A Comparative Analysis Of Pretrained Convolutional Neural Networks For Colposcopy-Based Cervical Cancer Classification Under Imbalanced And Augmented Data Conditions

ChandraPrabha R [1], Seema Singh[2]

[1]Dept. Electronics and Communication Engineering, BMSIT&M, Karnataka, India
[2]Dept. Electronics and Communication Engineering, BMSIT&M, Karnataka, India
[1]chandra@bmsit.in
[2]seemasingh@bmsit.in

ABSTRACT

In medical image processing and diagnosis, a robust and generalized deep learning model is extremely important to produce a precision decision. Deep learning models that can sustain stability and accuracy in the context of restricted data availability are essential for reliable automated diagnosis. This work investigates the performance of various pretrained models when trained on both balanced and imbalanced image dataset. The data set is comprised of three classes, CIN1, CIN2, and CIN3, which are colposcopy-based cervical images.
The prediction rate quality metrics for several models with augmentation range from 40.4% to 99.4% across different classes. The quality metrics of prediction rate for various models without augmentation ranged from 40.6 to 98.6% for various classes. The average classification test accuracy prior to augmentation for Class 1, Class 2 and Class 3 are 0.59,0.645 and 0.4, respectively. The average classification test accuracy with augmentation for Class 1, Class 2, and Class 3 is 0.947, 0.99, and 0.99, respectively. The results demonstrate there is an enhancement in the performance of the models with data augmentation. The comparative study on the models is also evaluated to ensure an accurate classification rate of colposcopy-based cervical cancer images.

KEYWORDS: Accuracy, artificial intelligence, deep learning, hyper parameters, image augmentation, machine learning, quantitative measures, recall, specificity.

How to Cite: Chandra Prabha R, Seema Singh., (2025) A Comparative Analysis Of Pretrained Convolutional Neural Networks For Colposcopy-Based Cervical Cancer Classification Under Imbalanced And Augmented Data Conditions, Vascular and Endovascular Review, Vol.8, No.11s, 212--221.

INTRODUCTION

Globally, cervical cancer is a foremost origin for the decease of females, with 662,044 active cases besides 348,709 demises [1]. The cervical tumour has a long preinvasive stage and is determined by dedicated clinicians, experienced medical professionals, and paramedical workers through manual examinations. The prevention and medication of cervical cancer are achievable, if the cases are timely detected and classified. Colposcopy is one of the vital diagnostic system for detecting healthy and unhealthy lesions through visual examination [2].

In today's world, the continuing development of machine learning algorithms, especially deep learning, has rendered big data analysis utilizing artificial intelligence (AI) prevalent throughout numerous domains, including medicine.

In recent years, the fusion of artificial intelligence (AI) with the medical domain has developed as a field of chief potential as well as resolution, signifying the change in providing the chances to improve the precision, efficiency, and accessibility of healthcare services. Artificial intelligence denotes the emulation of human cognitive processes by computers, which encompasses learning, thinking, and self-correction.

In healthiness diagnostics, AI analyzes the medical statistics and information, identifies observations, and estimates predictions, frequently with superior speed and precision compared to human practitioners. Artificial intelligence can facilitate the management of these difficulties by enhancing human capacities, resulting in more prompt and precise diagnoses. Moreover, the utilization of AI in diagnostics may diminish healthcare expenses and enhance patient experiences by providing tailored and efficient care [3-4].

A REVIEW STUDY

A significant accomplishment in image recognition and classification with the classified image label as output is possible through the deep learning convolution neural network.

In an outmoded colposcopy inspection, the diagnosis of cervical intraepithelial neoplasia (CIN) is extremely dependent on the medical expert's skilled practice and expertise. Manual observations limit the accuracy and diagnostic ability in identifying initial and advanced cervical lesions. The false negative rates vary due to differences among physicians and the regions from which samples are collected. Thus, to lessen the incorrect medical evaluation of cancerous lesions, gynecologists must have augmented samples [1]. The oral data such as categorical, Boolean collected from the patient and non-patient integrated with machine learning algorithms will help out the doctors to identify the unhealthy cases, but the accuracy will not be satisfactory as few patients may provide the inadequate data[5]. In conventional practice, a precise classification of colposcopy data by a physician depends on the medical doctors proficiency and skill.

A pretrained densely coupled convolutional network, the colposcopic images are classified with higher diagnostic accuracy. With VGG19 an accuracy of 73.3% is achieved but with Colposcopy Ensemble Network the classification accuracy model is improved by 19% [6]. The Dense-U-Net model achieves the diagnosis accuracy of 89% for CIN3 and 75% for CIN2 [2]. Author [7] recommends a classification model with ResNet with a sensitivity of 85.38% and a specificity of 82.62%. The U-Net and Mask R-CNN models can detect HSIL lesions. A deep learning-based CAD system that integrates ResNet and clinical features to classify NC and LSIL+ exhibits an area under the receiver operating characteristic curve (AUC) of 0.953, with accuracy, sensitivity, specificity, positive predictive value (PPV), and negative predictive value (NPV) of 0.886, 0.932, 0.846, 0.838, and 0.936, respectively. The AUC, accuracy, sensitivity, specificity, PPV, and NPV for the categorization of HSIL− and HSIL+ were 0.900, 0.807, 0.823, 0.800, 0.618, and 0.920, respectively [8].

