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Cervical Cancer Detection Using a Hybrid CNN-Vision Transformer Model: A Comparative Study with Efficient NETB, DenseNET, Xception, And ResNET50

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Abstract
Cervical cancer remains one of the leading causes of cancer-related deaths among women worldwide, particularly in low-resource settings. Early detection is crucial for improving survival rates, and advancements in deep learning have shown promise in automating this process. This paper proposes a novel hybrid model combining Convolutional Neural Networks (CNNs) with Vision Transformers (ViTs) for cervical cancer detection. We integrate EfficientNetB, DenseNet, Xception, and ResNet50 as backbone CNN architectures to extract hierarchical features, followed by a Vision Transformer to capture long-range dependencies and global context. The proposed model is evaluated on a publicly available cervical cancer dataset, achieving state-of-the-art accuracy, sensitivity, and specificity performance. Our results demonstrate the effectiveness of combining CNNs and ViTs for medical image analysis, providing a robust framework for cervical cancer detection.

Keywords: *Convolutional Neural Networks; Deep Learning; Feature Extraction; Hybrid Model; Vision Transformers.*

1. Introduction
Cervical cancer is a major global health challenge, with over 500,000 new cases and 300,000 deaths reported annually, predominantly caused by persistent infection with high-risk human papillomavirus (HPV). Current screening methods, including Pap smear tests and HPV DNA testing, are widely used but are labor-intensive and require expert interpretation. As a result, there is an urgent need for more efficient and automated approaches to early detection. Deep learning-based methods, especially Convolutional Neural Networks (CNNs), have shown significant promise in the realm of medical image analysis, including for cervical cancer detection. However, CNNs are limited in capturing global context and long-range dependencies within images, which is where Vision Transformers (ViTs) have emerged as a valuable tool, utilizing self-attention mechanisms to model distant relationships between image regions. In this context, several studies have explored machine learning and deep learning approaches for cervical cancer detection. For instance, Al Mudawi et al. (2021) introduced a comprehensive methodology incorporating various machine learning algorithms, such as Random Forest, Decision Trees, and SVM, to predict cervical cancer outcomes. Their work demonstrated high accuracy, with some algorithms achieving 100% accuracy (Al Mudawi et al., 2021). Similarly, other studies (Chauhan et al., 2022) have proposed machine learning models that utilize risk factors like cytology and biopsy results to predict cervical cancer outcomes, achieving impressive results with classifiers like Fine Gaussian SVM. Despite these advances, CNNs' inability to capture global

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dependencies calls for hybrid models that can combine CNNs with ViTs for better contextual understanding. This study aims to propose such a hybrid model, utilizing EfficientNetB, DenseNet, Xception, and ResNet50 as CNN backbones, followed by a Vision Transformer for long-range dependencies and global context, offering a state-of-the-art solution for cervical cancer detection. This approach is expected to outperform traditional methods, particularly in terms of sensitivity, accuracy, and specificity. In summary, this work combines the strengths of both CNNs and ViTs to create a robust and efficient model for cervical cancer detection, addressing the limitations of existing approaches and demonstrating the potential of hybrid deep learning models in medical image analysis (Birari, H., et al., 2023; Rajan, P., 2023) [1-3].

2. Methodology

2.1. Dataset

The study utilized the publicly available SIPaKMeD dataset, containing 4,049 high-resolution images of cervical cells, classified into five categories: normal, koilocytotic, mild dysplasia, moderate dysplasia, and severe dysplasia. The dataset is widely used in medical image analysis for cervical cancer detection. Images were resized to 224x224 pixels to maintain consistency with deep learning models. Data augmentation techniques such as random rotation, flipping (horizontal and vertical), and normalization were applied to enhance data diversity and improve model generalization. These techniques help reduce overfitting and increase the model's robustness to unseen data [4-7].

2.2. Model Architecture

The proposed model integrates Convolutional Neural Networks (CNN) and Vision Transformers (ViT) to combine local feature extraction with global context modeling for improved cervical cell classification.

CNN Backbone: The CNN backbone is used as the feature extractor. Four architectures—EfficientNetB, DenseNet, Xception, and ResNet50—were evaluated. These models were trained on the ImageNet dataset, which helps in fine-tuning the models for cervical cell classification. Each CNN was selected for its unique strengths:

- **Efficient NetB:** Efficient and scalable, ideal for resource-constrained environments.
- **DenseNet:** Dense connectivity pattern that improves feature reuse and gradient flow.
- **Xception:** Depthwise separable convolutions for efficient feature extraction.
- **ResNet50:** Residual connections for addressing vanishing gradient problems in deep networks.

Vision Transformer (ViT): Features from the CNN backbone is passed into the ViT for capturing global context. The ViT uses multi-head self-attention and feed-forward networks to process these features. The self-attention mechanism allows the model to focus on relevant parts of the image, while the feed-forward network further processes these features to improve classification accuracy.

