RESEARCH PAPER

Deep Learning Based Framework for Cervical Cancer Diagnosis through Feature Extraction and Classification

Sushma V*[1], Dr. J V Gorabal[2]
Orcid Id : 0000-0002-1994-9545 [1] 0000-0001-5842-6387 [2]

[1]Research Scholar, Department of Computer Science and Engineering, ATME College of Engineering, Mysuru, and Assistant Professor, Department of Computer Science and Engineering, Seshadripuram Institute of Technology, Mysuru, Email : sushmavaradaraju21@gmail.com
[2] Professor, Department of Computer Science and Engineering, ATME College of Engineering, Mysuru, India Email : jvgorabal@gmail.com

Abstract

Cervical-cancer continues to be a significant contributor to cancer-related fatalities among women worldwide, highlighting the importance of early identification in lowering mortality rates. Traditional methods of cervical cancer detection, such as Pap smear tests, are highly dependent on the expertise of the examiner, often leading to misclassifications. The problem this work addresses is the need for an accurate, automated system that can classify Pap smear images into multiple classes for cervical cancer detection. Hence, this work proposed a deep learning-based approach using Convolutional-Neural-Network Visual-Geometry-Group-16 (CNN-VGG16) for cervical-cancer classification in Pap-Smear images. The methodology comprised preprocessing input images through resizing and normalization, followed by feature extraction using convolutional-layers. The features extracted were then classified utilizing pre-trained VGG16 model. The CNN-VGG16 approach achieved better results, with 99.59% accuracy for 2-class classification, 99.35% for 5-class classification on SIPaKMeD and 99.59% accuracy for 2-class classification and 99.23% for 7-class classification on Herlev datasets. The novelty of work lies in integration of feature extraction with CNN-VGG16, which enhances the model's performance. The findings also show that CNN-VGG16 method outperforms existing approaches.

Keywords

Cervical Cancer, CNN-VGG16, Feature Extraction, Classification, SIPaKMeD

How to cite this article: Sushma V, Gorabal JV. Deep Learning Based Framework for Cervical Cancer Diagnosis through Feature Extraction and Classification. Int J Drug Deliv Technol. 2026;16(28s):696-702. DOI: 10.25258/ijddt.16.28s.87

1. Introduction

Cervical-cancer is a type of carcinoma which develops from cells located in cervix. The primary cause is a constant infection from high-risk kinds of Human-Papilloma-Virus (HPV). Cervical-cancer stands among the majority of prevalent cancers impacting women worldwide, representing a significant risk, especially in areas where healthcare facilities and testing initiatives are scarce [1]. Every year, cervical-cancer affects hundreds of thousands of women. According to World-Health-Organization (WHO), over 600,000 new cases were reported in 2020, with more than 340,000 deaths attributed to the disease [2]. The challenge is particularly severe in countries with low to middle incomes, where there is a lack of arranged testing and preventive medical care [3]. The adoption of routine cervical-cancer testing, primarily by means of Pap-smears tests and HPV testing, has led to a substantial decrease among the prevalence and mortality of cervical-cancer [4]. At the precancerous and initial phases, cervical-cancer is extremely curable, therefore screening aids in early discovery, which is crucial. Countries that have implemented robust screening programs have observed a significant reduction in cervical-cancer cases in recent years [5].

Despite the success of these programs, human error in screening and diagnosis remains a significant concern. Pathologists can misinterpret slides due to fatigue, variability in sample quality, and subjective judgment. These limitations have paved the way for integrating Artificial Intelligence (AI) into diagnostic workflows, particularly through Deep Learning (DL) techniques. DL, especially Convolutional-Neural-Networks (CNNs) [6, 7], has shown immense promise in medical image analysis. CNN architectures like Dense Network (DenseNet) [8] and Visual Geometry Group 16 (VGG16) [9] have demonstrated high performance in classifying cervical-cancer using Pap-smear images. These methods autonomously acquire hierarchical features from unprocessed image data, allowing for a significant level of accuracy in distinguishing among normal and abnormal cells. However, many existing CNN-based approaches do not explicitly focus on feature extraction before classification, which can limit their effectiveness. To enhance detection and classification accuracy, it is crucial to prioritize robust feature extraction from input images before classification. Hence, in this work, we propose a method that employs multiple convolutional layers for extracting discriminative features from cervical Pap-smear images. These features are then passed on to the VGG16 model, which performs the final classification. By separating and emphasizing the feature extraction phase, the model is better equipped to recognize complex patterns in cytological images, thereby improving the accuracy and reliability of the diagnosis. The contribution of the work are as follows

- This work introduces a pre-processing and feature extraction mechanism using multiple convolutional layers before the classification stage.