A colposcopic multimodal fusion convolutional neural network is proposed for 7106 cases of colposcopy images. The models achieves an accuracy, macro-area under the curve, and macro F1-score of 92.70%, 98.56%,and 92.74%, respectively [9]. EfficientNet-b0 classifies HSIL, LSIL, and normal with an accuracy of 91.18% [10]. CNN Deep learning classifies at the rate of accuracy in the training stage above 92%, and the highest achieved accuracy was 99% [11]. The ColpoNet, driven by the DenseNet model, produces with an accuracy of 81.353% [12]. RetinaNet is proposed to detect lesion areas in colposcopic images [13]. The author presents the use of segmentation with U-Net and classification with SVM achieving 70% of sensitivity, 48.8% of specificity, and 58% of accuracy [14].

EfficientNetB0 and MobileNetV2 are proposed to capture critical lesion features. The extracted features are then combined and passed through an ensemble of three classifiers: logistic regression, XGBoost, and Cat Boost attaining the validation accuracy up to 99.85% [15]. A gated recurrent convolutional neural network for colposcopic image processing incorporates time series and integrated multistate cervical images for cervical intraepithelial neoplasia grading achieving ed an accuracy, a sensitivity, and a specificity of 96.87 %, 95.68 %, and 98.72 % respectively [16]. An imbalanced dataset will restrict the proper functioning of deep learning models with respect to the classification of abnormal cases from normal cases. Therefore, to achieve effective classification, a substantial dataset and a balanced sample distribution must be established by augmentation [17]. The essential criteria for structuring an intensive deep learning model are the quality and amount of the training data.

Data augmentation process increases the small data set to higher value.
The techniques for image augmentation involve random rotations, image resizing, image random reflection, image random scaling, feature space augmentation, generative adversarial networks. Image augmentation, a type of regularization to avoid model overfitting [18].

Artificial intelligence with image processing evaluates medical statistics, ecommerce, recognizes patterns, and forecasts outcomes, often with more speed and accuracy than human professionals.

Artificial intelligence can aid in addressing these challenges by augmenting human abilities, leading to more timely and accurate diagnoses of unhealthy conditions. [24-28].

The comprehensive review specifies that AI is indispensable for the initial detection and treatment of diseases without delaying. The application of deep learning models in the medical field has extensively enhanced classification efficiency. According to the survey, there is a constraint in which not all pretrained models are applied in the classification task of colposcopy images with augmentation in order to attain the findings.

This research paper is organized methodically. The article begins with a comprehensive examination of prior research, proposed methodology, descriptions of models and datasets, and an evaluation of the results.

MATERIALS AND METHODOLOGY

A. Data Set

The data set with colposcopy based cervical images are publicly available [19] and has a limited number of abnormal and normal cases. Colposcopy is a low-powered microscopic examination of the epithelium of the lower genital tract, enhanced by light illumination.The colposcopy based cervical images include three classes of images, namely CIN1, CIN2, and CIN3, which indicate levels of abnormality. Cervical dysplasia is a precancerous condition in which abnormal cells breed on the surface of the cervix. The three grades of CIN are based on the thickness of the cervical lining. In CIN 1—Approximately one-third of the cervical lining's thickness contains cells that are abnormal. CIN 2—Abnormal cells can be seen in the cervical lining up to two-thirds of its thickness. CIN 3—the full thickness of the lining covering the cervix has abnormal cells.

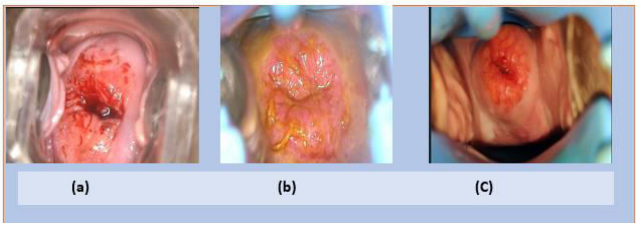


Fig. 1. Cervical Dysplasia (CIN): (a) CIN1 (b) CIN2 (c) CIN3

Fig. 1 depicts the samples belonging to low grade, high grade with one-third thickness, and high-grade images with full thickness. In this research, CIN1, CIN2, CIN3 classes are designated as class 1, class 2, and class 3.

