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RESEARCH ARTICLE

ACERNET: AUTOMATED CERVICAL CANCER DETECTION SYSTEM VIA HYBRID RESNET AND RANDOM FOREST

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Abstract – Globally, cervical cancer is one of the top causes of death for women, especially in areas with poor access to medical treatment. Early detection and diagnosis are critical for effective treatment, yet conventional screening techniques, such HPV testing and Pap smears, often face challenges related to subjectivity, time constraints, and the need for skilled professionals. To overcome these challenges, a novel deep learning-based ACERNET model is proposed an automated cervical cancer detection. Initially, the input cervicography images are collected from Publicly available dataset. Then the image is preprocessed using Gaussian filters (GF) to enhance clarity by reducing noise. The deep learning-based ResNet50 is used for extracting features from the Cervical cancer. Finally, the extracted features are subsequently fed into Random Forest (RM) classifier that classify Adenocarcinoma and Squamous cell carcinoma. The effectiveness of the proposed ACERNET was evaluated using F1 score, accuracy, precision, recall, and specificity. The proposed ACERNET model achieved a classification accuracy of 98.88%. The proposed model enhanced the total accuracy by 0.67%, 5.91%, 1.04% better than Cervi Former, CYENET, C^{3}Net respectively.

***Keywords** – Cervical cancer, Gaussian Filter, deep learning Random Forest, ResNet50, Cervicography images.*

1. INTRODUCTION

Cervical cancer is a kind of cancer that arises in the cervix, which is the low portion of the uterus that joins the vagina. [1] It remains most common cancer though its incidence has significantly declined in countries with effective screening programs and widespread vaccination against the human papillomavirus (HPV). [2] Cervical cancer development is primarily associated with ongoing infection by high-risk HPV strains, which cause over 70% of instances of cervical cancer overall. [3, 4] Although the immune system usually gets rid of HPV infections, some high-risk strains might cause the cervix to develop abnormal cells. [5] These aberrant cells could become precancerous lesions and eventually progress to cervical cancer. This process typically occurs over several years, providing an opportunity for early detection through regular screening [6].

In recent years, deep learning-based methods to improve traditional screening methods like Pap smears and HPV tests for the early diagnosis and identification of cervical cancer. [7, 8] Convolutional Neural Networks (CNNs), in particular, can automatically detect precancerous lesions and classify them into different stages, helping clinicians make more informed decisions [9]. In multimodal data, deep learning models offer a quicker, more precise, and easier-to-use diagnostic tool, where traditional screening methods may be less available [10].

Despite these advancements, a major issue is the delayed diagnosis, as the slow and asymptomatic, making early detection crucial for effective treatment. [12] The lack of comprehensive screening programs and underutilization of existing technologies contribute to high mortality rates, particularly in underserved populations. Additionally, the complexity and subjectivity of manual examination of cervical cytology samples pose significant challenges to accurate diagnosis [13]. However, further research is needed to refine these models, ensure their clinical applicability, and expand their use in low-resource settings to make significant strides in cervical cancer prevention and treatment. To overcome this problem, a novel ACERNET model is proposed for classifying the Cervical cancer detection. The major research contributions are mentioned below:

- The main goal of this strategy is to develop an ACERNET method proposed for the classification of Cervical cancer. The input cervicography images are collected from Publicly available dataset.
- Initially the input images are pre-processed using Gaussian Filter to remove noise from the images.
- In the deep learning-based Resnet model is used for extracting features from the Cervical cancer images.
- Finally, the extracted features are subsequently fed into Random Forest (RM) classifier that

classify Adenocarcinoma and Squamous cell carcinoma.

- The effectiveness of the proposed ACERNET was evaluated using F1 score, accuracy, precision, recall, and specificity.

The remainder of the work is organized accordingly. Section 2 provides a summary of the literature review; Section 3 discusses about the proposed model and Section 4 focuses at the performance of the proposed approach and compares it to other methods. Section 5 provides a final explanation of the conclusion and future scope.

