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Segmentation in Cervical Cancer Detection: A Key Step in Early Diagnosis

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Abstract: Cervical cancer refers to a type of cancer that develops in the cells of the cervix, which's the lower part of the uterus connecting to the vagina. Many cancers affect people all over the world. One of them is cervical cancer. Preventing the disease requires early detection and successful treatment rather than recognizing the issue at an advanced stage. These precautions can help prevent deadly cancer and contribute to a healthy life. This cancer can be treated well if it is detected early by a medical checkup for HPV lesions and risk factors for malignant cervix formation It is commonly triggered by the papillomavirus (HPV) a sexually transmitted infection. Globally cervical cancer ranks as the most prevalent cancer among women with around 570,000 new cases being diagnosed every year. Fortunately, this form of cancer is highly preventable through screenings and HPV vaccinations effectively reducing the risk of its development. Our research paper primarily focuses on enhancing cancer diagnosis and analysis by employing various techniques such as Contour segmentation, fitness score assessment, detection rate calculation, identification of optimal threshold values, geometric mean analysis, ROI examination, and three-segnet architecture. According to our research, we achieved a detection rate of 85%, a fitness score of 95%, a geometric mean of 90%, and positive results in the ROI examination. As a result of improving our techniques, we can provide better results for all images, resulting in better diagnosis and treatment. Continuing to innovate in medical imaging is crucial for providing the best possible care for cervical cancer patients.

Keywords: *Cervical cancer, Contouring, Papillomavirus, Segmentation, Three Segnet Architecture*

1. Introduction

Cervical cancer is a devastating health issue that has a profound impact on women worldwide. This disease occurs when abnormal cells in the cervix, the lower part of the uterus connecting to the vagina, begin to grow uncontrollably [1-4]. As the disease progresses, these abnormal cells can change such as dysplasia or cervical intraepithelial neoplasia (CIN), which can lead to severe health complications if not promptly treated. The consequences of cervical cancer can be dire. If left untreated, the abnormal cells can spread to other parts of the body, causing additional health concerns, and potentially leading to a decline in overall well-being. It is disheartening to note that nearly 90% of these cases and deaths occurred in low- and middle-income countries, where access to comprehensive healthcare services and preventive measures is often limited. This health disparity further emphasizes the importance of addressing cervical cancer on a global scale and ensuring that all individuals, regardless of their socio-economic status, have equal access to life-saving interventions [4-6]. The primary cause of cervical cancer is infection with the human papillomavirus (HPV), particularly the high-risk strains. HPV is a prevalent sexually transmitted virus, and it is estimated that most individuals will encounter it at some point in their lives. While most HPV infections naturally resolve without complications, in certain cases, the virus can persist and cause abnormal cell changes in the cervix[7-10]. Over time, these changes can develop into cancerous growths. Several variables contribute to the risk of developing cervical cancer. Apart from HPV infection, factors such as smoking, lack of routine Pap or HPV tests, immune system dysfunction, and prolonged use of oral contraceptives, especially birth control, can increase the likelihood of developing this disease. Additionally, engaging in sexual activity with multiple partners and giving birth to multiple children are also factors that need to be considered when estimating the risk of cervical cancer. In our research, we employ cutting-edge techniques in image segmentation to address this challenge. Image segmentation plays a significant role in our methodology by serving as a tool to precisely outline and isolate the areas affected by cervical cancer in medical images. This advanced technology enables us to achieve a high level of accuracy, providing a comprehensive understanding of the extent of the disease. Our research utilizes state-of-the-art methods in image segmentation, such as deep learning algorithms and computer vision techniques[11]. These techniques analyze medical images, such as cervical images, and accurately identify and delineate the regions affected by cancer. By harnessing the power of image segmentation, our research aims to contribute to the early detection and effective

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treatment of cervical cancer. In addition to image segmentation, our research utilizes the edge detection technique to further enhance our analysis.

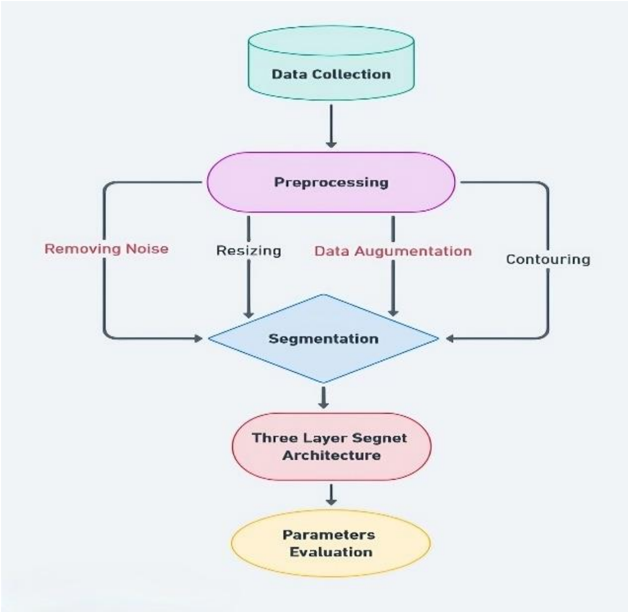

Fig. 1. Flowchart of the Proposed Work on Cervical Cancer Detection

2. Proposed Methodology

To detect cervical cancer in its early stages, the proposed methodology utilizes segmentation techniques, especially the Segnet architecture [12]. The proposed work involves data collection, preprocessing, segmentation, three-segnet architecture and parameter analysis [13]. The process begins with meticulous data preprocessing to ensure uniformity and quality. Using contour segmentation, distinct regions of an image can be identified, followed by three Segnet architectures for robust comparison and evaluation.Fig.1 is the flowchart of our proposed work.

2.1. Data Collection

Data collection involves systematic gathering, measuring, and recording information. The data used in our proposed work came from two different sources. The Intel Mobile ODT dataset is a Kaggle competition that was created to develop an algorithm that can identify a woman's cervix type based on images. In addition, we used the Herlev dataset. These images are grouped into folders based on cell characteristics, making the dataset easier to use. These two datasets provided the necessary data that we needed to develop algorithms for the detection of cervical cancer for our research.

