ORIGINAL PAPER



Integrating artificial intelligence and holographic imaging for advanced cervical cancer diagnosis

Asifa Nazir¹ · Ahsan Hussain¹ · Mandeep Singh² · Assif Assad¹

Received: 11 February 2025 / Revised: 7 March 2025 / Accepted: 21 March 2025 © The Author(s), under exclusive licence to Springer-Verlag London Ltd., part of Springer Nature 2025

Abstract

This study investigates a novel approach to cervical cancer diagnosis by applying "Artificial Intelligence (AI)" to holographic imaging data. Specifically, it investigates AI's role in medical image analysis through "Machine Learning (ML)" and "Deep Learning (DL)", with an emphasis on holography microscopic imaging as an emerging diagnostic technique. An analysis of previous studies revealed a significant gap in exploring the potential of holographic imaging for cervical cancer diagnosis using DL approaches. This study uniquely applies Explainable AI (XAI) methods to holography microscopic imaging data for cervical cancer, filling a gap no prior research has addressed. A thorough experimentation using ML and DL approaches is done to bridge this research gap and improve diagnostic accuracy. Various pre-trained DL approaches, including "DenseNet121", "Xception", "InceptionV3", "VGG-16", "ResNet50" and "EfficientNetB4", were utilized for feature extraction. These extracted features were then classified using algorithms such as "Support Vector Machines (SVM)", "Random Forest (RF)", "K-Nearest Neighbors (KNN)", "Decision Trees (DT)", "AdaBoost" and "Gradient Boosting Machine (GBM) to enhance diagnostic accuracy. The combination of DenseNet121 and SVM achieved the highest performance across all metrics, attaining 100% accuracy, precision, recall, F1-score, and AUC-score (1.00). Additionally, it recorded a Mean Squared Error (MSE) of 0.00 and a Root Mean Squared Error (RMSE) of 0.00, indicating perfect classification performance. Moreover, cross-validation on both the original dataset and the Synthetic Minority Over-sampling Technique-augmented dataset exhibited improved performance. The augmented dataset achieved higher accuracy, precision, and recall, effectively addressing class imbalance thereby enhancing classification. 5-fold cross-validation surpassed 3-fold, which demonstrated moderate accuracy (66.67–75%), high losses (0.36–0.69), and inconsistent metrics, with some folds having 0.0 precision, recall, and F1-score. In contrast, 5-fold attained near-perfect accuracy (100%), minimal loss, and consistently 1.00 across all key metrics, ensuring superior model stability and performance. A comparative analysis using Convolutional Neural Network (CNN) models trained from scratch has been performed to evaluate the performance of holographic and bright-field images, demonstrating the superior effectiveness of holographic imaging for cervical cancer diagnosis. Out of three customized models CNN Arch 1 and CNN Arch 2 achieved perfect classification with 100% test accuracy, an AUC of 1.00, and optimal precision, recall, and F1-scores on holographic imaging data. However, CNN_Arch_3 exhibited a slight decline in test accuracy (93%) with reduced recall (0.80) and F1-score (0.89) for class 1. On bright-field imaging, CNN_Arch_2 maintained strong performance (98% training, 93% test accuracy) with consistently high metrics. In contrast, CNN_Arch_3 showed lower test accuracy (75%), particularly in class 1, where recall dropped to 0.60, leading to a lower F1 score (0.60). A different configuration of CNN Arch 1 struggled further, achieving 81% test accuracy with diminished overall metrics (MCC: 0.56, AUC: 0.98), highlighting the dataset's impact on model performance. Furthermore, XAI techniques, including "Gradient-weighted Class Activation Mapping(Grad- CAM)", "Grad-CAM ++", and "Local Interpretable Model- Agnostic Explanations (LIME)", are used with the "VGG-16" and "DenseNet201" models to improve interpretability thereby offering clearer insights into the model's decision-making process. With the implementation of these explainability techniques to holographic imaging data, this research work highlights its novelty in cervical cancer diagnosis compared to previous studies.

Keywords Cervical cancer \cdot Convolutional neural networks \cdot Deep learning \cdot Early diagnosis \cdot Gradient-weighted class activation mapping \cdot Holography

Extended author information available on the last page of the article