2. LITERATURE SURVEY

In this section, the state-of-the-art in the domains that are pertinent to the work that is being presented, including data, deep learning, machine learning methods, and related studies. Related studies are listed in the following paragraphs, with an emphasis on those that make use of Cervical Cancer detection.

In 2021 Park, Y.R., et al., [14] devised the classification of pre-processed cervicography images using the same methodologies allowed for an objective evaluation and comparison of the ML and DL approaches. In the three machine learning techniques, the ResNet-50 model performed 0.15 points better than the average (0.82) ($p < 0.05$).

In 2022 Lilhore, U.K., et al., [15] proposed Boruta analysis and the SVM approach are used to address this difficulty by creating an effective selection of features and prediction model for cervical cancer datasets. According to the experimental findings, Boruta analysis performed better than alternative machine learning-based methods.

In 2021 Chandran, V., et al., [16] proposed deep learning-based using colposcopy images, Cervical cancer is detected using CNN architectures, namely the CYENET and VGG19 (TL) models. The CNN architecture studies employ VGG19 as a transfer learning tool. The developed model's sensitivity, specificity, and accuracy are estimated. VGG19 has a 73.3% classification accuracy.

In 2021 Tripathi, A., et al., [17] presents a benchmark for evaluating upcoming classification approaches, deep learning classification algorithms were applied to the SIPAKMED pap-smear picture dataset. Using this technique, 94.89% classification accuracy was the maximum achieved by the ResNet-152 architecture.

In 2022 Alquran, H., et al., [18] proposed the first algorithm to successfully Sort pap smear pictures into seven different classifications. To classify the irregularity in A technique for computer-aided diagnosis that uses cervical imaging cells is designed using Pap smear images. Although all seven classes' combined test accuracy is approximately 92% during the test phase and achieves 97.3% overall, the total training accuracy for all cases is 100%.

In 2022 Habtemariam, L.W., et al., [19] developed a comprehensive and reliable solution that automatically classifies cervix type and cervical cancer using deep learning algorithms. The cervix type and cervical cancer the accuracy of the classification test was 96.84% and 94.5%, respectively, while the region of interest (ROI) extraction test obtained 99.88% mean average precision (mAP).

In 2023 Youneszade, N., et al., [20] introduced on DL-based systems that evaluate and categorize cervical screening images using image segmentation and classification methods. To further the CC classification in multimodal feature selection can be studied with DL algorithms like VGG19, Faster RCNN, and RCNN.

In the literature review, above existing techniques had developed using various DL and ML approaches to detecting the Cervical Cancer. However, existing methods like Pap smears and HPV testing are time-consuming, prone to human error, and may miss subtle abnormalities. Additionally, these methods require skilled professionals and infrastructure, which are often unavailable in low-resource settings. In this research, ACERNET method was proposed for classifying the Cervical Cancer.

3. PROPOSED METHODOLOGY

In this research, a novel ACERNET model is proposed for classifying the Cervical Cancer from the dataset. Figure.1 shows the general process of the proposed ACERNET methodology.

3.1 Dataset Description

In this study the cervicography images are collected from publicly available dataset. The use of one of three Cervicam devices, 4119 cervicography images were captured. The Dr. Cervicam produced photographs with a resolution of 1280 x 960 pixels, the Dr. Cervicam WiFi produced images with a resolution of 1504 x 1000 pixels, and the Dr. Cervicam C20 produced images with a resolution of 2048 x 1536 pixels. 2,135 aberrant positive images and 1,984 normal negative images made up the dataset, and tissue biopsy was used to confirm the accuracy of all the data.