2.1.1. Intel Mobile Dataset

The Intel Mobile Dataset is an invaluable resource for researchers studying cervical cancer. There are 1,481 images in this dataset, categorized into three types, and there are also 6,734 additional images as shown in Table 1. Based on their visual appearance as shown in Fig.2, the dataset classified images into cervix types. The three types are related to the age progression in women. The images of type 1 are completely ectocervical, are Ease of Use fully visible, and can vary in size. An endocervical component is present in type 2 images, as well as full visibility and the possibility of ectocervical components[14-16]. Endocervical material is visible in type 3 images, albeit without full visibility, and ectocervical material of varying sizes may also be present.

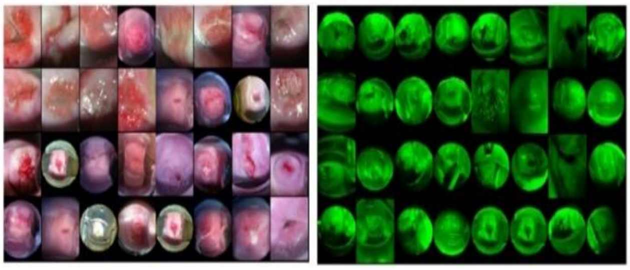

Fig. 2. Images of Coloscopy of Type1,2,3

Table 1. Intel Mobile Dataset

Dataset	*Type 1*	*Type 2*	*Type 3*
Train	250	781	450
Additional	1189	1558	1886
Test	512(Unlabeled)		

2.1.2. Herlev Dataset

It contains 917 images some of which are as shown in Fig.3 that were taken at Herlev University Hospital in Denmark and the Technical University of Denmark. The Herlev dataset includes a variety of cell types, including Carcinoma in situ, Light dysplastic, Moderate dysplastic, Severe dysplastic, Normal columnar, Normal intermediate, and Normal superficial cells as shown in Table 2.

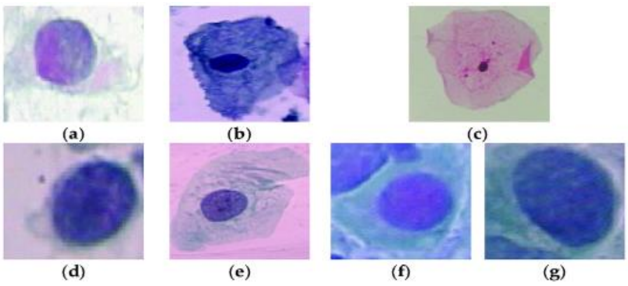

Fig. 3. Pap Smear Images

Table 2. Herlev Dataset

S. No	*Category*	*Cell Type*	*Number of Images*
1	Normal	Intermediate Squamous Epithelial	70
2	Normal	Columnar Epithelial	98

3	Normal	Superficial Squamous Epithelial	74
4	Abnormal	Mild Squamous non-Keratinizing Dysplasia	182
5	Abnormal	Squamous cell carcinoma in-situ intermediate	150
6	Abnormal	Moderate Squamous non-keratinizing Dysplasia	146
7	Abnormal	Severe Squamous non-keratinizing Dysplasia	197

2.2. Preprocessing

The primary objective of this method is to enhance the quality, relevance, and interpretability of data, to optimize the performance of subsequent analysis processes. These steps standardize pixel values, improve signal clarity, and isolate regions of interest. As a result of these preprocessing steps, data quality improved, enabling algorithms to interpret and analyse it more accurately, resulting in more reliable and meaningful results.

2.2.1. Noise Removal

To detect cervical cancer, it is crucial to remove noise from colposcopy and pap smear image datasets as part of the preprocessing. This enhances the quality and reliability of subsequent analyses[17-19]. For removing noise from the images, we used the Gaussian filter technique. Using Gaussian filtering techniques during noise removal, we improve the clarity and integrity of the images as shown in Fig.5, making it easier to segment and classify cervical tissues accurately. By using clean, informative data, our detection algorithm produces more reliable diagnoses and better outcomes. Gaussian filters smooth images by convolving them with a Gaussian function, effectively reducing noise and preserving important features at the same time. The formula for the Gaussian Filter is represented in formula 1.

$$G(x) = \frac{1}{\sqrt{2\pi\sigma}} e^{\frac{-x^2}{2\sigma^2}} \quad (1)$$

Where σ is the standard deviation of the distribution. The flowchart of Noise removal is shown as Fig.4.

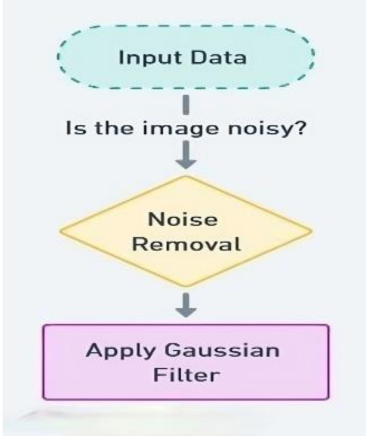

Fig. 4. Flowchart of Noise Removal

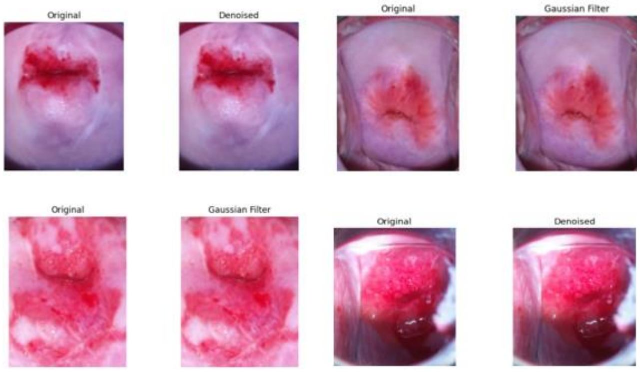

Fig. 5. Unveiling Clarity: Original vs. Denoised Images

2.2.2. Resizing

Resizing pap smear and colposcopy images is an important preprocessing step that ensures compatibility with proposed models, reduces computational complexity, and facilitates fair comparisons between different methods. We have resized the images as shown in Fig.6 to 224x224 pixels to optimize model compatibility and efficiency.