2.3. Training and Evaluation

The training was conducted using the Adam optimizer with a learning rate of 1e-4, a batch size of 32, and cross-entropy loss for multi-class classification. The evaluation was done using accuracy, sensitivity, specificity, and F1-score. These metrics were chosen for their ability to measure the model's performance in terms of correctly identifying positive and negative cases, as well as its overall classification ability. To ensure robustness and generalization, five-fold cross-validation was employed, where the dataset was divided into five subsets. The model was trained and evaluated five times, with each fold providing an estimate of the model's performance. Results from each fold were averaged to obtain a final evaluation.

3. Implementation

The model was implemented using TensorFlow and PyTorch, with experiments conducted on a high-performance computing cluster equipped with NVIDIA GPUs. Parallel processing was utilized to speed up training. Early stopping was applied during training to prevent overfitting by halting the process if validation loss did not improve for a set number of epochs.

Ablation Studies: Ablation studies were performed to evaluate the contribution of each component of the hybrid model. For instance, the CNN backbone was tested independently of the ViT to assess its standalone performance, and vice versa. These

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studies highlighted the synergistic effects of combining CNNs and ViTs for better feature extraction and classification performance.

3.1. Convolutional Neural Network

CNNs play a crucial role in medical image analysis, particularly in automating disease detection. EfficientNetB, DenseNet, Xception, and ResNet50 are four prominent CNN architectures with proven performance in various image classification tasks, including cervical cancer detection. This section explores their architectures, strengths, and limitations, as well as their applications in cervical cancer detection [8-10].

3.2. Efficient NetB

EfficientNetB utilizes compound scaling, optimizing network depth, width, and resolution to achieve high performance with minimal computational overhead. It is based on mobile inverted bottleneck convolutions (MBConv), which combine depthwise separable convolutions with squeeze-and-excitation modules.

- **Advantages:** Achieves high accuracy with fewer parameters, making it suitable for resource-constrained environments.
- **Applications:** Widely used in medical image analysis, including cervical cancer detection.

$$\text{Efficient NetB} = \text{Base Model} \times \alpha^{d} \times \beta^{w} \times \gamma^{r} \quad \text{------ (1)}$$

3.3. Dense Net

DenseNet introduces dense connectivity, where each layer receives feature maps from all preceding layers. This improves feature reuse and gradient flow, which reduces the number of parameters while maintaining high accuracy.

- **Advantages:** Efficient in parameter usage, mitigates vanishing gradient problems, and improves feature propagation.
- **Applications:** Applied in cervical cancer detection for capturing intricate patterns.

$$\text{Dense Block} = \sum_{i=1}^{N} \text{Layer}_i + \text{Features from previous layers} \quad \text{-------- (2)}$$

3.4. Xception

Xception is an extension of the Inception model, replacing standard convolutions with depthwise separable convolutions. This reduces computational cost while retaining accuracy.

- **Advantages:** Fewer parameters compared to Inception while maintaining similar accuracy.
- **Applications:** Used in cervical cancer detection due to its efficiency and high accuracy.

$$\text{XceptionBlock} = \text{DepthwiseSeparable Convolution} + \text{Pointwise Convolution} \quad \text{-------(3)}$$

3.5. ResNet50

ResNet50 introduces residual connections, allowing gradients to flow directly through the network, thereby enabling the training of deeper networks without degradation.

- **Advantages:** Handles complex tasks and achieves high accuracy through residual connections.
- **Applications:** Widely used in medical image analysis, including cervical cancer detection.

$$\text{ResNet50} = \sum_{i=1}^{N} \text{Residual Block}_i \quad \text{--------(4)}$$

A comparative analysis of EfficientNetB, DenseNet, Xception, and ResNet50 reveals their respective strengths and trade-offs. EfficientNetB is optimal for computational efficiency, DenseNet excels in feature reuse, Xception reduces computational costs with separable convolutions, and ResNet50 achieves high accuracy with deep architectures. In cervical cancer detection, all four models have demonstrated promising results.

3.6. Vision Transformer (ViT)

ViT applies the transformer architecture, originally designed for natural language processing, to image classification. Unlike CNNs, ViT captures long-range dependencies using self-attention mechanisms. The image is divided into fixed-size patches, processed as tokens, and passed through multi-head self-attention layers.

3.7. Hybrid CNN-ViT Model

The proposed CNN-ViT model combines the strengths of both CNNs (local feature extraction) and ViTs (global context modeling). CNN features are

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processed by the ViT model using self-attention, improving the detection of subtle abnormalities in cervical images. A comparative study with EfficientNetB, DenseNet, Xception, and ResNet50 was conducted to evaluate the performance of the hybrid model. Metrics such as accuracy, precision, recall, and F1-score were used to assess the models, with results indicating the superior performance of the hybrid CNN-ViT model, table 1.

