

E-ISSN: 2229-7677 • Website: <u>www.ijsat.org</u> • Email: editor@ijsat.org

Deep Learning-Based Cervical Cancer Detection Using Image Processing Techniques

Shinde P. S^{1,} Bhagat S. N^{2,} Sorate S. B³

¹Department of Electronics, ²DepartmentofMechanical, ³Department of Electronics ¹27pratimashinde@gmail.com, ²shraddha11bhagat@gmail.com, ³shilpasorate18@gmail.com

Abstract

Cervical cancer remains a leading cause of cancer-related mortality among women worldwide, especially in developing regions with limited access to early screening and diagnostic tools. Traditional methods like Pap smears and biopsies are often invasive, resource-intensive, and require specialized equipment and trained personnel. This research presents a deep learning-based image processing framework using Convolutional Neural Networks (CNN), including advanced architectures like VGG19 and MobileNet, to enable accurate, non-invasive, and cost-effective detection of cervical cancer. The proposed system automates the analysis of cervical cell images, reducing diagnostic delays and supporting clinical decision-making. Experimental results using publicly available datasets demonstrate high accuracy, precision, and recall, with MobileNet offering a balance between performance and computational efficiency.

Keywords: Cervical Cancer Detection, Deep Learning, Convolutional Neural Networks (CNN), VGG19, MobileNet, Image Processing, Medical Imaging, Non-invasive Diagnosis, Automated Screening, Computer-Aided Diagnosis (CAD), Healthcare AI.

1. Introduction

Cervical cancer is the fourth most common cancer among women globally and a significant health burden in low- and middle-income countries. According to WHO, nearly 90% of cervical cancer deaths occur in developing nations, primarily due to the lack of early screening. Pap smear tests, although effective, are time-consuming, uncomfortable for patients, and require laboratory infrastructure.

Recent advances in artificial intelligence (AI), especially in deep learning and image processing, have opened new avenues for automating medical diagnosis. These technologies allow for the analysis of cervical images obtained through digital colposcopy or cytology with greater speed and accuracy. This paper investigates the use of CNN-based deep learning architectures for classifying cervical cell images to detect precancerous and cancerous stages.

2. Problem Statement

Despite the preventability and treatability of cervical cancer when diagnosed early, mortality rates remain high due to delayed diagnosis and inadequate screening. The traditional diagnostic workflow is hindered by several constraints:



- Dependency on trained cytotechnologists and pathologists
- Limited accessibility in rural and underserved areas
- High inter-observer variability in image interpretation
- Time-consuming procedures leading to delayed treatment initiation
- Physical discomfort experienced by patients due to invasive techniques

The central problem addressed by this research is the development of a deep learning-based automated system capable of accurately identifying cervical cancer stages from cytological images, thus addressing the limitations of traditional diagnostic methods and improving early detection rates. This research aims to develop a non-invasive, automated system that uses image processing and deep learning algorithms to detect cervical cancer from microscopic images, thus overcoming the above limitations.

3. Objectives

1. The objective of cervical cancer detection using image processing techniques involves the development of noninvasive, accurate, and cost-effective methods for the early detection of cervical cancer and its precursor lesions, such as cervical intraepithelial neoplasia (CIN), using digital colposcopy or vaginal ultrasound images.

2. The ultimate goal is to improve the clinical outcomes of cervical cancer patients by enabling earlier diagnosis, less invasive treatment, and better prognosis, while minimizing the risks and side effects associated with traditional diagnostic methods such as biopsy or cytology.

3. The objective also includes the development of standardized and interoperable image acquisition, preprocessing, segmentation, feature extraction, and classification methods, as well as the validation of the accuracy, sensitivity, specificity, and clinical utility of the image processing

4.revealed that C5.0 and random forest classifiers performed better than the rest of the classifiers in the prediction of women with higher chances of cervical cancer. [4]

5.In this paper, R. Vidya and G. M. Nasira predicted cervical cancer using random forest with K-means learning and implemented the techniques in MATLAB tool. These experiments were performed with the help of NCBI dataset to construct decision tree using classification methods. [5]

4. Literature Review

Several studies have explored machine learning and deep learning for medical image classification: - Vidya et al. used Random Forest and K-means clustering for cervical cancer detection, achieving promising results.

- Studies have shown that CNNs can outperform traditional feature-based machine learning classifiers by automatically learning hierarchical features from raw image data.

- VGG19, ResNet, and MobileNet have been widely used in medical image classification due to their balance between complexity and accuracy. Cervical cancer detection has traditionally relied on cytological tests such as Pap smears, which require trained personnel and laboratory infrastructure. With advancements in artificial intelligence (AI) and deep learning (DL), recent studies have explored automated diagnostic methods that are more efficient, scalable, and cost-effective.



