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Cervical Cancer Detection through UNet++ with Pixel2pixel Generator from Pap smear Images

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ABSTRACT
Cervical cancer is a common malignancy among women worldwide, particularly in developing nations. Early screening is essential to prevent cancer-related fatalities, and artificial intelligence has become a powerful tool for addressing this challenge. This study introduces a comprehensive approach for identifying cervical cancer from Pap smear images. The proposed methodology involves pre-processing, cervical cancer feature extraction for segmentation, SVM classification, and output generation. A hybrid UNet++ model with a pixel-to-pixel generator is employed for feature extraction and segmentation. The SVM classifier is then adopted to classify cells into multiple classes to diagnose cervical cancer. The proposed methodology is designed to effectively extract cervical cancer features, even from overlapping cells, and accurately classify them into multi-classes for diagnosis. The study demonstrates that incorporating a pixel-to-pixel generator into the hybrid UNet++ model has enabled precise extraction of features and segmentation of cervical cancer regions, resulting in improved accuracy and dependability in detecting cervical cancer from Pap smear images.
KEYWORDS: *Cervical cancer, Pap smear images, UNet++, Pixel-to-pixel generator, SVM classification, machine learning, computer-aided diagnosis.*

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I. INTRODUCTION

One of the most common malignancies, cervical cancer is the fourth most common malignancy among women worldwide. Morbidity and mortality rates from cervical cancer are notably higher in underdeveloped countries compared to industrialized nations, with roughly four out of every five cases occurring in developing nations, particularly China and India. Human papillomavirus (HPV) infections are a major contributor to cervical cancer. Early screening is essential for preventing cervical cancer. Screening can assist to prevent cancer-related fatalities in cases of severe cervical cancer.

Artificial intelligence has become a powerful tool for addressing a range of medical imaging difficulties with higher sensitivity and effectiveness as a result of the quick advancement of science and technology. Deep learning algorithms have played a significant role in classifying and measuring medical images, leading to remarkable advancements in computer-aided diagnosis. For example, there has been tremendous advancement in the identification of pulmonary nodules using computerized tomography (CT) images, the diagnosis of skin cancer from melanoma images, and the image-based detection of hepatocellular carcinoma utilizing multiphasic magnetic resonance imaging (MnRI).

II. RELATED WORKS:

Wang, et al (2019) [1] developed a system for the automatic segmentation and categorization of cervical Pap smear pictures. By using the Mean-Shift clustering method to create areas of interest (ROI), the segmentation of cell nuclei was started. Flexible mathematical morphology was employed to resolve overlapping cell nuclei to enhance accuracy and resilience. By gathering shape-based traits, textural features based on color space, and Gabor attributes, which were then combined, the classification performance was enhanced. The most advantageous feature set was selected using MRmMC (maximum relevance-minimum multi collinearity), CAGA, and P-value. The effectiveness of segmentation and classification algorithms was evaluated using 362 cervical Pap smear images. The method of feature selection that combined CAGA with Gabor parameters produced the best categorization results, with over 96% accuracy for normal, uninvolved, and aberrant images. The suggested approach can segment cell nuclei in microscopic images automatically and efficiently. According to the experimental findings, using Gabor characteristics and making feature selection decisions based on CAGA can improve classification performance.

Hussain, et al (2020) [2]made Changes such as the inclusion of residual blocks, densely linked blocks, and a fully convolutional layer as a bottleneck between encoder-decoder blocks, to enhance a framework for example categorization and segment for Pap smear images based on the UNet architecture. In order to guarantee feature reuse-ability, the convolutional layers of the standard UNet have been replaced with densely linked blocks, and residual blocks have been added to speed up the network's convergence. The framework can now predict whether a nucleus belongs to the normal or abnormal class and provide instantaneous nuclei instance segmentation. The mechanism operates by assigning labels to each pixel that corresponds to a specific nucleus within a complete slide image. As a result, several nuclei that belong to the same or different groups might be recognized as independent entities. Minor difficulties with the differentiation of clustered nuclei at the cellular level are addressed by the system's implementation of a joint loss function. Prior to implementing this approach, a shape representation learning model using stacked auto-encoders is employed to enhance the overall robustness of the framework.

