

PAPER

A Multi-Representation Hybrid CNN Feature Extraction Framework for Cervical Pre-Cancer Image Classification

Hilman Fauzi^(✉), Salsabila Aurellia^(ID), Fenty Alia^(ID)

Telkom University,
Bandung, Indonesia

hilmanfauzitsp@telkomuniversity.ac.id

ABSTRACT

Cervical cancer remains a major cause of mortality among women, particularly in low-resource settings, highlighting the need for reliable image-based screening methods. Visual Inspection with Acetic Acid (VIA) is widely used in clinical practice; however, its diagnostic accuracy strongly depends on operator experience and subjective interpretation. This study systematically evaluates a multi-representation feature extraction framework for cervical pre-cancer image classification by comparing three paradigms: conventional handcrafted features, convolutional neural network (CNN)-based deep features from pre-trained networks, and hybrid features combining both representations. Experiments are conducted on three image representations, namely original VIA images, Frangi-filtered images, and morphology-based vessel images, using AlexNet, ResNet-50, and EfficientNet as deep feature extractors. All feature representations are classified using KNN and SVM under a strict evaluation protocol. The results show that hybrid feature extraction performs best on original images, with Hybrid-AlexNet achieving an accuracy, sensitivity, and specificity of 0.84. The findings indicate that representation-aware hybrid feature design provides a robust and interpretable solution for screening-oriented cervical pre-cancer detection.

KEYWORDS

cervical cancer, hybrid convolutional neural network (CNN) feature extraction, cervical image

1 INTRODUCTION

Cervical cancer remains one of the leading causes of mortality among women worldwide, particularly in developing countries where access to screening services is still limited [1]. Visual-based examinations such as Visual Inspection with Acetic Acid (VIA) and colposcopy are commonly used; however, their diagnostic performance is highly dependent on operator expertise and subjective visual interpretation, making them prone to inter-observer variability and delayed detection [2]. In recent years, medical image analysis using computer vision has emerged as a promising approach to support early detection of cervical pre-cancer, including

Fauzi, H., Aurellia, S., Alia, F. (2026). A Multi-Representation Hybrid CNN Feature Extraction Framework for Cervical Pre-Cancer Image Classification. *International Journal of Online and Biomedical Engineering (iJOE)*, 22(5), pp. 185–204. <https://doi.org/10.3991/ijoe.v22i05.59729>

Article submitted 2025-11-26. Revision uploaded 2026-01-21. Final acceptance 2026-01-21.

© 2026 by the authors of this article. Published under CC-BY.

lesion classification from colposcopy images using convolutional neural networks (CNNs) [3], [4], along with other deep learning techniques that have demonstrated substantial improvements in accuracy compared to traditional methods [5].

Nevertheless, several challenges persist. Cervical images exhibit complex characteristics, including heterogeneous epithelial textures, color gradients, vascular patterns, and the presence of artifacts such as specular reflections, mucus, or debris. Consequently, conventional handcrafted feature extraction methods and standalone CNN models often fail to capture the combined textural and vascular patterns that are strongly indicative of precancerous changes, resulting in suboptimal or unstable classification performance in real-world clinical settings [6]–[7]. Recent studies have explored the use of vascular segmentation and Frangi filtering to enhance structural vessel representation as discriminative indicators of cervical lesions [8]. Similarly, hybrid approaches that integrate handcrafted features with deep learning representations have been reported to improve performance in both cervical histopathology and colposcopy image analysis [9].

Despite these advances, research that simultaneously integrates original cervical images, Frangi-filtered images (capturing tubular and vascular structures), and morphological vessel images within a unified hybrid feature extraction framework remains limited. To address these gaps, this study proposes the development of a cervical pre-cancer classification system that leverages three complementary image representations (original images, Frangi-filtered images, and morphological vessel maps) and applies a hybrid CNN-based feature extraction method that combines the strengths of deep learning features with vascular and morphological descriptors. This approach aims not only to improve classification accuracy but also to enhance feature interpretability, enabling more reliable image-based early screening in primary healthcare settings.

Unlike most existing hybrid CNN-based approaches that primarily focus on fusing deep features with handcrafted descriptors extracted from a single image representation, this study introduces a multi-representation hybrid feature extraction framework for cervical pre-cancer classification. Specifically, the proposed method simultaneously exploits three complementary cervical image representations, namely original VIA images, Frangi-filtered images emphasizing tubular and vascular structures, and morphology-based vessel maps.

The novelty of this work lies not only in the integration of CNN features with conventional handcrafted descriptors but also in the systematic investigation of how different image representations influence hybrid feature effectiveness. By conducting a comprehensive comparative analysis across CNN models, conventional hybrid features, Hybrid-ResNet50, Hybrid-AlexNet, and Hybrid-EfficientNet models, this study provides new insights into the robustness, stability, and discriminative capability of hybrid CNN features in complex cervical imaging scenarios. Furthermore, the results demonstrate that aggressive vessel-enhancement preprocessing does not always improve classification performance, highlighting the importance of representation-aware hybrid feature design for reliable cervical pre-cancer screening.

The remainder of this paper is organized as follows. Section 2 reviews related works on cervical pre-cancer detection and hybrid feature extraction approaches. Section 3 describes the materials and methods, including the dataset, image preprocessing, and the proposed hybrid CNN-based feature extraction framework. Section 4 presents the experimental results and provides a comprehensive discussion of the classification performance. Section 5 concludes the paper by summarizing the main findings. Section 6 outlines potential directions for future work. Additional statements regarding acknowledgements, the declaration of AI-assisted content, references, and author information are provided in the subsequent sections.

2 RELATED WORKS

AI-based VIA analysis has progressed rapidly, demonstrating improvements in accuracy and objectivity compared with conventional screening. Early systems such as the ANN-PCA-based AVC achieved promising diagnostic performance [10], while recent transformer-based models such as HMCFormer have set new benchmarks with accuracy exceeding 96% [11]. Segmentation-driven approaches further support lesion localization, with U-Net providing strong Dice scores for VIA lesion mapping [12]. Large-scale deployments, such as VIAM with over 10,000 images, confirm clinical scalability of automated VIA interpretation [13].

Deep learning continues to dominate VIA research, with CNN-based models achieving robust cross-center performance [14], and traditional ML approaches such as KNN still offering competitive baselines [15]. EfficientNet-based implementations have demonstrated near-perfect classification metrics [16]. In Indonesia, real-world studies reveal high diagnostic performance across various hospitals using YOLO-based detection [17], GRNN-based classification [18], and commercial systems such as CerviCare AI [19] and VIA-AI [20]. Optimization studies highlight the importance of hyperparameter tuning, with recent YOLOv11 experiments showing substantial performance gains when optimized rigorously [21]–[22].

In addition to these global advancements, several prior works by Fauzi et al. have contributed significantly to the development of automated cervical cancer detection frameworks. Their earlier efforts explored deep residual networks for classifying cervical cancer images [23], followed by VIA-based pre-cancer detection using acetic acid visual inspection image processing [24]. Subsequent research introduced a smartphone-based VIA application enhanced with artificial intelligence for real-time lesion assessment [25]. More recent work further examined the role of hyperparameter optimization in improving YOLOv11 performance for VIA image analysis [26], underscoring the influence of model tuning on diagnostic accuracy.