The total data set includes 133 images, in which 52 belong to class 1, 49 belong to class 2, and 32 belong to class 3. The pretrained architecture models such as AlexNet, Google Net, Inception Net, Mobile Net, ResNet-50, and VGGNet are trained, validated, and tested with colposcopy images for cervical cancer classifications. The architectures are trained with hardware processor Intel(R) Xeon(R) E-2224G CPU @ 3.50 GHz 3.50 GHz. The software platform used is MATLAB R2025 Campus-Wide License.

TABLE I SPECIFICATION OF THE WORKSTATION

Units	Specification of the model
GPU	Multiple GPUs, 64-bit OS
Memory	23.70 TB

Table I indicates the specification of the workstation employed in experimenting with the work.
The tuned pre-trained architectures are trained, validated, and tested with hardware processor Intel(R) Xeon(R) E-2224G CPU @ 3.50GHz 3.50 GHz. The software platform utilized for this project is the MATLAB R2025 Campus-Wide License.
.

B. Data Preprocessing and Data Augmentation

The data set of colposcopy based cervical images for cervical cancer classification are sized at 640x480 dpi. All images are scaled to the required input dimensions of the pretrained network.

Table II Dimension Normalization for Pretrained CNN

Models	Image resized.	Total Augmented Images
Model 1	227 × 227 × 3	784
Model 2	224 × 224 × 3	784
Model 3	299 × 299 × 3	784
Model 4	224 × 224 × 3	784
Model 5	224 × 224 × 3	784
Model 6	224 × 224 × 3	784

The table II illustrates Images are adjusted to the standard resolution expected by the pretrained architecture. The robustness and generalizability of the models can be enhanced by training the model with large data. The small amount of data set can be augmented to larger volume. The different augmentation operations adopted are rotation, horizontal flip, vertical flip and translation. The class1, class2, class3 are increased by a ratio of 1:15.09, 1:16, 2:49 respectively.

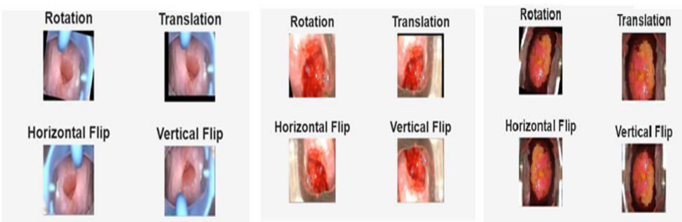


Fig. 2 .Spatially Augmented Images with Flip, Rotation, Translation (a) Class1 (b) Class 2 (c) Class3

The small amount of data set can be augmented to larger volume. The different augmentation operations adopted are rotation, horizontal flip, vertical flip and translation. The class1, class2, class3 are increased by a ratio of 1:15.09, 1:16, 2:49 respectively. In Fig. 2., the geometrical transformation of images is represented that is attained through augmentation.

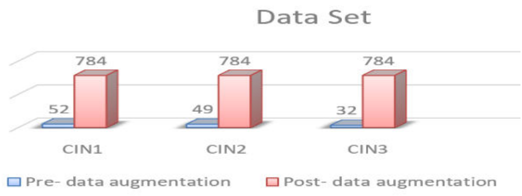


Fig. 2. Visual Variations among Dataset Images

Fig. 3. illustrates the amount of data set increased after augmentation. The total data set is augmented by increased factor of 17.68.

C. Methodology

The colposcopy cervical images are fed as input to the pre-trained model with a modified fully connected layer according to the number of output classes. In this work, the various architectures such as Model 1, Model 2, Model 3, Model 4, Model 5, and Model 6 that are designated as AlexNet, GoogleNet, InceptionNet, MobileNet, ResNet-50 are adopted to classify the images as class 1,class 2 and class 3. With deep learning, classification is more robust. The CNN architecture is a network for processing the data through convolutional layers.

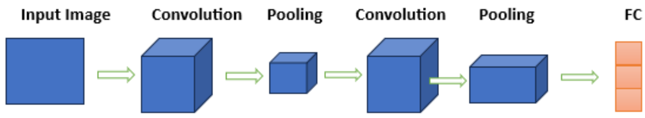
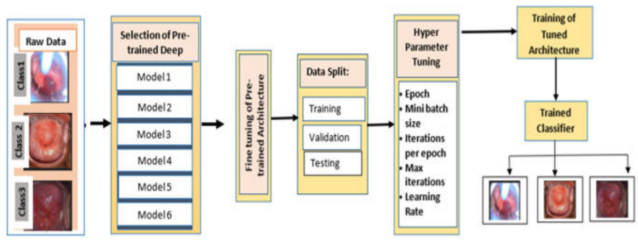


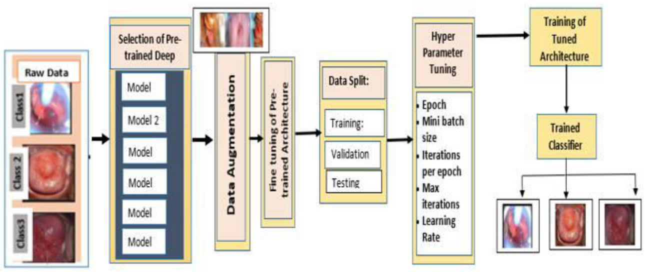
Fig. 4. The Architecture of CNN

It consists of a series of layers, typically starting with convolutional and pooling layers to acquire features, followed by fully connected layers that use the extracted features for classification, as shown in Fig.4.