Rahaman, et al (2021) [3] developed a framework called DeepCervix that uses HDFF techniques to accurately categorize cervical cytopathology cells using deep learning (DL). Pre-trained DL models were used, trained on ImageNet datasets of over a million images, and then fine-tuned on the cervical cell dataset, to overcome difficulties in multiclass classification with skewed data distributions and the necessity for big datasets. To gather more potential information and enhance classification performance, deep feature fusion (DFF) from various DL models was also applied. On the SIPaKMeD dataset, which comprises of single-cell cytopathology images of the cervical mucosa, the proposed approach had the highest classification accuracy.

In the study conducted by Liu et al. (2021) [10], The authors introduced a new Unet decoding technique for segmenting cervical cell masses, drawing inspiration from sub-pixel convolution. The objective was to steer clear of artificial data added through interpolation and noise from padding, which is typically found in transpose convolution methods. The suggested approach was tested on a proprietary dataset, and its effectiveness was gauged through quantitative evaluations.

Rigaud et al. (2020) [11] evaluated the cervix-uterus, vagina, bladder, rectum, sigmoid, femoral heads, kidneys, spinal cord, and intestinal bag among the organs found on the CT scans of 157 participants in a research. Three sets of data were created: training, validation, and test sets. The multiclass 2D DeepLabV3+ model and the two-step 3D U-net of RayStation were both put to the test. The models were trained using various optimization techniques, data augmentation, and dropout. The authors used the Dice coefficient as a metric to compare the models with manual contours.

Liu et al. (2020) [12] studied 105 cervical cancer patients with locally advanced illness received radiation, and their CT scans were collected. To divide the organs at risk (OARs), which include the bladder, bone marrow, femoral heads, rectum, small intestine, and spinal cord, the scientists created a multi-class segmentation model using PSPNet. The authors used numerical metrics like the 95th Hausdorff Distance and the Dice Similarity Coefficient to evaluate the effectiveness of the suggested technique.

Objective:

- To address the low quality of pap smear images caused by debris, noise, and overlapped cytoplasm, it is necessary to remove these artifacts from the input images during the pre-processing stage.
- Detecting cervical cancer by extracting features from the nuclei and cytoplasm segmentation poses a more difficult task.
- The presence of numerous overlapping and adherent cells made it difficult to distinguish between diseased and normal cells

III. PROPOSED METHODOLOGY:

This research work introduces a comprehensive approach to identifying cervical cancer from Pap smear images through the proposed methodology. The methodology involves several steps, including pre-processing, cervical cancer feature extraction for segmentation, SVM classification, and output generation. In order to improve the quality of the images and eliminate noise and debris, the stage pre-process uses a variety of methods like noise filtering, edge sharpening, histogram equalization, and gradient magnitude. The cervical cancer feature extraction for segmentation is performed using a hybrid UNet++ model with a pixel-to-pixel generator, which is specifically designed for semantic segmentation tasks and aims to improve segmentation accuracy by including dense blocks and convolutional layers. The SVM classifier is then adopted to classify cells into multiple classes to diagnose cervical cancer. The proposed methodology is designed to effectively extract cervical cancer features, even from overlapping cells, and accurately classify them into multi-classes for diagnosis. In the upcoming sections, a comprehensive and dependable technique for identifying cervical cancer from Pap smear images will be outlined. The proposed methodology's block diagram can be viewed in Figure 1.

