JuniKhyat

(UGC Care Group I Listed Journal)

ISSN: 2278-4632
Vol-13 Issue-01 Jan 2023

Cervical Cancer Diagnosis with Deep Learning: Current Architectures, Opportunities, and Research Gaps

GUNA GAYATHRI PRASEETHA K1, MALISETTY NIHITHA2

#1Assistant Professor, Department of CSE, PBR Visvodaya Institute of Technology and Science, Kavali

#2 Assistant Professor, Department of CSE-AI, PBR Visvodaya Institute of Technology and Science, Kavali

Abstract: The abstract highlights the significance of deep learning (DL) technology in addressing cervical cancer (CC), a leading cause of female mortality globally. With over 700 daily fatalities and an estimated 400,000 annual deaths by 2030, early detection is imperative. DL techniques offer accurate diagnoses, thereby improving treatment outcomes. The project integrates various DL models, including CNN, DenseNet, and Xception, for feature extraction, enabling the development of robust classification models such as SVM, KNN, Bayesian Networks, Decision Trees, and MLP. Additionally, DL-based detection techniques using YoloV5 and YoloV8 are explored for CC analysis. The utilization of these models significantly enhances diagnostic accuracy, with CNN and SVM achieving 99% accuracy in the base paper. The project's extension further improves performance by incorporating YoloV5 and YoloV8 for detection tasks, enhancing the system's capability to detect CC accurately. The implications of this project extend beyond improved diagnosis, benefiting women globally, particularly in low-income countries, by reducing morbidity and mortality rates. Healthcare professionals gain access to efficient diagnostic tools, enabling timely interventions and personalized therapy for better patient outcomes. Overall, the project underscores the pivotal role of DL technology in combating CC and improving healthcare outcomes.

Index Terms: Deep learning, classification, cervical cancer, colposcopy images, cytology images.

1. INTRODUCTION

In recent years, the rapid advancement of Artificial Intelligence (AI) and Machine Learning (ML) technologies, particularly in the realm of Deep Learning (DL), has revolutionized various sectors, including healthcare. DL, a subset of AI and ML, has shown remarkable success in applications such as computer vision recognition and processing, with capabilities that often surpass human performance in certain tasks [1]. This has led to its widespread adoption in medical domains, particularly in medical image analysis, where DL methods have demonstrated significant potential in detecting and diagnosing various types of cancers [2].

Cancer, characterized by uncontrolled cell division and growth, remains one of the most pressing global health challenges, with cervical cancer (CC) being a significant contributor to mortality rates, particularly

ISSN: 2278-4632
Vol-13 Issue-01 Jan 2023

among women. CC is the fourth most common cause of cancer death among women worldwide, with alarming projections estimating a substantial increase in mortality rates by 2030 [3], [4]. Despite being highly preventable and treatable if detected early, CC continues to pose significant challenges, especially in low-resource countries where access to healthcare services and specialized medical expertise is limited.

The current methods for CC detection primarily rely on Pap smear screening and colposcopy, which are highly dependent on the expertise of trained specialists and are often inaccessible in resource-constrained settings [5]. While previous studies have explored the integration of DL-based algorithms with conventional screening tests, their effectiveness in detecting early stages of CC remains limited [6]. Achieving accurate and timely diagnosis, particularly in the early stages of CC, is critical for initiating timely interventions and preventing morbidity and mortality, especially in underserved populations.

Therefore, there is a pressing need to develop and enhance DL-based digital solutions for cervical cancer diagnosis and detection, particularly focusing on improving accuracy and efficacy in identifying early-stage cervical abnormalities. This paper aims to address this need by leveraging DL techniques to develop robust and reliable systems for CC detection, with the ultimate goal of reducing morbidity and mortality associated with this devastating disease.

Through a comprehensive review of existing literature and the development of novel DL-based approaches, this study seeks to contribute to the advancement of cervical cancer diagnosis and detection, ultimately improving healthcare outcomes and saving lives.

2. LITERATURE SURVEY

Cervical cancer remains a significant global health challenge, particularly affecting women in developing countries. In recent years, researchers have increasingly turned to advanced technologies like deep learning and machine learning to improve cervical cancer detection and diagnosis. This literature survey provides an overview of key studies in this field, highlighting the use of various algorithms and methodologies for cervical cancer classification and detection.

One notable study by Jhingran et al. [4] provides comprehensive insights into cancers of the cervix, vulva, and vagina. This text serves as a foundational resource for understanding the epidemiology, pathology, and clinical management of cervical cancer. It underscores the importance of early detection and accurate diagnosis in improving patient outcomes.

Alyafeai and Ghouti [5] present a fully automated deep learning pipeline for cervical cancer classification. Their study demonstrates the efficacy of deep learning techniques in automating the classification process, thereby potentially reducing the burden on healthcare professionals and improving diagnostic accuracy. By leveraging deep learning models, such as convolutional neural networks (CNNs), the authors achieve promising results in cervical cancer classification.

Bray et al. [6] provide global cancer statistics for 2018, offering insights into the incidence and mortality rates of various cancers worldwide. This study underscores the urgency of addressing cervical cancer as a public health priority, especially in low-

ISSN: 2278-4632
Vol-13 Issue-01 Jan 2023

resource settings where access to screening and treatment may be limited.