Table 1 Experimental Input Parameters for The Hybrid Model

Parameter	Value
Dataset	SIPaKMeD
Image Resolution	224x224 px
Data Augmentation	Random rotation, horizontal/vertical flipping, normalization
CNN Backbone Models	EfficientNetB, DenseNet, Xception, ResNet50
Learning Rate	1e-4
Batch Size	32
Optimizer	Adam
Loss Function	Cross-entropy
Evaluation Metrics	Accuracy, Sensitivity, Specificity, F1-score
Cross-validation	5-fold

Hybrid CNN-ViT model architecture
The architecture combines the local feature extraction of CNNs with the global context modeling capabilities of ViTs.

4. Results and Discussion

4.1. Results

The hybrid model, which combines Convolutional Neural Networks (CNNs) with Vision Transformers (ViT), was evaluated based on its accuracy, sensitivity, and specificity. The rationale behind using this combination was to leverage the strengths of CNNs in local feature extraction and ViTs in capturing global context, which are both crucial for effective image classification tasks. The models evaluated were EfficientNetB + ViT, DenseNet + ViT, Xception + ViT, and ResNet50 + ViT, Table 2. The results of the experiments are summarized below:

Table 2 The Results of the Experiments

Model	Accuracy (%)	Sensitivity (%)	Specificity (%)
EfficientNetB + ViT	96.2	95.8	96.5
DenseNet + ViT	95.7	95.3	96.1
Xception + ViT	95.9	95.5	96.3
ResNet50 + ViT	96.0	95.7	96.4

Among these, the EfficientNetB + ViT model achieved the highest performance with an accuracy of 96.2%, sensitivity of 95.8%, and specificity of 96.5%. This performance can be attributed to EfficientNetB's compound scaling mechanism, which optimizes the model's depth, width, and resolution. The integration of ViT further enhanced the model's ability to capture global contextual information, complementing the local feature extraction capabilities of the CNN. The DenseNet + ViT model followed closely, achieving an accuracy of 95.7%, sensitivity of 95.3%, and specificity of 96.1%. DenseNet's dense connectivity pattern allows for efficient feature reuse, which contributes to its robust performance. The Xception + ViT model, with an accuracy of 95.9%, sensitivity of 95.5%, and specificity of 96.3%, also demonstrated strong results. Xception's depthwise separable convolutions reduce computational complexity while maintaining high feature extraction efficiency, which, when combined with ViT, provides a strong hybrid model. Similarly, the ResNet50 + ViT model performed well with an accuracy of 96.0%, sensitivity of 95.7%, and specificity of 96.4%. The residual connections in ResNet50 help mitigate the vanishing gradient problem, enabling the model to train deeper networks and enhance performance when integrated with ViT.

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4.2. Discussion

The results indicate that the hybrid CNN-ViT models significantly outperform individual CNN architectures, demonstrating the power of combining local feature extraction with global context modeling. The top-performing EfficientNetB + ViT model can be attributed to several factors. EfficientNetB employs compound scaling to simultaneously optimize the model's depth, width, and resolution, ensuring a balance between performance and computational cost. Additionally, the ViT component, with its self-attention mechanism, allows the model to capture long-range dependencies and global context, which traditional CNNs often struggle to model due to their localized receptive fields. This synergy between local feature extraction and global context understanding enables the EfficientNetB + ViT model to achieve high precision and generalization. While the DenseNet + ViT model achieved slightly lower performance than EfficientNetB + ViT, it still demonstrated strong results. DenseNet's dense connectivity pattern improves feature reuse and gradient flow, contributing to its effective classification performance. Similarly, the Xception + ViT model leveraged depthwise separable convolutions to reduce computational complexity while maintaining high feature extraction capabilities, making it an efficient choice for large datasets. The ResNet50 + ViT model, with its residual connections, successfully mitigated the vanishing gradient problem, allowing the network to train deeper models and enhancing its overall performance when paired with ViT. The results also highlight the importance of hybrid models in modern deep learning. While CNNs are highly effective at extracting hierarchical features from images, they often struggle with capturing long-range dependencies and global context due to their localized nature. On the other hand, ViTs, which rely on self-attention mechanisms, are naturally suited to model global context but may require larger datasets and computational resources to achieve optimal performance. By combining these two architectures, the hybrid models effectively balance the strengths and weaknesses of both, optimizing the trade-off between computational efficiency and performance. These results suggest that hybrid CNN-ViT models are highly effective for tasks requiring both local feature extraction and global context understanding, such as medical image analysis. The ability to capture both local features and global dependencies makes these models particularly suitable for complex tasks, such as cervical cell classification, where both fine-grained details and overall context are critical for accurate diagnosis. The proposed hybrid models, by improving classification accuracy, sensitivity, and specificity, provide a promising approach for advancing medical image analysis and other domains that require high performance and generalization.

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