IJARCCE ISSN (O) 2278-1021, ISSN (P) 2319-5940

International Journal of Advanced Research in Computer and Communication Engineering

Impact Factor 8.102 ⯊ Peer-reviewed & Refereed journal ⯊ Vol. 13, Issue 3, March 2024

DOI: 10.17148/IJARCCE.2024.13332

Cervical Abnormality Detection with Deep Learning Powered Colposcopy Analysis

Karthik Pai[1], Athmika C Jain[2], Chirag[3], Greeshma Jain[4], Maryjo M George[5*]

Dept. of Artificial Intelligence & Machine Learning, Mangalore Institute of Technology & Engineering,

Moodbidri, Karnataka, India[1-5]

Abstract: Cervical cancer represents a significant global health challenge, particularly in underserved regions where access to conventional screening methodologies is limited. In this study, we investigated the efficacy of deep learning models, including Densenet 201, Vgg16, and Vgg19, trained on the International Agency for Research on Cancer (IARC) Colposcopy Image Bank dataset. The dataset was partitioned into training and validation subsets, and the performance of each model was evaluated on the validation data. Our findings reveal that Densenet201 exhibits superior validation accuracy compared to Vgg16 and Vgg19. The primary objective of this research is to develop a robust and accessible tool for early detection and intervention, with the ultimate aim of alleviating the burden of cervical cancer screening in resource-constrained settings.

Keywords: Colposcopy, Cervical cancer screening, Deep learning.

I. INTRODUCTION

Cervical cancer remains a formidable global health challenge, especially prevalent in underserved regions where conventional screening methods encounter limitations. Despite advancements in medical technology, the burden of cervical cancer persists, marked by significant morbidity and mortality rates often attributed to delayed diagnosis and inadequate treatment options. Traditional screening approaches, such as Pap smears and HPV testing, though effective in many contexts, face logistical and infrastructural challenges in resource-constrained areas, resulting in missed opportunities for early detection and intervention.

To address the critical need for accessible and reliable cervical cancer screening methods, recent research has turned to the potential of deep learning techniques. Deep learning, a subset of artificial intelligence, exhibits remarkable capabilities in image recognition tasks, rendering it well-suited for analysing medical images, including those obtained through colposcopy of the cervix. Utilizing extensive datasets such as the International Agency for Research on Cancer (IARC) Colposcopy Image Bank, researchers have endeavoured to train deep learning models to recognize patterns indicative of cervical abnormalities, potentially paving the way for automated and scalable screening solutions.

This study aims to contribute to the field by exploring the feasibility of utilizing deep learning models, specifically Densenet 201, Vgg16, and Vgg19, for cervical cancer screening. The primary objective is not merely to evaluate the models, but rather to assess their performance in detecting cervical abnormalities using images from the IARC Colposcopy Image Bank dataset. Through rigorous experimentation and validation, we seek to determine the efficacy of these models in providing accurate and timely identification of potential precancerous lesions or abnormalities. By harnessing the power of deep learning, our ultimate goal is to develop a reliable and accessible tool for early detection and intervention in cervical cancer, with the potential to alleviate the burden of the disease in resource-constrained settings and improve outcomes for women globally.

II. LITERATURE REVIEW

In [1] Uterine Cervical Cancer computer-aided-diagnosis it on a Computer-Aided-Diagnosis (CAD) system for uterine cervical cancer screening and colposcopy adjunct. The CAD system is designed to automatically analyse data acquired from the uterine cervix, providing tissue and patient diagnosis, as well as examination adequacy assessment. The system architecture is open, modular, and feature-based, allowing for multi-data, multi-sensor, and multi-feature fusion. For cervical cancer screening, the CAD system can be integrated into instruments such as handheld devices. It analyses digital RGB images of the cervix post-acetic acid application, detecting features like acetowhite epithelium, vessel structure, and lesion margins to provide diagnostic results and exam adequacy assessment. The system's flexible design allows for progressive enhancements with new algorithms and data sources.

IJARCCE ISSN (O) 2278-1021, ISSN (P) 2319-5940

International Journal of Advanced Research in Computer and Communication Engineering

Impact Factor 8.102 ⋇ Peer-reviewed & Refereed journal ⋇ Vol. 13, Issue 3, March 2024

DOI: 10.17148/IJARCCE.2024.13332

Recent advancements in cervical cancer detection have been shaped by the promising integration of deep learning methodologies. A notable study by Chandran V et al. [2] showcased commendable sensitivity, specificity, and kappa scores through the use of VGG19 and SKYNET architectures. Despite these successes, challenges in effectively differentiating various grades of cervical intraepithelial neoplasia were identified, casting a limitation on the broader applicability of these models.

