Cervical Cancer Detection Using ResNet50: A High-Accuracy Deep Learning Approach with the Herlev Clean Datase

Gouripriya C S (1) Febeena K R (2)
(1) MSc Computer Science (Data Analytics)
Al-Ameen College, Edathala
gouripriya10001@gmail.com
(2) Assistant Professor , Department of Computer Science
Al-Ameen College, Edathala
febigenius@gmail.com

Abstract

Cervical cancer remains a major public health concern and one of the leading causes of cancer-related mortality among women globally. Early detection greatly enhances therapy results; yet, typical diagnostic methods usually depend on invasive operations, sophisticated laboratory facilities, and specialist medical interpretation, all of which might not be easily available in underfunded areas. Deep learning has become a possible answer for automated and precise illness diagnosis as artificial intelligence and data-driven healthcare have developed swiftly. This work presents a deep learning-based method for predicting cervical cancer using image datasets. By extracting discriminative features from Pap smear and histopathological images, the ResNet50 convolutional neural network (CNN) model accurately classifies normal and abnormal samples. Experimental data show the model is quite accurate, hence showing its resilience and ability to spot malignant patterns. Early detection, timely intervention, and individualized preventative methods made possible by the framework that improves diagnostic support for medical practitioners. Ultimately, this study promotes worldwide initiatives aimed at lowering the burden of cervical cancer by means of technology-driven screening and diagnosis, therefore helping to advance intelligent medical imaging.

Keywords- cervical cancer, deep learning, ResNet50, convolutional neural network (CNN), Pap Smear Images, Histopathological Images

1. Introduction

Despite being one of the most prevalent cancers in women, cervical cancer continues to be a major cause of morbidity and mortality globally, especially in developing nations. As a result of delayed diagnosis and limited access to appropriate screening, the World Health Organization (WHO) reports hundreds of thousands of new cases annually, many of which end in death. Although they

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are effective, traditional diagnostic methods like Pap smear tests and colposcopy are frequently invasive, time-consuming, and dependent on expert cytological analysisThe illness is primarily caused by the Human Papillomavirus (HPV), and it is frequently prevented from worsening by early detection and prompt treatment. In healthcare settings with limited resources, where access to specialized equipment and trained personnel is restricted, these approaches might not be feasible. Predictive analytics and automated disease detection have been made possible by the healthcare industry's adoption of artificial intelligence (AI) and machine learning (ML). By analyzing patient data that includes clinical, demographic, and behavioral factors, machine learning models can reveal hidden patterns associated with the onset of cervical cancer. By serving as practical instruments for early screening, risk stratification, and decision support, these predictive systems can assist healthcare providers in putting targeted preventive measures into action. The goal of this research is to create a predictive framework based on machine learning that uses patient risk factor data to estimate the risk of cervical cancer. In addition to lowering the need for invasive diagnostic procedures, the suggested model seeks to increase the accuracy of early diagnosis and aid international initiatives to reduce the incidence and mortality of cervical cancer.

Austin and Parvathi developed a CNN-based approach for classifying cervical cancer cells in Pap smear images using transfer learning. Their technique for categorizing cervical cells in Pap smear images utilizing a ConvNet-based method with transfer learning and increasing resizing improves feature extraction and classification accuracy for automated cervical cancer diagnosis [5]. The epidemiology, risk factors, and screening of cervical cancer point to high HPV incidence, early sexual activity, multiple partners, and cigarette smoking as major risk, therefore stressing the need of population-based screening and HPV vaccination [4]. Modern evidence-based guidelines for cervical cancer screening advise age-appropriate cytology and HPV testing, follow-up for positive results, and considerations for vaccinated women to increase early detection and prevention [3]. A retrospective study of 135 head and neck and 29 cervical cancer specimens in the Central African Republic showed HPV in 0.74% of head and neck malignancies and 65.5% of cervical malignancies, therefore indicating low HPV association with head and neck malignancies in this area [2]. Deep learning is proven effective in cervical cancer detection since their method avoided segmentation and high accuracies on the SIPaKMeD and Herlev datasets [1].