AlexNet is a deeper network architecture with five convolutional layers and three fully connected layers, which significantly improves image classification performance. In order to improve the problem of calculation speed, ResNet is a deep residual network[20] structure that employs residual modules and residual connections and The GoogleNet contains 22 concealed layers [21]. Inception-v3 is a deep pre-trained convolutional neural network model, and it is able to acquire and distinguish complex patterns and features in medical images. [22] MobileNets are efficient models for mobile vision application using depth wise separable convolution with strong performance on classification [23-24]



(a)



(b)

Fig. 5. The flow of implementation of the work (a) Pre-data augmentation (b) Post data augmentation

Fig. 5. illustrates the work flow in classification of cervical images to class1, class2 and class3. The cervical colposcopy images are pre-processed, augmented and propagated to pre-trained models. For all the pre-trained models, the fully connected layer is modified based on number of classes. In this experimental work, the fully connected layer is modified to 3 classes. For medical applications, building a model from scratch is unpractical due to limited clinical data and the requirement of computational

resources. Hence the concept of transfer learning arises[25]. The modified models are tuned through hyper parameters. Later, the network is trained with the training data and validated with the reserved percentage of validation data. The trained model is tested with the unseen data. The data set splitting is 70 percent for training the model, 15% for validating the network, and the remaining 15% is reserved for testing the trained model. Stochastic gradient descent optimizer was fixed for all the modified pretrained models. The hyperparameter-tuned with a learning rate of **0.0001**, momentum of **0.8**, batch size of **128, 180 epochs**, and a weight-decay regularization value of **0.0001**, along with data augmentation to ensure robust classification. Later, the same models were re-tuned with an different hyper-parameter set using a learning rate of **0.0001**, momentum of **0.9,** batch size of **128, 180 epochs**, and a higher weight-decay regularization value of **0.01**. The hyper-tuned models underwent training until convergence was reached, guaranteeing satisfactory and consistent performance.

Results And Discussions

The models were trained with hyper-parameters that had been fine-tuned to achieve a converged and effective classifier. The hyper parameter tuning makes the system steadier and more effective.

After the training, the converged models were evaluated on different data to verify their generalization efficacy. The performance metrics for each tuned model are recorded, and a comparative analysis both with and without augmentation, is presented. During the training phase, Model 2 and Model 4 were forced for early manual stopping to prevent overfitting.

All deep learning models underwent training, validation, and testing in both augmented and non-augmented conditions. The distribution of samples for the training, testing, and validation subgroups across all categories is summarized in Table IV.

Table IV. Distribution of Samples Across Training, Validation, and Testing Sets

Pre-augmentation

	Class 1	Class 2	Class 3	Total
Images	52	49	32	133
Training	36	34	22	92
Testing	8	8	5	21
Validation	8	7	5	20

Post- augmentation

	Class 1	Class 2	Class 3	Total
Images	784	784	784	2352
Training	549	118	117	1647
Testing	549	118	117	351
Validation	549	118	117	354

In multiclass classification, quantitative metrics are recorded and plotted. Four properties of class Ci—true positive (TP), true negative (TN), false positive (FP), and false negative (FN)—are used to determine accuracy, precision, specificity, false negative rate, false positive rate, recall, AUC score.

