [59], [60]. This technology also assists in pathology by automating the analysis of histopathology slides for cancer diagnosis. In the field of diagnostics, deep learning supports medical practitioners by analyzing large volumes of patient information—including clinical symptoms and medical records—to recommend possible diagnoses and appropriate treatment strategies. It also plays a crucial role in early disease detection, identifying conditions like Alzheimer's and cardiovascular diseases before symptoms fully manifest. In personalized treatment, DL accelerates drug discovery by predicting molecular interactions and toxicity, while also facilitating precision medicine through tailored treatment plans based on genomic and clinical data. Moreover, DL enhances healthcare operations by predicting patient admission rates, optimizing resource allocation, and improving workflow efficiency. It supports telemedicine by enabling remote patient monitoring and enhancing diagnostic accuracy through wearable devices and data analytics. In summary, deep learning's advancements in healthcare underscore its transformative potential in improving diagnostic precision, personalized medicine, operational efficiency, and medical research, albeit with ongoing considerations around data privacy, interpretability, and regulatory frameworks.

DL can be utilized to interpret X-ray images by harnessing the extensive repository of digitized data stored in the Picture Archiving and Communication System (PACS), a system that has been widely adopted for more than two decades [61]. Recently, hundreds of studies have utilized DL for X-ray image analysis [62]. The application of DL to X-ray images primarily includes three tasks: classification, detection, and segmentation [29]. Classification involves categorizing images into classes such as the presence or absence of disease and determining whether tumors are malignant or benign [20], [63]. Detection can identify enlarged lymph nodes

or colon polyps in CT images and microbleeds in brain MRI [39], [64]. Segmentation identifies the pixels or voxels that make up a specific organ or structure [65], [66]. A comprehensive diagnostic system may need to combine these methods to achieve accurate results [67].

3.3. Deep learning in cervical cancer cell detection

DL has revolutionized the detection of CC cells by leveraging CNNs to analyze digital images from Pap smears and other procedures. These models excel at automatically identifying and categorizing abnormal cell patterns, enhancing the accuracy of diagnostics. Semantic segmentation capabilities allow DL to precisely delineate ROI within cervical cell images, aiding in the detection and classification of abnormalities such as precancerous or cancerous cells. By automating these processes, DL reduces reliance on subjective manual interpretation, thereby improving efficiency in screening programs. Key challenges involve the requirement for large, accurately annotated datasets to train reliable models, maintaining uniform image quality, and verifying the clinical relevance of these approaches. Nevertheless, DL shows significant potential in enhancing early diagnosis and enabling personalized treatment strategies for CC, which may ultimately contribute to better patient outcomes through prompt intervention and tailored therapies.