3.2. Gaussian Filter (GF)

The GF that uses Finite Impulse Response (FIR) to cut down on image noise. It can be used with a 2D matrix of coefficients, also known as a kernel, or a vertical and horizontal 1D convolution. Each 1D coefficient is obtained using Eq. 1, where $ksize$ is the kernel size, σ is the variance, i is an index varying from 0 up to $ksize - 1$, and α is a scale factor that makes $\sum_{i}^{ksize-1} G(i) = 1$. The 2D kernel is an $N \times N$ matrix in which the 1D kernel is multiplied by its transpose $(2D = 1D \times 1D^T)$.

$$G(i) = \alpha \times e^{\frac{(i-(ksize-1)/2^2}{2\times\sigma^2}} \quad (1)$$

The 3×3, 5×5, and 7×7 kernels are evaluated in this paper. Using Eq. 1 and a variance of 1.36, the floating-point coefficients for every 1D kernel were determined. The 2D kernel was then obtained by multiplying each 1D kernel size by its transposition. To obtain an initial estimate, the 2D coefficients for every kernel size were rounded to integer values. Compared to floating-point arithmetic, the rounding of coefficients lowers implementation complexity and hardware consumption.

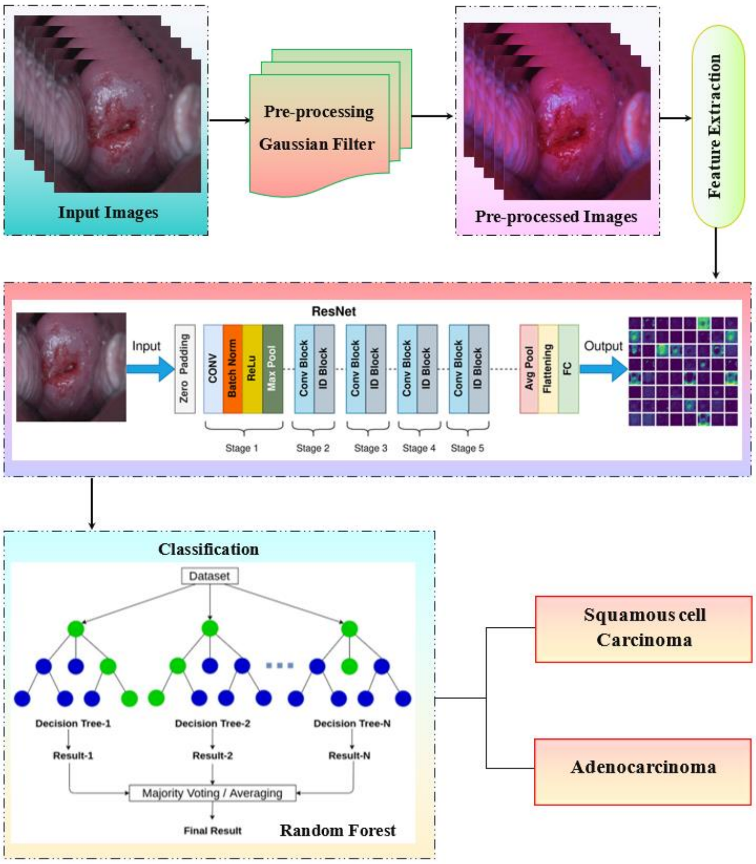


Figure 1. Proposed ACERNET method

The integer coefficients utilized in this work for 3×3, 5×5, and 7×7 kernels are shown in Eq. 2, 3, and 4, respectively.

$$\begin{bmatrix} 15 & 19 & 15 \\ 19 & 24 & 19 \\ 15 & 19 & 15 \end{bmatrix} \quad (2)$$

$$\begin{bmatrix} 2 & 4 & 5 & 4 & 2 \\ 4 & 9 & 12 & 9 & 4 \\ 5 & 12 & 15 & 12 & 5 \\ 4 & 9 & 12 & 9 & 4 \\ 2 & 4 & 5 & 4 & 2 \end{bmatrix} \quad (3)$$

$$\begin{bmatrix} 0 & 1 & 1 & 1 & 1 & 1 & 0 \\ 1 & 2 & 4 & 5 & 4 & 2 & 1 \\ 1 & 4 & 8 & 10 & 8 & 4 & 1 \\ 1 & 5 & 10 & 13 & 10 & 5 & 1 \\ 1 & 4 & 8 & 10 & 8 & 4 & 1 \\ 1 & 2 & 4 & 5 & 4 & 2 & 1 \\ 0 & 1 & 1 & 1 & 1 & 1 & 0 \end{bmatrix} \quad (4)$$