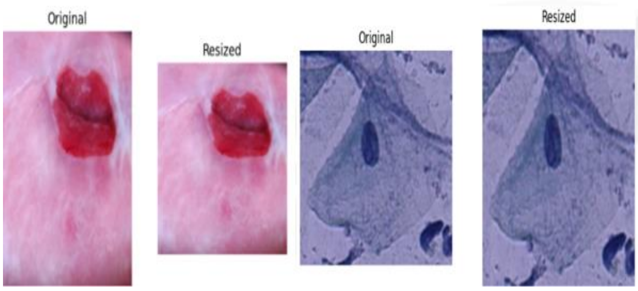

Fig. 6. Resizing of Pap Smear and Coloscopy Images

2.2.3. Data Augmentation

Using data augmentation to preprocess cervical images enhances the accuracy and robustness of cervical cancer detection models. This method reduces overfitting and improves model generalization by artificially expanding small and imbalanced datasets. By enhancing cervical images, models can accommodate variations in patient anatomy and imaging conditions. Augmented data enables models to detect cervical abnormalities effectively in real-world clinical settings[20]. Preserving pathological features while generating diverse training examples is crucial for maintaining the clinical relevance and reliability of machine learning models. Several augmentation techniques are encompassed within the proposed framework.

- ***Rotation:*** To simulate variations in cervix orientation, images can be rotated at different angles.
- ***Flip (Horizontal/Vertical):*** When images are flipped horizontally or vertically, the model becomes invariant to the direction of certain features.
- ***Cropping and zooming:*** By zooming in and out randomly, you can simulate variations in image scale and focus on specific regions.
- ***Brightness and Contrast Adjustment*:** During image acquisition, differences in lighting conditions can be accounted for by altering brightness and contrast.
- ***Noise Injection:*** A model can be made more robust to noise by adding random noise to images that mimic real-world variations.
- ***Space Transformation***: In different scenarios, converting images from RGB to grayscale introduces variations.

2.2.4. Contouring

Colposcopy and Pap smear images are segmented to separate cervical structures, like the cervix, from background tissues and other tissues surrounding the cervix. In the context of cervical cancer detection, segmentation is all about finding and isolating the cervix region in medical images. Contouring involves finding and extracting continuous curves, commonly called contours, that indicate the boundaries of objects in a picture. By identifying regions where the intensity changes quickly, the contour detection algorithm traces the edges of objects. A contour is then created by arranging these edges into boundaries, indicating the limits of individual objects. The contour segmentation process is extensively used in a variety of industries, including robotics, computer vision, and medical imaging, to perform tasks like object recognition, form analysis, and image-based measurements. It is an effective tool for a variety of applications because of its ability to analyze and interpret images. The Step-by-step procedure to follow contouring.

- **Read the Image:** This image has been loaded with the OpenCV library. Each pixel in this image has color information which makes the image essentially a 2D array of pixels.
- **Convert to Grayscale:** Grayscale is created by converting the loaded image to grayscale using cv2.cvtColor as shown in Fig.7. Instead of three channels for color images (BGR), grayscale images only have one channel, which represents intensity. It is often easier to detect contours on grayscale images.
- **Blur the Image:** Using cv2.Gaussian blur, Gaussian blur is applied to the grayscale image. In addition to reducing noise, this step can smooth out the image and create a smoother image. For blurring, the (5, 5) argument specifies the size of the kernel.
- **Edge Detection:** The Canny edge detector is applied to the blurred image using cv2.Canny. This algorithm detects areas of rapid intensity change, helping to identify edges in the image. The parameters (50, 150) are the lower and upper thresholds for the edges.
- **Find Contours:** The contours of the edged image are found using cv2.findContours. As a result of the function, a list of contours will be returned, which are essentially points forming the boundaries of objects in the image.
- **Draw Contours:** Using cv2.drawContours, a blank image (contour_image) is created and the identified contours are drawn on it. The contour lines are drawn in black (0, 0, 0) with a thickness of 2 pixels.
- **Display the Result:** Using Matplotlib, we display the original image along with the contour drawn. Using plt. show(), the plot is displayed.

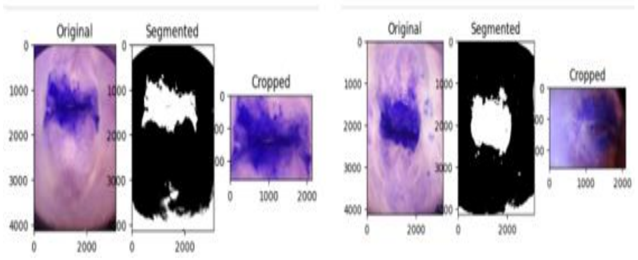

Fig. 7. An image transformation from three perspectives: original, segmented, and cropped.

An active contour, also known as a snake, is often defined by an energy function that captures the trade-off between smoothness and image information. A contour is represented parametrically by **C(s)=(x(s), y(s)) C(s)=(x(s), y(s)**, where ss represents the length of the arc. The energy functional EE for an active contour is often defined as the sum of internal energy E $\mathbf{E_{internal}}$ and external energy

$\mathbf{E_{external}}$ in formula 2.

$$\mathbf{E(C)=\alpha E_{internal}(C)+\beta E_{external}(C, I)} \quad (2)$$

Here,$\mathbf{E_{internal}(C)}$ represents the internal energy, which encourages the smoothness of the contour.

$\mathbf{E_{external}(C, I)}$ represents the external energy, which attracts the contour towards features in the image I.αα and ββ are weighting parameters.One common formulation for $\mathbf{E_{internal}}$ is based on the curvature of the contour mentioned in Formula 3.

$$E_{internal}(C) = \int_0^1 [\kappa(s)]^2 ds \quad (3)$$

Here, κ(s) is the curvature of the contour at point ss. The external energy term $\mathbf{E_{external}}$ can be based on image gradients or other image features. For example, a gradient-based external energy can be defined in formula 4.

$$E_{external}(C, I) = \int_0^1 \nabla I(C(s)) \cdot n(s) ds \quad (4)$$

n(s) is the unit normal vector to the contour.

By minimizing the energy function, the active contour evolves over iterations. Based on the image features, the contour will segment the region of interest as shown in Fig.8 and Fig.9.