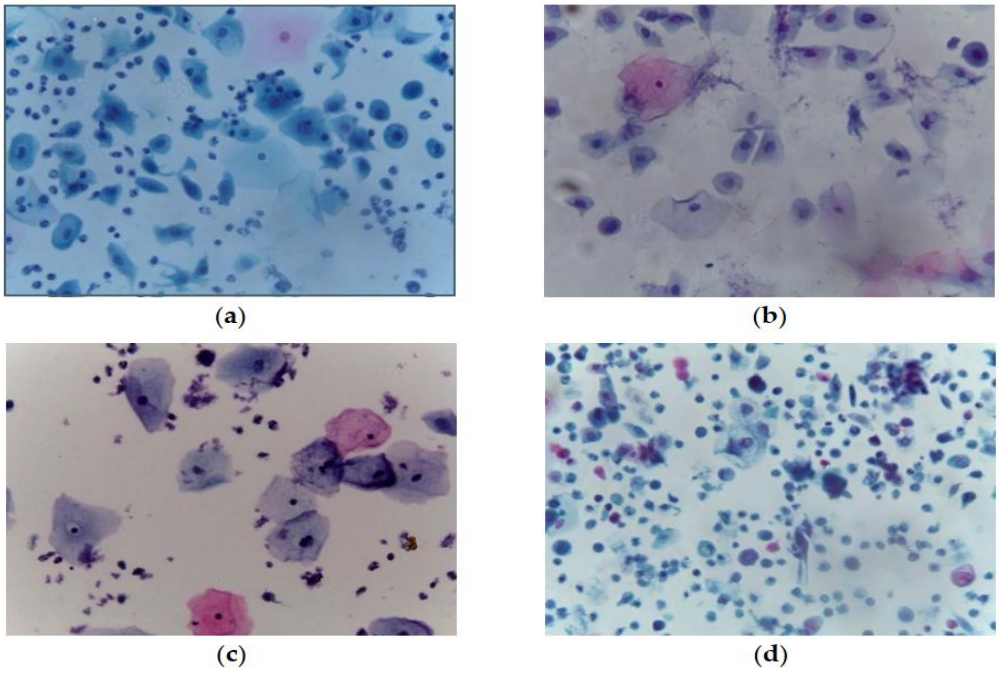

Figure 3. *The Pap Smear dataset consists of annotated cervical cell images used primarily for CC diagnosis; (a) Class includes slides showing more severe abnormalities, (b) Class represents slides with mild abnormalities, (c) Class features slides where no significant cellular abnormalities or malignancies, and (d) class includes slides showing cancerous cells [68]*

Traditional CAD models have used classical ML methods to extract features from CC cell smear slides. For instance, in the study [18], discrete cosine transform (DCT) and discrete wavelet transform (DWT) were applied for feature extraction and dimensionality reduction, followed by application to seven ML classifiers achieving 81.11% accuracy in CC subgroup classification. In another study [17], C-means clustering was used for cell segmentation and extraction of structural features like GLCM, reduced using PCA, achieving 94.86% accuracy with KNN classification. Similarly, in [53], C-means clustering was employed to segment cervical cells, followed by the extraction of shape and structural features using the Binary Histogram Fourier (BHF) method. These extracted features were then further refined and optimized using the Quantum Grasshopper Optimization (QGH) algorithm to enhance classification performance. In [69], a two-stage CAD

approach: initial threshold-based segmentation and MULTP feature extraction, achieved 98.9% accuracy after neural network parameter tuning.

Among the common CC screening tools is the LBC technique. The Mendeley LBC dataset comprises 963 Pap smear images, categorized into four classes based on the Bethesda System, with 613 images of non-malignant cases and 350 images of abnormal cases (as shown in Figure 3). Cervical smear samples were collected from 460 infected cases at 40x magnification and used for the LBC method [68]. The CAD process involves five steps: image preparation, DL feature extraction, manual feature extraction, feature fusion and dimensionality reduction, and diagnosis [56]. Initially, images are prepared, resized, and enhanced. Three compact pre-trained CNN models are then retrained using these images to extract spatial DL features. Simultaneously, manual features, including texture and statistical properties, are extracted. These manual features are combined with DL features and reduced using Principal Component Analysis (PCA). Finally, multiple SVM classifiers are applied to the reduced feature sets for diagnosis. The CAD workflow is introduced in Figure 4.

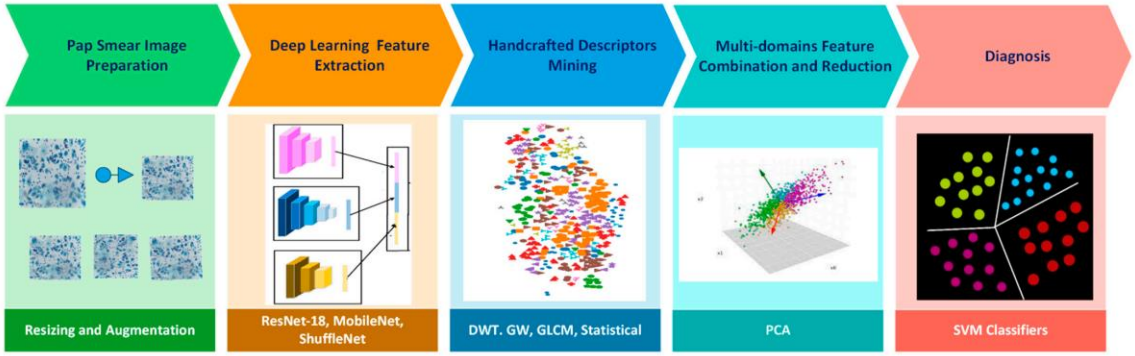

Figure 4. *The workflow enhances the efficiency and accuracy of CC diagnosis [56]*

This proposed research introduces a three-stage approach for cancer detection from cell images, as shown in Figure 5. Firstly, abstract features are extracted from the hidden layers of the LeNet-5 model, combined with structural, morphological, and textural features from standard methods like GLCM, Fourier, Gabor, and Markov [70]. This synthesis process enhances the feature representation before feeding them into an SVM classifier for image cell classification. This method underscores the importance of optimizing and integrating diverse features to improve the accuracy of cancer detection. The study's findings promise a robust tool for medical and clinical research applications, aiming to enhance diagnostic and therapeutic decisions based on image analysis effectively and reliably.