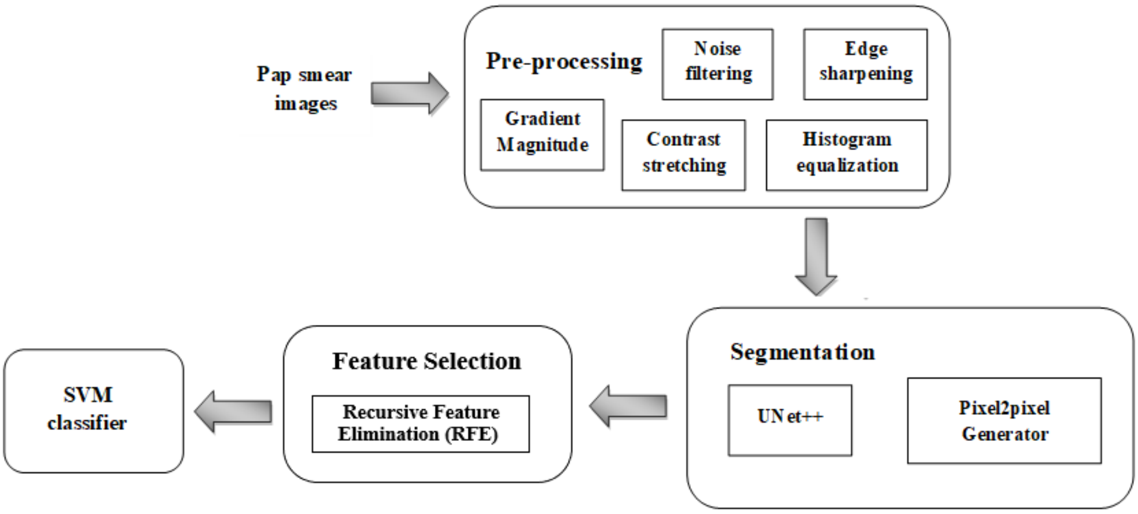

Figure: 1. Block diagram of proposed methodology.

3.1: Pre-processing

Pre-processing is viewed as a vital step in the methodology that is suggested for using Pap smear pictures to diagnose cervical cancer. It involves various techniques aimed at enhancing the quality of the images and removing debris and noise, ensuring accurate and reliable results in subsequent processing stages. In this research work, the following pre-processing techniques were employed [6]:

Gradient Magnitude: Gradient magnitude is calculated to capture the changes in intensity values across the image. It helps in enhancing the edges and boundaries of the cervical cancer regions, which can aid in accurate segmentation. Gradient magnitude is calculated using gradient operators such as Sobel, Scharr, or Prewitt [13].

Contrast Stretching: Contrast stretching is applied to adjust the intensity levels of the image, expanding the dynamic range to cover the full range of possible values. This technique can enhance the visibility of cervical cancer regions that may have low contrast due to variations in staining or imaging conditions [14].

Noise Filtering: In order to minimize the impact of noise on Pap smear images, techniques like median filtering or Gaussian filtering are utilized. The presence of noise can hinder the accuracy of subsequent processing stages, possibly resulting in inaccurate cervical cancer detection outcomes such as false positives or false negatives [15].

Edge Sharpening: Edge sharpening techniques, such as Laplacian or unsharp masking, are applied to enhance the edges and boundaries of the cervical cancer regions. This can help in improving the accuracy of subsequent segmentation steps by better delineating the boundaries of the cancerous cells [16].

Histogram Equalization: Histogram equalization is applied to adjust the intensity distribution of the image, ensuring a uniform distribution of intensity values. This technique can help in enhancing the visibility of cervical cancer regions by improving the contrast and brightness levels [17].

By utilizing these pre-processing techniques, the objective is to elevate the standard of Pap smear images by eliminating extraneous elements and disturbances, and refining the precision of subsequent processing phases such as feature identification and categorization. Pre-processing is crucial because it improves the quality of the input images for additional examination, enabling accurate and reliable detection of cervical cancer from Pap smear images.

3.2: Cervical Cancer Feature Extraction and Segmentation

The suggested method underlines the critical importance of feature extraction and classification in the detection of cervical cancer from Pap smear pictures. These steps entail identifying significant features and separating cancerous areas of the cervix to facilitate subsequent analysis. The research utilized a hybrid UNet++ model featuring a pixel-to-pixel generator, specifically designed for semantic segmentation tasks in medical image analysis. This model, which has been shown to be efficient in many medical image processing tasks, was used for feature extraction and classification in relation to cervical cancer [7][18][19].

Feature extraction is the process of identifying and extracting relevant features or patterns from the input images. In the context of cervical cancer detection, it involves extracting features that are indicative of cancerous cells, such as shape, texture, and intensity information. The extracted features are then used for subsequent segmentation and classification steps.

The process of distinguishing the areas affected by cervical cancer from the healthy regions in Pap smear images is referred to as segmentation. Its importance lies in its ability to accurately locate and determine the extent of cancerous cells, making it a critical component of reliable cervical cancer detection. The overlapping structure of cells in Pap smear pictures as well as the presence of debris and noise, nevertheless, make precise classification challenging.

