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Cervical cancer: empowering diagnosis with VGGNet transfer learning

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ABSTRACT

This study addresses the critical issue of cervical cancer, which stands as the fourth most prevalent cancer among women. With early detection being pivotal for successful treatment, the research focuses on evaluating the effectiveness of deep learning-based models in cervical cancer detection. Leveraging the widely employed Papanicolaou (Pap) smear test, the study proposes a transfer learning approach, incorporating contrast limited adaptive histogram equalization for image enhancement. Convolutional neural network models, including AlexNet, visual geometry group (VGGNet)-16, and VGGNet-19, are employed to accurately distinguish between cancerous and non-cancerous cervical cell images. The evaluation metrics encompass accuracy, precision, sensitivity, specificity, F1-score, and the matthew correlation coefficient (MCC). Notably, the findings reveal the exceptional performance of the VGGNet-19 model, achieving an accuracy of 98.71%, sensitivity of 98.33%, and specificity of 99% for a single smear cell. This research marks a significant advancement in the application of deep learning for precise cervical cancer detection. The promising results underscore the potential of these models to enhance early diagnosis and contribute to improved treatment outcomes, thereby addressing a crucial aspect of women's health.

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1. INTRODUCTION

Cervical cancer originates in the lining cells of the cervix, with normal cervical cells undergoing gradual precancerous changes before progressing to a cancerous state. Unfortunately, cervical cancer ranks fourth among the leading causes of death from female cancers. The grim mortality statistics underscore the urgency of addressing this issue. However, there is hope in the fact that early detection significantly enhances the prospects of effective treatment. Regular screenings for cervical cancer are strongly recommended as a proactive measure. An in-depth analysis reveals that a staggering 90% of individuals diagnosed with cervical cancer exhibit first-stage infections. This alarming prevalence is often attributed to the absence of basic healthcare facilities in certain communities. Governments equipped with advanced healthcare systems strive to mitigate this issue by implementing screening technologies capable of identifying precancerous cells that may evolve into aggressive cancer.

Globally, the most widely used method for cervical cancer detection is the Papanicolaou (Pap) smear test. Developed by George N. Papanicolaou in 1928, the Pap smear test has become a cornerstone in the early detection and prevention of cervical cancer. Its widespread adoption has played a crucial role in identifying abnormalities in cervical cells, enabling timely intervention and potentially saving countless lives.

The Pap smear test's cost efficiency is its key benefit. According to George N. Papanicolaou, a cell sample from a vaginal smear can be used to identify abnormal cells. Dr. Herbert Traut, a pathologist, and Dr. Papanicolaou, a gynecologist, worked together to give scientific evidence of the cervix's capability for identifying cervical alterations [1]. A professional cytologist examines hundreds of pap smear photos manually using a microscope. As a result, the analysis is a labour-intensive, error-prone process. Because of the variability in human perception, the analysis is vulnerable to error. To lessen these shortcomings, an automated method is therefore needed. The modern approach uses computer-aided image analysis. It is utilized to help in the artificial diagnosis of cell abnormalities or malignancies in histopathological examination by providing an accurate and unbiased assessment of nuclear morphology. It is advised to create a trustworthy computer-based system for diagnosing the condition since the number of cervical cancer patients rises daily. Machine learning (ML) algorithms may be the best fit for such a system because they can detect cervical cancer in its early stages [2], [3]. In the last few decades, image processing techniques have been used to rapidly construct an automated cervical cancer screening system.