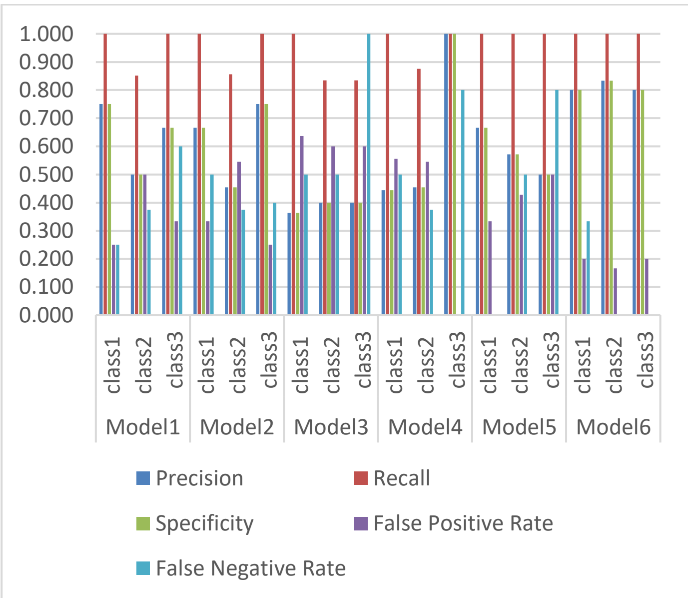


Fig. 6. Plot of Performance metric for various models with pre-augmentation

The performance metrics precision, recall, specificity, False Positive Rate, False Negative Rate and F1are measured for each model with pre-augmentation is represented in the Fig.6. From figure 4, Model 5 and Model 6 are predicting lesser false positive rates and model 3 is exhibiting high false positives whereas model 4. Model 5 and Model 6 can detect every positive case since all Classes recall is 100% and 0.8 of specificity. From the observations the model 6 predicts less false alarms due less FPR and FNR.

Area Under the ROC Curve (AUC) is a critical metric to evaluate the classification model depicted in Fig.7. Based on the analysis of Fig. 7, model 6 performs best classification separation with AUC for class1, class2 and class3 as 0.971, 0.894 and 0.962 respectively. Model 3 has AUC for all three classes are 0.471, 0.567, and 0.563.

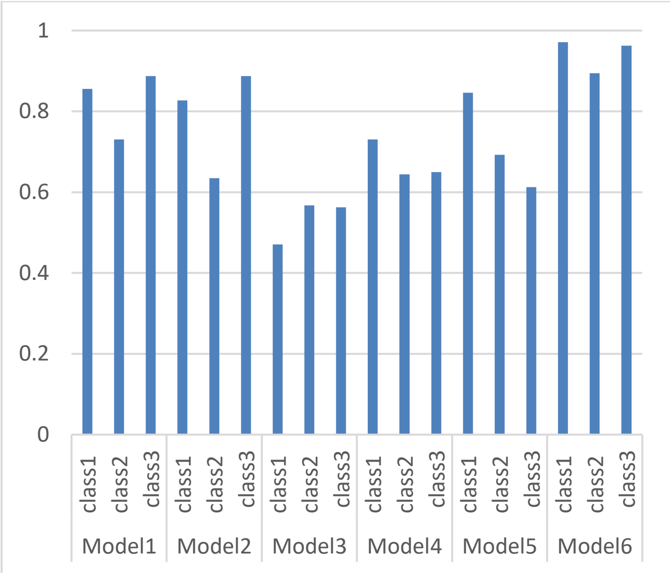


Fig.7. AUC plot for various model with pre augmentation

In multiclass classification, accuracy for each class is evaluated against all classes. From the Fig.8. model 6 performs classification with high accuracy. Model 5 is showing moderate classification towards class1 and class2.

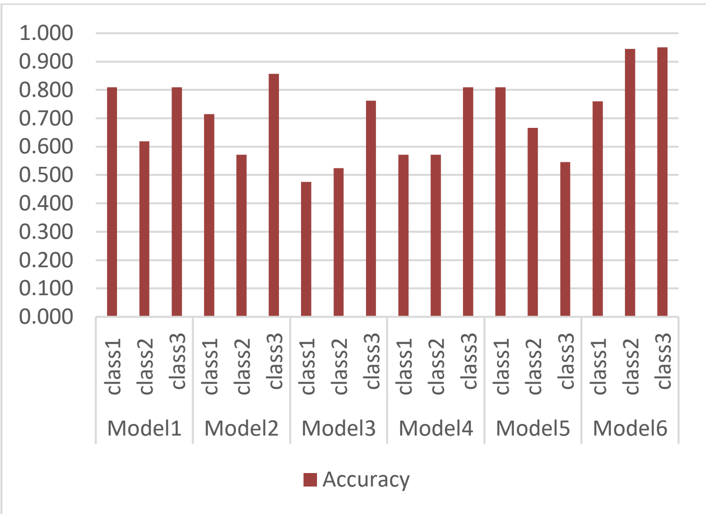


Fig.8. Measured accuracy of each class with models on pre-augmented data

Later the models are trained, tested and validated on augmented data set. When the classifier work with huge data post augmentation, the performance metrics records display an enhanced improvement.