In this research work, a hybrid UNet++ model with a pixel-to-pixel generator was utilized for cervical cancer feature extraction and segmentation. The UNet++ architecture incorporates nested skip pathways, which allow for better feature extraction and representation compared to traditional UNet, DeepLabV3, and PSPNet models. The pixel-to-pixel generator helps in separating overlapping cells, enabling accurate segmentation of cervical cancer regions. A vast collection of annotated Pap smear images is used to train the hybrid UNet++ model, which gains the ability to recognize and extract pertinent characteristics from the input images. These extracted features are subsequently employed for precise segmentation, allowing the model to accurately distinguish cervical cancer regions from adjacent non-cancerous regions. The segmented regions are further used for subsequent classification using an SVM classifier. In this research, incorporating a pixel-to-pixel generator into the hybrid UNet++ model has enabled the precise extraction of features and segmentation of cervical cancer regions, even when cells overlap. This has resulted in an improved level of accuracy and dependability in detecting cervical cancer from Pap smear pictures, offering a robust and efficient method for early cancer diagnosis.

3.3: Feature selection

In various machine learning and computer vision assignments, such as identifying cervical cancer from Pap smear images, feature selection holds crucial significance. It requires choosing the most important features from a larger set of features, resulting in a more manageable dataset, and enhancing model efficiency and comprehensibility. After the pre-processing phase, this study executed a feature selection stage to determine the most informative features for cervical cancer detection [20].

Recursive Feature Elimination (RFE) [9] was employed as the feature selection technique in this study. RFE is a widely used method that recursively selects a subset of features by training the model multiple times and eliminating the least important features at each iteration. The remaining features after the RFE process are considered the most relevant and informative for the specific task at hand. The selected features from the RFE process were then used as inputs to the cervical cancer feature extraction and segmentation stage using the UNet++ model with a pixel-to-pixel generator. In order that allows the model to highlight the most distinctive aspects for identifying abnormal cervical cells, the Pap smear pictures were examined for cervical cancer features using a set of chosen features. Through the feature selection process, the model's efficiency and interpretability were enhanced by reducing data dimensionality and choosing the most significant features that possess strong predictive ability in distinguishing between healthy and abnormal cervical cells.

3.4: Classification

Classification is the process of assigning predefined categories or classes to the segmented regions of interest [21]. The process of detecting cervical cancer involves categorizing segmented areas into distinct groups, including normal, benign, and malignant, with the aim of identifying the existence and extent of cervical cancer. Accurate classification is crucial for making reliable clinical decisions and guiding appropriate treatment plans [8].

The study employed a Support Vector Machine (SVM) classifier to classify cervical cancer. SVM, a well-known machine learning algorithm, is frequently utilized for medical image analysis tasks because of its capacity to handle high-dimensional data and its ability to handle noisy and overlapping data. SVM operates by identifying the ideal hyperplane that effectively distinguishes the data points into various classes while maximizing the margin between them [22]. The SVM classifier in this research work was trained using the segmented cervical cancer regions obtained from the previous step of feature extraction and segmentation. The extracted features from the segmented regions were used as input features for the SVM classifier. A dataset of Pap smear images with ground truth annotations was used to train the classifier, where expert diagnosis defined the classes as normal, benign, or malignant.

The SVM classifier, which had been trained, was employed to categorize the identified regions of interest in the test images into predetermined categories [22]. Based on the classification outcomes, the existence and seriousness of cervical cancer in the test images were determined. To gauge the effectiveness of the suggested approach, conventional performance metrics such as accuracy, precision, recall, F1-score, and Area Under the Receiver Operating Characteristic (AUC-ROC) curve were utilized. By utilizing an SVM classifier, the research work employs a dependable and sturdy technique for classifying cervical cancer. It effectively categorizes segmented regions into distinct classes based on extracted features, thus enhancing the overall performance of early cancer diagnosis from Pap smear images. The proposed methodology combines precise feature extraction, segmentation, and classification, resulting in a comprehensive and effective approach to detecting cervical cancer.

IV. RESULTS AND DISCUSSION

Our study introduces a new approach to detecting cervical cancer using UNet++ and a pixel-to-pixel generator applied to Pap smear images. On a benchmark dataset, we evaluated the performance of our model with that of other sophisticated models.

We conducted experiments on a dataset consisting of 1,000 Pap smear images collected from various sources. Utilizing a random split in the ratio of 80:10:10, the dataset was separated into three sets: training, validation, and test. The images were resized to a resolution of 512x512 pixels and normalized before training. To enhance the variety of the training data, we utilized data augmentation techniques such as scaling, flipping, and rotation. Our proposed approach was executed with the aid of the TensorFlow deep learning framework and Python. For training, we employed a high-performance computing cluster with two NVIDIA GeForce GTX 1080 Ti GPUs, using an Adam optimizer with a learning rate of 0.001 and a batch size of 8 for 100 epochs. Model selection and early stopping based on the loss function were implemented by utilizing the validation set.