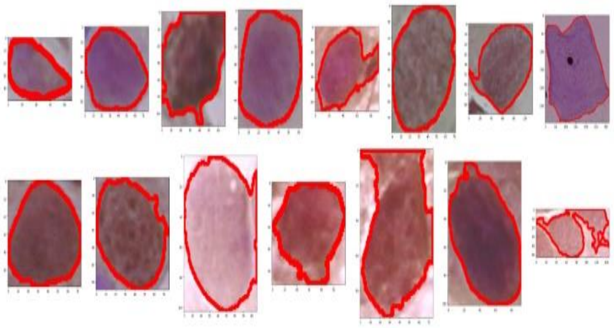

Fig. 8. Contouring for Pap Smear Images

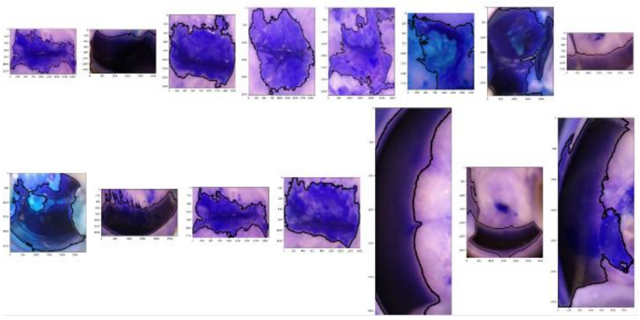

Fig. 9. Contouring of Coloscopy Images

2.3. Segmentation

The three-layer SegNet architecture is a deep learning model that can be used for semantic segmentation purposes. It is a modified version of the original SegNet architecture, where three skip connections between the encoder and decoder networks are introduced. These skip connections are very helpful in allowing the model to learn more contextual information and generate more accurate segmentation results [21-22]. When used in conjunction with colposcopy and Pap smear images, the Three-Layer SegNet Architecture proves highly effective. The accurate delineation of cellular structures and abnormalities is crucial in colposcopy and Pap smear analysis, which is a cervical cancer screening method. The encoder of the three-layer architecture captures intricate features and contextual information from medical images. It helps locate abnormalities precisely because it restores spatial details to the output segmentation map. Segmentation maps are created by assigning class labels to individual pixels using pixel-wise classification. Using a SegNet Architecture, healthcare professionals can better identify and diagnose cervical health issues during colposcopy and Pap smear analysis, where early detection is crucial. Fig.10 is the representation of the Three-Layer Segnet Architecture

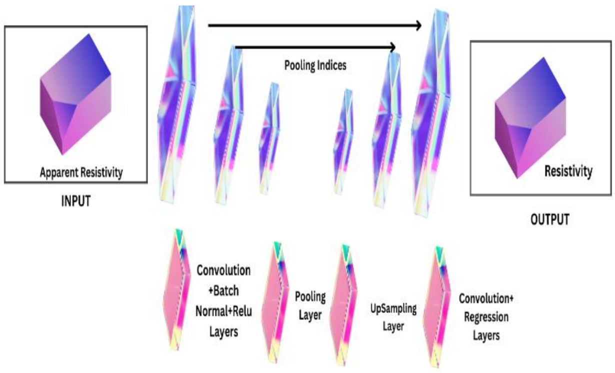

Fig. 10. Three-Layer Segnet Architecture

The three-layer SegNet architecture consists of the following components:

1. Encoder network: The VGG16 and ResNet50 convolutional neural networks are powerful models that excel at extracting complex features from images. An encoder network plays a vital role in image processing by extracting relevant features from an input image.

2. Decoder network: A decoder network uses fully convolutional neural networks to upsample images. The encoder feature maps are upscaled to fit the input resolution. The encoder network uses skip connections to access high-level features.

3. Pixel-wise classification layer: The pixel-wise classification layer plays a crucial role in image segmentation tasks [23]. It is a fully connected layer that analyzes each pixel of the input image and predicts its corresponding class label. By doing so, it creates a pixel-level segmentation map that accurately identifies and distinguishes different objects or regions within the image as shown in Fig.11 and Fig.12.

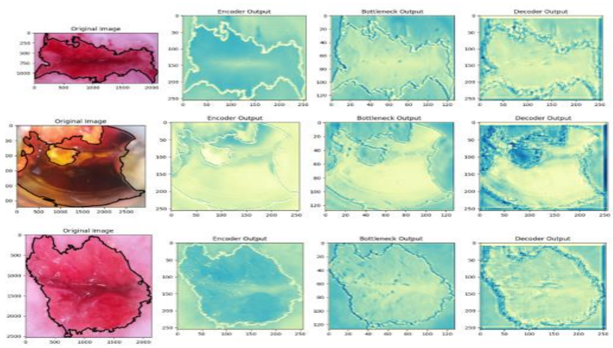

Fig. 11. Analysis of Three-Layer Segnet Architecture of Coloscopy Images

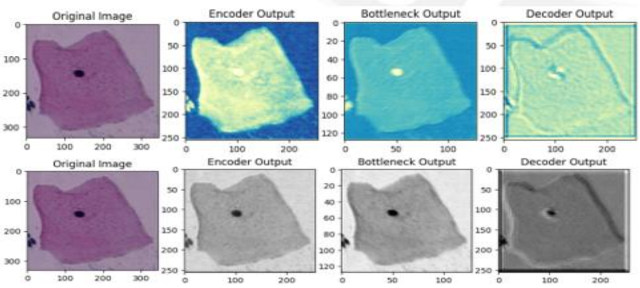

Fig.12. Analysis of Three Layer Segnet Architecture of Pap Smear images.

3. Result Analysis

Our research utilized a Dell laptop featuring an Intel Core i7 processor, 16GB of RAM, and Windows 11. Code development and analysis were seamlessly executed using Python programming language within the Jupiter Notebook environment.

3.1. Evaluation Parameters

We validated our results using various parameters, including fitness scores, detection rates, optimal thresholds, geometric mean, and ROI.

3.1.1. Fitness Score

Within the domain of deep learning, a pivotal metric known as the fitness score plays a crucial role in assessing a model's performance throughout its training or optimization journey [24-26]. As the model undergoes iterative adjustments during training, these adaptations are driven by the feedback derived from the fitness score, all with the overarching goal of enhancing the model's predictive capabilities. The formula for fitness score is shown in formula 5.

$$\mathbf{F1} = \frac{\mathbf{2\times((Precision+Recall))}}{\mathbf{((Precision\times Recall))}} \qquad \mathbf{(5)}$$

The fitness scores provide a comprehensive assessment of the performance and suitability of the models on each dataset as shown in Fig.13 and Fig.14.