Various solutions are offered, with a particular emphasis on segmentation, feature extraction, and classification. Devi *et al.* [4] suggested a graph-cut based segmentation strategy for cervical cancer diagnosis that leveraged the benefits of Neutrosophic graph cut (NGC) by deleting the nucleus and cytoplasmic borders of Pap test cells. The findings of this NGC based cervical cancer diagnosis methodology have been proven to be 13% better on average than typical graph cut orientated cancer detection methodologies. Magaraja *et al.* [5] proposed a hybrid linear iterative clustering and bayes classification-based GrabCut Segmentation (HLC-BC-GCST) method for detecting cervical cancer. The derived energy function is produced from the linear iterative clustering characteristics of the gaussian mixture model (GMM) model and then used to recreate the graph cut model using bayes classification for enhanced calculation and implementation. The recommended HLC-BC-GCST system outperforms the competition by 6%. Palanisamy *et al.* [6] suggested a modified deep learning system based on dual tree complex wavelet transform (DTCWT) to classify Pap smear cell images into four classes. For the automated categorization of Pap smear cell pictures, this suggested study consists of DTCWT, convolutional neural networks, and data augmentation modules. The automated Pap smear cell image categorization method has a normal Pap smear detection rate of nearly 99%. Huang *et al.* [7] proposed the generative adversarial network known as Cell-GAN. Remarkable results were achieved for segmenting single and overlapping cells images with 94.3% dice coefficient and 7.9% false negative rate, and 89.9% dice coefficient and 6.4% false negative rate, respectively. According to the findings of the experiment, employing Cell-GAN, the recommended strategy may adaptively reach cell boundary lines in cervical cell images to deal with a range of overlapping instances.

Yu *et al.* [8] devised a deep learning technique for automatically differentiating abnormal from normal cells. The Baoding Central Hospital in China provided the dataset for the Thin Prep cytologic test. Four separate categorization models were created. The first model used a convolutional neural network (CNN) with ten levels, the second one included a spatial pyramid pooling layer, and the third one substituted the CNN layers with the inception module. The spatial pyramid pooling layer and the inception module were combined into the first in the fourth model, however. The testing findings showed that the fourth model performs better than the others. The feature extraction and modelling algorithms used in standard ML techniques are two different steps. From the nucleus and cytoplasm, features such as morphometric, textual, colour histogram, geometric, and local binary patterns were retrieved [9]. Repetitive features are discarded using feature selection techniques like particle swarm optimization (PSO), filter methods, quantum-behaved PSO, wrapper methods, embedded methods, and genetic algorithm-based feature selection [10], [11].

Several ML approaches, including Multilayer perceptron, random forest, K-nearest neighbors (KNN), CNN, extreme learning machine (ELM) Bayesian classifier, and support vector machine (SVM) have been utilized in the development of classification models for cervical cells [12]. Cervical cell analysis using SVM and MLP was presented utilizing 40 different shape and texture-based features was proposed by Mulmule *et al.* [13]. The MLP classifier outperforms the SVM classifier in all performance metrics, with a classification accuracy of 97.14%. A novel two stage classification approach with in depth feature extraction was also presented in another research [14]. Table 1 provides an overview of the pertinent work.

Table 1. Related work using herlev pap smear dataset

Sr. No.	Author	Features	Classification
1	Hussain *et al.* [15]	Deep learning features	CNN
2	Taha *et al.* [16]	Pre-trained CNN architecture	SVM
3	Chankong *et al.* [17]	9 cell-based features	Artificial neural network (ANN)
4	Marinakis *et al.* [18]	Twenty cytoplasmic and nuclear attributes	Ensemble learning (EL)
5	Marinakis *et al.* [19]	Twenty cytoplasmic and nuclear attributes	EL
6	Zak *et al.* [20]	Deep leaning attributes	CNN
7	Nanni *et al.* [21]	Local binary attributes	SVM
8	Guo *et al.* [22]	Discriminative technique	KNN
9	Zhang *et al.* [23]	Deep leaning features	CNN
10	Shinde *et al.* [24]	Deep features; PCA	ANN
11	Kurnianingsih *et al.* [25]	Deep learning features	CNN
12	Ghoneim *et al.* [12]	Deep learning features	CNN and ELM
13	Chitra and Kumar [26]	Convolution neural network	CNN-LSTM
14	Waly *et al.* [27]	Deep learning attributes	ELM
15	Dewi *et al.* [28]	20 feature attributes	Naïve Bayes + Weighted-PCA