Clinical evaluations reinforce the need for continuous improvement, as shown by variable sensitivity values in expert-AI comparisons [27]. Alternative machine learning strategies such as gradient boosting have also shown strong classification capability [28]. Multi-institutional validation across different populations indicates consistent performance for models combining EfficientDet and MobileNet-V2 [29]. Conventional cytopathology studies provide context for comparison, illustrating the substantial accuracy gap that modern AI-based systems have addressed [30]–[33]. Advanced systems such as AVE based on Faster R-CNN further demonstrate high clinical relevance with AUCs above 0.90 [34], and reinforcement learning approaches offer adaptable alternatives to static classifiers [35]. Recent hybrid deep models, including optimized CNN-GRU architectures [36] and the Hologic GDDS system [37], demonstrate the direction toward integrated, clinically deployable AI platforms. Moreover, the latest VIA optimization work using YOLOv11 confirms that model tuning plays a critical role in maximizing performance [38].

3 MATERIALS AND METHODS

This study proposes a hybrid classification system for cervical cancer detection that integrates deep feature extraction using modern deep learning architectures with traditional machine-learning classifiers. The system is designed to classify cervical images obtained from VIA examinations into two diagnostic categories: VIA-positive and VIA-negative. The development of the system follows a machine learning-oriented framework, allowing the hybrid feature extraction method to be

analyzed more comprehensively in terms of its contribution to the final classification performance.

Overall, the cervical pre-cancer detection pipeline is divided into four main stages: data acquisition, pre-processing, feature extraction, and classification. The complete workflow of the proposed hybrid cervical pre-cancer classification system is illustrated in the Figure 1.

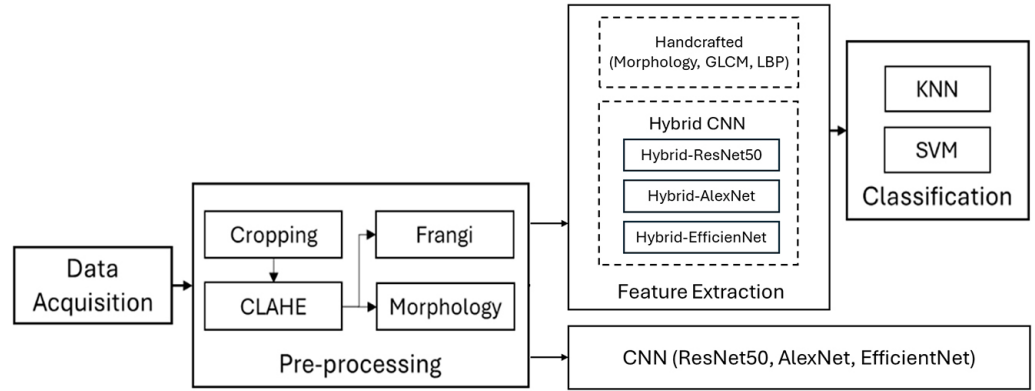


Fig. 1. System design block diagram

3.1 Ethical considerations and dataset characteristics

This study utilized a retrospective cervical image dataset that was collected as part of routine clinical screening procedures. All images were fully anonymized prior to analysis, and no personally identifiable information, such as patient names, identification numbers, or clinical records, was accessible to the authors. The dataset consisted solely of cervical images acquired for research and educational purposes, and individual patient consent was obtained at the time of data collection in accordance with institutional and national ethical guidelines. The study did not involve direct patient interaction or any intervention beyond secondary data analysis.

Regarding demographic characteristics, detailed patient-level information such as ethnicity and clinical history was not available due to anonymization constraints. While this limits demographic stratification analysis, it ensures patient privacy and complies with data protection regulations. The dataset exhibits class imbalance between precancerous and normal cases, which reflects real-world screening conditions and was addressed in this study through appropriate evaluation strategies.

3.2 Data acquisition

This study utilized a dataset obtained from VIA examinations conducted at Hasan Sadikin Hospital, Bandung, under ethical approval number LB.02.01/X.6.5/57/2021. Data were collected directly by trained medical personnel from female respondents aged 28–53 years. Cervical images were acquired using a digital camera with a minimum resolution of 8 megapixels, at an approximate distance of 10–15 cm, focusing on the cervix after acetic acid application. The images were captured under room illumination levels ranging from 200 to 500 lux and subsequently stored in .jpg format for further analysis. The dataset comprises 319 cervical images categorized into two diagnostic classes: 166 VIA-positive images and 153 VIA-negative images.

In this study, cervical images obtained from VIA examinations were further transformed to highlight lesion texture patterns, epithelial tissue structures, and cervical blood vessels using Frangi filtering and morphological processing algorithms. Accordingly, three types of image data were utilized in this study: original images, Frangi-filtered images, and morphology-based vessel images. Examples of the image representations used in this study are shown in Figure 2.

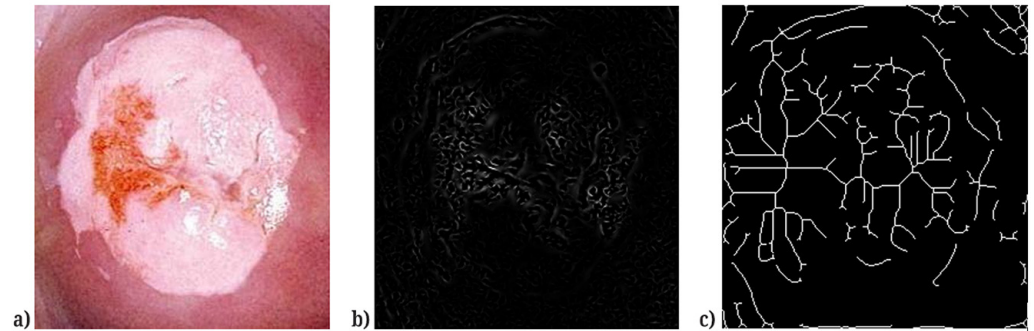


Fig. 2. Cervical images used in the study: (a) Original cervical image, (b) Frangi-filtered cervical image, and (c) Morphology-based cervical vessel image

3.3 Pre-processing

In the pre-processing step, the cervical VIA images were cropped to isolate the cervix region. Subsequently, Contrast Limited Adaptive Histogram Equalization (CLAHE) was applied to enhance the visual quality of the images by improving local contrast without introducing excessive noise. CLAHE operates by dividing the image into small contextual regions and adaptively redistributing pixel intensities within each region, thereby enhancing fine anatomical details such as lesion boundaries, vascular structures, and aceto-white areas to be more clearly identified [39], [40]. In this study, CLAHE was employed to normalize illumination inconsistencies caused by variations in imaging devices or clinical examination conditions, ensuring that morphological, textural, and CNN-based features could be extracted in a more consistent and informative manner.

The CLAHE-enhanced images were subsequently processed using adaptive thresholding and morphological filtering to perform adaptive segmentation of aceto-white lesions. This step emphasizes the white-lesion regions that appear after the application of acetic acid during VIA examination.

3.4 Feature extraction

This study implements three different feature extraction frameworks, namely handcrafted feature extraction, CNN-based feature extraction, and hybrid feature extraction. This design enables a systematic comparison between conventional descriptors, deep learning representations, and their combinations for cervical pre-cancer image classification. All three frameworks are evaluated under the same experimental protocol and applied to three image representations, i.e., original VIA images, Frangi-filtered images, and morphology-based vessel images.

A) Handcrafted Feature Extraction: In the handcrafted feature extraction framework, conventional image descriptors are employed to represent cervical image

characteristics in terms of shape, texture, and color information. Specifically, morphological features including area, perimeter, eccentricity, solidity, and extent are extracted to describe the geometric properties of the detected aceto-white regions. In addition, texture features are computed using Gray-Level Co-occurrence Matrix (GLCM), gradient-based descriptors, and Local Binary Pattern (LBP) to capture local structural variations and tissue texture patterns. Furthermore, color information is represented using the mean values of the L*, a*, and b* channels in the CIE Lab color space, which is more perceptually uniform and robust to illumination changes.