- This work demonstrates how the integration of feature extraction with VGG16 leads to higher classification performance compared to standard approaches.
- This approach aims to reduce human dependency in Pap smear screening by providing an automated, AI-driven solution.
- This work has been validated using standard publicly available cervical cancer datasets, where findings show that the approach has achieved higher accuracy.

The manuscript is organized in the following way. Section II discusses the current approaches presented for classification of cervical cancer. Section III presents the proposed methodology, which discusses the preprocessing step, feature extraction, classification. In Section IV, the results of the CNN-VGG16, which have also been compared with existing approaches discussed in literature survey. Finally, Section V discusses conclusion and future work.

2. Literature Survey

This section discusses the current existing approaches presented for classification of cervical cancer. In [10], proposed method for cervical-cancer classification using pap-smear images, called CerviFormer which utilized a cross-attention transformer model. CerviFormer model utilized cross-attention approach for consolidating input data to compact-latent-transformer segment that enabled for handling large-scale inputs for classification. Evaluations were conducted on two datasets, i.e., Herlev dataset and SIPaKMeD dataset. For Herlev dataset binary classification, CerviFormer achieved 94.57% accuracy and for SIPaKMeD three class classification, CerviFormer achieved 93.70% accuracy. In [11], presented Residual Deep-Convolutional Generative-Adversarial-Network (Res-DCGAN) approach for augmenting cervical cancer data to create more samples and handle class imbalance and utilized Residual Network50V2 (ResNet50V2) self-attention approach for classification. In the Res-DCGAN, residual block was added for enhancing data-flow and creating high-quality images. Moreover, a self-attention approach was included in ResNet50V2 for extracting features from the images for classification. In their work, they also classified using Xception and Dense Network121 (DenseNet121). Evaluations were conducted on SIPaKMeD and Pomeranian datasets. For the Pomeranian dataset, the Xception achieved 94% accuracy, Xception+DCGAN and DenseNet121+DCGAN achieved 95% accuracy for binary classification. For SIPaKMeD, for binary classification, ResNet50v2 achieved 91.6% accuracy and DenseNet121+DCGAN achieved 92% accuracy. For binary classification, DenseNet121 achieved 87% accuracy and DenseNet121+DCGAN achieved 89% accuracy.

In [12], presented Cross Entropy-based Multi-Deep Transfer-Learning (CEMDTL) approach, which consisted of preprocessing, feature extraction, feature fusion, feature reduction and feature classification. In preprocessing, images were initially resized to 64×64 size, to map it to Deep-Neural-Network (DNN). Different DL approaches which included ResNet50, RegNet, Xception, EfficientNet, DenseNet and MobileNet were used for extracting features. For reducing feature size, Principal-Component-Analysis (PCA) was used. In classification a loss-function called smoothing cross-entropy was presented. Evaluations were conducted on SIPaKMeD, where CEMDTL achieved 97% accuracy. In [13], for classifying cervical cancer, used 16 pre-trained DL approaches and evaluated the approaches using two datasets, SIPaKMeD and Herlev datasets. Findings show that for Herlev dataset, for seven-class and two-class classification, ResNet50 achieved 83.78% and 95.10% accuracy. For SIPaKMeD dataset, for five-class and two-class classification, VGG16 achieved 98.66% and 99.95% accuracy, whereas for three-class classification, DenseNet121 achieved 97.65% accuracy.

In [14], presented A2SDNet121, which was built by enhancing DenseNet121 for achieving higher accuracy during cervical cancer classification. In A2SDNet121, first a Squeeze-Excitation (SE) is included in DenseNet121 for capturing features and neglecting similar features. Further, in Stem layer, the size of pooling window and convolutional kernel were adjusted for capturing more details and features. Finally, four Atrous-Dense Block (ASB) were incorporated in DenseNet121 for capturing local and global salient features. Evaluations were conducted on SIPaKMeD and Herlev datasets. The A2SDNet121 achieved 99.14% and 99.75% accuracy for seven and two-class Herlev dataset classification. Also, for SIPaKMeD, A2SDNet121 achieved 99.22%, 99.75% and 99.55% accuracy for five, three and two class classification.