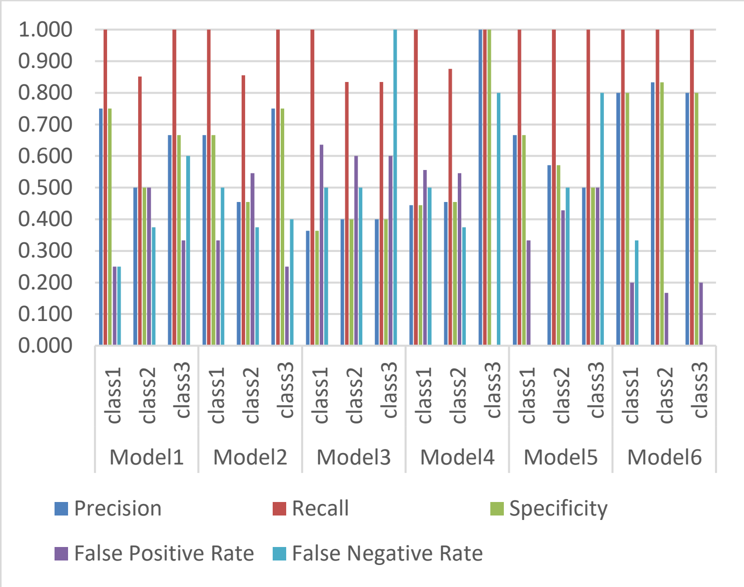


Fig. 8. Metrics measured for the models on post-augmentation

From Fig.8., the Model 1 provides a lower false negative rate. Models 3 a weak performance due high error rates. Classifier 6 clearly highlights the high specificity and low FPR and FNR.

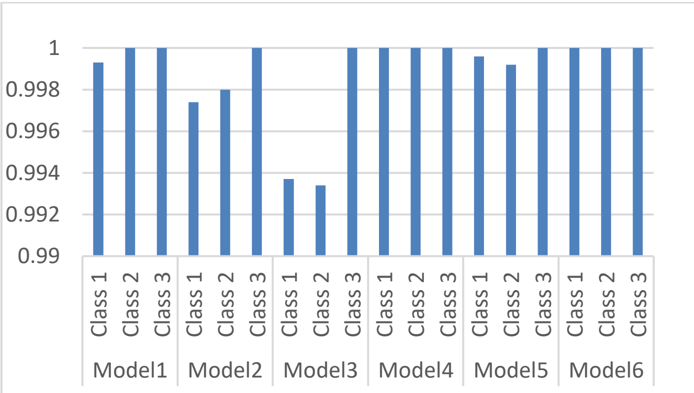


Fig.9. AUC with data augmentation

The AUC values are recorded for all the models trained with augmented data. The AUC values are ranging from 0.9934 to 1. The values represented from Fig.9. reflects the model's efficiency on separating classes. Model 6 indicates strong capability in separating the cancer images to different grades

The Accuracy (One to Many) values range from 0.934 to 1, illustrating the strong classification capability. From the observation of Fig.10., model 3 demonstrates the less stable performance with lowest accuracy for class1 and class2. The model performance excels classification with average accuracy of 99.3%.

Fig.10. Plot of accuracy (one to many) with augmented data

Based on the results evaluated for all models handling with augmentation and without augmentation.
A comparative analysis of models is evaluated and illustrated on Fig. 11. A comprehensive comparison of the pre- and post-augmentation accuracies reveals that data augmentation produced a marked enhancement in classification performance across all six models and for all three classes. For Model 1, the accuracy for Class 1 increased from 0.810 to 0.989, Class 2 improved substantially from 0.619 to 0.991, and Class 3 rises from 0.810 to 0.997, reflecting considerable gains particularly in the previously underperforming Class 2. Model 2 exhibited a similar improvement pattern, with Class 1 increasing from 0.714 to 0.991, Class 2 from 0.571 to 0.986, and Class 3 from 0.857 to 0.994. Model 3, which demonstrated the lowest baseline performance, achieved noticeable improvements following augmentation, attaining accuracies of 0.934, 0.937, and 0.997, respectively. Model 4 performance also improves significantly, with Class 1 improving from 0.571 to 0.991, Class 2 from 0.571 to 0.977, and Class 3 from 0.810 to 0.986, indicating intensified robustness after augmentation. In Model 5, augmentation raised the accuracy of Class 1 from 0.810 to 0.986, Class 2 from 0.667 to 0.991, and Class 3 from 0.545 to 0.994, with the most substantial relative improvement observed in Class 3. Even Model 6, which already exhibited high pre-augmentation accuracy (Class 1 = 0.760, Class 2 = 0.944, Class 3 = 0.950), demonstrated further enhancement, increasing to 0.989, 0.989, and 1.000, respectively.

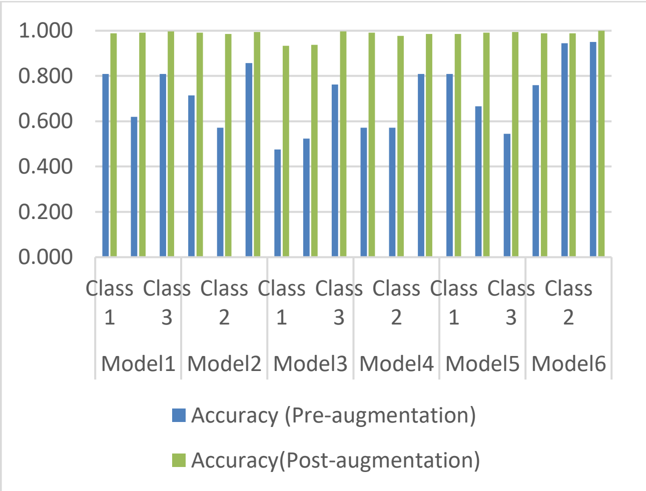


Fig. 11. Comparative study of the pretrained models with and without data augmentation for cervical cancer classification.