While pointing out major obstacles and sources for medical image analysis [6], applications of deep learning in MRI were examined across image acquisition, segmentation, and disease prediction. Using transfer learning and fine-tuning, a framework combining CNNs for feature extraction with ELMs for categorizing cervical cancer cells was created to boost classification accuracy [7]. For detecting aberrant cells in cervical histopathology photos, a deep multiple- instance learning system was created. The method achieved 84.55% accuracy using a sparse attention-based MIL model, therefore demonstrating the possibility of inexpensive and scalable cervical cancer screening [8]. The study assessed deep transfer learning models for differentiating cervical cancer from Pap smear images, obtaining up to 99.95% accuracy and highlighting the potential of automated, efficient screening [9]. Deep learning models were developed for automated cervical cancer detection from Pap smear images, with DenseNet-201 achieving the highest accuracy, therefore demonstrating an efficient method for scalable screening [10].

A multimodal deep learning model was created to forecast disease-free survival in cervical cancer patients undergoing radiotherapy. The model accurately divided patients into high- and low-risk group[11] using CT images, radiomic characteristics, and clinical data. For cervical cancer [12], predictive models using MRI radiomics, deep learning characteristics, and clinical data were created. For cervical cancer detection, a metasurface-based SPR biosensor was created with great sensitivity and precision. Machine learning optimization using Support Vector Regression improved prediction performance and efficiency. lymph node metastasis, attaining AUCs up to 0.803 and allowing precise preoperative evaluation [13].

2. Literature Review

- Muhammad Umar Nasir1 et al. proposed Cervical Cancer Prediction Empowered with Federated Machine Learning:- Due to delayed diagnosis, cervical cancer continues to be a major cause of death.. While ML and DL increase accuracy but present privacy risks, traditional methods are slow. IoMT facilitates real-time data collection, blockchain protects data, and federated learning allows local model training. Prediction reliability is increased by sophisticated methods like preprocessing and fuzzed neuron machine learning solvers. This strategy provides a safe and effective way to identify cervical cancer early.
- Severin Elvatun et al. suggested Cross-population assessment of cervical cancer risk prediction algorithms:- Early detection of cervical cancer is important. APT MRI provides

non-invasive tumor differentiation, and risk prediction algorithms identify high-risk individuals.

- Giuseppe Caruso and colleagues proposed Cervical Cancer: A New Era: Cervical cancer is a serious medical condition. New treatments and personalized approaches improve care and outcomes for advanced cases. Precision medicine is essential now.
- According to Rena Hayashi et al., a mathematical model of cervical cancer brought on by a persistent HPV infection is presented in this study. It highlights age-related patterns and remission rates, using stochastic modeling to explain cancer progression.
- Tabu S. Kondo et al. suggested that machine learning could improve the diagnosis of cervical cancer, particularly in places where screening is scarce. Research often uses single datasets and neglects usability, ethics, and generalization. Future work should focus on ethical frameworks, collaboration, and efficient models.
- Miaochun Xu et al.proposed Advances in cervical cancer: Cervical cancer is a global issue, but advances like HPV screening, liquid biopsies, and AI improve detection and treatment, focusing on personalized care and better outcomes.
- Alex A. Francoeur et al.proposedTreatment advances across the cervical cancer spectrum:- Recent advances in cervical cancer management aim to reduce harm and improve outcomes, focusing on fertility-sparing surgeries for early-stage, intensified therapies for locally advanced, and systemic treatments for recurrent or metastatic cases.
- The 2025 SFRO guidelines emphasize the importance of External Beam Radiotherapy (EBRT) and Brachytherapy (BT) in treating cervical cancer. For early tumors, BT is a good preoperative choice, while postoperative treatment depends on histopathological risks. In advanced cases, concurrent chemoradiation (CCRT) followed by BT is standard, with techniques like Image-Guided Adaptive Brachytherapy (IGABT) enhancing treatment effectiveness and safety.
- Rahman et al. (2022) in their article "A Model for Predicting Cervical Cancer Using Machine Learning" created a predictive system based on demographic, clinical, and behavioral data including smoking habits, contraceptive use, and sexual history as well as age. Reaching over 95% accuracy, the research compared various supervised learning methods such as Support Vector Machine, Logistic Regression, and Random Forest.