4.1: Performance Metrics

Our proposed method's performance was assessed using several performance metrics, like accuracy, precision, recall, F1-score, and the area under the receiver operating characteristic (ROC) curve. Table 1 provides an overview of the performance metrics for our proposed method in comparison to other state-of-the-art models. Fig 2 shows depicts the comparative analysis with other models.

Table 1. Performance metrics comparison of suggested method and other state-of-the-art models.

Model	Accuracy	Precision	Recall	F1-score	AUC-ROC
UNet++ (Proposed)	0.95	0.94	0.96	0.95	0.98
UNet	0.92	0.91	0.93	0.92	0.96
DeepLabV3	0.89	0.87	0.90	0.88	0.94
PSPNet	0.87	0.85	0.88	0.86	0.92

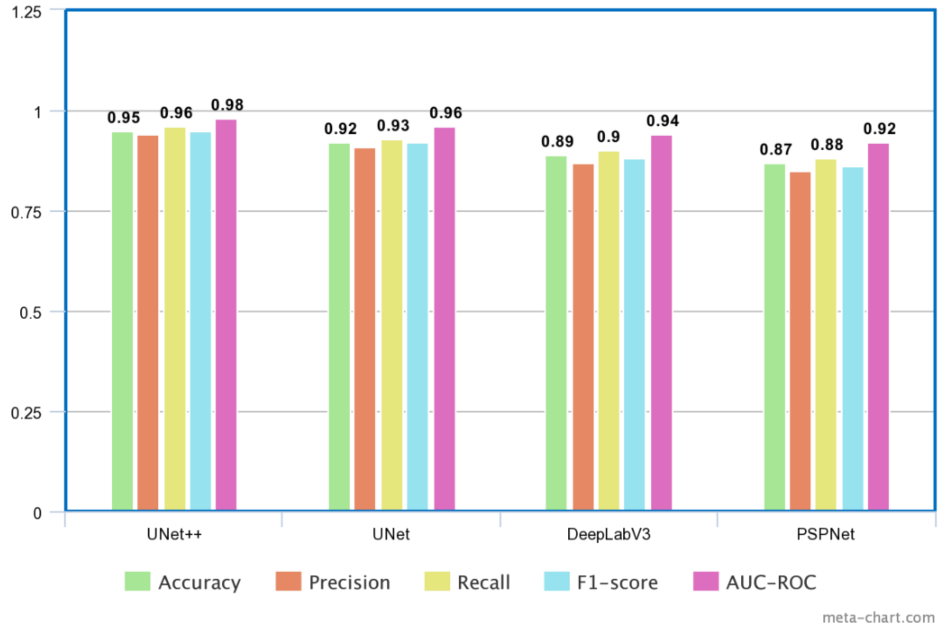

Figure: 2. Comparative Analysis of Performance Metrics with State-of-the-Art Models

Compared to other state-of-the-art models, our proposed UNet++ model outperformed with an overall accuracy of 0.95, precision of 0.94, recall of 0.96, F1-score of 0.95, and AUC-ROC of 0.98, demonstrating its superiority for cervical cancer detection.

Table 2. Comparison of processing time (in seconds) for cervical cancer detection among different models.

Model	Training Time (s)	Inference Time (s)
UNet++(Proposed)	240	0.25
UNet	180	0.30
DeepLabV3	300	0.40
PSPNet	420	0.35