Feature fusion techniques [3] enhance the classification accuracy of cervical cancer by integrating information from multiple sources or modalities. This integration can include combining imaging data from different modalities (such as colposcopy and histology) or incorporating clinical variables (such as patient demographics or medical history). By synthesizing diverse information, feature fusion enables the model to capture complementary aspects of the underlying data, leading to more robust and reliable predictions.

The fine-tuning of pre-trained convolutional neural networks (CNNs) [4] for grading systems like CIN and LAST involves adapting the parameters of the pre-trained network to better suit the characteristics of cervical lesion grading. This process involves updating the network's weights during training to learn task-specific features that are relevant to the grading criteria established by medical professionals. Fine-tuning enables the model to effectively discriminate between different grades of cervical lesions, aiding in accurate diagnosis and risk stratification.

III. SCOPE AND METHODOLOGY

Scope

The main aim of the project it developing and implementing deep learning algorithms to analyze colposcopic images for the detection of cervical abnormalities. This technology aims to democratize access to accurate and timely diagnostics, overcoming barriers such as geographical location and practitioner expertise. The project seeks to bridge the gap between the need for accessible and standardized cervical health examination and the limitations of colposcopy by empowering a broader range of healthcare professionals to provide precise diagnostic insights. Key components include developing robust algorithms, integrating them into existing healthcare systems, and evaluating the effectiveness and scalability of the approach in enhancing the reach and quality of cervical health examinations. Additionally, considerations will be made for factors such as cost-effectiveness, regulatory compliance, and user-friendliness to ensure successful adoption and impact in diverse healthcare settings.

Methodology

The study utilized the IARC Colposcopy Image Bank dataset, a comprehensive collection of cervical colposcopy images, for evaluating the efficacy of deep learning models in detecting cervical abnormalities. The dataset was preprocessed to ensure uniformity and quality, including resizing images to a consistent resolution and standardizing image formats. Three deep learning models, namely Densenet 201, Vgg16, and Vgg19, were selected for comparison based on their popularity and performance in image classification tasks. These models were implemented using established deep learning frameworks, such as TensorFlow or PyTorch, leveraging pre-trained weights obtained from prior training on large-scale image datasets like ImageNet. The dataset was split into training, validation, and test sets to facilitate model training, validation, and evaluation. Data augmentation techniques, including rotation, flipping, and scaling, were applied to augment the training data and enhance model generalization.

Training of the deep learning models involved optimizing model parameters using stochastic gradient descent or its variants, with adaptive learning rate scheduling techniques to improve convergence and prevent overfitting. Model performance was monitored using metrics such as accuracy, precision, recall, and F1-score during training and validation phases.Hyperparameter tuning was performed to optimize model architecture-specific parameters, including learning rates, batch sizes, and regularization techniques, to maximize performance on the validation set while avoiding overfitting.Cross-validation techniques, such as k-fold cross-validation, were employed to assess the robustness and generalization ability of the models across different subsets of the dataset.

Model evaluation was conducted on the held-out test set to assess real-world performance in detecting cervical abnormalities. Performance metrics, including accuracy, sensitivity, specificity, and area under the receiver operating characteristic curve (AUC-ROC), were calculated to quantify the efficacy of each model. Statistical analysis, including hypothesis testing and confidence interval estimation, was performed to compare the performance of different models and identify statistically significant differences.

Finally, qualitative analysis was conducted to interpret model predictions and identify potential areas of improvement or further research. Visualizations, such as confusion matrices and saliency maps, were generated to gain insights into model behaviour and decision-making processes.

IJARCCE ISSN (O) 2278-1021, ISSN (P) 2319-5940

International Journal of Advanced Research in Computer and Communication Engineering

Impact Factor 8.102 ⁘ Peer-reviewed & Refereed journal ⁘ Vol. 13, Issue 3, March 2024

DOI: 10.17148/IJARCCE.2024.13332

IV. DESIGN AND IMPLEMENTATION

System design is a crucial phase following the Software Development Life Cycle (SDLC). It starts with requirement analysis and progresses to designing the overall system structure. The main goal of system design is to outline the architecture, modules, their relationships, purposes, and how they integrate. This phase provides a comprehensive overview of the system flow and architecture.