The literature review highlights a significant gap in research focusing on deep learning-based methods for cervical cancer detection, with a predominant emphasis on image-based approaches. Existing studies predominantly lean towards traditional ML methods, leaving a limited exploration of deep learning techniques. To address these deficiencies, the current research aims to fill critical research gaps identified in conventional cervical cancer detection systems by introducing novel methodologies to overcome these challenges. The key contributions and resolutions of the proposed system are outlined below:
- Transfer learning: the research underscores the significance of transfer learning, a technique capable of automatically recognizing images, extracting features, learning classification, and processing data using sophisticated algorithms. This approach is positioned as a crucial advancement in the realm of cervical cancer detection.
- PEP smear test integration: transfer learning is specifically applied in conjunction with the Pap smear test for early screening and diagnosis of cervical cancer. This integration is deemed valuable in addressing challenges related to limited human resources and enhancing diagnostic accuracy.
- Introduction of AI technologies: the article aims to introduce recent advancements in artificial intelligence (AI) technologies and demonstrates their utility and potential in the screening and early diagnosis of cervical cancer. This emphasis on AI technologies represents a progressive step towards more effective and accurate detection methodologies.

In summary, this research paper seeks to fill existing gaps in literature by providing a comprehensive exploration of transfer learning in the context of cervical cancer detection, particularly utilizing the PEP smear test. The integration of AI technologies is highlighted as a pivotal step towards more efficient and accurate screening and early diagnosis of cervical cancer, addressing critical research gaps in the field.

2. METHODS AND MATERIAL

A standard setup includes dataset collection, preprocessing, and classification. Figure 1 depicts the steps of a standard cancer screening system. The image is preprocessed to remove noise content and improve visual quality. A classification phase is used to train the classifier and distinguish cancerous from non-cancerous cells.

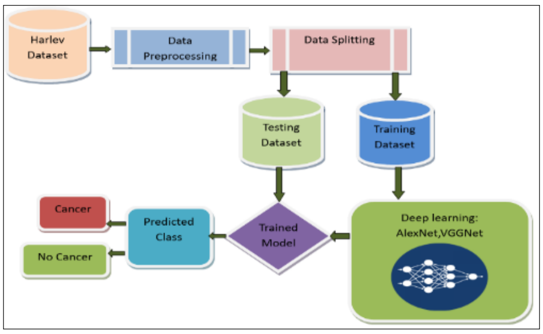
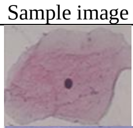
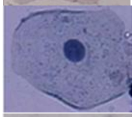
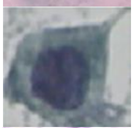


Figure 1. Workflow of proposed work

2.1. Database: Herlev dataset

Herlev dataset, produced by Herlev University Hospital, is openly accessible [29]. Microscopes and digital cameras are used to capture photos of the cells. The cell images in the databases have a resolution of 0.201 um per pixel. The specimens are produced using traditional Pap smear staining and processing. The Herlev Pap smear dataset includes 917 single cell cervical cell images that have been segmented and classified using ground truth. Seven different stage classifications have been assigned to the cells. Cytologists and clinicians make diagnoses for these seven classes to improve diagnostic accuracy. Additionally, these seven types are divided into two groups: malignant and benign. First through third grade classes are considered normal or healthy, while fourth through seventh grade classes are considered abnormal or cancerous. The nucleus of aberrant or malignant cells is significantly bigger than the nucleus of normal cells. The seven categories include superficial squamous. The specifics of the normal and malignant image classes are shown in Table 2 as tabular data [28].

Table 2. Harlev dataset description

Main class	Sub class	Sample image	Characteristics	No. of images	Total images
Normal	Superficial squamous (N1)		They are shaped like circles.	74	242
	Intermediate squamous (N2)		The nucleus is small.	70	
	Columnar (N3)		Cytoplasm and nucleus have similar sizes.	98	
Cancerous	Mild dysplasia (C1)		Cells arranged in circular patterns.	182	675
	Moderate dysplasia (C2)		The nucleus is extremely big in size.	146	
	Severe dysplasia (C3)		Cytoplasm and nucleus are close together.	197	
	Carcinoma in situ (C4)		Columns hold the cells in order.	150	

2.2. Image pre-processing

Pre-processing is a step-in image processing that lowers an image's inherent noise for better use. As input for processing, a Pap Smear picture in red, green, and blue (RGB) format is provided. Because of contamination, the intensity distribution of the input picture may be non-uniform. The Gaussian filter is used to disperse the image's intensity properly. The use of Gaussian filters smoothes out the picture. An edge sharpening filter is used to sharpen the borders of cytoplasm and nuclei. This is accomplished by subtracting the original picture from a scaled unsharp version. The final image is disassembled into its RGB components. Each component is subjected to contrast limited adaptive histogram equalization (CLAHE). CLAHE breaks the picture down into smaller tiles. For each tile, a histogram of intensity values is discovered. The histogram values are then utilized to disperse the image's lightness levels. The image's local contrast has been boosted. CLAHE improves the image's characteristics. The nuclei and cytoplasm can be distinguished from the background, and the picture has been preprocessed.