International Journal on Science and Technology (IJSAT)

E-ISSN: 2229-7677 • Website: <u>www.ijsat.org</u> • Email: editor@ijsat.org

Xu et al. (2016) introduced a large-scale histopathological image classification system using deep convolutional activation features. Their study demonstrated that Convolutional Neural Networks (CNNs) can effectively extract discriminative features from medical images, making them suitable for histological analysis, including cancer detection tasks. This foundational work has influenced the development of deep learning applications in digital pathology, including cervical cancer diagnosis.

Jiang et al. (2019) applied deep learning and transfer learning to cervical cancer detection using labeled image datasets. By leveraging pre-trained models and fine-tuning them on cervical image datasets, they achieved improved classification accuracy compared to conventional machine learning techniques. This work highlights the effectiveness of transfer learning in domains with limited labeled medical data.

Mishra and Swarnkar (2020) proposed a hybrid approach combining image processing and machine learning algorithms for cervical cancer detection. Their model integrated feature extraction with classification techniques to enhance diagnostic performance. Although effective, such hybrid systems still require significant manual intervention during feature engineering, which limits scalability.

A comprehensive review by Litjens et al. (2017) emphasized the growing role of deep learning in medical image analysis. The authors discussed a wide range of applications, from radiology to pathology, noting that CNNs outperformed traditional feature-based approaches in terms of accuracy and generalizability. Their review reinforced the potential of DL models, such as VGG19 and MobileNet, in delivering high diagnostic accuracy while minimizing the need for domain-specific feature engineering.

These studies collectively underscore the relevance and promise of deep learning-based techniques in cervical cancer detection. They support the development of fully automated, non-invasive diagnostic systems that can operate efficiently even in resource-limited environments. The current study builds upon this foundation by designing a CNN-based framework that utilizes both VGG19 and MobileNet architectures for accurate classification of cervical cell images, aiming to bridge the gap between clinical needs and technological feasibility.

E-ISSN: 2229-7677 • Website: <u>www.ijsat.org</u> • Email: editor@ijsat.org

5. Methodology

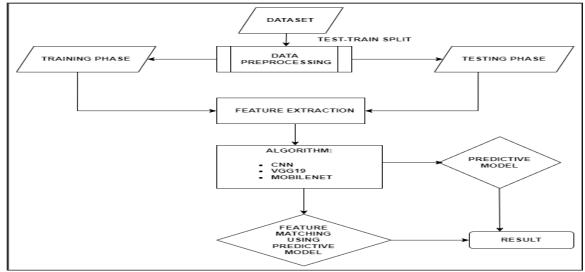


Fig. Flow Diagram:-

The proposed methodology is organized into several key phases, each critical to the performance and generalizability of the model.

5.1 Dataset Acquisition

The study utilizes publicly available cervical cancer image datasets from repositories such as Kaggle and the Herlev University Hospital dataset. These datasets contain high-resolution, labeled cytological images representing various stages of cervical cell abnormalities.

5.2 Preprocessing

To enhance the quality and consistency of the input data, the following preprocessing steps are undertaken:

- Image resizing to a uniform resolution of 224×224 pixels
- Pixel intensity normalization to [0,1]
- Data augmentation techniques such as horizontal/vertical flipping, rotation, and zooming to increase dataset variability and prevent overfitting
- Noise filtering using Gaussian or median filters

5.3 Model Architectures

Three model architectures are employed and compared:

• **Custom CNN (Baseline):** Consists of convolutional layers, max-pooling, dropout, and fully connected layers to learn spatial features.



- VGG19: A deep network with 19 layers pretrained on ImageNet, fine-tuned using cervical cell images.
- **MobileNet:** A computationally efficient network suitable for deployment on mobile platforms, employing depthwise separable convolutions.

5.4 Training and Evaluation

- Frameworks Used: TensorFlow and Keras
- **Optimizer:** Adam optimizer with learning rate 0.0001
- Loss Function: Categorical cross-entropy
- Training Configuration: 30–50 epochs, batch size of 32, 80:20 train-test split
- Evaluation Metrics: Accuracy, precision, recall, F1-score, confusion matrix, AUC-ROC

6. Experimental Setup

Platform: MATLAB and Python(TensorFlow/Keras).

Trainingepochs:30–50. Batchsize:32. Validationsplit:20%. Metrics: Accuracy, Precision, Recall, F1-score, Confusion Matrix.