All extracted handcrafted features are concatenated into a single feature vector and subsequently normalized. To reduce feature redundancy and suppress noise, Principal Component Analysis (PCA) is applied to obtain a compact and more discriminative representation before classification.

- B) CNN-Based Feature Extraction:** In the CNN-based feature extraction framework, deep features are extracted directly from pre-trained CNNs without using handcrafted descriptors. In this study, three widely used CNN architectures are employed as backbone networks, namely AlexNet, ResNet-50, and EfficientNet. These models are selected to represent different design paradigms of deep CNNs, ranging from relatively shallow architectures (AlexNet) and deep residual networks (ResNet-50) to parameter-efficient compound-scaled networks (EfficientNet).

For each input image, the activations from the high-level feature layers of the respective CNN are used as deep feature representations. All CNN models are used with pre-trained weights and are not fine-tuned on the dataset so that they function purely as fixed feature extractors. This strategy reduces the risk of overfitting given the limited dataset size and ensures a fair comparison across different CNN backbones. The extracted deep feature vectors are then normalized using z-score normalization and further reduced in dimensionality using PCA before being passed to the classifiers.

EfficientNet is included in this study due to its strong performance–efficiency trade-off and its compound scaling strategy that jointly scales network depth, width, and input resolution. This design allows EfficientNet to produce compact yet highly discriminative feature representations with fewer parameters compared to conventional CNN architectures, making it particularly suitable for small and medium-sized medical imaging datasets.

- C) Hybrid Feature Extraction:** In the hybrid feature extraction framework, handcrafted features and CNN-derived deep features are combined to exploit complementary information from both low-level and high-level representations. The motivation of this approach is to integrate explicit structural and textural descriptors, which are often interpretable in a clinical context, with the high-level semantic representations learned by deep neural networks.

Specifically, the handcrafted feature vector and the CNN-based deep feature vector are concatenated into a unified hybrid feature representation. This combined feature vector is then normalized and reduced in dimensionality using PCA to suppress redundancy and stabilize the feature space. In this study, three hybrid models are constructed based on different CNN backbones, referred to as Hybrid-AlexNet, Hybrid-ResNet50, and Hybrid-EfficientNet, respectively. These hybrid representations are subsequently evaluated using KNN and SVM classifiers to analyze the effectiveness and robustness of hybrid feature integration across different image representations.

3.5 Classification

After feature extraction, all three feature representation frameworks, handcrafted features, CNN-based deep features, and hybrid features, are evaluated using two conventional machine learning classifiers, namely K-nearest neighbors (KNN) and support vector machine (SVM). This unified classification strategy ensures a fair and consistent comparison across different feature extraction approaches and image representations. For the KNN classifier, the performance of each feature representation is evaluated using multiple values of K ($K = 3, 5, \text{ and } 7$) and various distance metrics, including Euclidean, City block, Chebyshev, Minkowski, Cosine, Correlation, Spearman, Hamming, and Jaccard. This comprehensive configuration is designed to analyze the sensitivity of each feature representation to neighborhood size and similarity measures and to identify the most suitable distance metric for cervical pre-cancer image classification. For the SVM classifier, three kernel functions are employed, namely linear, polynomial, and radial basis function (RBF) kernels. These kernels are selected to evaluate the capability of SVM in modeling both linear and non-linear decision boundaries in the handcrafted, CNN-based, and hybrid feature spaces.

To ensure reliable and unbiased performance evaluation, the dataset is divided into independent training and testing sets using a stratified hold-out strategy with an 80:20 ratio, preserving the class distribution between VIA-positive and VIA-negative samples. The data splitting is performed at the image level before any preprocessing, feature extraction, or dimensionality reduction steps. All feature normalization, PCA fitting, and classifier training are conducted exclusively on the training set, and the learned transformations are then applied to the testing set. This strict protocol prevents any form of data leakage and guarantees that the reported results reflect genuine generalization performance rather than optimistic bias.

All experiments are conducted under the same evaluation protocol for all three feature extraction frameworks and all image representations (original, Frangi-filtered, and morphology-based images), ensuring a fair and systematic comparison between handcrafted, CNN-based, and hybrid classification approaches.

4 RESULTS AND DISCUSSION

This study presents experimental results and analytical evaluation of various feature extraction frameworks, including handcrafted approaches utilizing morphological features, GLCM, and LBP; CNN-based methods employing ResNet-50, AlexNet, and EfficientNet architectures; as well as hybrid methods that combine handcrafted feature extraction with CNN-based representations. These three frameworks were subsequently applied to three types of cervical images: original images, morphology-enhanced images, and Frangi-filtered images, which were subsequently evaluated using KNN and SVM classifiers. The system performance was evaluated using accuracy, sensitivity, specificity, and F1-score as assessment metrics.

4.1 Evaluation of handcrafted, CNN, and hybrid CNN performance

In the evaluation of the handcrafted feature extraction framework, the results demonstrate that morphology-based handcrafted features combined with the KNN

classifier yield the most effective performance for cervical pre-cancer image classification, achieving the highest accuracy (0.73) and F1-score (0.69). In contrast, classification using normal images exhibits limited sensitivity, while Frangi-filtered images improve specificity at the expense of reduced true positive detection. Overall, KNN consistently outperforms SVM in terms of sensitivity and diagnostic balance, underscoring its suitability for screening-oriented biomedical imaging applications. A comprehensive summary of the experimental results is presented in Table 1.

Table 1. Evaluation results of handcrafted feature-based cervical image classification

Images	KNN						SVM				
	Dist.	K	Acc	Sens	Spes	F1-Sc	Kernel	Acc	Sens	Spes	F1-Sc
Original	City	5	0.64	0.52	0.76	0.58	Linear	0.58	0.39	0.76	0.47
Morph.	Euc	3	0.73	0.68	0.73	0.69	rbf	0.60	0.26	0.91	0.38
Frangi	Euc	7	0.62	0.42	0.82	0.52	Linear	0.55	0.35	0.73	0.43

The experimental evaluation of the cervical pre-cancer classification system using CNN-based approaches demonstrates that classification performance is strongly influenced by both image representation and network architecture. Among all evaluated configurations, AlexNet applied to original cervical images achieved the best overall performance, attaining the highest accuracy (0.81), specificity (0.86), and F1-score (0.82), which indicates strong discriminative capability without the need for additional image enhancement. Although ResNet-50 exhibited very high sensitivity on original images (0.95), its performance decreased when applied to morphology-enhanced and Frangi-filtered images, suggesting limited robustness to feature transformation. Frangi-filtered images provided more balanced but moderate performance across CNN architectures; however, they did not outperform the original image representation. Overall, these findings indicate that CNN-based models—particularly AlexNet—are most effective when directly applied to original cervical images, while morphology and Frangi preprocessing do not consistently improve CNN-based classification for cervical pre-cancer detection. The detailed results of CNN-based system evaluation are presented in Table 2.

Table 2. Evaluation results of handcrafted feature-based cervical image classification

Images	CNN	Acc	Sens	Spes	F1-Score
Original	ResNet-50	0.75	0.95	0.53	0.81
	AlexNet	0.81	0.77	0.86	0.82
	EfficientNet	0.70	0.89	0.42	0.77
Morph.	ResNet-50	0.68	0.33	0.97	0.47
	AlexNet	0.68	0.60	0.77	0.67
	EfficientNet	0.60	0.53	0.67	0.58
Frangi	ResNet-50	0.72	0.67	0.76	0.72
	AlexNet	0.67	0.75	0.58	0.70
	EfficientNet	0.53	0.70	0.35	0.65

Note: Bold values indicate the best performance among all methods.