Architectural Design

Architectural design in software engineering entails the detailed description and visualization of a system's structure, serving as a blueprint for understanding its components, attributes, and interactions. This comprehensive process involves defining the system's building blocks, including modules, layers, and components, along with their externally visible properties and behaviors. Through architectural design, the relationships and dependencies among these components are meticulously delineated, guiding the system's behavior and functionality.

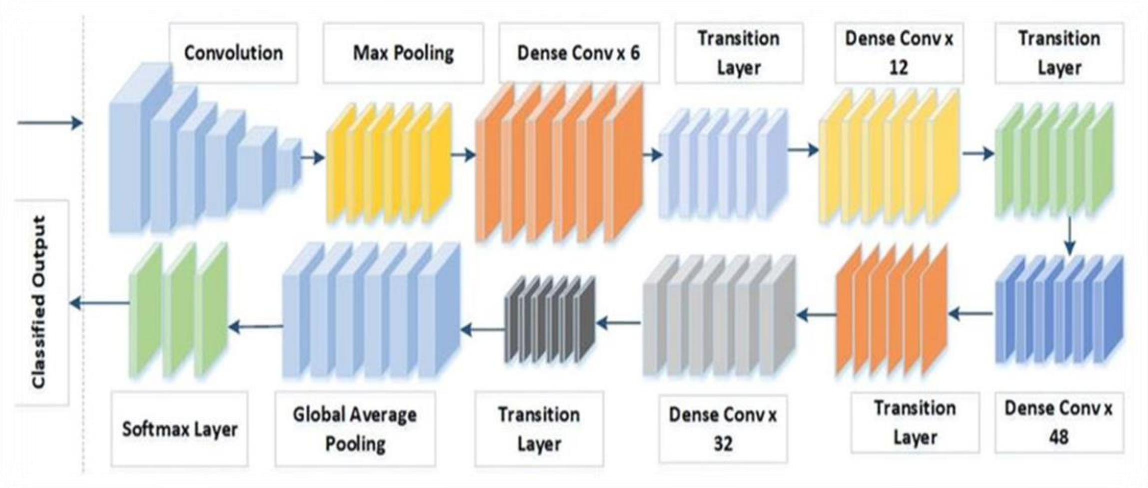

Fig 1. Architecture diagram of DenseNet 201

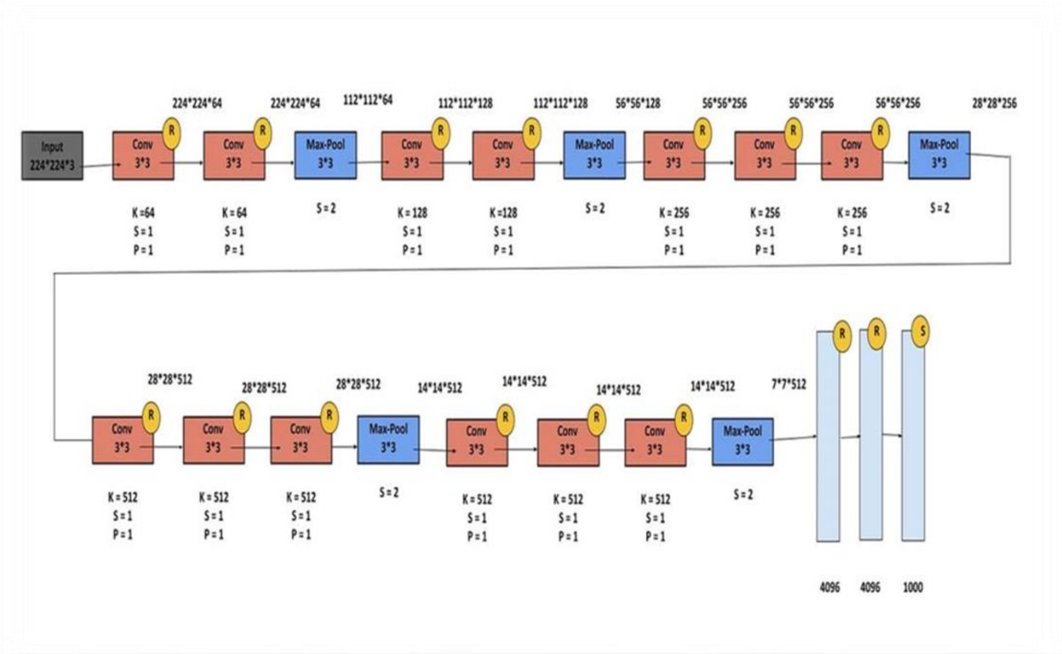

Fig 2. Vgg-16 and Vgg-19 CNN Architectures

IJARCCE ISSN (O) 2278-1021, ISSN (P) 2319-5940

International Journal of Advanced Research in Computer and Communication Engineering