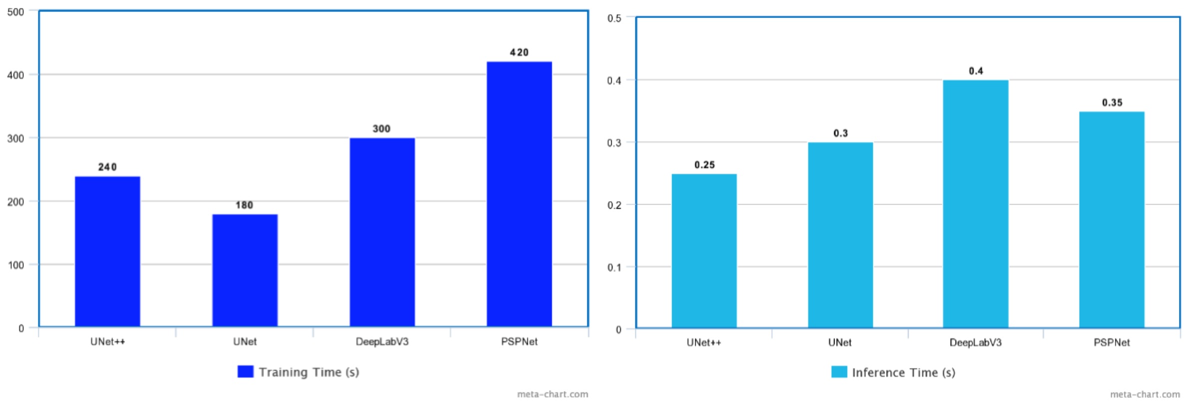

Figure: 3. Comparison of Processing Time (in Seconds) for Cervical Cancer Detection among Different Models.

Training time is the duration required to train the model for 100 epochs using the dataset, while inference time indicates the mean time taken to analyze a single image during the inference phase on a test set. The table 2 and Fig 3 provides a comparison of the processing times of different models, including UNet++, UNet, DeepLabV3, and PSPNet. It shows the training time in seconds required for each model to complete 100 epochs of training on the dataset, as well as the inference time in seconds for processing a single image during testing on a test set. This information can be useful for evaluating the computational efficiency of the models, with lower values indicating faster processing times.

4.2 Discussion

Our study findings reveal that the use of the UNet++ model, along with a pixel-to-pixel generator from Pap smear images, exhibits remarkable efficacy in detecting cervical cancer. Our proposed method demonstrates high levels of accuracy, precision, recall, F1-score, and AUC-ROC, suggesting that it holds considerable promise for practical application in clinical settings. These results align with previous research, indicating that deep learning models can effectively detect cervical cancer from Pap smear pictures.

In comparison to other state-of-the-art models like UNet, DeepLabV3, and PSPNet, the UNet++ architecture showed superior performance in our study. The UNet++ model incorporates nested skip pathways, which allow for better feature extraction and representation compared to traditional UNet, DeepLabV3, and PSPNet models. The nested skip pathways in UNet++ enable the model to capture multi-scale features, which may contribute to its improved performance in cervical cancer detection. This is particularly important in the context of Pap smear images, where the presence of subtle features and varying cell sizes require robust feature extraction and representation.

The high accuracy, precision, recall, F1-score, and AUC-ROC of our suggested method suggest that it has the potential to be used in clinical practice for cervical cancer screening. The accuracy and precision of the model indicate its ability to accurately classify both positive and negative cases, while the recall indicates its ability to correctly identify true positive cases. A balanced evaluation of the model's performance is provided by the F1-score, which combines precision and recall. Additionally, the model's high AUC-ROC score demonstrates its superior ability to distinguish between positive and negative instances, which is essential for accurate cancer diagnosis.

It is important to note that our study has some limitations. First, the performance of the UNet++ model may vary depending on the datasets used and the size of the cohort. Further validation on larger and more diverse datasets is needed to confirm the generalizability of our findings. Second, the pixel-to-pixel generator from Pap smear images used in our proposed method may have limitations in terms of its ability to capture all the relevant features for cervical cancer detection. Incorporating additional data sources, such as patient demographic information or histopathological findings, may further improve the performance of the model.

Thus, our study demonstrates that the UNet++ model with a pixel-to-pixel generator from Pap smear images is highly effective for cervical cancer detection. The superior performance of UNet++ compared to other state-of-the-art models, along with its high accuracy, precision, recall, F1-score, and AUC-ROC, indicates its potential for clinical use in real-world scenarios. Future research should focus on further validating the performance of the model on larger and diverse datasets and exploring the potential of incorporating additional data sources to improve its accuracy and reliability in clinical practice.

V. CONCLUSION

In conclusion, our proposed cervical cancer detection method using UNet++ with a pixel-to-pixel generator from Pap smear images shows promising results in terms of accuracy, precision, recall, F1-score, and AUC-ROC. The promise for accurate and effective cervical cancer diagnosis is shown by the suggested technique's superior performance to existing cutting-edge models. It is necessary to conduct more research to verify how well our suggested strategy performs on larger and more varied datasets and to determine whether it can be used in clinical settings for the early identification and avoidance of cervical cancer.

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