Yang et al. [7] propose a cervical cancer risk prediction model based on machine learning algorithms. By analyzing various risk factors, including demographic, lifestyle, and clinical variables, the authors develop a predictive model to assess an individual's likelihood of developing cervical cancer. This approach highlights the potential of machine learning in personalized risk assessment and preventive healthcare.

Koh et al. [8] present guidelines for the management of cervical cancer, emphasizing the importance of comprehensive and multidisciplinary care. Their study underscores the need for integrated approaches that encompass screening, diagnosis, treatment, and supportive care to improve patient outcomes and quality of life.

Almubarak et al. [9] explore the application of convolutional neural networks (CNNs) for localized classification of uterine cervical cancer digital histology images. Their study demonstrates the potential of CNNs in analyzing histological images to detect cancerous regions with high accuracy. This approach could aid pathologists in interpreting histology slides more efficiently and accurately.

Guo et al. [10] propose a deep learning model for assessing image focus in automated cervical cancer screening. By leveraging convolutional neural networks (CNNs), the authors develop a model capable of evaluating image quality and identifying images suitable for screening. This approach streamlines the screening process and improves the overall efficiency of cervical cancer screening programs.

Kudva et al. [11] investigate the automation of cervical cancer detection using convolutional neural networks (CNNs). Their study demonstrates the potential of CNNs in automatically detecting cancerous regions in cervical images, thereby facilitating early diagnosis and treatment. This approach has the potential to reduce the reliance on manual screening methods and improve the accuracy of cervical cancer detection.

Wojtyla et al. [12] examine cervical cancer mortality trends in young adult European women. Their study highlights the importance of targeted interventions and screening programs to address the rising incidence of cervical cancer in this population. By understanding the demographic and epidemiological factors driving cervical cancer mortality, healthcare systems can develop more effective strategies for prevention and control.

Phoulady [13] proposes adaptive region-based approaches for cellular segmentation of bright-field microscopy images. This study contributes to the development of image processing techniques for analyzing cellular structures, which could have applications in cancer research and diagnosis.

Ghoneim et al. [14] explore the classification of cervical cancer using convolutional neural networks (CNNs) and extreme learning machines (ELMs). Their study demonstrates the effectiveness of deep learning algorithms in accurately classifying cervical cancer images, paving the way for automated diagnostic systems.

Overall, these studies highlight the diverse approaches and methodologies employed in cervical cancer detection and diagnosis. From deep learning models to machine learning algorithms and image

ISSN: 2278-4632
Vol-13 Issue-01 Jan 2023

processing techniques, researchers are continually innovating to improve the accuracy, efficiency, and accessibility of cervical cancer screening and diagnosis. As technology continues to advance, the potential for leveraging artificial intelligence in cervical cancer care holds promise for reducing mortality rates and improving patient outcomes.

3. METHODOLOGY

a) Proposed Work:

The proposed work entails the development of a comprehensive system for preprocessing and classifying cervical cancer data obtained from the "Cervical Cancer - CC Roboflow Data" dataset. ImageDataGenerator is utilized to preprocess the data, implementing techniques such as rescaling, shear transformation, and zooming to enhance the quality and diversity of the dataset.

The next phase involves feature extraction using Convolutional Neural Networks (CNN), DenseNet, and Xception. These advanced deep learning architectures are leveraged to extract high-level features from the preprocessed images, capturing intricate patterns and characteristics indicative of cervical cancer.

Subsequently, the extracted features are fed into traditional classifiers, including Support Vector Machines (SVM), k-Nearest Neighbors (KNN), Bayesian Networks, Decision Trees, and Multi-Layer Perceptrons (MLP). By training these classifiers on the extracted features, the proposed system aims to improve the accuracy and efficiency of cervical cancer classification.

Through this approach, the proposed system seeks to harness the strengths of both deep learning and traditional machine learning techniques, effectively combining them to achieve superior performance in cervical cancer diagnosis. By enhancing the classification accuracy and efficiency, the system aims to contribute to early detection and effective management of cervical cancer, thereby improving patient outcomes and reducing mortality rates.

b) System Architecture:

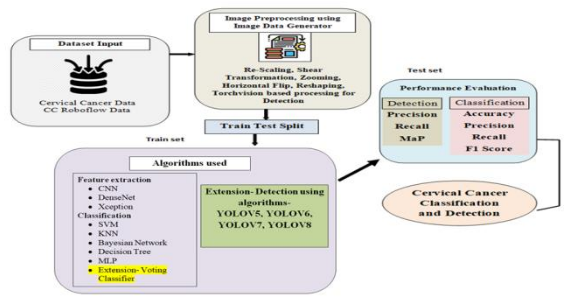


Fig 1 Proposed Architecture

c) Dataset:

The Cervical Cancer Roboflow dataset is a comprehensive collection of medical images specifically curated for the purpose of cervical cancer research and diagnosis. This dataset encompasses a wide range of high-resolution images depicting various aspects of cervical cancer pathology, including different stages of the disease, diverse tissue samples, and varying magnification factors.

The dataset includes images obtained from medical imaging procedures such as colposcopy and Pap smear screening, providing a comprehensive representation of cervical cancer cases. Each image is meticulously annotated with relevant metadata,

ISSN: 2278-4632
Vol-13 Issue-01 Jan 2023

including patient demographics, clinical history, and diagnostic outcomes.