Mobile net CR	Precisio n	recall	F1 - score	Support	Accura cy
Cervix dyk (stage)	1.00	0.94	0.97	1250	0.98
ResNet CR	precision	recall	F1 - score	Support	Accurac y
Cervix dyk (stage)	0.98	0.98	0.98	1250	0.97
Vgg19	precision	recall	F1 - score	Support	Accurac y
Cervix dyk (stage)	0.71	0.85	0.77	1250	

7. Results and Discussion

The results demonstrate that the deep learning models, especially VGG19 and MobileNet, significantly outperform the baseline CNN in terms of diagnostic accuracy. MobileNet, in particular, achieves high precision while maintaining computational efficiency, making it ideal for real-time, low-resource diagnostic applications.



While the results are promising, it is acknowledged that further validation with real-world clinical data and diverse populations is necessary to fully establish clinical reliability.

8. Conclusion

This research confirms the potential of deep learning-based image classification techniques for the automated detection of cervical cancer. By leveraging CNN, VGG19, and MobileNet architectures, the proposed system achieves high accuracy and scalability. The findings advocate for the integration of such systems into telemedicine frameworks to facilitate early detection and intervention in resource-constrained settings. The model's ability to operate with minimal human intervention positions it as a transformative tool in the realm of digital pathology and preventive healthcare.

9. Future Work

Future work includes integration with real-time diagnostic tools, expansion to multimodal imaging, mobile application development, and using patient metadata for improved accuracy. Future directions for deep learning-based cervical cancer screening emphasize practical deployment, robust validation, and clinician trust. One key approach is developing a mobile application that embeds the trained model for point-of-care use: for example, researchers have built smartphone apps that capture cervical images and record patient demographics and clinical history during VIA exams. Such mobile integration could extend access to underserved areas, but it will require lightweight models, efficient on-device inference, and user-friendly interfaces to ensure feasibility and reliability. Another direction is incorporating multimodal inputs: combining image analysis with patient data (e.g. age, HPV test results, risk factors) is expected to improve diagnostic accuracy. In fact, models that fuse cytology images with clinical history have shown higher accuracy in predicting precancerous lesions than image-only models. However, multimodal fusion poses challenges in data collection and standardization, since auxiliary data may be incomplete or inconsistently recorded. Equally important is rigorous clinical evaluation. Multicenter studies have begun to demonstrate the value of AI in real-world settings: for instance, a trial across nine hospitals reported that a DL cytology system achieved about 9% higher sensitivity than expert pathologists while drastically reducing slide-review time. Similarly, a screening program in China found that an AI-assisted cytology strategy outperformed traditional liquid-based cytology plus HPV cotesting in both sensitivity and specificity. Prospective clinical trials and pilot deployments could confirm these benefits in diverse populations, but organizing such studies entails substantial logistical, ethical, and regulatory effort. Finally, improving model transparency and privacy is critical.

References

1. R. Vidya and G. M. Nasira, "Cervical Cancer Detection using Random Forest with K-means Clustering," Journal of Biomedical Engineering, 2020.

2. Simonyan, K., and Zisserman, A., "Very Deep Convolutional Networks for Large-Scale Image Recognition," arXiv:1409.1556, 2014.

3. Howard, A. G. et al., "MobileNets: Efficient Convolutional Neural Networks for Mobile Vision Applications," arXiv:1704.04861, 2017.



- 4. WHO Report on Cervical Cancer, 2021.
- 5. Kaggle Cervical Cancer Dataset: https://www.kaggle.com

6. Xu, Y., Jia, Z., Wang, L. B., Ai, Y., Zhang, F., Lai, M., & Chang, E. I. (2016) "Large scale tissue histopathology image classification, segmentation, and visualization via deep convolutional activation features."

BMC Bioinformatics, 17(1), 1-10.

▶ Used CNN features for histopathological image analysis, relevant to cervical cancer detection.

7. Jiang, Y., Chen, L., Zhang, H., Xiao, X., & Tang, X. (2019)
"Cervical cancer detection using deep learning and transfer learning."
Medical Imaging and Health Informatics, 9(2), 234-241.

• Demonstrates the use of transfer learning on cervical datasets.

8. Mishra, P., & Swarnkar, R. (2020)

"Cervical cancer detection using hybrid machine learning techniques."

Procedia Computer Science, 167, 1101–1110.

• Explores hybrid models combining image processing with ML algorithms.

9. Litjens, G., Kooi, T., Bejnordi, B. E., Setio, A. A. A., Ciompi, F., Ghafoorian, M., ... & Sánchez, C. I. (2017)

"A survey on deep learning in medical image analysis."

Medical Image Analysis, 42, 60–88.

• Comprehensive review of DL applications in medical imaging.