The 3×3, 5×5, and 7×7 kernel functions shown in Eq. 5, 6, and 7 were obtained by multiplying the 2D kernel coefficients by a generic block. The variables i_γ are the pixels from the input block, with γ being the pixel's position within the block. Because of the zero-product condition, the terms that used coefficients 0 were removed from Eq. 7.

$$Y_{3\times3} = 15i_0 + 19i_1 + 15i_2 + 19i_3 + 24i_4 + 19i_5 + 15i_6 + 19i_7 + 15i_8 \quad (5)$$

$$Y_{5\times5} = 2i_0 + 4i_1 + 5i_2 + 4i_3 + 2i_4 + 4i_5 + 9i_6 + 12i_7 + 9i_8 + 4i_9 + 5i_{10} + 12i_{11} + 15i_{12} + 12i_{13} + 5i_{14} + 4i_{15} + 9i_{16} + 12i_{17} + 9i_{18} + 4i_{19} + 2i_{20} + 4i_{21} + 5i_{22} + 4i_{23} + 2i_{24} \quad (6)$$

$$Y_{7\times7} = i_1 + i_2 + i_3 + i_4 + i_5 + i_6 + i_7 + 2i_8 + 4i_9 + 5i_{10} + 4i_{11} + 2i_{12} + i_{13} + i_{14} + 4i_{15} + 8i_{16} + 10i_{17} + 8i_{18} + 4i_{19} + i_{20} + i_{21} + 5i_{22} + 10i_{23} + 13i_{24} + 10i_{25} + 5i_{26} + i_{27} + i_{28} + 4i_{29} + 8i_{30} + 10_{31} + 8i_{32} + 4i_{33} + i_{34} + i_{35} + 2i_{36} + 4i_{37} + 5i_{38} + 4i_{39} + 2i_{40} + i_{41} + i_{42} + i_{43} + i_{44} + i_{45} + i_{46} + i_{47} \quad (7)$$

The design space exploration is increased by processing the blocks using equations. Additionally, it offers more space to use methods to decrease the hardware implementation area or increase power efficiency. The literature contains a variety of methods for investigating Gaussian filter topologies with an eye on power efficiency.

3.3. Feature Extraction

ResNet50, is a highly effective tool for feature extraction in cervical cancer diagnosis. Figure 2. show incorporates residual connections, which mitigate network to learn both features at the low and high levels. This capability makes ResNet50 particularly suited for identifying subtle abnormalities in cervical cancer images, such as precancerous lesions and malignant cell structures

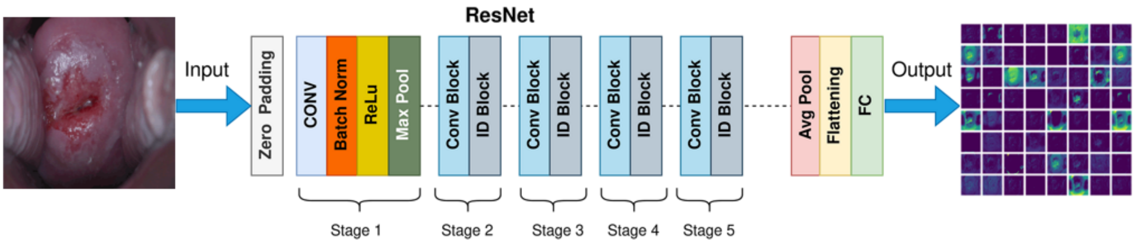


Figure 2. The proposed Architecture of ResNet50

The use ResNet50 for cervical cancer feature extraction, a pretrained model is commonly employed to leverage its learned weights. Features are typically extracted from intermediate layers, such as the global average pooling layer, which provides a compact and representative feature vector. ResNet50 lies in its ability to capture rich spatial and semantic features. Its deep architecture, combined with residual connections, ensures robust learning of both general and specific patterns, which is crucial for cervical cancer diagnosis. Moreover, its scalability allows it to adapt well to various datasets, including histopathology and cytology images, making it a versatile choice in medical imaging applications. The mathematical representation of ResNet50 feature extraction given below:

$$F = GAP(f(X; W, b)) \tag{8}$$

Where GAP is the global average pooling, f represents the ResNet50 transformations and W, b are the model parameters. ResNet50 is a powerful feature extractor for cervical cancer due to its robust architecture, ability to generalize across domains, and high accuracy in identifying critical patterns. Its integration into deep learning workflows can significantly enhance automated cervical cancer diagnosis and improve early detection rates.

3.4. Random Forest

Random forests (RF) are nonlinear models used for regression or classification, consisting of an ensemble of decision trees. The forest is constructed using a random sample of the data trees being generated independently from one another. It is a popular and effective method for classifying medical images due of its ability to manage data with several dimensions with resilience and its ability to rank feature importance. The process begins with preprocessing the images through isolate regions of interest such as cells or tissues. Feature extraction follows, where critical attributes like texture histopathological characteristics and color properties are derived from the images. The Random Forest model itself makes a classification, and the majority vote determines the outcome. RF is particularly advantageous because it reduces overfitting and is capable of managing large, feature-rich, complicated datasets. Additionally, it offers a feature priority ranking that aids in determining which features are most pertinent for classification while reducing dimensionality. Random Forest is a robust tool for medical image analysis, excelling in tasks like tissue classification, Cervical Cancer grade classification, and subtype differentiation due to its adaptability to noisy data.

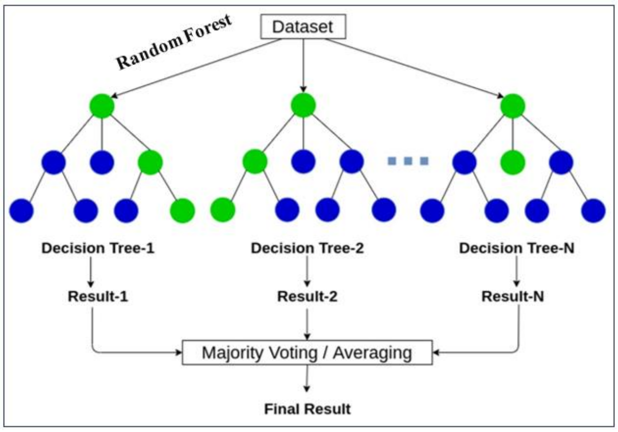


Figure 3. The Visual representation of Random Forest

The mathematical representation of Random Forest, the image I is represented as,

$$I \rightarrow X = \{x_1, x_1, \dots, x_n\} \tag{9}$$

Where X is the feature vector consisting of n features. Random Forest is an ensemble of T decision tree $\{h_1(X), h_2(X), \dots., h_T(X)\}$. Mathematically, the decision function of each tree can be represented as:

$$h_t(X) = argmax \sum_{x_i \in X'} (Information\ Gain) \tag{10}$$

Where the information gain is calculated based on the impurity reduction at each split. The Random Forest algorithm offers a powerful and versatile approach for effectively classifying Cervical Cancer and other medical imaging tasks by leveraging its robustness against noise and ability to manage complex datasets.

4. RESULT AND DISCUSSION

The proposed ACERNET technique was evaluated in this section utilizing several metrics like recall, specificity, accuracy, precision, and F1 score, depending on the gathered datasets.