Researchers and medical professionals can leverage this dataset for a multitude of purposes, including algorithm development, training and validation of machine learning models, and exploration of image processing techniques for cervical cancer diagnosis and classification. The dataset's diversity and richness make it a valuable resource for advancing research in cervical cancer detection, prognosis, and treatment.

Fig 2 Dataset

d) Image Processing:

Image processing plays a crucial role in preparing and augmenting images for various tasks such as classification and detection.

Using ImageDataGenerator:

Re-scaling the Image: This involves scaling down or up the pixel values of the image to a specific range, typically between 0 and 1. It ensures that the input pixel values are within a manageable range for efficient processing.

Shear Transformation: Shear transformation involves shifting one part of the image horizontally or vertically, creating a "sheared" effect. This can help introduce variability in the dataset and improve model generalization.

Zooming the Image: Zooming involves magnifying or reducing the size of the image. This can help simulate images taken at different distances or scales, enhancing the model's robustness to varying image sizes.

Horizontal Flip: Flipping the image horizontally can help increase the diversity of the dataset by generating mirror images. It helps prevent overfitting and improves the model's ability to generalize to unseen data.

Reshaping the Image: Reshaping the image involves resizing it to a specific width and height. This step ensures that all images in the dataset have consistent dimensions, which is necessary for training deep learning models.

Torchvision-based Processing for Detection:

Loading and Preprocessing Images: Using Torchvision, images are loaded and preprocessed according to the requirements of the detection model. This may involve resizing, normalization, and converting the images to tensors.

Bounding Box Annotation: If the images are annotated with bounding boxes, Torchvision provides utilities to handle the bounding box annotations, including conversion to tensor format and augmentation if necessary.

Data Augmentation: Torchvision offers various data augmentation techniques tailored for object detection tasks, such as random horizontal flips, random scaling, and random cropping. These augmentations help improve the model's ability to detect objects under different conditions.

ISSN: 2278-4632
Vol-13 Issue-01 Jan 2023

By following these steps, researchers and practitioners can effectively preprocess and augment images for both classification and object detection tasks, ultimately enhancing the performance and robustness of their deep learning models.

e) Algorithms:

Feature extraction:

CNN: Convolutional Neural Networks (CNNs) are deep learning models designed specifically for processing visual data like images. They consist of multiple layers, including convolutional layers for feature extraction, pooling layers for downsampling, and fully connected layers for classification. In the project, CNNs are used for feature extraction from cervical cancer images. They analyze the images, detecting patterns and features that are essential for classification tasks. The extracted features are then passed on to subsequent layers for classification. CNNs are effective in capturing hierarchical patterns in images, making them suitable for tasks like cervical cancer detection and classification.

DenseNet: DenseNet, short for Dense Convolutional Network, is a type of convolutional neural network (CNN) architecture known for its dense connectivity pattern between layers. In DenseNet, each layer receives direct input from all preceding layers and passes its own feature maps to all subsequent layers. This connectivity pattern encourages feature reuse, facilitates gradient flow, and reduces the number of parameters. In the project, DenseNet is employed for feature extraction from cervical cancer images. Its dense connectivity enables efficient feature propagation and extraction, contributing to improved accuracy in cervical cancer classification tasks while maintaining model compactness and computational efficiency.

Xception: Xception, an extension of convolutional neural networks (CNNs), introduces depthwise separable convolutions as a replacement for traditional convolutions. This architecture aims to enhance feature extraction while reducing computational complexity. In the project, Xception is utilized for feature extraction from cervical cancer images. Its efficient depthwise separable convolutions enable effective representation learning, contributing to improved classification accuracy. By leveraging Xception's capabilities, the project achieves enhanced performance in cervical cancer detection tasks, demonstrating the efficacy of advanced CNN architectures in medical image analysis.

Classification:

SVM: Support Vector Machine (SVM) is a supervised machine learning algorithm used for classification and regression tasks. In the project, SVM is employed as a traditional classifier to classify cervical cancer images based on extracted features. SVM works by finding the hyperplane that best separates different classes in the feature space. It maximizes the margin between classes, making it effective for binary and multi-class classification tasks. SVM's ability to handle high-dimensional feature spaces and its robustness to overfitting make it suitable for analyzing complex medical image datasets like those in cervical cancer diagnosis.

KNN: K-Nearest Neighbors (KNN) is a simple yet powerful machine learning algorithm used for classification and regression tasks. In KNN, the class of an unlabeled instance is determined by the classes

ISSN: 2278-4632
Vol-13 Issue-01 Jan 2023

of its nearest neighbors in the feature space. In the project, KNN is employed as a classification model for cervical cancer detection. By measuring the similarity between instances based on their features, KNN effectively identifies patterns in the data and assigns labels accordingly. Its simplicity and flexibility make it suitable for various classification tasks, including medical image analysis for cervical cancer diagnosis.