In [15], presented an approach called AutoEffFusionNet, which incorporated ResNet-based auto-encoders having attention mechanisms using transfer learning and EffienctNet-B4 for feature fusion. In AutoEffFusionNet, Genetic-Algorithm (GA) was used for optimizing feature selection, keeping important features and removing not required features. Further, the features selected using GA were passed on to Support-Vector Machine (SVM) for classification. Evaluations were conducted on Mendeley and SIPaKMeD dataset, where achieved 100% and 99.26% accuracy for four and five class respectively. In [16], implemented Convolutional Neural Network, Xception and DenseNet201, where hyperparameters were optimized for feature extraction and cancer classification. Also, in their work, presented an ensemble approach for achieving higher accuracy during classification. Evaluations were conducted on SIPaKMeD dataset, where achieved 97% accuracy for five classes. In [17], presented an approach called CasualCervixNet for cervical cancer classification. The CasualCervixNet used CNN and a casual-insight module, which uncovered hidden casual factors during classification, thereby providing higher accuracy during classification. Evaluations were conducted considering three datasets, Herlev, SIPaKMeD and a self-collected data, where achieved 97.31%, 99.14% and 99.09% respectively.

The current literature showcases a variety of DL approaches for cervical cancer classification. However, most of these methods focus heavily on classification accuracy without adequately emphasizing the importance of feature extraction as a distinct and dedicated step before classification. For instance, CerviFormer [10] utilized a cross-attention transformer for classification but lacked an explicit multi-layered feature extraction strategy. Similarly, the Res-DCGAN approach [11] enhanced data through augmentation and used DenseNet121 and ResNet50V2 with attention, yet it did not isolate a robust feature extraction stage before classification, especially for complex multi-class tasks. While CEMDTL [12] integrated feature extraction and reduction, it did so using multiple external DL models without a unified CNN-based feature extraction mechanism. Approaches by [13], [14], and others like AutoEffFusionNet [15] and in [16] primarily focused on classification using advanced CNNs and ensemble techniques, but they too did not treat feature extraction as a standalone, integral process prior to classification—particularly across varied classification levels (2-class, 5-class, and 7-class). This omission has limited their model's ability to capture discriminative patterns, especially in subtle cytological differences. To overcome this limitation, the proposed approach introduces a dedicated multi-layer convolutional feature extraction pipeline prior to classification. By isolating and enhancing this step, more representative and meaningful features are captured from cervical Pap smear images. These refined features are then fed into the VGG16 classifier, significantly improving the model's performance across different classification tasks.

The accuracy of classification algorithm can be improved using a confusion matrix, where the 4 different parameter used assures the result with enhanced accuracy [18]. VGG19 and Alexnet were trained to achieve the accuracy of 97.78% for the aerial images. These images were further divided as overlapping subset of images, which results in higher categorizing rate among subset of images [19-22]. The Cervic Cancer Classification using Contour Based on Area of Nucleolus and Cytoplasm in Cells (CBANC) predicts the cancer cells through classification accuracy of 90% [23].

This proposed approach addresses the existing gap in literature and contributes to higher accuracy and robustness in cervical cancer detection and classification. The complete methodology of the proposed approach is discussed in the next section.

3. Methodology

This section outlines the methodology of the proposed work, where the overall flow and architecture of the system is discussed. Following this, the preprocessing technique used to resize the cervical cancer images and standardize them for uniform input to the model is detailed. Finally, the feature extraction process and the classification approach using the CNN and VGG16 model are discussed

3.1. Architecture

The complete architecture is presented in Figure 1, where the CNN-VGG16 first considers the cervical input image, which goes through preprocessing, where cervical cancer input image is resized from different size to 64×64 and then goes for feature extraction and then further is passed on to the VGG16 for classification. The complete process of preprocessing is presented in Section 3.2, feature extraction in Section 3.3 and classification in Section 3.