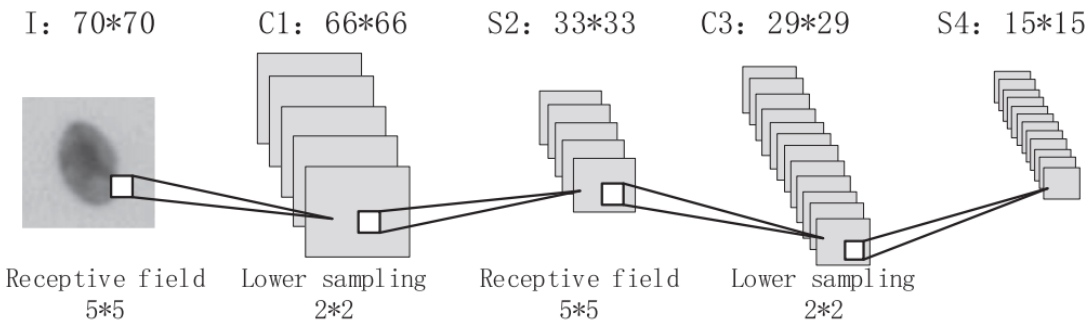

Figure 5. *The LeNet-5 model was used effectively for feature extraction in CC diagnosis from Pap smear slides [70]*

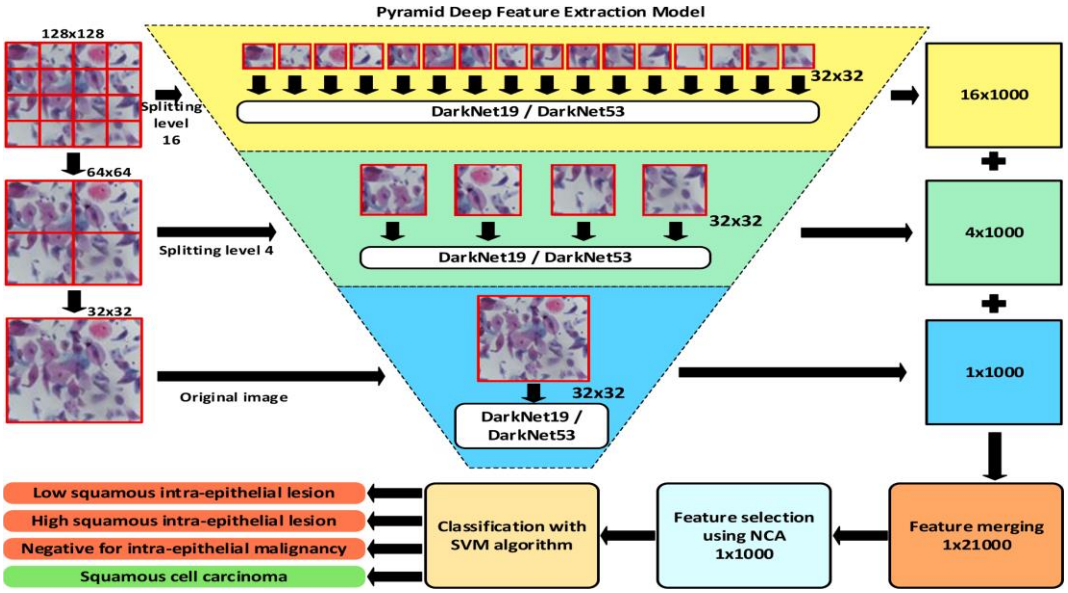

Figure 6. *The DarkNet-based Exemplar Pyramid Deep Feature Extraction Model combines DarkNet, a lightweight and efficient convolutional neural network architecture, with an Exemplar Pyramid structure to capture hierarchical features for accurate medical image analysis [71]*