Bayesian Network: Bayesian Network, also known as a belief network, is a probabilistic graphical model that represents a set of variables and their conditional dependencies via a directed acyclic graph. In the project, Bayesian Networks are utilized for cervical cancer diagnosis by modeling the relationships between various risk factors and symptoms associated with the disease. By incorporating probabilistic reasoning, Bayesian Networks can infer the likelihood of different outcomes based on observed evidence. This allows for effective decision-making in medical diagnostics, helping to identify potential risk factors and provide personalized recommendations for patients.

Decision Tree: Decision Tree is a machine learning algorithm used in the project for cervical cancer classification. It is a tree-like model where each node represents a feature, each branch represents a decision based on that feature, and each leaf node represents the outcome or class label. Decision Trees are employed to analyze and extract patterns from medical data, aiding in the identification of relevant features for cervical cancer diagnosis. The algorithm is particularly useful for its transparency, allowing healthcare professionals to interpret and explain the decision-making process. By constructing a decision tree, the model facilitates effective classification of cervical cancer cases, contributing to improved diagnostic accuracy and personalized healthcare recommendations.

MLP: Multilayer Perceptron (MLP) is a type of artificial neural network commonly used for cervical cancer classification in the project. It consists of multiple layers of nodes (neurons), including an input layer, one or more hidden layers, and an output layer. Each node in the hidden layers uses nonlinear activation functions to process information from the previous layer. MLPs are trained using backpropagation and gradient descent algorithms to optimize weights and biases, enabling them to learn complex patterns in the data. In the project, MLPs are employed as powerful classifiers, capable of accurately predicting cervical cancer outcomes based on extracted features from medical images and patient data.

Detection:

YoloV5: YOLOv5 (You Only Look Once) is a state-of-the-art real-time object detection algorithm utilized in the project for cervical cancer detection. It employs a single neural network to divide images into a grid and predict bounding boxes and class probabilities for each grid cell. YOLOv5 is renowned for its efficiency and accuracy in detecting objects, making it suitable for processing medical images efficiently. In the project, YOLOv5 is utilized to detect cervical cancer features within images, facilitating early diagnosis and improving treatment outcomes through automated detection and classification of cancerous regions.

YoloV8: YOLOv8, an enhanced version of the You Only Look Once (YOLO) object detection algorithm, is employed in the project for cervical cancer

ISSN: 2278-4632
Vol-13 Issue-01 Jan 2023

detection. It leverages advanced features such as Extended Efficient Layer Aggregation Network (E-ELAN) and Compound Model Scaling to improve learning capabilities and adaptability. YOLOv8 excels in real-time object detection with superior accuracy, making it ideal for processing medical images efficiently. In the project, YOLOv8 is utilized to detect cancerous regions within cervical cancer images, aiding in early diagnosis and enhancing treatment outcomes through automated detection and classification.

4. EXPERIMENTAL RESULTS

Precision: Precision evaluates the fraction of correctly classified instances or samples among the ones classified as positives. Thus, the formula to calculate the precision is given by:

Precision = True positives/ (True positives + False positives) = TP/(TP + FP)

$$\text{Precision} = \frac{\mathit{True\ Positive}}{\mathit{True\ Positive} + \mathit{False\ Positive}}$$

Recall: Recall is a metric in machine learning that measures the ability of a model to identify all relevant instances of a particular class. It is the ratio of correctly predicted positive observations to the total actual positives, providing insights into a model's completeness in capturing instances of a given class.

$$\mathit{Recall} = \frac{TP}{TP + FN}$$

F1-Score: F1 score is a machine learning evaluation metric that measures a model's accuracy. It combines the precision and recall scores of a model. The accuracy metric computes how many times a model made a correct prediction across the entire dataset.

$$\textbf{F1 Score} = \frac{2}{\left(\frac{1}{\text{Precision}} + \frac{1}{\text{Recall}}\right)}$$

$$\textbf{F1 Score} = \frac{2 \times \text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}$$

Accuracy: The accuracy of a test is its ability to differentiate the patient and healthy cases correctly. To estimate the accuracy of a test, we should calculate the proportion of true positive and true negative in all evaluated cases. Mathematically, this can be stated as:

Accuracy = TP + TN TP + TN + FP + FN.

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

mAP: The mAP for object detection is the average of the AP calculated for all the classes. mAP@0.5 means that it is the mAP calculated at IOU threshold 0.5. The general definition for the Average Precision(AP) is finding the area under the precision-

ISSN: 2278-4632
Vol-13 Issue-01 Jan 2023

recall curve.