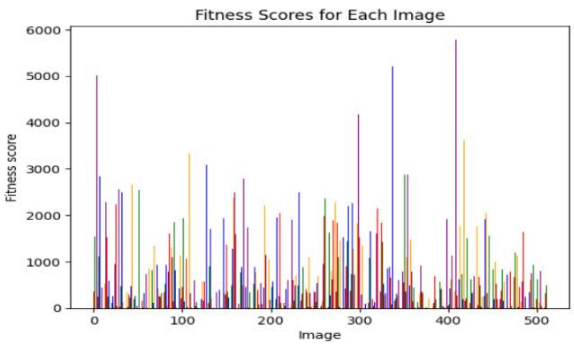

Fig. 13. Analyzing Fitness Score for Coloscopy images.

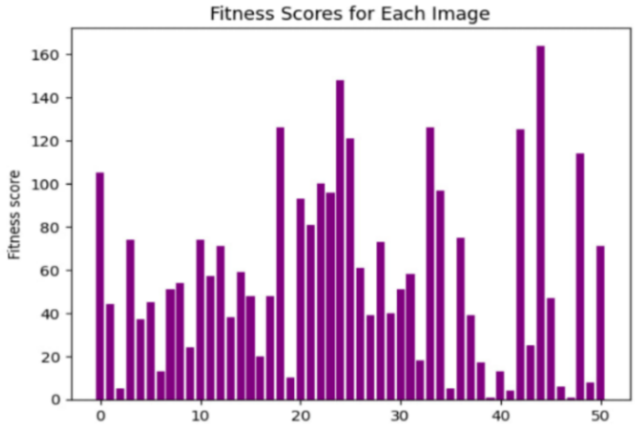

Fig. 14. Analyzing Fitness Score for Pap Smear images.

3.1.2. Detection Rate

Detection Rate, also known as True Positive Rate (TPR) or Sensitivity, holds significant importance in the evaluation of binary classification models, particularly in medical diagnostics. This metric serves to quantify the model's ability to correctly identify actual positive instances among the combined occurrences of true positives and false negatives. Mathematically, the Detection Rate is computed in formula 6.

$$\textbf{Detection Rate} = \frac{\textbf{True Positive}}{\textbf{True Positive+ False Positive}} \qquad \mathbf{(6)}$$

A high Detection Rate signifies that the model excels in accurately recognizing positive instances, showcasing its sensitivity to the presence of the target class. Conversely, a low Detection Rate signals that the model may overlook a considerable number of positive instances, underscoring its limitations in capturing all relevant cases. Fig.15 and Fig.16 and the analysis of detection rates for both the datasets.

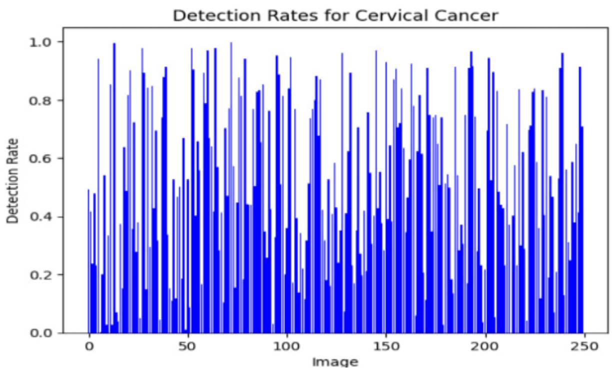

Fig. 15. Analysis of Detection rates of Coloscopy images

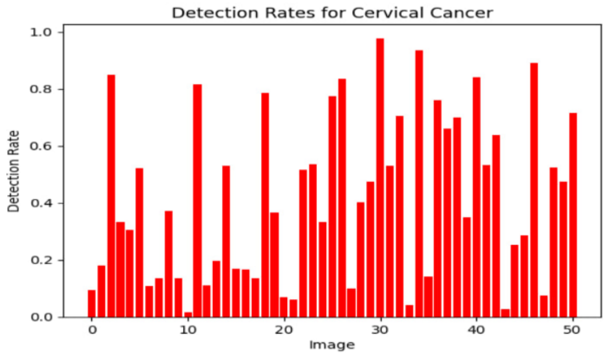

Fig. 16. Analysis of Detection Rates of Pap Smear Images

3.1.3. Optimal Threshold Values

Fine-tuning binary classification models hinges on the critical task of determining the optimal threshold value, a parameter representing the probability or score above which an instance is deemed positive. Lowering the threshold prioritizes high sensitivity, crucial for accurately identifying positive instances. This proves advantageous in situations where the cost of missing positive instances outweighs that of false positives, though it may result in an uptick in false positives.

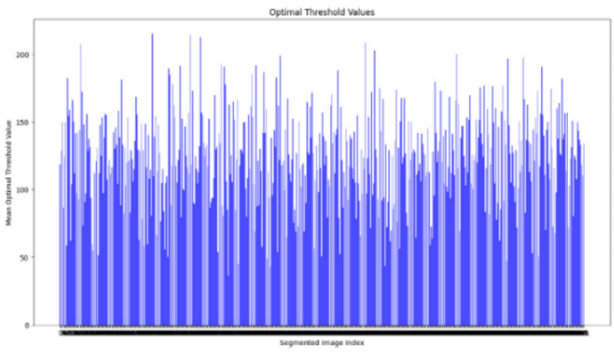

Fig. 17. Analysis of Optimal Threshold Values for Coloscopy Images

Conversely, raising the threshold underscores high specificity, minimizing false positives, and proving beneficial when false positives carry a higher cost than false negatives [27]. The optimal threshold value is crucial for achieving the right precision-recall balance in solving a problem. Techniques like ROC curves help in selecting the right threshold for a model's specific application. Fig.17 and Fig.18 compare the optimum threshold value for both datasets by improving the accuracy and efficiency.