The evaluation of the hybrid feature extraction framework combining hand-crafted and CNN features using the KNN classifier demonstrates that classification performance is strongly influenced by both image representation and CNN architecture. Among all configurations, Hybrid-AlexNet applied to original images achieved the best overall performance, yielding the highest accuracy (0.84), sensitivity (0.84), and specificity (0.85), indicating excellent discriminative capability. In contrast, hybrid approaches using EfficientNet features showed unstable performance, particularly reflected by extremely low sensitivity despite high specificity, limiting their effectiveness for screening purposes. Morphology- and Frangi-based hybrid representations provided moderate performance but did not surpass the original image configuration. Overall, these results indicate that hybrid feature extraction leveraging AlexNet features and KNN classification is most effective when applied to original cervical images, supporting its suitability for robust and efficient cervical pre-cancer screening systems. The results of the hybrid CNN-based method using KNN can be seen in Table 3.

Table 3. Performance of the hybrid CNN-based method using the KNN classifier

Images	Features Extraction Hybrid Method	KNN					
		Distance	K	Acc	Sens	Spes	F1-Score
Original	Hybrid-ResNet-50	Cosine	7	0.69	0.77	0.61	0.71
	Hybrid-AlexNet	Correlation	7	0.84	0.84	0.85	0.84
	Hybrid-EfficientNet	Hamming	7	0.52	0.00	1.00	0.00
Morph.	Hybrid-ResNet-50	Cityblock	5	0.67	0.58	0.76	0.63
	Hybrid-AlexNet	Cityblock	3	0.66	0.52	0.79	0.59
	Hybrid-EfficientNet	Correlation	3	0.54	0.04	1.00	0.06
Frangi	Hybrid-ResNet-50	Cityblock	5	0.64	0.74	0.55	0.67
	Hybrid-AlexNet	Cosine	5	0.59	0.52	0.67	0.55
	Hybrid-EfficientNet	Spearman	5	0.59	0.52	0.67	0.55

Note: Bold values indicate the best performance among all methods.

In the evaluation of additional hybrid CNN-based approaches, the experimental results indicate that the performance of the hybrid handcrafted–CNN feature extraction framework combined with the SVM classifier is strongly influenced by both image representation and CNN architecture. Among all evaluated configurations, Hybrid-AlexNet applied to original cervical images achieved the best overall performance, yielding the highest accuracy (0.84), sensitivity (0.84), and specificity (0.85), thereby demonstrating strong and well-balanced discriminative capability. Hybrid-ResNet-50 achieved competitive but slightly lower performance, whereas EfficientNet-based hybrid models consistently exhibited low sensitivity despite high specificity, limiting their suitability for screening-oriented applications. Hybrid representations based on morphological and Frangi-enhanced images resulted in moderate performance but did not outperform the original image configuration. Overall, these findings confirm that hybrid feature extraction combined with SVM is most effective when leveraging AlexNet features from original cervical images, supporting its applicability for robust cervical pre-cancer classification. The detailed results of the hybrid CNN-based method using SVM are presented in Table 4.

Table 4. Performance of the Hybrid CNN-based method using the SVM classifier

Images	Features Extraction Hybrid Method	SVM				
		Kernel	Acc	Sens	Spes	F1-Score
Original	Hybrid-ResNet-50	Linear	0.75	0.77	0.73	0.75
	Hybrid-AlexNet	rbf	0.84	0.84	0.85	0.84
	Hybrid-EfficientNet	Linear	0.59	0.39	0.79	0.48
Morph.	Hybrid-ResNet-50	rbf	0.67	0.65	0.70	0.65
	Hybrid-AlexNet	rbf	0.59	0.29	0.88	0.41
	Hybrid-EfficientNet	rbf	0.52	0.00	1.00	0.00
Frangi	Hybrid-ResNet-50	rbf	0.69	0.74	0.64	0.70
	Hybrid-AlexNet	rbf	0.64	0.55	0.73	0.60
	Hybrid-EfficientNet	Linear	0.58	0.42	0.73	0.49

Note: Bold values indicate the best performance among all methods.

The comparative evaluation demonstrates that image representation and feature extraction strategy play a crucial role in cervical pre-cancer image classification performance. Among all tested configurations, the hybrid model applied to original cervical images achieved the best overall results, yielding the highest accuracy (0.84), sensitivity (0.84), and F1-score (0.84), indicating strong and balanced discriminative capability. For morphology-enhanced images, the handcrafted approach slightly outperformed CNN and hybrid models in terms of accuracy and sensitivity, suggesting that explicit structural descriptors are more effective than deep features for this representation. In the case of Frangi-filtered images, CNN-based models provided superior performance, particularly in sensitivity (0.67), whereas handcrafted and hybrid methods exhibited reduced discriminative power. Overall, these findings highlight that hybrid feature extraction is most effective when applied to original images, while representation-specific feature strategies are required to achieve optimal performance across different enhancement techniques. The comparison of the best model in image types can be seen in Table 5.

Table 5. Comparison of the best model performance

Images	System Model	Acc	Sens	Spes	F1-Score
Original	Handcrafted	0.64	0.52	0.76	0.58
	CNN	0.81	0.77	0.86	0.82
	Hybrid	0.84	0.84	0.85	0.84
Morph.	Handcrafted	0.70	0.68	0.73	0.69
	CNN	0.68	0.60	0.77	0.67
	Hybrid	0.67	0.58	0.76	0.63
Frangi	Handcrafted	0.63	0.42	0.82	0.52
	CNN	0.72	0.67	0.76	0.72
	Hybrid	0.64	0.74	0.55	0.67

Note: Bold values indicate the best performance among all methods.

In Figure 3, the classification accuracy across original, morphology-enhanced, and Frangi-filtered cervical images using handcrafted, CNN-based, and hybrid models

is compared. The hybrid approach achieves the highest accuracy on original images, while handcrafted features perform best on morphology-enhanced images and CNN-based features yield superior accuracy on Frangi-filtered images. These results indicate that classification performance is strongly dependent on the compatibility between image representation and feature extraction strategy.