$$mAP = \frac{1}{n}\sum_{k=1}^{k=n} AP_k$$

$$AP_k = \text{the AP of class } k$$

$$n = \text{the number of classes}$$

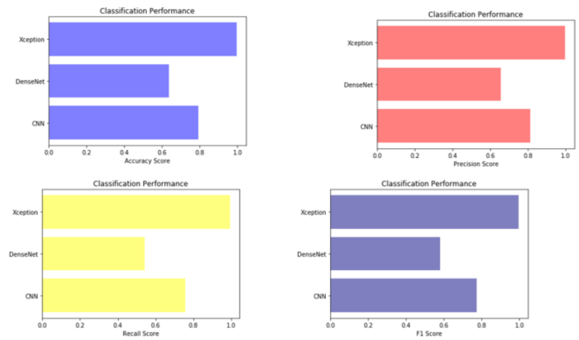


Fig 3 Comparison Graphs- Feature Extraction

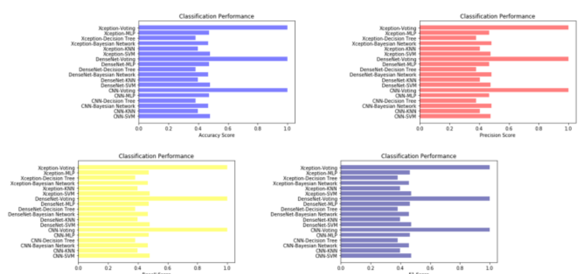


Fig 4 Comparison Graphs- Classification

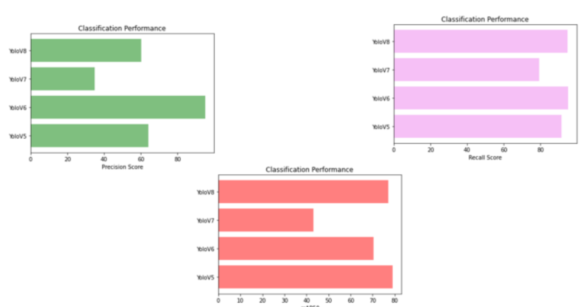


Fig 5 Comparison Graphs- Detection

	ML Model	Accuracy	Precision	Recall	F1-Score
0	CNN-SVM	0.480	0.476	0.480	0.472
1	CNN-KNN	0.398	0.404	0.398	0.397
2	CNN-BayesianNetwork	0.467	0.481	0.467	0.456
3	CNN-Decision Tree	0.381	0.380	0.381	0.381
4	CNN-MLP	0.472	0.468	0.472	0.464
5	**Extension- CNN-Voting Classifier**	**1.000**	**1.000**	**1.000**	**1.000**
6	DenseNet-SVM	0.480	0.476	0.480	0.472
7	DenseNet-KNN	0.398	0.404	0.398	0.397
8	DenseNet-BayesianNetwork	0.467	0.481	0.467	0.456
9	DenseNet-Decision Tree	0.381	0.380	0.381	0.381
10	DenseNet-MLP	0.472	0.468	0.472	0.464
11	**Extension- DenseNet-Voting Classifier**	**1.000**	**1.000**	**1.000**	**1.000**
12	Xception-SVM	0.480	0.476	0.480	0.472
13	Xception-KNN	0.398	0.404	0.398	0.397
14	Xception-BayesianNetwork	0.467	0.481	0.467	0.456
15	Xception-Decision Tree	0.381	0.380	0.381	0.381
16	Xception-MLP	0.472	0.468	0.472	0.464
17	**Extension- Xception-Voting Classifier**	**1.000**	**1.000**	**1.000**	**1.000**

Fig 6 Performance Evaluation Table – Classification

	ML Model	MaP	Precision	Recall
0	**Extension- YOLOV5**	**79**	**64.2**	**91.6**
1	Extension- YOLOV6	70.5	95.0	95.0
2	Extension- YOLOV7	43.2	35.0	79.2
3	Extension- YOLOV8	77.1	60.1	94.7

Fig 7 Performance Evaluation Table – Detection

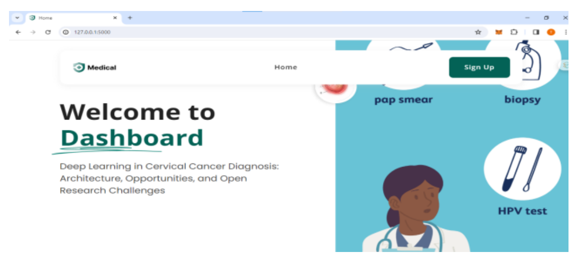


Fig 8 Home Page

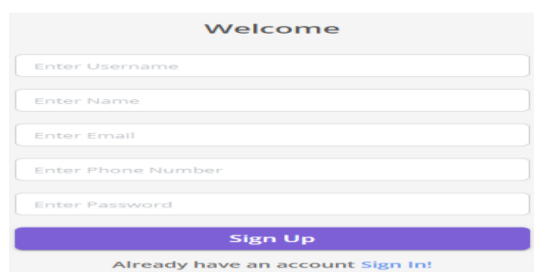
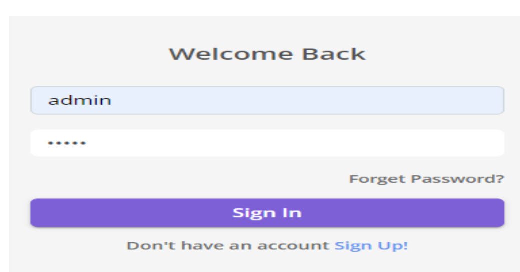