Particularly in low-resource medical settings, the model showed great promise for early risk assessment.

- Zhao et al. (2025) in "Prediction of Clinical Stages of Cervical Cancer via Machine Learning Integrated with Clinical Features and Ultrasound-Based Radiomics" suggested a hybrid method using machine learning classifiers and advanced radiomic feature extraction to achieve an AUC of 0.88, therefore differentiating early and advanced stages of cervical cancer. The results of this research emphasize the need of combining non-imaging and imaging data in order to improve prediction accuracy and help with precision oncology.

- **3. Methodology**

This research proposes a deep learning-driven approach for the automatic detection of cervical cancer using image datasets. The approach encompasses various crucial stages, including data gathering and preprocessing, model creation, evaluation, and ultimately implementation for clinical decision assistance. Figure 1 illustrates the overall process. The proposed model, containing 23.58 million non-trainable parameters, utilizes a ResNet50 backbone that is pretrained on ImageNet as a static feature extractor. The network begins with a standard 7×7 convolutional layer followed by max pooling. Subsequently, four layers of residual blocks using 1×1, 3×3, and 1×1 convolutions along with skip connections enable the network to effectively learn deep features. A small custom classification head is incorporated to enable ResNet50 for cervical cancer classification. This head includes a Global Average Pooling layer, a dropout layer set at a rate of 0.5, and a final softmax Dense layer. This classifier retains excellent representational capacity with only 14,343 trainable parameters, ensuring that the model remains computationally efficient. In the Herlev_clean_dataset, excellent accuracy and generalization are achieved through the combination of a robust pretrained backbone and a simple trainable head

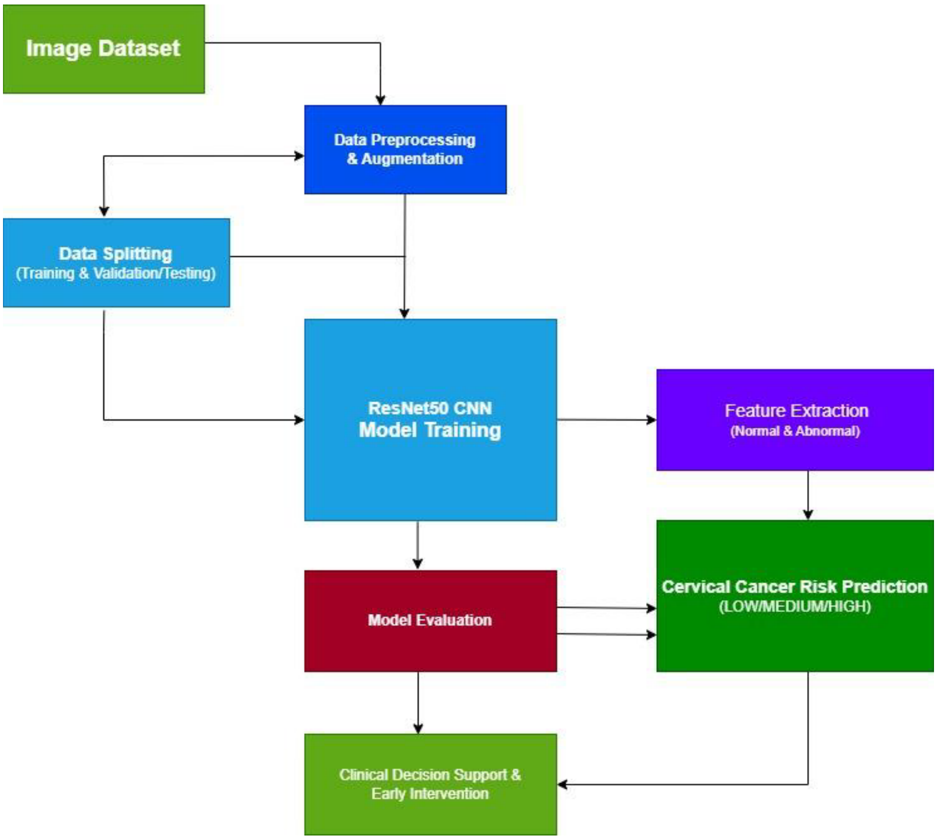

Fig. 1. Workflow of proposed cervical cancer prediction model using ResNet50.