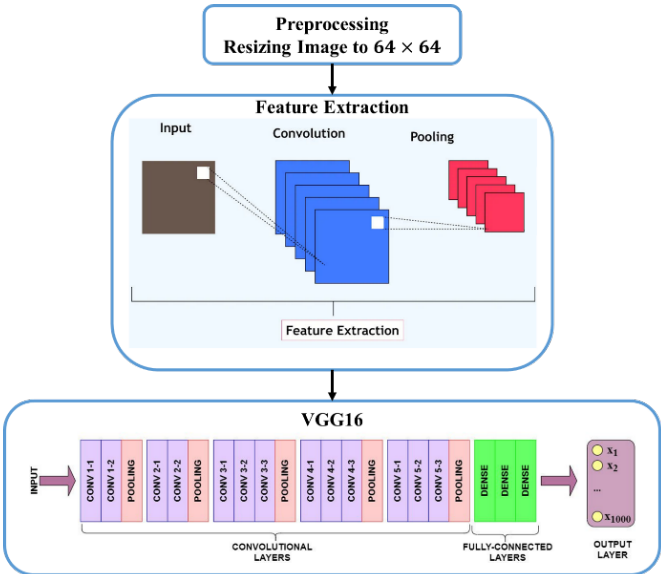

Figure 1. CNN-VGG16

3.2. Preprocessing

Consider the cervical cancer pap-smear input image from the datasets. The input image can be denoted as Eq. (1).

$$I \in \mathbb{R}^{H\times W\times C} \tag{1}$$

In Eq. (1), I denotes input image, H represents image-height, W represents image-width and C represents total color channels. For ensuring uniform input to the model, this work resized image to 64×64 pixels, which is mathematically represented as Eq. (2)

$$I_{resized} = R(I), I_{resize} \in \mathbb{R}^{64\times 64\times 3} \tag{2}$$

In Eq. (2), R(·) denotes resizing function. In this work, during preprocessing normalization was also applied to scale pixel values using Eq. (3).

$$I_{norm} = \frac{I_{resized}}{255} \tag{3}$$

From the Eq. (3), the final preprocessed image is attained, which can be represented as $I_{norm} \in [0,1]^{64\times 64\times 3}$. The final preprocessed image is then passed on the feature extraction layer.

3.3. Feature Extraction

Before inputting to classification network (VGG16), this work extracts features using convolutional operations. In this work, multiple convolutional layers are utilized for extracting features from the preprocessed image. The convolutional layer is mathematically represented as Eq. (4).

$$F^{(l)} = \sigma\left(W^{(l)} * F^{(l-1)} + b^{(l)}\right) \tag{4}$$

In Eq. (4), $F^{(l)}$ denotes output feature-map at l^{th} layer, $F^{(l-1)}$ denotes input feature for l^{th} layer (initially I_{norm}), $W^{(l)}$ denotes learnable filter (kernel) weights, $b^{(l)}$ denotes bias term, $*$ denotes convolutional operation and $\sigma(\cdot)$ denotes activation-function, i.e., Rectified-Linear-Unit (ReLU). The multiple convolutional layers consisting of pooling and convolutional layers are stacked together, which form the final feature extractor layer $\mathcal{F}_{extractor}$. This is mathematically denoted as Eq. (5).

$$F_{features} = \mathcal{F}_{extractor}(I_{norm}) \tag{5}$$

After extracting the specific features from the preprocessed cervical cancer par-smear input image, the features are passed on to the VGG16, where classification is done.

3.4. Classification

In this work, VGG16 DL model is used, which is a 16-layer Deep CNN pretrained model on ImageNet. The VGG16 architecture comprises thirteen convolutional-layers, three fully connected (dense) layers and softmax output function for classification. Consider $\mathcal{V}$ which denotes the pretrained VGG16 model. Then the features extracted passed on to the VGG16 model is mathematically denotes as Eq. (6).

$$F_{vgg} = \mathcal{V}(I_{norm}) \tag{6}$$

The output $F_{vgg} \in \mathbb{R}^n$, where n denotes number of features after flattening the last convolutional layer. Further, let the output from VGG16 be passed to a fully connected network $\mathcal{C}$ for classification. This step predicts class probabilities using softmax function, defined in Eq. (7).