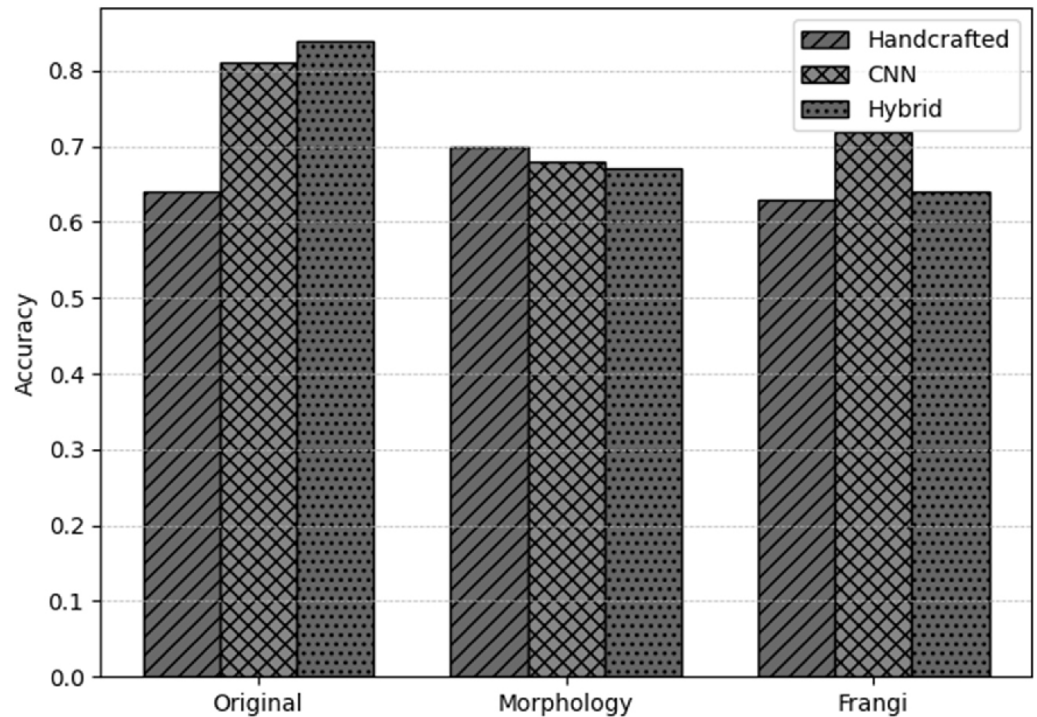


Fig. 3. Accuracy comparison across image types and models

4.2 Statistical significance analysis

To statistically validate the observed performance differences between the evaluated models, a non-parametric Wilcoxon signed-rank test was conducted on the per-fold performance metrics. This test was selected due to its suitability for paired comparisons without assuming normal data distribution.

The Wilcoxon signed-rank test results indicate that the statistical significance of performance differences is highly dependent on image representation and feature extraction strategy. Significant differences ($p < 0.05$) are predominantly observed when comparing handcrafted methods with hybrid models, particularly Hybrid-AlexNet, across original, morphology-enhanced, and Frangi-filtered images, for both KNN and SVM classifiers. In contrast, comparisons between standalone CNN architectures and their hybrid counterparts generally do not exhibit statistically significant differences, suggesting comparable performance when deep features are integrated with handcrafted descriptors. Notably, Frangi-filtered images show more consistent significant improvements with hybrid approaches, highlighting the effectiveness of feature integration for vessel-enhanced representations. Overall, these findings confirm that hybrid feature extraction provides statistically validated performance gains over handcrafted methods while offering marginal but stable improvements over CNN-only models, supporting its robustness for cervical pre-cancer classification. The details of significant test results across the Feature Extraction framework model can be seen in Table 6.

Table 6. The Wilcoxon signed-rank test results across the Feature Extraction framework model

Images	Model Comparison	p-Value (KNN)	p-Value (SVM)
Normal	AlexNet vs. Hybrid-AlexNet	0.224	0.079
	ResNet-50 vs. Hybrid-ResNet-50	0.787	0.043
	EfficientNet vs. Hybrid-EfficientNet	1.000	0.685
	Handcrafted vs. Hybrid-AlexNet	0.043	0.043
	Handcrafted vs. Hybrid-ResNet	0.079	0.067
	Handcrafted vs. Hybrid-EfficientNet	0.079	0.138
Morph.	AlexNet vs. Hybrid-AlexNet	0.500	0.892
	ResNet-50 vs. Hybrid-ResNet-50	0.068	0.079
	EfficientNet vs. Hybrid-EfficientNet	0.500	0.060
	Handcrafted vs. Hybrid-AlexNet	0.079	0.043
	Handcrafted vs. Hybrid-ResNet	1.000	0.589
	Handcrafted vs. Hybrid-EfficientNet	0.892	0.224
Frangi	AlexNet vs. Hybrid-AlexNet	0.043	0.043
	ResNet-50 vs. Hybrid-ResNet-50	0.043	0.043
	EfficientNet vs. Hybrid-EfficientNet	0.418	1.000
	Handcrafted vs. Hybrid-AlexNet	0.043	0.043
	Handcrafted vs. Hybrid-ResNet	0.285	0.043
	Handcrafted vs. Hybrid-EfficientNet	0.067	0.043

Note: Bold values indicate statistically significant results ($p < 0.05$).

Based on the types of images, the statistical significance analysis reveals that image representation has a significant impact on classification performance. Based on the Wilcoxon signed-rank test, statistically significant differences ($p < 0.05$) are observed between normal and morphology-enhanced images as well as between normal and Frangi-filtered images for both KNN and SVM classifiers, indicating that image enhancement substantially improves discriminative performance. In contrast, the comparison between morphology-enhanced and Frangi-filtered images does not show a statistically significant difference, suggesting comparable effectiveness between these two enhancement strategies. Overall, these results confirm that feature-enhanced cervical images significantly outperform normal images, while morphology and Frangi representations provide statistically equivalent performance for cervical pre-cancer classification. The details of significance test results can be seen in Table 7.

Table 7. The Wilcoxon signed-rank test results are based on the type of images

Image Comparison	KNN		SVM	
	p-Value	Desc.	p-Value	Desc.
Normal vs. Morphology	0.043	Significant	0.043	Significant
Normal vs. Frangi	0.043	Significant	0.043	Significant
Morphology vs. Frangi	0.079	Insignificant	0.589	Insignificant

4.3 The best-performing feature extraction framework model

Based on all evaluations results, the Hybrid-AlexNet method demonstrated the highest performance across both classifiers, particularly on the original dataset, indicating that deeper feature representations extracted by AlexNet effectively capture the discriminative visual patterns relevant for cervical precancer detection. The best-performing configuration with SVM was further evaluated using additional metrics such as Precision, Cohen's Kappa, Matthews Correlation Coefficient (MCC), Balanced Accuracy, and underfitting/overfitting analysis.

The best performance of the Hybrid-AlexNet model demonstrates the effectiveness of leveraging pre-trained deep-learning architectures in combination with classical classifiers for cervical precancer screening. Despite the variations introduced during preprocessing, the integration of CNN-derived deep features with statistical classification methods enhances overall diagnostic precision. The confusion matrix illustrating the system's performance using Hybrid-AlexNet on the original dataset is presented in Figure 4.

True Class	Positive	28	5
	Negative	5	26
		Negative	Positive
		Predicted Class	

Fig. 4. Confusion matrix

The SVM classifier achieved an overall accuracy of 0.84, with 26 true positive and 28 true negative cases correctly identified. Both sensitivity (0.84) and specificity (0.85) indicate a balanced recognition between positive and negative samples, minimizing bias in classification. The low false-negative rate (0.09) demonstrates that the system is effective for early detection of cervical cancer cases. These results confirm that the hybrid feature approach integrating CNN, morphological, and texture descriptors significantly enhances the robustness and reliability of the diagnostic model.

The findings of this study indicate that hybrid deep feature models in AlexNet substantially improve classification performance compared to handcrafted and CNN-only models. SVM demonstrated greater robustness to feature variability, while

the choice of image preprocessing methods exerted a considerable influence on the model's ability to capture relevant visual patterns.

Based on the radar chart, evaluation demonstrates a well-balanced performance across all eight metrics, with values ranging from 0.8 to 0.9. The model achieved high accuracy (0.87), sensitivity (0.82), and specificity (0.90), indicating a robust balance between true-positive and true-negative classification. The F1-score (0.85) and MCC (0.78) further confirm the model's consistency and reliability, while the Kappa coefficient (0.76) reflects substantial agreement with ground truth labels. These results suggest that the hybrid-AlexNet KNN model exhibits strong generalization capability and clinical reliability for cervical pre-cancer image classification. The radar chart can be seen in Figure 5.