2.3. Classification CNN

The CNN stands out as one of the most widely utilized deep learning architectures for image classification tasks. Similar to traditional neural networks, CNNs encompass an input layer, hidden layers, and an output layer. However, what distinguishes CNNs is their intricate network structure, often comprising thousands of hidden layers, making them more sophisticated compared to standard neural networks. In the CNN architecture, the input layer is responsible for receiving raw pixel values extracted from an image. Meanwhile, the output layer consists of neurons corresponding to the number of output classes, facilitating the classification process. For the specific focus of this study, notable CNN architectures selected include AlexNet, VGGNet-16, and VGGNet-19. These architectures have demonstrated significant success in various image classification tasks, contributing to their prominence in the field of deep learning.

2.3.1. AlexNet

AlexNet stands as the pioneering large-scale CNN that demonstrated remarkable proficiency in image classification on the ImageNet dataset. This groundbreaking model comprises eight trainable layers and strategically applies rectified linear unit (ReLU) activation in all layers, with the exception of the output layer. Notably, the output layer integrates max pooling, followed by three fully connected layers to further refine the classification process. A key innovation lies in the utilization of ReLU activation throughout the network, contributing to faster and more efficient training. Additionally, the model incorporates dropout layers, a crucial mechanism to mitigate overfitting risks during training. The strategic combination of these architectural elements has proven instrumental in AlexNet's success, setting a precedent for subsequent advancements in deep learning and image classification tasks.

2.3.2. VGGNet

The fundamental concept behind VGGNet is to construct a deeper neural network featuring a smaller filter, specifically with 16 to 19 layers. VGGNet's input comprises a RGB image set at a fixed size of 224 * 224 pixels. To maintain post-convolutional spatial resolution, VGGNet employs the smallest convolutional filters (3 * 3) with a 1-pixel stride. Additionally, a 1 * 1 convolution filter is incorporated, which linearly transforms the input before applying the ReLU activation function. The architectural design includes five max-pooling layers with a window size of 2 * 2 and a stride of 2, facilitating pooling operations post-convolution. Towards the end of the network, three fully interconnected layers are introduced, culminating in a final SoftMax layer. This architecture aims to enhance the network's ability to capture intricate features through the depth of its layers, contributing to its effectiveness in tasks such as image classification.

3. RESULT and DISCUSSION

In this study, the performance of the model is assessed using key parameters including accuracy, precision, sensitivity, specificity, F-score, and matthews correlation coefficient (MCC). These metrics collectively provide a comprehensive evaluation of the classifier's effectiveness. Certainly, let's delve into a discussion about the findings presented in the context of using ML models, specifically AlexNet and VGGNet, for the diagnosis of cervical cancer. The experimental results, as outlined in Table 3, showcase the robust performance of VGGNet-19 in the classification of normal and cancerous cervical images. With an accuracy of 98.7%, sensitivity of 98.33%, and specificity of 99%, VGGNet-19 stands out as the most effective model among those evaluated. This level of accuracy is particularly noteworthy in the context of medical diagnostics, where precision is crucial for timely and accurate interventions.

The high accuracy of VGGNet-19 suggests that the deep and complex architecture of the VGGNet, with its 19 layers, contributes significantly to the model's ability to discern subtle patterns and features indicative of cervical cancer. The model's superior sensitivity is crucial as it indicates the capacity to correctly identify most of the actual positive cases, reducing the likelihood of false negatives. Similarly, the impressive specificity underscores the model's capability to accurately identify negative cases, minimizing false positives.