$$\hat{y} = softmax(W_c \cdot F_{vgg} + b_c) \tag{7}$$

In Eq. (7), $\hat{y} \in \mathbb{R}^k$ which denotes predicted class probabilities, k denotes number of classes (2 class, 5 class and 7 class), W_c denotes weights and b_c denotes bias. The $softmax$ is evaluated using Eq. (8).

$$\hat{y}_i = \frac{e^{z_i}}{\sum_{j=1}^{k} e^{z_j}} \tag{8}$$

In Eq. (8), $z_i = \left(W_c \cdot F_{vgg}\right)_i + b_{c_i}$. Further, in the VGG16 model, this work has used a categorical cross-entropy loss during training. The cross-entropy function was evaluated using Eq. (9).

$$\mathcal{L}(y, \hat{y}) = \sum_{i=1}^{k} y_i \log(\hat{y}_i) \tag{9}$$

In Eq. (9), y denotes true label vector and $\hat{y}$ denotes predicted probability vector. Further, in this work, the weights were updated using gradient descent using Adam optimizer using Eq. (10).

$$\theta \leftarrow \theta - \eta \left(\frac{\partial \mathcal{L}}{\partial \theta}\right) \tag{10}$$

In Eq. (10), θ denotes set of all learnable parameter in VGG16 and η denotes learning-rate. The final classification results achieved using feature extractor and VGG16 model is discussed in detail in the next section.

4. Results And Discussion

This section presents results of CNN-VGG16 approach. This section first discusses the performance metrics used for evaluation. Next, datasets utilized for the study, i.e., SIPaKMeD and Herlev datasets are discussed. Further, the performance outcomes of the CNN-VGG16 model are analyzed. Finally, a comparative study is conducted comparing proposed CNN-VGG16 model against existing approaches.

4.1. Performance Metrics

The performance metrics used in this study for the classification are discussed from Eq. (11) to Eq. (14).

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

$$Precision = \frac{TP}{TP + FP} \tag{12}$$

$$Recall = \frac{TP}{TP + FN} \tag{13}$$

$$F - Score = 2 \times \frac{Precision \times Recall}{Precision + Recall} \tag{14}$$

In Eq. (11) to Eq. (14), TN denotes true-negative, TP denotes true-positive, FN denotes false-negative and FP denotes false-positive.

4.2. SIPaKMeD dataset

The SIPaKMeD dataset is a publicly open-accessible collection of cytology images [23] designed to aid in evaluation of methods for cervical-cancer screening. It consists of 966 cluster-cell images of individual cells, categorized into five distinct classes: dyskeratotic, metaplastic, koilocytotic, parabasal and superficial-intermediate. These images were extracted from Pap smear slides and annotated by expert pathologists, making the dataset a valuable resource for training and testing ML models in cell classification and medical image analysis. The dataset is open-accessible and can be downloaded from [24].

4.3. Herlev dataset

The Herlev dataset, also known as the Herlev Pap Smear dataset, is a widely used medical image dataset for research in cervical cancer detection and classification. It contains 917 single-cell images derived from Pap smear tests, each manually labeled by expert cytotechnologists. The images are classified into seven categories representing different stages of cervical cell abnormalities, ranging from normal cells to those showing signs of carcinoma. With high-quality annotations and a balanced representation of cell types, the Herlev dataset serves as a benchmark for developing and evaluating automated diagnostic systems and ML models in cytopathology. The dataset is open-accessible and can be downloaded from [25].

4.4. Performance Evaluation

The results of CNN-VGG16 model demonstrate good performance on SIPaKMeD dataset for both binary (2-class) and multi-class (5-class) classification tasks, as presented in Figure 2. For 2-class classification, the model achieved 99.59% accuracy. These results show model's strong ability to correctly distinguish normal and abnormal cervical cell images with minimal FPs or

FNs. In the more complex 5-class classification scenario, which involves differentiating between five distinct cell types, the CNN-VGG16 model maintained high performance, achieving 99.35% accuracy. These results show effectiveness of the feature extraction and classification strategy employed in CNN-VGG16 architecture.