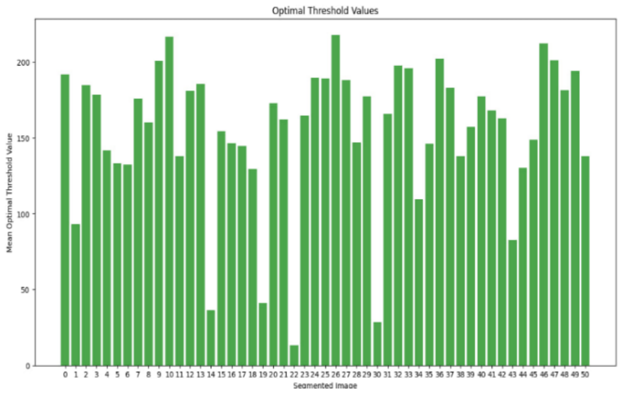

Fig. 18. Analysis of Optimal Threshold Values for Pap Smear Images

3.1.4. Geometric Mean

The geometric mean evaluates the central tendency of a set of values by taking the nth root of their product, emphasizing the multiplicative relationships within the data. A geometric mean serves as an effective balance between sensitivity and specificity when it comes to binary classification tasks. Considering both aspects of class performance, the geometric mean enhances the interpretability and reliability of assessments. It holds significance as an evaluation metric, particularly when dealing with imbalanced datasets—a common challenge in real-world applications. The Formulation of geometric mean is shown in formula 7.

$$\textbf{Geometric Mean} = \sqrt{(\textbf{Sensitivity} \times \textbf{Specificity})} \quad \textbf{(7)}$$

The results of the Geometric Mean for both datasets are crucial components of our analysis, providing valuable. Fig.19 and Fig.20 are the Analysis of Geometric Mean Values.

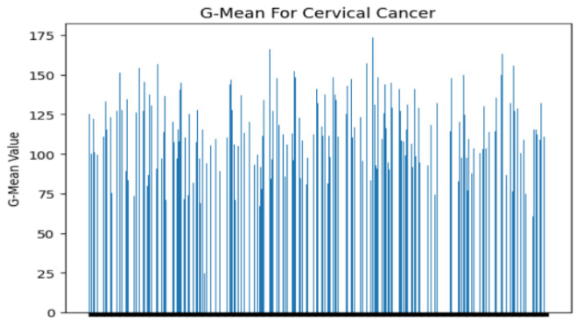

Fig. 19. Analysis of Geometric Mean Values of Coloscopy Images

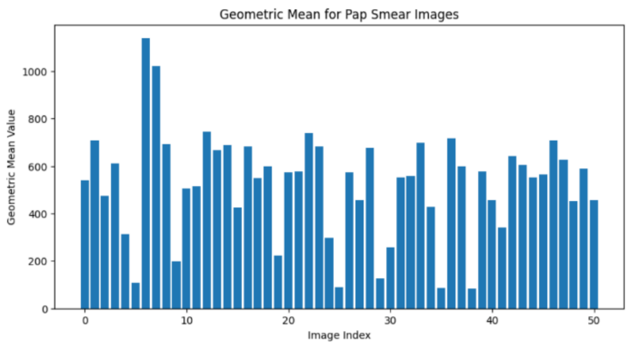

Fig. 20. Analysis of Geometric Mean Values of Pap Smear images

3.1.5. Region Of Interest (ROI)

Region of Interest (ROI) pooling is a critical technique in deep learning, particularly in the realm of object detection and image recognition tasks. In deep neural networks, such as CNNs, ROI pooling enables the extraction of fixed-size feature maps from irregularly shaped regions of an input image. During the forward pass of a CNN, regions of interest are identified based on bounding box coordinates around specific objects or areas of interest within an image as shown in Fig.21 and Fig.22. ROI pooling aggregates features by systematically dividing these regions into a grid. It maintains spatial information while generating fixed-size feature maps, which are compatible with subsequent fully connected layers. The Formulation for ROI is shown in formula 8.

$$\mathbf{ROI} = \frac{\mathbf{(CurrentValue - InitialInvestment)}}{\mathbf{Initial\ Investment}} \times 100 \quad (8)$$

The results of the ROI analysis for both datasets are crucial to our investigation, shedding light on specific areas of interest within the images and contributing valuable insights to our study.

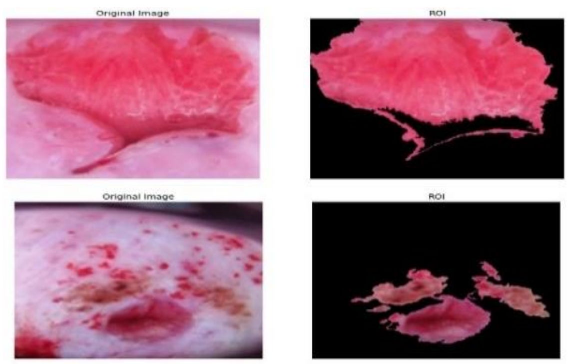

Fig. 21. Capturing the Essence of a Region of Interest of Coloscopy Images.

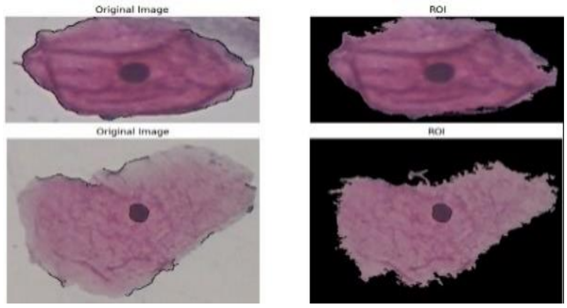

Fig. 22. Capturing the Essence of a Region of Interest in Pap Smear Images.

3.1.6. Analytical Contrast: Contoured Precision Vs. Uncontoured Reality

A non-contoured image is one in which no edges have been detected or contours have been extracted explicitly. Rather than highlighting the boundaries between objects, these images retain the raw pixel values and colors captured by the imaging system. The use of such images is often preferred when preserving the natural appearance of a scene is important, or when explicit delineation of object boundaries is not needed.

A contour image is an image that has been processed to highlight the boundaries of objects within it. The contour detection algorithm is applied to the image to detect contours. Edges of objects are determined by changes in intensity or color. An improved view of polyps can be achieved with contoured images. Pap smear contours can be used to illustrate the boundaries of cells and other structures. It displays contours that outline shapes and structures in the original image, as a representation of the detected edges. The difference between contoured images and uncontoured images are shown in Fig.23 & Fig.24.