This study proposes an innovative framework for deep feature extraction in Pap smear image classification, referred to as the "exemplar pyramid deep feature extraction" method [71]. As depicted in Figure 6, this approach extracts multi-scale deep features from a sample Pap smear image using a hierarchical, pyramid-based model, capturing both fine and coarse details to enhance classification accuracy. It utilizes two pre-trained networks, DarkNet19 and DarkNet53, to extract detailed features from pap-smear images by partitioning them into smaller regions and applying these networks for feature extraction. Initially, Red Green Blue (RGB) images are resized to 128×128 and subdivided into 16 smaller patches of 32×32 pixels. Features are extracted from each patch using both DarkNet19 and DarkNet53. For blurred images, 16 sets of 1000 features are derived from each patch. Next, images are resized to 64×64 and divided into 4 patches of 32×32 pixels. Similarly, four sets of 1,000 features are extracted from the image patches. Subsequently, the images are resized to 32×32 pixels, and an additional set of 1,000 features is obtained using either the DarkNet19 or DarkNet53 architecture. Features from these three stages are combined into a comprehensive feature vector of size 1×21000 for each pap-smear image. This approach has been implemented and evaluated on both DarkNet19 and DarkNet53 to enhance classification accuracy and feature extraction capabilities for pap-smear images.

This article presents a framework combining Inception v3 with artificial feature extraction for the enhanced recognition of cervical cells, achieving higher accuracy than traditional methods [72]. The goal is to develop a practical system for CC diagnosis supported by advanced computer technology. To address the complexity of cervical cell structure and significant variability among individuals, simple artificial feature extraction methods are deemed ineffective. Instead, this article proposes an effective cell identification algorithm by integrating features extracted automatically from a CNN classification model with the Inception v3 architecture. Nine manually selected features from different aspects of cervical cells are integrated into this DL model through fully connected layers.

Recent advances in transfer learning have demonstrated promising results in automating cervical cancer diagnosis. For example, the study of Göker [73] reported in 2024 proposed an image processing framework combining histogram equalization and Gaussian filtering for enhancement, followed by evaluation using multiple pre-trained CNNs (see Figure 7) (AlexNet,

DenseNet201, MobileNetV2, ResNet50, Xception, and VGG19) on a dataset of 917 cervix images. VGG19 emerged as the top-performing model, achieving 98.26% accuracy, an F1-score of 0.9671, and high specificity (0.9896) and sensitivity (0.9631). These findings highlight the potential of transfer learning in reducing diagnostic workload while maintaining high precision.