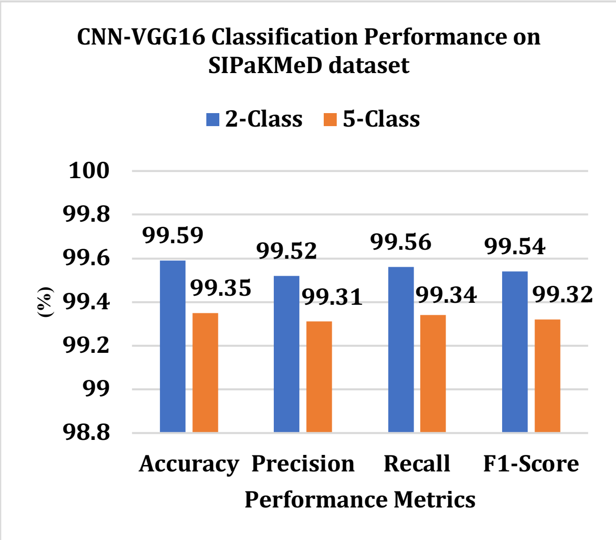

Figure 2. Classification Performance on SIPaKMeD dataset using CNN-VGG16

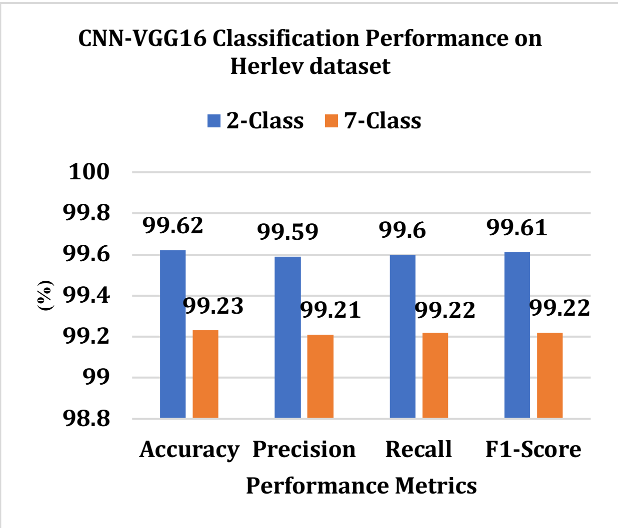

Figure 3. Classification Performance on Herlev dataset using CNN-VGG16

The evaluation of CNN-VGG16 model on Herlev dataset further confirms its effectiveness in cervical cancer classification tasks, as presented in Figure 3. For the binary (2-class) classification, the model achieved 99.62% accuracy. The performance achieved reflect the model's high reliability in accurately distinguishing between normal and abnormal cells with minimal misclassification. In the more challenging 7-class classification task, which involves identifying seven distinct cervical cell types, the model still performed remarkably well, achieving an accuracy of 99.23%. These results show strength of CNN-VGG16 feature extraction approach and the VGG16 architecture in capturing critical patterns in Pap smear images for precise classification.

4.5. Comparative Study

This section presents the comparative study. The comparative study for 2-class classification on the SIPaKMeD dataset, as shown in Table 1, clearly show good performance of CNN-VGG16 model over existing approaches. The ResNet50v2 approach from [11] achieved 91.6% accuracy, whereas DenseNet121 + DCGAN model slightly improved upon this with an accuracy of 92%. However, the proposed CNN-VGG16 model significantly outperformed both, achieving a remarkable 99.59% accuracy. This substantial improvement highlights the effectiveness of the proposed feature extraction strategy prior to classification, as well as the robustness of the VGG16 architecture in accurately identifying cervical cancer from Pap smear images in binary classification tasks.

Table 1. SIPaKMeD dataset 2-Class Comparative Study

Ref	Model	Accuracy	Precision	Recall	F1-Score
[11]	ResNet50v2	91.6	91.8	91.6	91.6
	DenseNet121 +DCGAN	92	92	92	92
Proposed	CNN-VGG16	99.59	99.52	99.56	99.54

The comparative study for 5-class classification on SIPaKMeD dataset, as shown in Table 2, shows strong performance of CNN-VGG16 model in comparison to other existing models. In [11] achieved 87% accuracy, whereas DenseNet121+DCGAN improved the results slightly, with 89% accuracy. In contrast, [12] significantly outperformed both, achieving 97% accuracy. Also [13] performed well with 98.66% accuracy, but the model in [14] achieved 99.22% accuracy. The model in [16] provided 97% accuracy, but the proposed CNN-VGG16 model outperformed all these approaches with 99.35% accuracy. These results show CNN-VGG16 model not only achieves high accuracy but also excels in precision, recall, and F1-score, making it a highly reliable approach for multi-class cervical cancer classification.