Fig 9 Registration Page



ISSN: 2278-4632
Vol-13 Issue-01 Jan 2023

Fig 10 Login Page

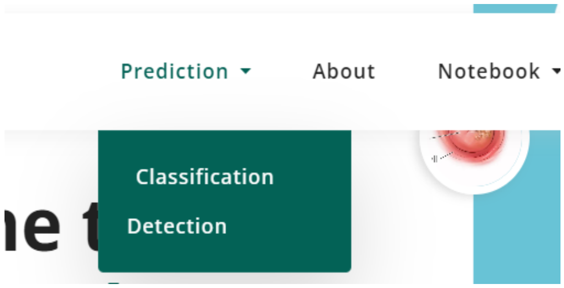


Fig 11 For Classification

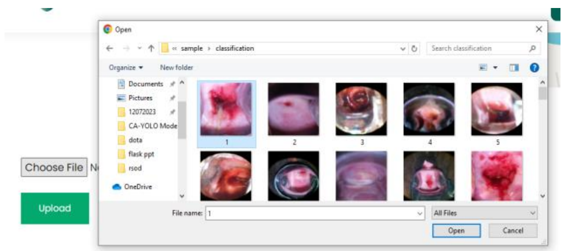


Fig 12 Upload Input Image

Fig 13 Predicted Results

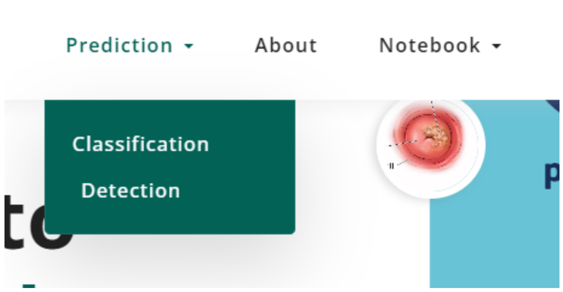


Fig 14 For Detection

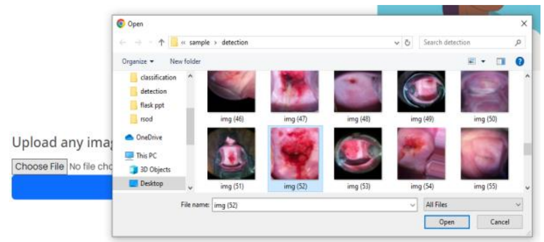


Fig 15 Upload Input Image

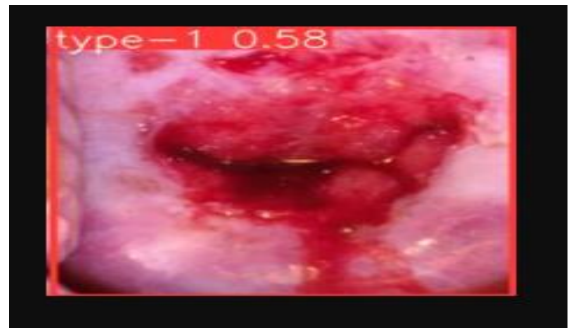


Fig 16 Final Outcome

5. CONCLUSION

The review of DL-based solutions for cervical screening images underscores their pivotal role in CC cytopathology and colposcopy image processing. CNNs have shown remarkable performance in segmentation and classification, aiding early detection, diagnosis, and treatment. Despite their success, there's room for improvement, urging exploration of compound algorithms and advanced DL techniques.

Existing literature favors CNN architectures like ANFIS, Caps Net, ResNet, VGGNet, and AlexNet for feature extraction and classification. Future research should explore mixed feature selection with DL algorithms such as RCNN, Faster RCNN, and VGG19 to advance CC classification.

In essence, DL integration in cervical screening analysis highlights the ongoing quest for refinement

ISSN: 2278-4632
Vol-13 Issue-01 Jan 2023

and innovation. By leveraging diverse DL architectures and methodologies, researchers can enhance accuracy, efficiency, and ultimately, patient outcomes in the fight against cervical cancer.

6. FUTURE SCOPE

Future research in DL-based cervical screening image analysis could explore novel approaches such as multi-modal fusion techniques to leverage complementary information from different imaging modalities. Additionally, investigating semi-supervised and self-supervised learning methods could mitigate the reliance on large annotated datasets, thus facilitating model deployment in resource-constrained settings. Furthermore, integrating domain adaptation and transfer learning strategies could enhance model generalization across diverse patient populations and healthcare settings. Embracing interpretability and explainability techniques would also foster trust and adoption of DL models in clinical practice. Overall, these advancements hold promise for refining CC classification systems and fostering personalized patient care.

REFERENCES

[1] P. Meyer, V. Noblet, C. Mazzara, and A. Lallement, ‘‘Survey on deep learning for radiotherapy,’’ Comput. Biol. Med., vol. 98, pp. 126–146, Jul. 2018, doi: 10.1016/j.compbiomed.2018.05.018.

[2] J. Chmelik, R. Jakubicek, P. Walek, J. Jan, P. Ourednicek, L. Lambert, E. Amadori, and G. Gavelli, ‘‘Deep convolutional neural network-based segmentation and classification of difficult to define metastatic spinal lesions in 3D CT data,’’ Med. Image Anal., vol. 49, pp. 76–88, Oct. 2018, doi: 10.1016/j.media.2018.07.008.

[3] S. K. Singh, R. Singh, and A. Goyal, ‘‘Semi-automatic segmentation of overlapping cells in pap smear image,’’ in Proc. 4th Int. Conf. Comput. Sci. (ICCS), Aug. 2018, pp. 161–165, doi: 10.1109/ICCS.2018. 00034.

[4] A. Jhingran et al., ‘‘Cancers of the cervix, vulva, and vagina,’’ in Abeloff 's Clinical Oncology, Amsterdam. The Netherlands: Elsevier, 2020, pp. 1468–1507.