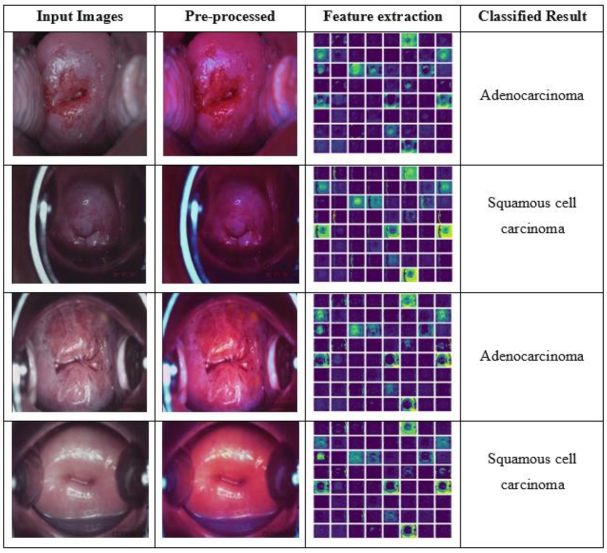


Figure 4. The Experimental result of Proposed ACERNET model

The outcomes of the proposed experiment approach ACERNET are shown in Figure 4. In column 1, the input Cervical cancer images. Gaussian Filter is used to improve the clarity of the image and remove the noises from Cervical Cancer images in column 2. In Feature extraction using ResNet50 for extracting features from the images in column 3. Finally Random Forest is used to classify Adenocarcinoma and Squamous cell carcinoma in column 3.

4.1 Performance Analysis

The Common metrics used to evaluate the performance of a classification method include accuracy, precision, recall, specificity, and the F1 score.

$$accuracy = \frac{TP+TN}{TP+TN+FP+FN} \tag{11}$$

$$Specificity = \frac{TN}{TN+FP} \tag{12}$$

$$Precision = \frac{TP}{TP+FP} \tag{13}$$

$$recall = \frac{TP}{TP+FN} \tag{14}$$

$$f_1 = 2\left(\frac{precision*recall}{precision+recall}\right) \tag{15}$$

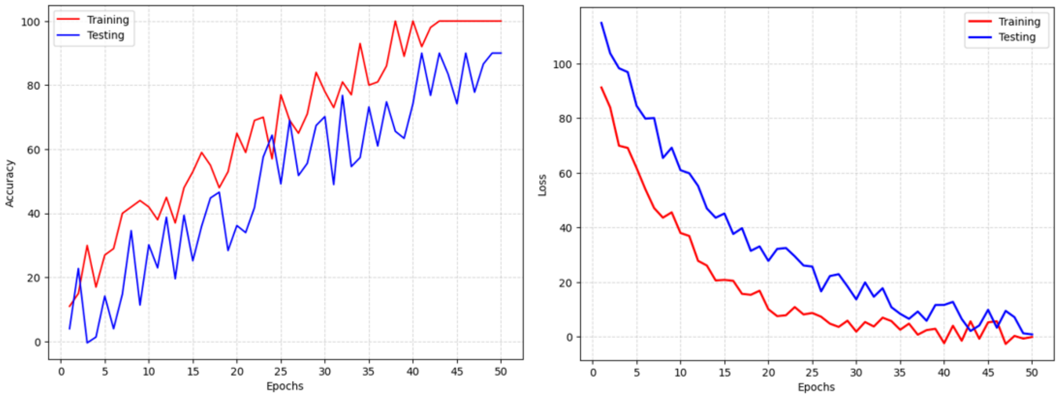
where T_{pos} and T_{neg} indicates the actual benefits and drawbacks of the provided images, F_{pos} and F_{neg} shows the sample images false positives and negatives.

Table 1. Performance analysis of ACERNET model

Classes	Accuracy	Specificity	precision	Recall	F1score
Adenocarcinoma	99.31 %	98.23 %	99.54 %	97.48%	97.22%
Squamous cell carcinoma	98.46 %	98.65 %	98.78 %	96.65%	98.73%

Table 1 displays precision, recall, F1 score, accuracy, and specificity proposed technique for various classes. The efficiency metrics of the proposed approch are show in Table 1 for the following classes: Normal Glaucoma and Abnormal Glaucoma. The suggested method's accuracy is 99.84% for Normal Glaucoma and 98.98% for Abnormal Glaucoma.