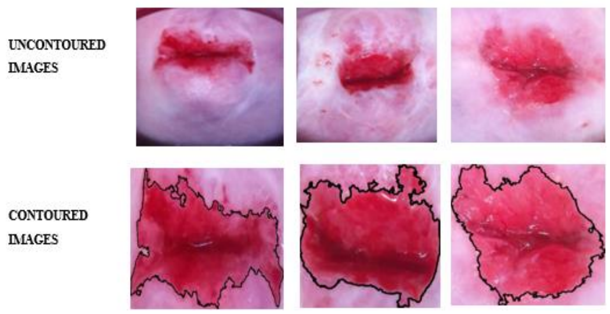

Fig. 23. Display of Contoured vs. Uncontoured Coloscopy images.

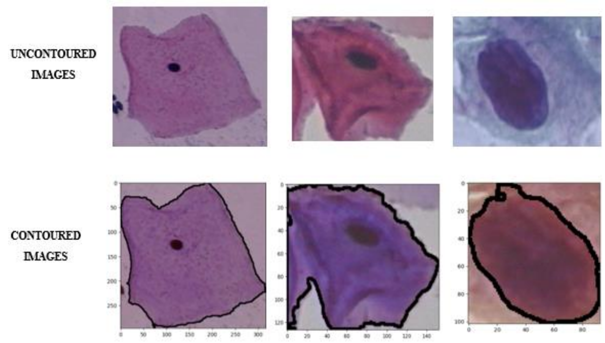

Fig. 24. Display of Contoured vs. Uncontoured Pap Smear images.

3.2. Robustness Test

Robustness tests are designed to assess an image processing or computer vision algorithm's resilience and stability under diverse conditions. To ensure that the algorithm performs smoothly and consistently across a variety of scenarios, including lighting, image quality, noise levels, and distortions, this training is crucial. Often, robustness tests are conducted in medical image processing when precision is crucial, for instance when illumination conditions vary or when imaging equipment has artifacts. The robustness test is a key element of algorithm development and validation, ensuring that algorithms demonstrate resilience in the face of real-world complexities, resulting in greater effectiveness and applicability.

3.2.1. Rotation

During robustness testing, image rotations play a crucial role in assessing how resilient and adaptable image processing algorithms are to dynamic real-world conditions. Fig.25 & Fig.26 illustrates that rotation is crucial to identifying potential vulnerabilities and challenges in robustness testing resulting from changes in image orientation.

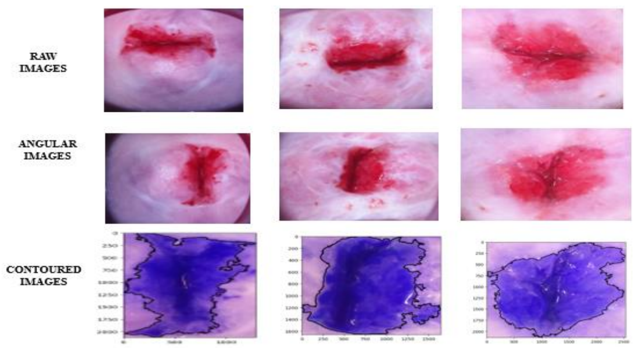

Fig. 25. Navigating Robustness - Results Unveiled Through Colposcopy Image Rotations

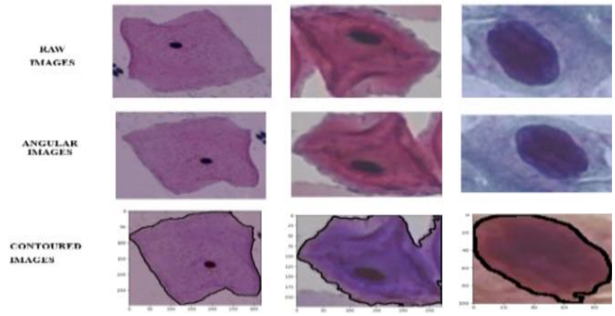

Fig. 26. Navigating Robustness - Results Unveiled through Pap Smear Image Rotations

3.2.2. Scaling

The process of scaling involves resizing copied areas within a specified range, usually expressed as a percentage increase or decrease. As part of the robustness test, the algorithm is evaluated by rescaling images at different factors to simulate potential abnormalities, such as lesions during colposcopy or cellular features on pap smears as shown in Fig.27 & Fig.28. With a step size of 2% and a scaling factor range of 91% to 109%, for example, a diverse set of test images is generated.

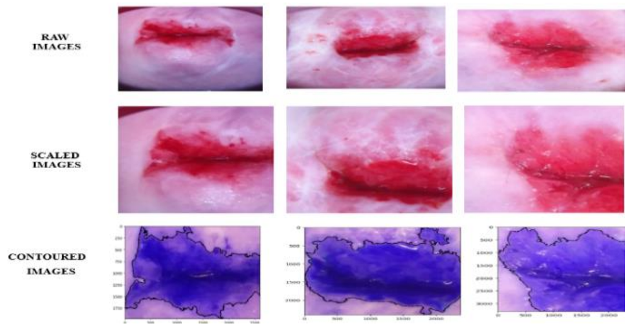

Fig. 27.

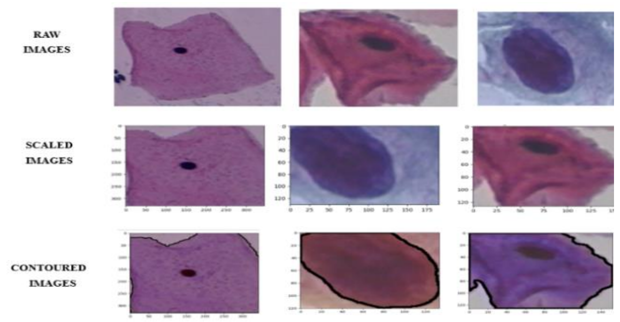

Fig. 28.