[5] Z. Alyafeai and L. Ghouti, ‘‘A fully-automated deep learning pipeline for cervical cancer classification,’’ Exp. Syst. Appl., vol. 141, Mar. 2020, Art. no. 112951, doi: 10.1016/j.eswa.2019.112951.

[6] F. Bray, J. Ferlay, I. Soerjomataram, R. L. Siegel, L. A. Torre, and A. Jemal, ‘‘Global cancer statistics 2018: GLOBOCAN estimates of incidence and mortality worldwide for 36 cancers in 185 countries,’’ CA, Cancer J. Clin., vol. 68, no. 6, pp. 394–424, 2018, doi: 10.3322/caac.21492.

[7] W. Yang, X. Gou, T. Xu, X. Yi, and M. Jiang, ‘‘Cervical cancer risk prediction model and analysis of risk factors based on machine learning,’’ in Proc. 11th Int. Conf. Bioinf. Biomed. Technol., May 2019, pp. 50–54, doi: 10.1145/3340074.3340078.

[8] W. J. Koh, B. E. Greer, N. R. Abu-Rustum, S. M. Apte, S. M. Campos, K. R. Cho, C. Chu, D. Cohn, M. A. Crispens, O. Dorigo, and P. J. Eifel, ‘‘Cervical cancer, version 2.2015,’’ J. Nat. Comprehensive Cancer Netw., vol. 13, no. 4, pp. 395–404, 2015, doi: 10.6004/jnccn.2015.0055.

ISSN: 2278-4632
Vol-13 Issue-01 Jan 2023

[9] H. A. Almubarak, R. J. Stanley, R. Long, S. Antani, G. Thoma, R. Zuna, and S. R. Frazier, ''Convolutional neural network based localized classification of uterine cervical cancer digital histology images,'' Proc. Comput. Sci., vol. 114, pp. 281–287, 2017, doi: 10.1016/j.procs.2017.09.044.

[10] P. Guo, S. Singh, Z. Xue, R. Long, and S. Antani, ''Deep learning for assessing image focus for automated cervical cancer screening,'' in Proc. IEEE EMBS Int. Conf. Biomed. Health Informat. (BHI), May 2019, pp. 1–4, doi: 10.1109/BHI.2019.8834495.

[11] V. Kudva, K. Prasad, and S. Guruvare, ''Automation of detection of cervical cancer using convolutional neural networks,'' Critical Rev. Biomed. Eng., vol. 46, no. 2, pp. 135–145, 2018, doi: 10.1615/CritRevBiomedEng.2018026019.

[12] C. Wojtyla, K. Janik-Koncewicz, and C. La Vecchia, ''Cervical cancer mortality in young adult European women,'' Eur. J. Cancer, vol. 126, pp. 56–64, Feb. 2020, doi: 10.1016/j.ejca.2019.11.018.

[13] H. A. Phoulady, Adaptive Region-Based Approaches for Cellular Segmentation of Bright-Field Microscopy Images. Univ. South Florida, May 2017.

[14] A. Ghoneim, G. Muhammad, and M. S. Hossain, ''Cervical cancer classification using convolutional neural networks and extreme learning machines,'' Future Gener. Comput. Syst., vol. 102, pp. 643–649, Jan. 2020, doi: 10.1016/j.future.2019.09.015.

[15] B. Harangi, J. Toth, G. Bogacsovics, D. Kupas, L. Kovacs, and A. Hajdu, ''Cell detection on digitized pap smear images using ensemble of conventional image processing and deep learning techniques,'' in Proc. 11th Int. Symp. Image Signal Process. Anal. (ISPA), Sep. 2019, pp. 38–42.

[16] H. Zhu, F. Meng, J. Cai, and S. Lu, ''Beyond pixels: A comprehensive survey from bottom-up to semantic image segmentation and cosegmentation,'' J. Vis. Commun. Image Represent., vol. 34, pp. 12–27, Jan. 2016, doi: 10.1016/j.jvcir.2015.10.012.

[17] R. Achanta, A. Shaji, K. Smith, A. Lucchi, P. Fua, and S. Süsstrunk, ''SLIC superpixels compared to state-of-the-art superpixel methods,'' IEEE Trans. Pattern Anal. Mach. Intell., vol. 34, no. 11, pp. 2274–2282, Nov. 2011.

[18] D. Comaniciu and P. Meer, ''Mean shift: A robust approach toward feature space analysis,'' IEEE Trans. Pattern Anal. Mach. Intell., vol. 24, no. 5, pp. 603–619, May 2002.

[19] A. Kaul, ''A fundamental review on hyperspectral segmentation algorithms,'' in Applications of Networks, Sensors and Autonomous Systems Analytics. Berlin, Germany: Springer, 2022, pp. 165–185.

[20] M. Chikhaoui, F. Smail, A. B. S. Aissa, H. Benhamida, and R. Hamri, ''A retrospective study on cervical cancer screening using pap smear and related factors among women living in tiaret, Algeria,'' Indian J. Gynecologic Oncol., vol. 18, no. 4, pp. 1–8, Dec. 2020.