Impact Factor 8.102 ⁜ Peer-reviewed & Refereed journal ⁜ Vol. 13, Issue 3, March 2024

DOI: 10.17148/IJARCCE.2024.13332

V. RESULT AND CONCLUSION

Result

Our study aimed to evaluate the efficacy of deep learning models, including Densenet 201, Vgg16, and Vgg19, in detecting cervical abnormalities using the IARC Colposcopy Image Bank dataset. Through rigorous experimentation and validation, we found that Densenet 201 exhibited superior validation accuracy compared to Vgg16 and Vgg19. The validation results showed that Densenet 201 achieved an accuracy of 88.93%, outperforming the other models. On the other hand, Vgg19 demonstrated an accuracy of 63.93%, indicating its comparatively lower performance. These findings suggest that Densenet 201 may offer higher sensitivity and specificity in identifying potential precancerous lesions or abnormalities, thus holding promise for improving cervical cancer screening outcomes.

Furthermore, our analysis provided valuable insights into the performance characteristics of each deep learning model. While all models demonstrated proficiency in detecting abnormalities, Densenet 201 stood out due to its dense connectivity pattern and feature reuse mechanism, enabling robust performance across diverse image datasets. In contrast, Vgg16 and Vgg19 showed limitations in capturing intricate details relevant to cervical abnormalities, highlighting the importance of selecting appropriate deep learning architectures tailored to specific medical imaging applications.

Conclusion

In conclusion, our study contributes significant advancements in the application of deep learning models for cervical cancer screening. By demonstrating the superior performance of Densenet 201 and its potential for more accurate and efficient diagnostic tools, we underscore the transformative impact of artificial intelligence in healthcare. Moving forward, further research and development efforts are warranted to refine and optimize these models for real-world clinical settings, ensuring their seamless integration into existing cervical cancer screening programs.

Moreover, the successful integration of deep learning models into screening programs holds promise for enhancing diagnostic accuracy, reducing false positives, and ultimately improving patient outcomes. Collaborative efforts between researchers, clinicians, and policymakers are essential to facilitate the translation of these findings into clinical practice effectively. By embracing innovation and harnessing the power of technology, we can advance the fight against cervical cancer and contribute to the global effort to eliminate this devastating disease.

REFERENCES

[1]. Lange, H. and Wolters, R.H., STI Medical Systems LLC, 2010. *Uterine cervical cancer computer-aided-diagnosis (CAD)*. U.S. Patent 7,664,300.C.

[2]. Chandran, Venkatesan, et al. "Diagnosis of cervical cancer based on ensemble deep learning network using colposcopy images." BioMed Research International 2021.

[3]. Yu, Hui, et al. "Segmentation of the cervical lesion region in colposcopic images based on deep learning." Frontiers in Oncology 12 (2022): 952847

[4]. Cho, Bum-Joo, et al. "Classification of cervical neoplasms on colposcopy photography using deep learning." Scientific reports 10.1 (2020): 13652.

[5]. Chen, Mingyang, et al. "Evaluating the Feasibility of Machine-Learning-Based Predictive Models for Precancerous Cervical Lesions in Patients Referred for Colposcopy." Diagnostics 12.12 (2022): 3066.J. Hwang, J. Kim and H. Choi, "A review of magnetic actuation systems and magnetically actuated guidewire-and catheter-based microrobots for vascular interventions", *Intell. Serv. Robot*., vol. 13, no. 1, pp. 1-14, 2020.

[6]. Chen, Xiaoyue, et al. "Application of EfficientNet- B0 and GRU-based deep learning on classifying the colposcopy diagnosis of precancerous cervical lesions." Cancer Medicine 12.7 (2023): 8690- 8699.B.

[7]. Pacal, Ishak, and Serhat Kılıcarslan. "Deep learningbased approaches for robust classification of cervical cancer." Neural Computing and Applications 35.25 (2023): 18813-18828.

[8]. Park, Ye Rang, et al. "Comparison of machine and deep learning for the classification of cervical cancer based on cervicography images." Scientific Reports 11.1 (2021): 16143.