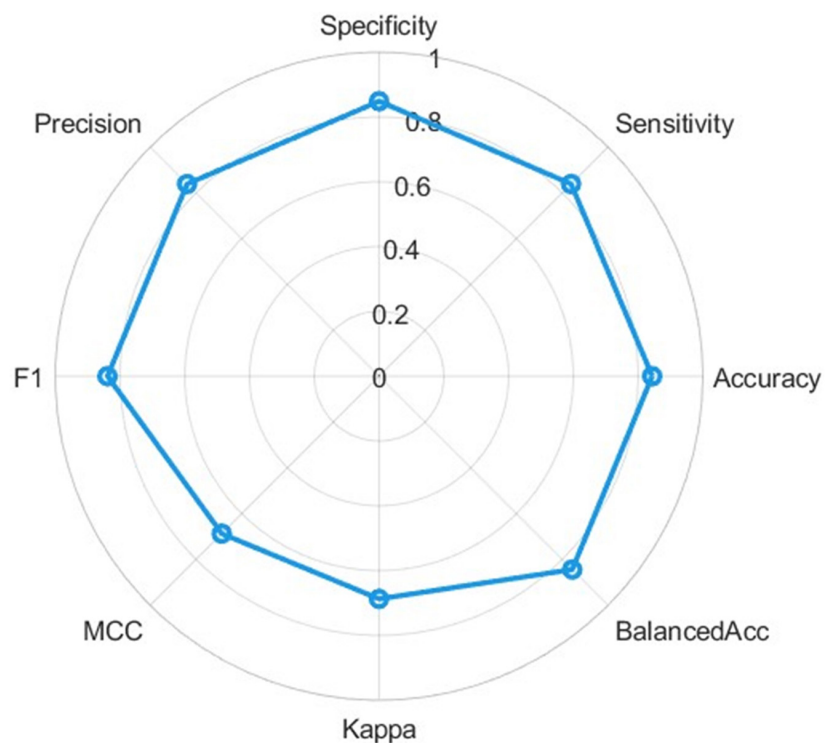


Fig. 5. Radar chart

The overfitting–underfitting analysis shows that the performance of the KNN model improves as the size of the training dataset increases, with a progressively smaller accuracy gap between the training and testing sets. This trend indicates strong generalization capability and a minimal risk of overfitting, suggesting that the model is sufficiently stable for application to new clinical data. However, it should be noted that the dataset used in this study does not provide detailed demographic information, which may limit the assessment of potential population-specific bias. In addition, the data were collected from a limited number of clinical sources, which could affect generalizability. Future studies will focus on multi-center datasets with richer demographic annotations to further validate the proposed framework.

The Graphic of the underfitting/overfitting test based on the test result can be seen in Figure 6. Figure 6 shows the effect of the number of training samples on the training and testing accuracies to analyze underfitting and overfitting behavior. When the training data are limited, a noticeable gap between training and testing accuracies is observed, indicating insufficient generalization. As more training

samples are added, both accuracies increase and gradually converge, suggesting improved model stability and generalization capability. The small gap between the two curves at larger sample sizes indicates that severe overfitting does not occur, although minor fluctuations remain due to the limited dataset size.

It is also important to emphasize that a strict evaluation protocol was applied in this study to avoid any form of data leakage. The dataset was split into training and testing sets before any preprocessing, feature extraction, or dimensionality reduction steps. All transformations, including PCA fitting and feature normalization, were learned exclusively from the training set and then applied to the testing set. This ensures that no information from the test set was used during model training or feature learning. Furthermore, the CNN models were used only as fixed feature extractors without fine-tuning. This strict separation protocol guarantees that the reported performance reflects genuine generalization ability rather than optimistic bias caused by information leakage.

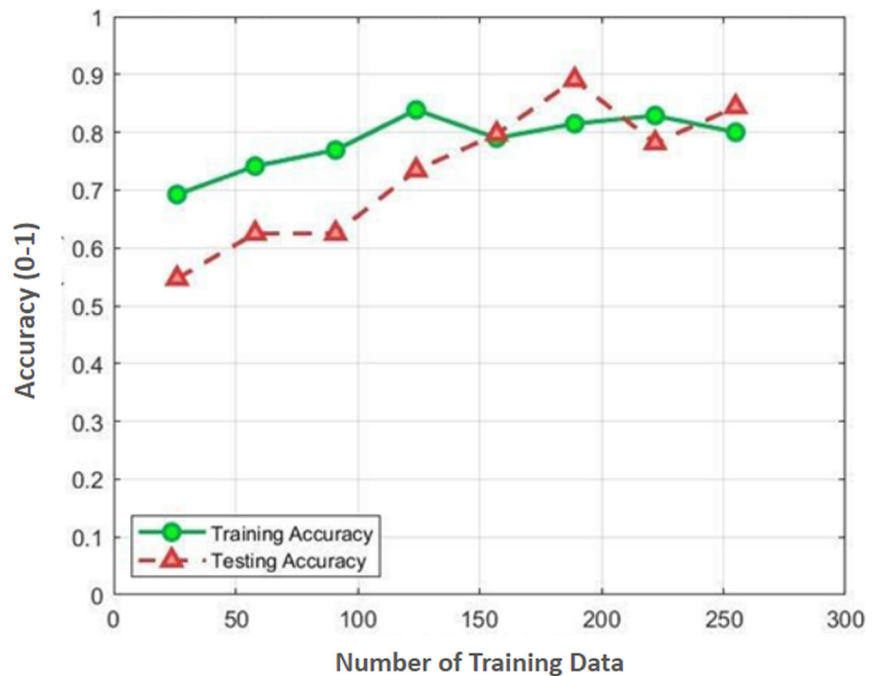


Fig. 6. Underfitting/overfitting test results graph

Despite the promising classification performance achieved by the proposed multi-representation hybrid CNN framework, several limitations should be acknowledged. First, although the dataset size (319 VIA cervical images) is larger than many early-stage clinical imaging studies, it remains relatively limited compared with large-scale multi-center benchmarks. This constraint mainly reflects the practical and ethical challenges of collecting labeled VIA data in real clinical settings, including restricted access, regulated acquisition protocols, and anonymization requirements. Therefore, this study is positioned as a methodological and feasibility investigation focusing on comparative analysis of feature extraction strategies across multiple image representations, rather than as a definitive large-scale clinical validation.

To mitigate the risk of overfitting associated with limited data, the proposed pipeline was designed to reduce model complexity: the CNN backbones (AlexNet, ResNet-50, and EfficientNet) were used only as fixed feature extractors without

fine-tuning, while dimensionality reduction (PCA) and classical classifiers (KNN and SVM) were employed to avoid excessive parameter learning. In addition, the stratified hold-out evaluation protocol and the observed generalization behavior (underfitting–overfitting analysis) suggest no severe overfitting under the current experimental setting.

Nevertheless, generalizability may still be affected by the limited diversity of acquisition sources and the absence of detailed demographic information, which restricts the assessment of population-specific bias. Future work will focus on validating the proposed framework using larger multi-center datasets with richer demographic annotations to further confirm robustness and clinical applicability.

5 CONCLUSION

This study proposes a multi-representation hybrid CNN feature extraction framework for cervical pre-cancer image classification, integrating handcrafted morphological and texture descriptors with deep features extracted from multiple CNN architectures. Comprehensive experiments across original, morphology-enhanced, and Frangi-filtered images demonstrate that classification performance is strongly influenced by the compatibility between image representation and feature extraction strategy. Among all evaluated configurations, Hybrid-AlexNet applied to original cervical images consistently achieved the best overall performance, yielding balanced accuracy, sensitivity, and specificity, and was further supported by statistical significance analysis using the Wilcoxon signed-rank test. The results confirm that hybrid feature integration provides statistically validated improvements over handcrafted methods and stable gains over CNN-only models while remaining computationally efficient. The main contribution of this work lies in demonstrating that combining multi-representation image analysis with hybrid deep and handcrafted features significantly enhances robustness, generalization, and diagnostic reliability, making the proposed framework a promising and interpretable solution for screening-oriented cervical pre-cancer detection in biomedical imaging applications.