The training and testing accuracy is shown in Figure 5 (a), which also displays epochs on the x-and y-axes. Considering the accuracy of its testing and training curves, the proposed exhibits and accuracy level of 98.88% for epochs. A loss curve plotted against epochs in shown in Figure 5 (b), showing that the loss reduces with increasing epochs. The proposed procedure yields an accurate result with low loss of 1.12%.



(a) (b)

Figure 5. Training and Testing curve (a) Accuracy (b) Loss of the ACERNET model

4.2 Comparative Analysis

In a comparison between the proposed model and was assessed in comparison to existing approaches to demonstrate its accuracy and efficiency. When the performance of this methodology is compared with traditional methods, it performs better than those methods. Performance is assessed using F1 score, recall, accuracy, precision, specificity, and specificity. The proposed model is benchmarked against three current deep learning methodologies in this comparative analysis.

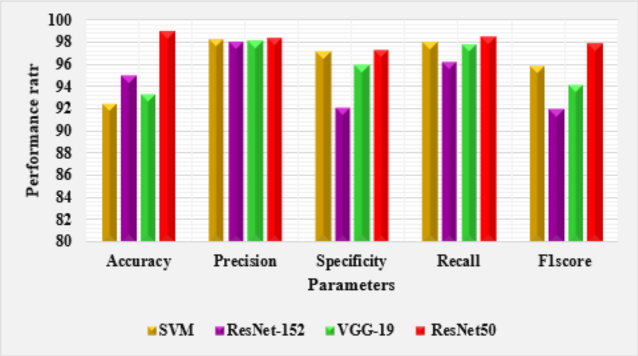


Figure 6. Comparison between existing and proposed method

Figure 6 illustrate that traditional network such as SVM, ResNet-152, and VGG-19 approach produced more accurate findings, although at a lower level of precision. The proposed method maintains excellent curacy accuracy ranges 98.88%. The proposed method achieves a higher accuracy rate compared to the existing models. Therefore, the proposed ACERNET method shows performs better than other techniques.

Table 2. Comparison of the existing and proposed model

Authors	Methods	Accuracy
Deo, B.S., et al., (2024) [10]	Cervi Former	98.21%
Chandran, V., (2021) [16]	CYENET	93.03%
Alquran, H., et al., (2022) [28]	C^3Net	97.85%
Proposed	ACERNET	98.88%

Table 2 shows a comparison of networks that is not as precise as the proposed ACERNET model. The proposed technique maintains excellent accuracy levels of 98.88%. The proposed ACERNET model enhances the total accuracy by 0.67%, 5.91%, 1.04% better than Cervi Former, CYENET, C^3Net respectively. The comparison above indicates that in terms of accuracy, the effectiveness of the proposed ACERNET model is superior to that of the existing models.

5. CONCLUSION

In this research a novel ACERNET model is proposed for the classification of Cervical cancer. Initially, the input cervicography images are collected from Publicly available dataset. Then the image is preprocessed using Gaussian filters (GF) to enhance clarity by reducing noise. The deep learning-based ResNet50 is used for extracting features from the Cervical cancer. Finally, the extracted features are subsequently fed into Random Forest (RM) classifier that classify Adenocarcinoma and Squamous cell carcinoma. Accuracy, precision, recall, specificity, and F1 score were used to assess the efficacy of the proposed ACERNET. The classification accuracy of the proposed ACERNET model was 98.88%. The proposed model enhanced the total accuracy by 0.67%, 5.91%, 1.04% better than Cervi Former, CYENET, C3Net respectively. Future research can integrate multimodal data like demographics and biomarkers for personalized cervical cancer diagnosis. Exploring transformer-based models and lightweight architectures could improve performance and enable deployment in resource-constrained settings.

CONFLICTS OF INTEREST

The authors declare that there is no conflict of interest.

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