Table 2. SIPaKMeD dataset 5-Class Comparative Study

Ref	Model	Accuracy	Precision	Recall	F1-Score
[11]	DenseNet121	87	87	87	87
	DenseNet121+DCGAN	89	89	89	89
[12]	CEMDTL	97	97	97	97
[13]	VGG16	98.66	98.6	97.7	97.9
[14]	A2SDNet121	99.22	99.22	99.24	99.22
[16]	Ensemble	97	96.8	96.6	96.8
Proposed	CNN-VGG16	99.35	99.31	99.34	99.32

The comparative study for 2-class classification on the Herlev dataset, as presented in Table 3, shows performance of CNN-VGG16 model in comparison to previous approaches. The model in [10] achieved 94.57% accuracy, whereas model in [13] performed slightly better, with 95.1% accuracy. In contrast, the proposed CNN-VGG16 model outperformed both of these methods by a significant margin, achieving 99.62%

accuracy. These results underscore the effectiveness of the proposed feature extraction and classification pipeline, demonstrating its ability to achieve better performance in distinguishing between normal and abnormal cervical cells on the Herlev dataset.

Table 3. Herlev dataset 2-Class Comparative Study

Ref	Model	Accuracy	Precision	Recall	F1-Score
[10]	CerviFormer	94.57	92.5	93.5	92.5
[13]	ResNet50	95.1	94.3	95.4	94
Proposed	CNN-VGG16	99.62	99.59	99.6	99.61

The comparative study for 7-class classification on the Herlev dataset, as shown in Table 4, demonstrates performance of CNN-VGG16 model when compared to existing models. The model in [10] achieved 94.57% accuracy, whereas model in [13] achieved 83.78% accuracy, while model from [24] performed slightly worse with 81.18% accuracy. In contrast, the model in [24] achieved a significantly higher performance, with 97.31% accuracy. However, the proposed CNN-VGG16 model outperformed all the previous methods, achieving better accuracy of 99.23%. These results clearly highlight the efficacy of the proposed model in accurately classifying cervical cancer images into seven distinct classes, demonstrating its robustness and superiority in handling complex multi-class classification tasks.

Table 4. Herlev dataset 7-Class Comparative Study

Ref	Model	Accuracy	Precision	Recall	F1-Score
[10]	CerviFormer	94.57	92.5	93.5	92.5
[13]	ResNet50	83.78	86.3	85	85.3
[17]	ResNet50	81.18	82.5	82.6	82.4
	CICNN-ResNet50	97.31	97.9	97.8	97.8
Proposed	CNN-VGG16	99.23	99.21	99.22	99.22

5. Conclusion

Cervical-cancer is a type of carcinoma which develops from cells located in cervix. The primary cause is a constant infection from high-risk kinds of HPV. This work aims enhancing accuracy and efficiency of cervical-cancer detection by proposing a CNN-VGG16 approach for Pap smear images classification into multiple classes, addressing challenges in feature extraction and classification. The CNN-VGG16 approach included preprocessing steps such as resizing and normalization of images to standardize the input, followed by feature extraction using convolutional layers. The extracted features are then passed to a pre-trained VGG16 model for classification. The results show better performance, with CNN-VGG16 model achieving 99.59% accuracy for 2-class classification, 99.35% for 5-class classification on the SIPaKMeD, and 99.59% accuracy for 2-class classification and 99.23% for 7-class classification on Herlev datasets. The key takeaway from this work is that the integration of feature extraction techniques before classification significantly improves the model's performance. As future work, the preprocessing step can be enhanced by incorporating noise removal techniques to further improve the quality of input images, potentially providing better model's accuracy.

Author contributions

Sushma V: Survey, Methodology, Identification of Architecture, Drafting, Visualization, Tool usage to run the code with various datasets, Performance Evaluation.
Dr. J V Gorabal: Investigation, Data curation, Performance Evaluation, Verification, Editing, Conclusion and discussion.

Conflicts of interest

The author declares no conflicts of interest.

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