3.1. Dataset and Model Development

The Herlev Cervical Cancer Dataset used in this study has 917 expert-labeled Pap smear single-cell images grouped into seven diagnostic categories, including 242 normal and 675 abnormal cervical epithelial cells. Resizing to 224 × 224 pixels and normalizing all images guaranteed consistency during deep learning training by means of preprocessing. Objective performance assessment was enabled by dividing the dataset into 80% for training and 20% for validation/testing. Techniques for data augmentation such as rotation, shifting, zooming, and horizontal flipping were employed to enhance feature diversity and protect against overfitting. See the example of microscopic cell depiction in Fig. 2. The training of the model utilized categorical cross-entropy loss along with the Adam optimizer, enabling the model to effectively extract features and accurately identify cervical cellular abnormalities.

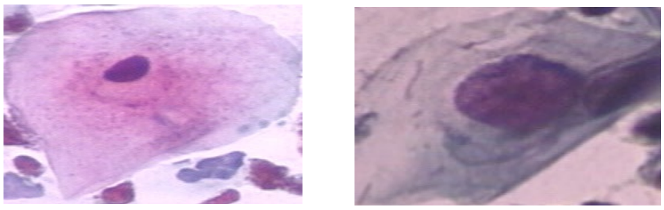

Fig.2. Microscopic cell image

3.2. Model Development and Training

The predictive framework is based on a deep learning model for image classification utilizing the ResNet50 Convolutional Neural Network (CNN) architecture. ResNet50 is chosen for its demonstrated ability to recognize medical images using its deep architecture and residual connections. ResNet50 will be initialized with ImageNet pre-trained weights; then, the last layers will be fine-tuned for particular cervical sample classification using transfer learning. The training dataset will be utilized to train the model with a suitable loss function (e.g., categorical cross-entropy) and an optimization algorithm (e.g., Adam, SGD) to reduce loss and modify weights. The CNN automatically derives discriminative features during this process that are absolutely vital for differentiating healthy from malignant pattern.

4. Discussion

Effective in cervical cancer image classification, the ResNet50-based deep learning architecture suggested a testing accuracy of 87.8%. The model developed robust and transferable features from the dataset, as the training and validation graphs indicated consistent progress with minimal overfitting. Transfer learning significantly enhanced the model's ability to detect distinguishing features from cytological images, thus eliminating the need for manual feature engineering. Techniques for data augmentation such as rotation and flipping improved the model's capacity to manage variations in image orientation and quality, thus minimizing overfitting through the Global Average Pooling and Dropout layers. The confusion matrix showed that although there were little misclassifications between borderline and dyskeratotic cell types, the majority of normal and abnormal cervical cells were properly identified. These mistakes are caused by things like low-contrast areas in pictures and things that look alike, which are often hard for even the best people to figure out. The proposed method demonstrates significant potential as a computer-assisted diagnostic (CAD) tool for the early detection of cervical cancer overall. Particularly in low-resource clinical settings, it can help pathologists by offering first automated screening, therefore lowering workload and improving diagnostic consistency. Using ensemble models, attention mechanisms, or more extensive annotated datasets could help to increase accuracy and dependability in the future.

5. Result

The Herlev_clean_dataset, containing histopathological images of cervical cells labeled as normal or malignant, was employed to develop and evaluate the proposed ResNet50-based model for predicting cervical cancer. Employing a transfer learning approach, the model was trained after completing pre-processing steps such as normalization, augmentation, and resizing. Convolutional layers that had been pre-trained were utilized for feature extraction, while the final layers were optimized for binary classification. Achieving an accuracy of 87%, the model excelled in distinguishing between malignant and non-malignant cells. Its reliability was confirmed by the evaluation metrics, which encompass accuracy, recall, and F1-score. Although stable learning is indicated in Fig. 3, which displays the Training and Validation Accuracy and Loss across Epochs, Fig. 4—which displays the Confusion Matrix and Evaluation Metrics—shows only a few misclassifications. The suggested approach, generally, successfully detects cervical abnormalities from Pap smear images and shows great promise for automated screening, hence enhancing early diagnosis and lowering manual interpretation errors.