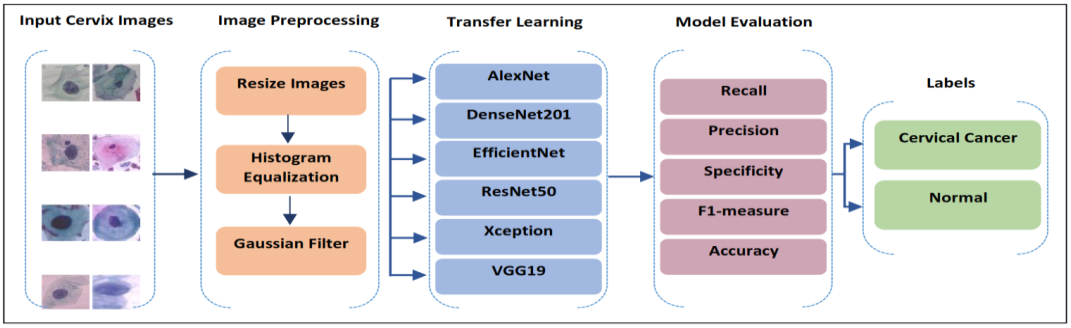

Figure 7. *Transfer learning models for cervical cancer diagnosis. [73]*

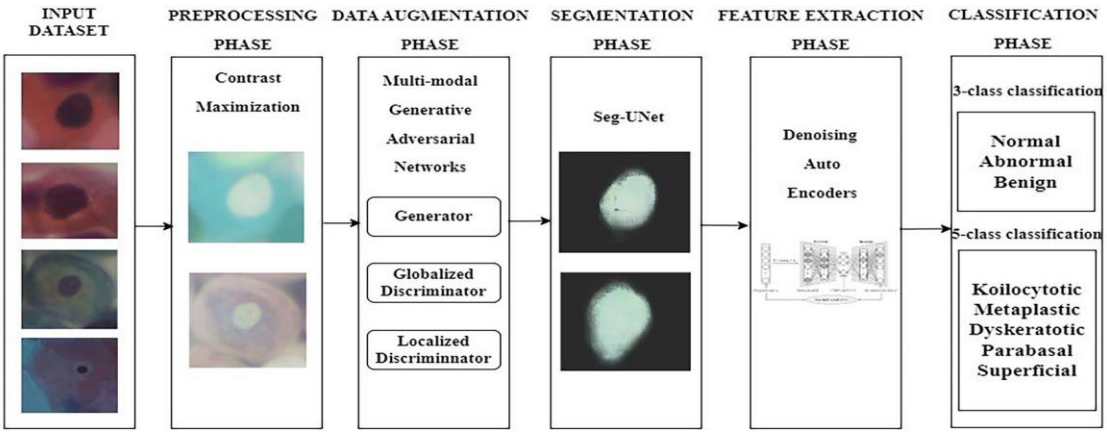

Figure 8. *Deep learning for cervical cancer classification based on the Dense CapsNet model [74]*

Figure 8 presents the performance of the Dense CapsNet model in three-class classification Normal, Abnormal, and Benign [74]. The model demonstrated high accuracy by correctly classifying 1,613 out of 1,618 normal images (only five misclassified cases). To comprehensively evaluate its effectiveness, standard performance metrics including accuracy, precision, recall, F1-score, and Matthews Correlation Coefficient (MCC) were utilized. The results consistently reflect strong performance across all categories. Specifically, the Normal class achieved 99.69% accuracy, 99.62% precision, 99.45% recall, and 99.57% F1-score. The Abnormal class showed 99.57% accuracy, 99.47% precision, 99.52% recall, and 99.61% F1-score. Meanwhile, the Benign class obtained 99.50% accuracy, 99.43% precision, 99.62% recall, and 99.56% F1-score. These outcomes underscore the Dense CapsNet model's robust capability for accurate and reliable multi-class classification of CC images.

VGGNet, GoogleNet, and DenseNet121 models were utilized for comparison of classifying cervical cancer stages (normal, precancerous, cancerous) in Pap smear images [75]. The study employed data augmentation and normalization before model training. Results indicated that DenseNet121 demonstrated the highest classification accuracy at 93% and achieved an AUC of 0.97, indicating strong discriminative performance. In contrast, GoogleNet delivered the fastest training time among the evaluated models, highlighting its suitability for deployment in environments with limited computational resources. VGGNet, though computationally intensive, underscored the impact of model depth on diagnostic performance. This work emphasizes the

trade-off between accuracy and efficiency in medical AI applications. Additionally, Mask R-CNN with ResNeXt101-FPN and ResNet101-FPN were applied for multi-class segmentation aligned with the Bethesda System (TBS) [76]. Using the SIPaKMeD dataset with stratified partitioning, both architectures achieved mAP scores of 89% and 88%, along with high sensitivity (89%) and specificity (88%). This result represents the first application of Mask R-CNN for seven-class cervical cell segmentation, demonstrating its potential to streamline cytological analysis and reduce manual workload.

Recently, many DL models such as YOLOv5 (CSPNet backbone), Faster R-CNN (RPN), and Detectron2 (ResNeXt) have been investigated for classifying cervical cells using the same CRIC dataset [77] (Figure 9). After preprocessing and augmentation (via Roboflow), YOLOv5 achieved the highest mAP (83%) for binary classification (Normal vs. Abnormal), outperforming other models across varying IoU (Intersection over union) thresholds. The study highlights the role of data augmentation and model architecture selection in optimizing detection performance.