When data augmentation is applied, the AUC values for each of the six models show consistent and significant improvement. AUC values varied greatly prior to augmentation, and several models, especially Models 3 and 4, had moderate to poor discriminative performance for certain classes (e.g., Model 3: Class 1 = 0.4711, Class 2 = 0.5673, Class 3 = 0.5625; Model 5: Class 3 = 0.6125).

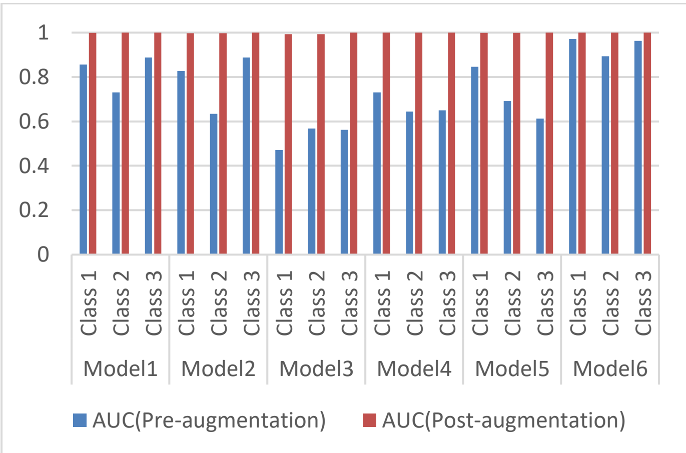


Fig. 12. Performance comparison of the selected deep learning models

After augmentation, all models and classes showed a significant improvement in AUC values as in Fig. 12. In Model 1, Class 1's AUC increased from 0.8557 to 0.9993, while Classes 2 and 3's AUC reached 1.000. Model 2 showed a similar pattern, with AUC values for Classes 1, 2, and 3 rising from 0.8269, 0.6346, and 0.8875 to 0.9974, 0.998, and 1.000, respectively. Model 3, which had the lowest pre-augmentation AUCs, showed full recovery in class separability, improving to 0.9937, 0.9934, and 1.000.

CONCLUSION

A neural network-based AI model for diagnosing cervical abnormalities is very much required to assist doctors in early diagnosis. Timely diagnosis will lessen the death rate in females due to cervical cancer. In this work, a deep learning technique is employed in the classification of cervical cancer with colposcopy based cervical images as input data. This research is to enhance the efficiency of artificial intelligence in the early identification of cervical precancerous lesions. The various state of art pretrained models is utilized in this work to classify the colposcopy based cervical images to class1, class 2 and class 3. The work also involves the comparisons of the models prior to and subsequent to augmentation. The models performance enhanced with the utilize of data augmentation for classification task.

The average classification test accuracy prior to augmentation for class 1, class2 and class 3 are 0.59, 0.59, 0.645 and 0.4 respectively. The pretrained models were able to generalize across all three classes, and reduce the amount of overfitting that occurred through the use of augmentation.

The average classification test accuracy with augmentation for Class 1, Class 2, and Class 3 is 0.947, 0.99, and 0.992877, respectively. By utilizing augmentation process, the solutions influence to the support of the robust model that is used to assist the medical domain.

The theoretical studies can be extended in future to design a practical medical diagnostic structure.