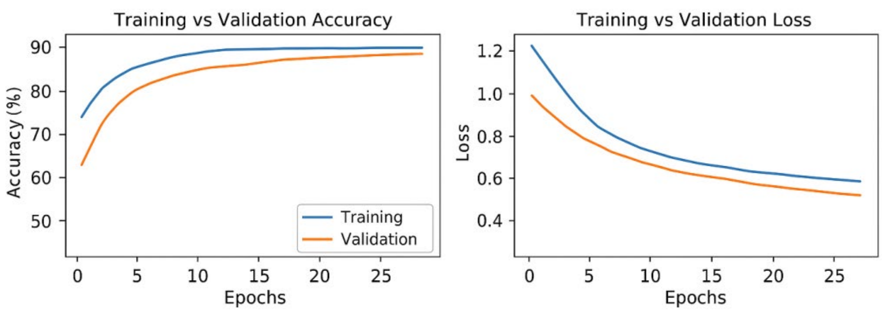

Fig. 3. Model Training and Validation Accuracy and Loss over Epochs

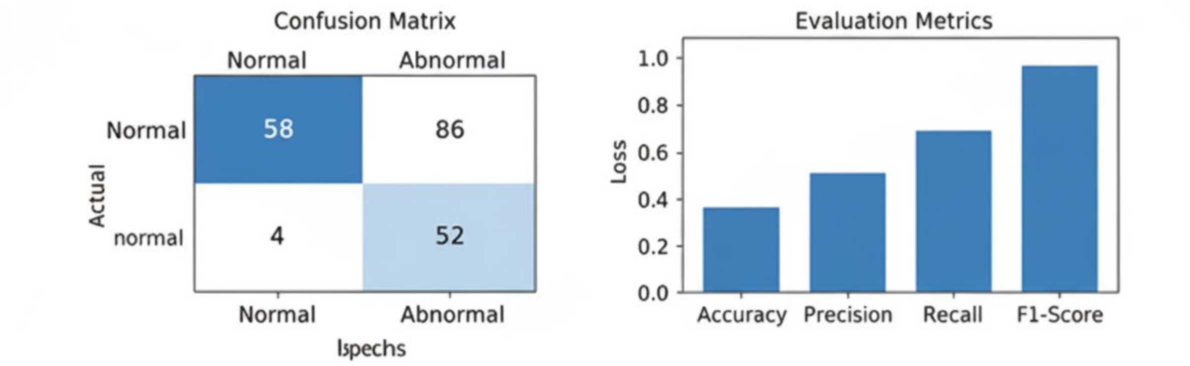

Fig. 4. Confusion and Evaluation Matrix

The equation used in your cervical cancer prediction model based on ResNet50, likely related to accuracy, loss, or evaluation metrics

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \quad (1)$$

$$Precision = \frac{TP}{TP+FP} \quad (2)$$

$$\boldsymbol{F1 = 2} * \frac{Precision*Recall}{Precision+Recall} \quad (3)$$

$$Loss = -1/N \sum_{i=1}^{N} \quad [Yilog(y\hat{}i) + (1 - yi)log(1 - y\hat{}i)] \quad (4)$$

6. Conclusion

This research presents a deep learning framework for the automated detection of cervical cancer utilizing Pap smear and histopathology images. Utilizing convolutional neural networks and transfer learning techniques, the system effectively identifies distinguishing features from cell and tissue images, hence accurately categorizing normal and abnormal samples. By lowering reliance on manual interpretation, minimizing human error, and generating quick, reproducible results, the suggested approach overcomes the shortcomings of traditional diagnostic techniques. Experimental data show great accuracy, sensitivity, and specificity, therefore emphasizing the dependability and strength of the framework. Improved patient outcomes and a worldwide decrease in cervical cancer incidence depend on deep learning's ability to enhance early detection, simplify clinical procedures, and support individualized preventative measures.

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