6 FUTURE WORK

The implementation of the system into a web-based decision support system screening platform and integration with a digital colposcope device is currently being developed by researchers. Also, in future work, this study will be extended using a larger and more diverse dataset collected from multiple clinical sources to improve model generalization, robustness, and clinical reliability.

7 DECLARATION OF GENERATIVE AI AND AI-ASSISTED TECHNOLOGIES IN THE WRITING PROCESS

During the preparation of this work, the authors used ChatGPT (OpenAI) for writing refinement and language enhancement to improve the clarity of the manuscript. After using this tool, the authors reviewed and edited the content as needed and take full responsibility for the final version of the publication.

8 ACKNOWLEDGEMENT

This study was supported by the Research and Community Service Directorate of Telkom University and the Ministry of Education and Culture of the Republic of Indonesia with a registered research code 125/C3/DT.05.00/PL/2025; 7925/LL4/PG/2025; 072/LIT07/PPM-LIT/2025.

9 REFERENCES

- [1] M. Mashora, M. Taylor, and S. Dlamini, "Health education programs and cervical cancer control in resource limited settings: A narrative review," *Discover Public Health*, vol. 22, no. 1, 2025. <https://doi.org/10.1186/s12982-025-01130-3>
- [2] J. K. Bae *et al.*, "Quantitative screening of cervical cancers for low-resource settings: Pilot study of smartphone-based endoscopic visual inspection after acetic acid using machine learning techniques," *JMIR Mhealth and Uhealth*, vol. 8, no. 3, p. e16467, 2020. <https://doi.org/10.2196/16467>
- [3] J. Kim, C. M. Park, S. Y. Kim, and A. Cho, "Convolutional neural network-based classification of cervical intraepithelial neoplasias using colposcopic image segmentation for acetowhite epithelium," *Scientific Reports*, vol. 12, no. 1, p. 17228, 2022. <https://doi.org/10.1038/s41598-022-21692-5>
- [4] R. Viñals, M. Jonnalagedda, P. Petignat, J.-P. Thiran, and P. Vassilakos, "Artificial intelligence-based cervical cancer screening on images taken during visual inspection with acetic acid: A systematic review," *Diagnostics*, vol. 13, no. 5, p. 836, 2023. <https://doi.org/10.3390/diagnostics13050836>
- [5] C. Nakisige *et al.*, "Artificial intelligence and visual inspection in cervical cancer screening," *International Journal of Gynecological Cancer*, vol. 33, no. 10, pp. 1515–1521, 2023. <https://doi.org/10.1136/ijgc-2023-004397>
- [6] M. A. Raza *et al.*, "Advanced feature extraction for cervical cancer Image classification: Integrating neural feature extraction and AutoINT models," *Sensors*, vol. 25, no. 9, p. 2826, 2025. <https://doi.org/10.3390/s25092826>
- [7] Y. X. Li, F. Chen, J. J. Shi, Y. L. Huang, and M. Wang, "Convolutional neural networks for classifying cervical cancer types using histological images," *Journal of Digital Imaging*, vol. 36, no. 2, pp. 441–449, 2022. <https://doi.org/10.1007/s10278-022-00722-8>
- [8] A. Sharma and R. Parvathi, "Enhancing cervical cancer classification: Through a hybrid deep learning approach integrating DenseNet201 and InceptionV3," *IEEE Access*, vol. 13, pp. 9868–9878, 2025. <https://doi.org/10.1109/ACCESS.2025.3527677>
- [9] Ł. Jeleń, I. Stankiewicz-Antosz, M. Chosia, and M. Jeleń, "Optimizing cervical cancer diagnosis with feature selection and deep learning," *Applied Sciences*, vol. 15, no. 3, p. 1458, 2025. <https://doi.org/10.3390/app15031458>
- [10] I. Baleyrier *et al.*, "Study protocol for a two-site clinical trial to validate a smartphone-based artificial intelligence classifier identifying cervical precancer and cancer in HPV-positive women in Cameroon," *PLoS ONE*, vol. 16, no. 12, p. e0260776, 2021. <https://doi.org/10.1371/journal.pone.0260776>
- [11] B. Feng, C. Xu, Z. Li, and C. Zhang, "HMCFormer (hierarchical multi-scale convolutional transformer): A hybrid CNN+Transformer network for intelligent VIA screening," *Peer J. Computer Science*, vol. 11, p. e3088, 2025. <https://doi.org/10.7717/peerj-cs.3088>
- [12] H. Sinohar *et al.*, "Lesion detection in VIA images using U-Net segmentation," *J. Med. Syst.*, vol. 47, no. 3, pp. 1–10, 2023.

- [13] G. W. Yim *et al.*, “A pilot study of upcycled smartphone-based colposcopy for visual inspection of cervix performed by community healthcare workers in rural Vietnam,” *International Journal of Gynecology & Obstetrics*, vol. 168, no. 2, pp. 518–524, 2024. <https://doi.org/10.1002/ijgo.15867>
- [14] J. Sami *et al.*, “Smartphone-based visual inspection with acetic acid: An innovative tool to improve cervical cancer screening in low-resource setting,” *Healthcare*, vol. 10, no. 2, p. 391, 2022. <https://doi.org/10.3390/healthcare10020391>
- [15] L. A. Kusumawardani, R. Rulaningtyas, and W. Winarno, “Classification of cervical cancer cells using the K-nearest neighbor (KNN) method based on geometric feature extraction,” *AIP Conference Proceedings*, vol. 2858, p. 030003, 2023. <https://doi.org/10.1063/5.0167165>
- [16] K. P. Battula and B. S. Chandana, “Deep learning based cervical cancer classification and segmentation from pap smears images using an EfficientNet,” *International Journal of Advanced Computer Science and Applications*, vol. 13, no. 9, 2022. <https://doi.org/10.14569/IJACSA.2022.01309104>
- [17] S. Nurmaini *et al.*, “Cervical lesion detection using deep learning-based object detection in VIA images,” *Heliyon*, vol. 9, no. 11, p. e21043, 2023. <https://doi.org/10.1016/j.heliyon.2023.e21043>
- [18] P. Sahoo, S. Saha, S. Mondal, M. Seera, S. K. Sharma, and M. Kumar, “Enhancing computer-aided cervical cancer detection using a novel fuzzy rank-based fusion,” *IEEE Access*, vol. 11, pp. 145281–145294, 2023. <https://doi.org/10.1109/ACCESS.2023.3346764>
- [19] S. Ouh *et al.*, “Clinical validation of a deep learning-based automated visual inspection with acetic acid (VIA) system for cervical cancer screening,” *Scientific Reports*, vol. 14, pp. 1–11, 2024. <https://doi.org/10.1038/s41598-024-51880-4>
- [20] S. K. Mathivanan, D. Francis, S. Srinivasan, V. Khatavkar, P. Karthikeyan, and M. A. Shah, “Enhancing cervical cancer detection and robust classification through a fusion of deep learning models,” *Scientific Reports*, vol. 14, no. 1, p. 10812, 2024. <https://doi.org/10.1038/s41598-024-61063-w>
- [21] M. Z. H. Ontor, M. M. Ali, S. S. Hossain, M. Nayer, K. Ahmed, and F. M. Bui, “YOLO_CC: Deep learning based approach for early stage detection of cervical cancer from cervix images using YOLOv5s model,” in *2022 Second International Conference on Advances in Electrical, Computing, Communication and Sustainable Technologies (ICAECT)*, 2022, pp. 1–5. <https://doi.org/10.1109/ICAECT54875.2022.9807871>
- [22] E. H. I. Eliwa and T. A. El-Hafeez, “A robust deep learning pipeline for multi-class cervical cancer cell identification,” *Egyptian Informatics Journal*, vol. 32, p. 100787, 2025. <https://doi.org/10.1016/j.eij.2025.100787>
- [23] H. Fauzi, R. B. Ansori, T. Siadari, A. B. Harsono, and Q. N. Rahmah, “Classification of cervical cancer images using deep residual network architecture,” *International Journal of Artificial Intelligence Research*, vol. 7, no. 1, p. 56, 2023. <https://doi.org/10.29099/ijair.v7i1.955>
- [24] H. Fauzi, G. Surya, R. Magdalena, A. B. Harsono, and T. N. Azhar, “Sistem Deteksi Pra-Kanker Serviks dengan Pengolahan Citra Hasil Inspeksi Visual Asam Asetat,” *Techno Com*, vol. 20, no. 2, pp. 290–299, 2021. <https://doi.org/10.33633/tc.v20i2.4285>
- [25] A. B. Harsono *et al.*, “Cervical pre-cancerous lesion detection: Development of smartphone-based VIA application using artificial intelligence,” *BMC Research Notes*, vol. 15, no. 1, p. 356, 2022. <https://doi.org/10.1186/s13104-022-06250-6>
- [26] N. P. Adilla, H. Fauzi, and F. Alia, “Analysis of the hyperparameters effect on the performance of evaluation metrics in YOLOv11 for cervical cancer detection in acetic acid visual inspection images,” in *2025 IEEE International Symposium on Future Telecommunication Technologies (SOFTT)*, 2025, pp. 434–440. <https://doi.org/10.1109/SOFTT67007.2025.11213407>