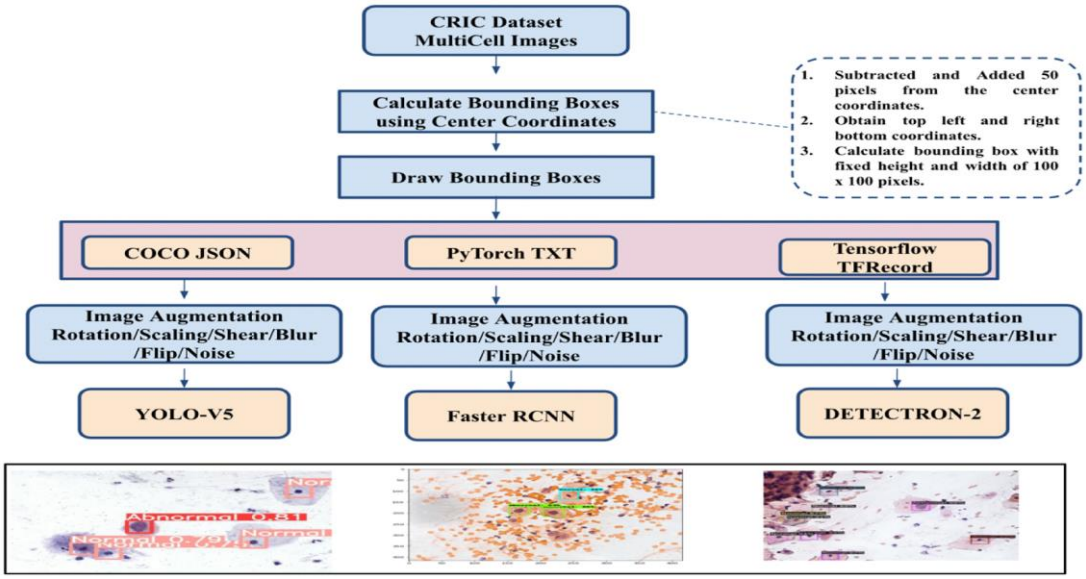

Figure 9. *CerviCell-detector methods including YOLO-V5, Faster CNN, and Detectron-2 to detect the normal and abnormal cells [77]*

3.4. Opportunities for research and future directions in deep learning for cervical cancer

DL presents numerous opportunities to advance CC research across multiple fronts [78], [79]. A key application lies in enhancing cervical cell image analysis, where DL algorithms can automate the detection and classification of abnormal cells from microscopic images, enabling earlier and more accurate diagnosis. Future work in this area should focus on improving image quality by addressing artifacts like mirror reflections [82], expanding datasets to include diverse populations [45], [80], [81], and developing real-time diagnostic tools that integrate seamlessly with clinical workflows. Predictive modeling represents another promising direction, with the potential to forecast disease progression and personalize treatment plans based on individual patient characteristics [84]. By integrating multi-omics data [82], [83], DL can provide comprehensive insights into the molecular mechanisms of CC, facilitating the discovery of novel therapeutic targets and drug repurposing opportunities. However, realizing these applications requires overcoming several challenges, including the need for larger, more diverse datasets [80], [81], improved model interpretability, and better generalization across different populations.

Researchers should prioritize establishing standardized benchmarks, optimizing model architectures to reduce overfitting [84], and fostering collaborations between AI experts and

clinicians. The development of open-access repositories for high-quality annotated images [45], [55], [80], [81], [84] and the implementation of ethical AI practices will be crucial for translating these technological advancements into clinical practice. By addressing these research gaps and opportunities, DL has the potential to significantly improve CC screening, diagnosis, and treatment, ultimately reducing the global burden of this preventable disease. Future studies should balance technical innovation with practical considerations to ensure these solutions are both effective and clinically applicable.

4. Conclusion

This article delves into current research on the application of DL in analyzing CC screening images. It focuses on image classification and segmentation techniques used to process and analyze cervical cell images. The article discusses key components of DL techniques and important methods, highlighting their significance in diagnosing and treating cervical cancer. CNNs are particularly noted for their outstanding achievements in classification and segmentation tasks, aiding early detection and effective treatment. However, challenges such as improving performance and accuracy persist. Recent studies have employed complex algorithms like Dense CapsNet, VGGNet, GoogleNet, and DenseNet121, and suggest further research into architectures such as Mask R-CNN, CerviCell-detector, and Transfer learning to enhance classification capabilities. As DL technology advances, it holds the promise to transform CC screening by delivering more precise, efficient, and widely accessible diagnostic solutions. Continued research and future breakthroughs in this field are crucial for alleviating the global impact of cervical cancer and enhancing health outcomes for women worldwide.

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