Navigating Robustness: Results Unveiled Through Image Scaling

3.2.3. JPEG Compression

Images are compressed with varying quality factors, typically ranging from 20 to 100 with 10-step steps. Using JPEG compression in robustness tests serves many purposes. Firstly, it provides a practical evaluation of algorithm performance by simulating the real-life conditions where images are compressed during transmission or storage. Further, JPEG compression in robustness tests can be used to evaluate the algorithm's ability to detect anomalies and forgeries in deliberately compressed images. The location outcomes of the JPEG compression attack with different quality factors (40, 60, 80, and 90) as shown in Fig.29 & Fig.30.

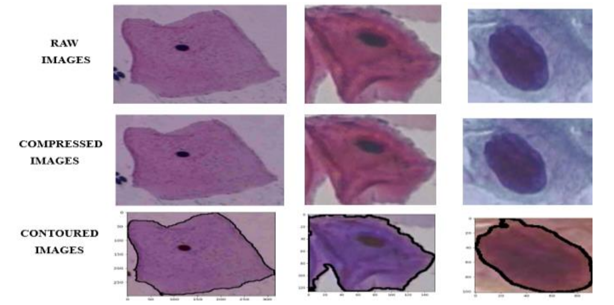

Fig. 29. Navigating Robustness: Results Unveiled Through JPEG Compression in Pap Smear Images

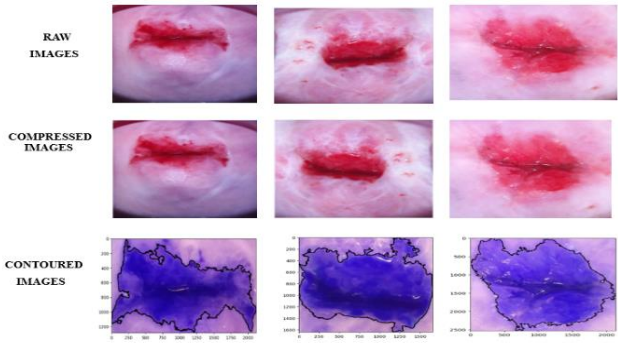

Fig. 30. Navigating Robustness: Results Unveiled Through JPEG Compression in Colonoscopy Images.

3.2.4. Noise Addition

The objective of noise addition is to assess an algorithm's performance under less-than-ideal conditions by intentionally adding disturbances to images. During image acquisition, transmission, or storage, this robustness test determines if an algorithm can maintain its effectiveness under unpredictable distortions. It may appear in various forms, such as Gaussian, salt-and-pepper, or speckle noise, each mimicking different scenarios in real life. A robustness test simulates unintentionally corrupted or distorted images by exposing them to controlled levels of noise. Our proposed approach is robustly tested by incorporating zero mean Gaussian noise with varying standard deviations between 0.02 and 0.1 as shown in Fig.31 & Fig.32. Although the image was subjected to these diverse transformations, its contours and ability to identify affected areas remained intact.

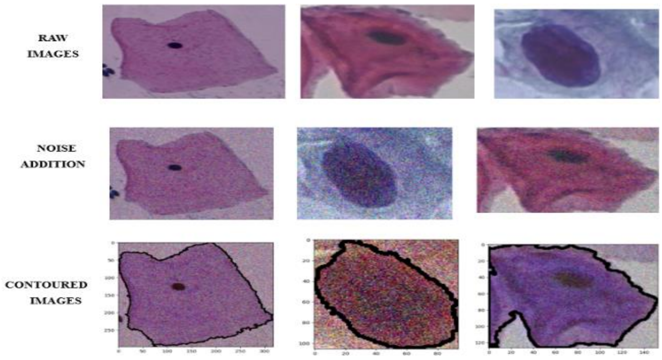

Fig. 31. Navigating Robustness: Results Unveiled Through Noise Addition in Pap Smear Images

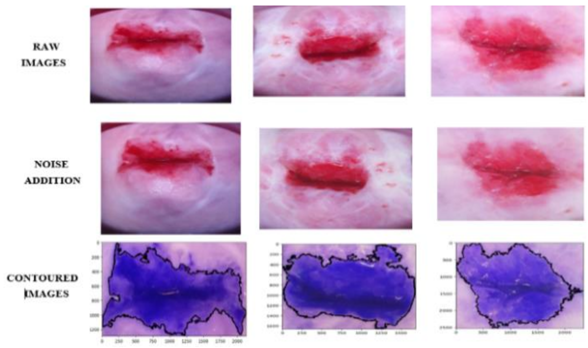

Fig. 32. Navigating Robustness: Results Unveiled Through Noise Addition in Coloscopy Images.

4. Conclusion

During our cervical cancer detection study, we analyzed two datasets: the Herlev collection of pap smear images, and the Intel MobileNet collection of colposcopy images. Our analysis of the images was hampered by the absence of meticulous preprocessing. Both datasets were analyzed using segmentation and contouring techniques to identify and highlight affected regions. Using a three-layer SegNet architecture, we were able to identify and classify diseased areas, resulting in robust results. The SegNet's ability to capture intricate details, especially in cervical tissues, demonstrated its effectiveness. The results of our study highlight the importance of preprocessing and the effectiveness of the SegNet architecture in the detection of cervical cancer. In robustness testing, we found that our approach exceeded standard methods, providing commendable results. This demonstrates the reliability of our findings. By combining tailored segmentation methods, the effectiveness of SegNet architectures, and robust techniques, our study stands out as a notable contribution to the field. Our research offers a promising avenue for future advancements in cervical cancer detection and diagnosis, with a specific emphasis on robustness.

5. Future Work

In our future work, we plan to investigate the effectiveness of a 5-layer SegNet architecture for the segmentation of cervical cancer. We hypothesize that by using a deeper network, we may be able to detect more intricate features of cervical cancer lesions, which would result in improved segmentation accuracy. Additionally, we intend to develop a method that would only segment the affected region of the cervix. Furthermore, we plan to evaluate the proposed method using a larger dataset of cervical cancer images to confirm its generalizability.

Author contributions

S.K & P.S.S.S contributed to the conception and design of the study. P.P. undertook the data collection, while P.S.S.S & K.H performed the data analysis and interpretation of results. J.S.S.N.S A, K.H & B.V.B were responsible for the draft manuscript preparation. All authors critically reviewed the results and approved the final version of the manuscript.

Conflicts of interest

The authors declare no conflicts of interest.

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