Table 3. Performance using CNN model

Sr. No.	CNN model	Accuracy (%)	Precision (%)	Sensitivity (%)	Specificity (%)	MCC parameter (%)	F1-score (%)
1	AlexNet	96	95.33	95.33	96.50	91.50	91.83
2	VGGNet-16	97.14	96.36	97	97.25	94.17	96.68
3	VGGNet-19	98.71	98.66	98.33	99	97.37	98.50

The use of ML models like AlexNet and VGGNet in the diagnostic process for cervical cancer offers several advantages. Firstly, it expedites the diagnostic process, traditionally reliant on time-consuming clinical examinations. The models can process a large number of images quickly and efficiently, providing rapid feedback to healthcare professionals. This speed is crucial in the context of cervical cancer, where early detection is pivotal for successful treatment outcomes.

Table 4 presents a comparative analysis, highlighting the superior accuracy achieved by the proposed method when compared to existing approaches documented in the literature. The integration of ML not only sets the proposed method apart but also addresses the inherent subjectivity associated with human-based diagnostics.

By leveraging ML models, this approach ensures an objective and standardized analysis of images, minimizing the likelihood of human errors and variations in interpretations. This objectivity not only fosters accuracy but also instills a higher level of consistency in results, ultimately bolstering the reliability of cervical cancer diagnoses. The results presented in table 4 highlight the significant contribution of our method to advancing cervical cancer detection and diagnosis.

In conclusion, the promising results of this study suggest that ML models, particularly VGGNet-19, hold great potential for revolutionizing the diagnostic landscape of cervical cancer. While further validation and testing are necessary, the findings pave the way for the integration of these technologies into clinical practices, potentially improving the efficiency and accuracy of cervical cancer diagnosis and contributing to better healthcare outcomes.

Table 4. Comparative assessment with existing techniques

Author	Method	Results
Song *et al.* [30]	Age factors, K-clustering classification, and HPV test.	83.21% sensitivity, 94.79% specificity
Xu *et al.* [31]	Deep network attributes.	87.83% sensitivity, 90% specificity
Xu *et al.* [32]	CNN classification and image conversion to feature vector.	78.41% accuracy, 80.87% sensitivity, 75.94% specificity
Gorantla *et al.* [33]	Hierarchical convolutional mixture.	96.77% accuracy, 96.82% sensitivity, 98.36% specificity, 96.69% precision, 0.97 F1-score
Proposed	VGGNet-19.	98.71 % accuracy, 98.33 % sensitivity, 99% specificity, 98.66% precision, 98.50% F1-score

4. CONCLUSION

Cervical cancer stands as the fourth most prevalent cancer affecting women, and its potential for high curability underscores its profound significance in public health. Recognizing the pivotal role of early detection, this research introduces a cervical cancer screening approach founded on transfer learning. Leveraging Pap smears from the publicly available Herlev dataset, the study aims to devise a robust method for identifying cervical cancer from PAP-smear images. The investigation delves into the efficacy of transfer learning using popular neural network architectures, including AlexNet, VGGNet-16, and VGGNet-19, in the task of detecting cervical cancer. The comparative analysis reveals that the proposed methodology outperforms recent state-of-the-art technology, achieving an impressive accuracy of 98.71%, sensitivity of 98.33%, and specificity of 99%. Notably, the VGGNet-19 convolutional neural network emerges as the most adept model for classifying cervical cancer, showcasing its potential in medical image analysis.

The application of this innovative methodology is poised to make a significant impact on the early identification of cervical cancer, particularly in regions where accessibility to advanced diagnostic tools may be limited. By harnessing the power of transfer learning and robust neural network architectures, this research provides a promising avenue for improving diagnostic capabilities in cervical cancer screening.

In the dynamic realm of medical research, our innovative approach to cervical cancer detection has proven to be a success, paving the way for a new era in early diagnosis. However, our journey doesn't end here; the future beckons us to refine and optimize our system, making it a precise tool capable of discerning specific categories of abnormal cervical cells. This not only promises a more practical application in clinics but also sets the stage for a revolutionary leap in medical diagnostics. Our proposed model, hailed for its success in the early detection of cervical cancer, is not just a solution for today-it's a steppingstone towards a future where such cutting-edge technology can unlock solutions for an array of medical challenges. The horizon is limitless, and our vision extends far beyond cervical cancer, envisioning a world where our model becomes a beacon of innovation, illuminating the path towards enhanced healthcare outcomes.

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