- [27] A. B. Harsono, H. Susiarno, D. Suardi, K. I. Mantilidewi, V. D. Wibowo, and Y. M. Hidayat, "Results comparison of cervical cancer early detection using Cerviray® with VIA test," *BMC Research Notes*, vol. 18, no. 1, p. 30, 2025. <https://doi.org/10.1186/s13104-025-07086-6>
- [28] K. T. Desai *et al.*, "The development of 'automated visual evaluation' for cervical cancer screening: The promise and challenges in adapting deep-learning for clinical testing," *International Journal of Cancer*, vol. 150, no. 5, pp. 741–752, 2021. <https://doi.org/10.1002/ijc.33879>
- [29] K. Maven *et al.*, "Multi-institutional validation of EfficientDet-Lite3 and MobileNet-V2 for VIA classification," *IEEE J. Biomed. Health Inform.*, vol. 29, no. 2, pp. 234–245, 2025.
- [30] A. A. Hashmi *et al.*, "Comparison of liquid-based cytology and conventional papanicolaou smear for cervical cancer screening: An experience from Pakistan," *Cureus*, vol. 12, no. 12, p. e12293, 2020. <https://doi.org/10.7759/cureus.12293>
- [31] B. Andersen, S. H. Njor, A. M. S. Jensen, T. Johansen, U. Jeppesen, and H. Svanholm, "HrHPV testing vs liquid-based cytology in cervical cancer screening among women aged 50 and older: A prospective study," *International Journal of Gynecological Cancer*, vol. 30, no. 11, pp. 1678–1683, 2020. <https://doi.org/10.1136/ijgc-2020-001457>
- [32] S. Consul, A. Agrawal, H. Sharma, A. Bansal, M. Gutch, and N. Jain, "Comparative study of effectiveness of Pap smear versus visual inspection with acetic acid and visual inspection with Lugol's iodine for mass screening of premalignant and malignant lesion of cervix," *Indian Journal of Medical and Paediatric Oncology*, vol. 33, no. 3, pp. 161–165, 2012. <https://doi.org/10.4103/0971-5851.103143>
- [33] Z. Vahedpoor, M. Behrashi, T. Khamsehchian, M. Abedzadeh-Kalahroudi, A. Moravveji, and M. Mohmadi-Kartalayi, "Comparison of the diagnostic value of the visual inspection with acetic acid (VIA) and Pap smear in cervical cancer screening," *Taiwanese Journal of Obstetrics and Gynecology*, vol. 58, no. 3, pp. 345–348, 2019. <https://doi.org/10.1016/j.tjog.2019.03.010>
- [34] K. T. Desai *et al.*, "The development of 'automated visual evaluation' for cervical cancer screening: The promise and challenges in adapting deep-learning for clinical testing," *International Journal of Cancer*, vol. 150, no. 5, pp. 741–752, 2021. <https://doi.org/10.1002/ijc.33879>
- [35] N. Wu, D. Jia, C. Zhang, and Z. Li, "Cervical cell extraction network based on optimized yolo," *Mathematical Biosciences & Engineering*, vol. 20, no. 2, pp. 2364–2381, 2022. <https://doi.org/10.3934/mbe.2023111>
- [36] D. Rohini and M. Kavitha, "ABC-optimized CNN-GRU algorithm for improved cervical cancer detection and classification using multimodal data," *International Journal of Advanced Computer Science and Applications*, vol. 15, no. 9, 2024. <https://doi.org/10.14569/IJACSA.2024.0150971>
- [37] Hologic Inc., "Clinical validation of Genius Digital Diagnostic System (GDDS) in CIN2+ screening," UPMC Clinical Report, 2024.
- [38] T. Takahashi *et al.*, "A systematic review of the application of artificial intelligence in colposcopy: Diagnostic accuracy for cervical intraepithelial neoplasia and cervical cancer," *Clinical Medicine Insights Oncology*, vol. 19, 2025. <https://doi.org/10.1177/11795549251374908>
- [39] I. M. Mohammed and N. A. M. Isa, "Contrast limited adaptive local histogram equalization method for poor contrast image enhancement," *IEEE Access*, vol. 13, pp. 62600–62632, 2025. <https://doi.org/10.1109/ACCESS.2025.3558506>
- [40] B. Bhan and S. Patel, "Efficient medical image enhancement using CLAHE enhancement and wavelet fusion," *International Journal of Computer Applications*, vol. 167, no. 5, pp. 1–5, 2017. <https://doi.org/10.5120/ijca2017913277>

10 AUTHORS

Hilman Fauzi is a researcher and Lecturer in the Biomedical Engineering Program at Telkom University, Indonesia. His research interests include biosignal processing, biomedical image processing, and artificial intelligence applied in health-care instrumentation and diagnostics (E-mail: hilmanfauzitsp@telkomuniversity.ac.id).

Salsabila Aurellia is a researcher and Lecturer in the Biomedical Engineering Program at Telkom University, Indonesia with research interests in the fields of artificial intelligence for biomedical image processing and the development of computational methods to support clinical decision-making (E-mail: salsabilaaurelliasa@telkomuniversity.ac.id).

Fenty Alia is a researcher and Lecturer in the Biomedical Engineering Study Program, School of Electrical Engineering, Telkom University, Indonesia. Her research interests include medical science, biomedical instrumentation, medical ultrasound, and biomedical measurement (E-mail: aliafenty@telkomuniversity.ac.id).