[21] A. A. Abdullah, A. Fonetta, D. Giong, N. Adilah, and H. Zahri, ''Cervical cancer detection method using an improved cellular neural network (CNN) algorithm,'' Indonesian J. Elect. Eng. Comput. Sci., vol. 14, no. 1, pp. 210–218, 2019, doi: 10.11591/ijeecs.v14.i1.pp210-218.

[22] Y. Miyagi, K. Takehara, Y. Nagayasu, and T. Miyake, ''Application of deep learning to the classification of uterine cervical squamous epithelial lesion from colposcopy images combined with HPV types,'' Oncol. Lett., pp. 1602–1610, Dec. 2019, doi: 10.3892/ol.2019.11214.

[23] S. Fekri-Ershad, ''Pap smear classification using combination of global significant value, texture statistical features and time series features,'' Multimedia Tools Appl., vol. 78, no. 22, pp. 31121–31136, Nov. 2019, doi: 10.1007/s11042-019-07937-y.

[24] T. Zhang, Y. Luo, P. Li, P. Liu, Y. Du, and P. Sun, ''Biomedical signal processing and control cervical precancerous lesions classification using pre-trained densely connected convolutional networks with colposcopy images,'' Biomed. Signal Process. Control, vol. 55, Jan. 2020, Art. no. 101566, doi: 10.1016/j.bspc.2019.101566.

[25] J. Liu, Y. Peng, and Y. Zhang, ''A fuzzy reasoning model for cervical intraepithelial neoplasia classification using temporal grayscale change and textures of cervical images during acetic acid tests,'' IEEE Access, vol. 7, pp. 13536–13545, 2019, doi: 10.1109/ACCESS.2019. 2893357.

[26] H. Chen, L. Yang, L. Li, M. Li, and Z. Chen, ''An efficient cervical disease diagnosis approach using segmented images and cytology reporting,'' Cognit. Syst. Res., vol. 58, pp. 265–277, Dec. 2019, doi: 10.1016/j.cogsys.2019.07.008.

[27] L. Hu, D. Bell, S. Antani, Z. Xue, K. Yu, M. P. Horning, N. Gachuhi, B. Wilson, M. S. Jaiswal, B. Befano, and L. R. Long, ''An observational study of deep learning and automated evaluation of cervical images for cancer screening,'' J. Nat. Cancer Inst., vol. 111, no. 9, pp. 923–932, Sep. 2019, doi: 10.1093/jnci/djy225.

[28] Y. Tanaka Ueda, R. Kakubari, M. Kakuda, S. Kubota, S. Matsuzaki, A. Okazawa, T. Egawa-Takata, S. Matsuzaki, E. Kobayashi, and T. Kimura, ''Histologic correlation between smartphone and coloposcopic findings in patients with abnormal cervical cytology: Experiences in a tertiary referral hospital,'' Amer. J. Obstetrics Gynecology, vol. 221, no. 3, p. 241, 2019, doi: 10.1016/j.ajog.2019.04.039.

[29] X. Zhang and S.-G. Zhao, ''Cervical image classification based on image segmentation preprocessing and a CapsNet network model,'' Int. J. Imag. Syst. Technol., vol. 29, no. 1, pp. 19–28, Mar. 2019, doi: 10.1002/ima.22291.

[30] P. Elayaraja and M. Suganthi, ''Automatic approach for cervical cancer detection and segmentation using neural network classifier,'' Asian Pacific J. Cancer Prevention, vol. 19, no. 12, pp. 3571–3580, Dec. 2018, doi: 10.31557/APJCP.2018.19.12.3571.

[31] B. K. Jaya and S. S. Kumar, ''Image registration based cervical cancer detection and segmentation using ANFIS classifier,'' Asian Pacific J. Cancer Prevention, vol. 19, no. 11, pp. 3203–3209, Nov. 2018, doi: 10.31557/APJCP.2018.19.11.3203.

[32] K. Gutiérrez-Fragoso, H. G. Acosta-Mesa, N. Cruz-Ramírez, and R. Hernández-Jiménez, ''Optimization of classification strategies of acetowhite temporal patterns towards improving diagnostic performance of colposcopy,'' Comput. Math. Methods Med., vol. 2017, pp. 1–10, Jul. 2017.

[33] Y. Fu, Y. Lei, T. Wang, W. J. Curran, T. Liu, and X. Yang, ‘‘Deep learning in medical image registration: A review,’’ Phys. Med. Biol., vol. 65, no. 20, Oct. 2020, Art. no. 20TR01.

[34] K. Doi, ‘‘Computer-aided diagnosis in medical imaging: Historical review, current status and future potential,’’ Comput. Med. Imag. Graph., vol. 31, pp. 198–211, Jun. 2007, doi: 10.1016/j.compmedimag.2007. 02.002.

[35] G. M. T. Brake, N. Karssemeijer, and J. H. C. L. Hendriks, ‘‘An automatic method to discriminate malignant masses from normal tissue in digital mammograms1,’’ Phys. Med. Biol., vol. 45, no. 10, pp. 2843–2857, Sep. 2000, doi: 10.1088/0031-9155/45/10/308.

DatasetLink:

Classification: https://www.kaggle.com/datasets/sakibapon/cervical-cancer-balanced-dataset

Detection : https://roboflow.com/convert/labelbox-json-to-yolov5-pytorch-txt