REFERENCES

1. "Wu, Jie, et al. 'Global burden of cervical cancer: current estimates, temporal trend and future projections based on the GLOBOCAN 2022.' Journal of the National Cancer Center (2025).".".
2. "“Dong, Binhua, et al. 'Classification and diagnosis of cervical lesions based on colposcopy images using deep fully convolutional networks: A man-machine comparison cohort study.' Fundamental Research 5.1 (2025): 419-428.".".
3. "R. Hamamoto, M. Komatsu, K. Takasawa, K. Asada, and S. Kaneko, 'Epigenetics analysis and integrated analysis of multiomics data, including epigenetic data, using artificial intelligence in the era of precision medicine,' Biomolecules, vol. 10, p. 62, 2020".
4. "M. Tian, Z. Shen, X. Wu, K. Wei, and Y. Liu, 'The application of artificial intelligence in medical diagnostics: A new frontier,' Academic Journal of Science and Technology, vol. 8, no. 2, pp. 57–61, 2023.".".
5. Ramakrishnappa, Chandra Prabha, and Seema Singh. "Prediction of Cervical Cancer With Application of Machine Learning Models." AI Healthcare Applications and Security, Ethical, and Legal Considerations. IGI Global, 2024. 211-221
6. "Chandran, Venkatesan, et al. "Diagnosis of cervical cancer based on ensemble deep learning network using colposcopy images." BioMed Research International 2021.1 (2021): 5584004.".
7. Yuan, Chunnv, et al. "The application of deep learning based diagnostic system to cervical squamous intraepithelial lesions recognition in colposcopy images." Scientific reports 10.1 (2020): 11639.
8. "Liu, Lu et al. “Computer-aided diagnostic system based on deep learning for classifying colposcopy images.” Annals of translational medicine vol. 9,13 (2021): 1045. doi:10.21037/atm-21-885".
9. "Fan, Yinuo, et al. "Colposcopic multimodal fusion for the classification of cervical lesions." Physics in Medicine & Biology 67.13 (2022): 135003.".
10. "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.".
11. "Youneszade, Nina, Mohsen Marjani, and Sayan Kumar Ray. "A predictive model to detect cervical diseases using convolutional neural network algorithms and digital colposcopy images." IEEE Access 11 (2023): 59882-59898".
12. "Saini, Sumindar Kaur, et al. "ColpoNet for automated cervical cancer screening using colposcopy images." Machine Vision and Applications 31.3 (2020): 15.".
13. "Chen, Jiancui, et al. "Detection of cervical lesions in colposcopic images based on the RetinaNet method." Biomedical Signal Processing and Control 75 (2022): 103589.".
14. "Jimenez Gaona, Yuliana, et al. "Radiomics diagnostic tool based on deep learning for colposcopy image classification." Diagnostics 12.7 (2022): 1694.".
15. "Chatterjee, Priyadarshini, and Shadab Siddiqui. "Multi-Modal Deep Learning Architecture for Improved Colposcopy Image Classification." (2024).".
16. "Yu, Yao, et al. "MSCI: A multistate dataset for colposcopy image classification of cervical cancer screening." International journal of medical informatics 146 (2021): 104352.".
17. "Moreno-Barea, Francisco J., José M. Jerez, and Leonardo Franco. "Improving classification accuracy using data augmentation on small data sets." Expert Systems with Applications 161 (2020): 113696..".
18. " Santos, Claudio Filipi Gonçalves Dos, and João Paulo Papa. "Avoiding overfitting: A survey on regularization methods for convolutional neural networks." ACM Computing Surveys (Csur) 54.10s (2022): 1-25..".
19. " M. Kalbhor and S. V. Shinde, “'Malhari Dataset,'” Mendeley Data, V1, 2023, doi: 10.17632/m5kxdj7m36.1," [Online].
20. "Zhu, Zongwei, et al. "Juggler-ResNet: A flexible and high-speed ResNet optimization method for intrusion detection system in software-defined industrial networks." IEEE Transactions on Industrial Informatics 18.6 (2021): 4224-4233.".
21. "U. Khan, X. Zhang, and R. Kumar, “Analysis of ResNet and GoogleNet models for malware detection,” Journal of Computer Virology and Hacking Techniques, vol. 15, no. 1, pp. 29–37, 2019.".

22. "Singh, Retinderdeep, et al. "InceptionV3 in Medical Imaging: Enhancing Precision in Acute Lymphoblastic Leukaemia Diagnosis." 2024 2nd International Conference on Computer, Communication and Control (IC4). IEEE, 2024.".
23. "Howard, A. G., Zhu, M., Chen, B., Kalenichenko, D., Wang, W., Weyand, T., ... & Adam, H. (2017). Mobilenets: Efficient convolutional neural networks for mobile vision applications. arXiv preprint arXiv:1704.04861.".
24. Ramakrishnappa, Chandra Prabha, and Seema Singh. "A Smart Agronomy: Deep Learning Process for Recognition and Classification Plant Leaf Diseases." Advanced Computational Methods for Agri-Business Sustainability. IGI Global, 2024. 18-35..
25. "Chandraprabha, R., and Seema Singh. "Analysis of Deep Learning Architecture-Based Classifier for the Cervical Cancer Classification." Emerging Research in Computing, Information, Communication and Applications: Proceedings of ERCICA 2022. Singapore: Sprin".
26. Mahesh, Vijayalakshmi GV, Alex Noel Joseph Raj, and R. Chandraprabha. "Implementation of a Deep Neural Network-Based Framework for Actigraphy Analysis and Prediction of Schizophrenia." Diagnosis of Neurological Disorders Based on Deep Learning Techniques..
27. Subrahmanya, Akshaya, M. P. Akhil, and Shubham Kulkarni. "Radiological Analysis with CNN for Respiratory Diseases." 2024 Fourth International Conference on Multimedia Processing, Communication & Information Technology (MPCIT). IEEE, 2024..
28. Hiremath, Shilpa, and Sushil Kumar. "An Investigation Screen for Sleep Disorders Using AI/ML." Advancing the Investigation and Treatment of Sleep Disorders Using AI. IGI Global Scientific Publishing, 2021. 161-183..