MRS Journal of Multidisciplinary Research and Studies
Abbreviate Title- MRS J Mul Res Stud
ISSN *(Online) 3049-1398*
Vol-2, Iss-4(April-2025)

Colorectal Polyps Shape Classification Based On CNN Models

Almo'men Bellah Alawnah*

Department of Industrial Engineering, Jordan University of Science and Technology, Irbid, Jordan

Corresponding Author Almo'men Bellah Alawnah

Department of Industrial Engineering, Jordan University of Science and Technology, Irbid, Jordan

Article History

Received: 14 / 03 / 2025

Accepted: 29 / 03 / 2025

Published: 02 / 04 / 2025

Abstract: Colorectal polyps are precursors to colorectal cancer, making their early detection and classification crucial for effective treatment. This study focuses on developing Convolutional Neural Networks (CNNs) to classify the shapes of colorectal polyps in endoscopic images. Various CNN architectures, including ResNet101, VGG16, and a custom CNN, were trained and evaluated on the Kvasir dataset, which consists of annotated endoscopic images classified into flat, sessile, and pedunculated polyps.

The dataset was divided into 75% for training and 25% for testing, with preprocessing techniques such as resizing, normalization, and augmentation applied to enhance model performance. Transfer learning was leveraged to enhance feature extraction, and the models were evaluated using metrics such as accuracy, recall, precision, and F1-score.

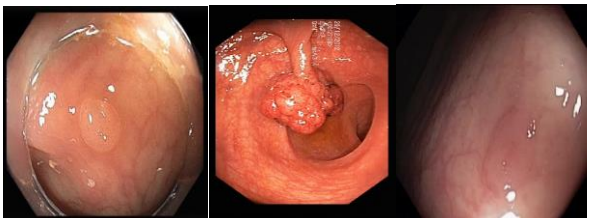
Experimental results showed that ResNet101 achieved the highest accuracy of 95.15%, followed by VGG16 (94.85%) and the custom CNN (94.24%). Models such as InceptionV3 and Xception exhibited comparatively lower performance. These findings suggest that CNNs, particularly ResNet101, can effectively classify colorectal polyp shapes, aiding in early diagnosis and treatment. Future work will focus on hyperparameter optimization, ensemble learning, and advanced deep learning techniques to further enhance classification accuracy.

Keywords: *Colorectal polyps shape, Deep learning, CNN models, PARIS classification.*

Cite this article: Alawnah, A. B., (2025 Colorectal Polyps Shape Classification Based On CNN Models. *MRS Journal of Multidisciplinary Research and Studies, 2 (4),1-5.*

1. Introduction

The gastrointestinal tract is essential for human health, playing a key role in digestion and nutrient absorption (Cheng et al., 2010). A delayed diagnosis of colorectal polyps can increase the risk of developing colorectal cancer, which is the second leading cause of cancer-related deaths worldwide, according to the International Agency for Research on Cancer (IARC) (Ferlay et al., 2019). Detecting and treating these polyps early can significantly lower both the incidence and mortality rates of colorectal cancer (Abraham et al., 2023). Identifying and removing colonic polyps can help prevent cancer from spreading. Colorectal polyps, which include various types of intestinal tumors, are among the most common disorders affecting the gastrointestinal tract (Huang et al., 2023). In most cases, colorectal cancer originates from initially benign polyps (Bond et al., 2000). Several factors contribute to the development of these polyps, including smoking, obesity, genetic predisposition, alcohol consumption, and aging (Hao et al., 2020). Colorectal Polyps are categorized into three shapes based on morphological classification: sessile, flat, or pedunculated (Shussman & Wexner, 2014). In shape classification based on the PARIS classification system, colorectal polyps are broadly categorized into polypoid and non-polypoid types (Bour et al., 2019). Polypoid polyps include sessile (0-Is), which have a broad base without a stalk, and pedunculated (0-Ip), which are attached to the mucosa by a stalk. Non-polypoid polyps include flat polyps (0-II), which are slightly elevated or depressed with minimal protrusion. Figure 1 illustrates the various shapes of colorectal polyps, including sessile, flat, and pedunculated types.



Flat Pedunculated Sessile

Figure 1: Colorectal polyps shapes

2. Related Work

Almo'men Bellah Alawnah. (2025). Developing a model for Colorectal polyp detection is essential for early diagnosis and prevention of colorectal cancer. This study evaluates various convolutional neural network (CNN) models for the binary classification of polyp images using a publicly available dataset comprising 3,000 images, including 1,500 polyps and 1,500 non-polyps. We compare deep learning architectures, including ResNet-101, ResNet-50, VGG-16, VGG-19, Xception, and R-CNN, evaluating their performance based on accuracy, recall, precision, F1-score, and training time. The results show that both ResNet101 and our CNN model achieved the highest performance metrics, with ResNet101 reaching an accuracy of 99.96% and our CNN model attaining 100% accuracy. However, in terms of computational efficiency, our CNN model demonstrated the shortest training time (1,302 MS), making it the optimal choice for striking a balance between accuracy and efficiency. These findings underscore the potential of CNN-based models for real-time polyp detection, offering a promising approach to enhancing early diagnosis and improving clinical outcomes.

Shen et al. (2023) developed an artificial intelligence (AI) system for classifying and identifying colorectal lesions using a combination of CNN and EfficientNet-b0 models. The dataset included approximately 256,220 colonoscopy images from around 5,000 patients diagnosed with colorectal cancer. The data were divided into training (70%), validation (15%), and testing (15%) sets. After completing the training, validation, and testing phases, the model underwent external validation using data from three institutions. In this phase, 385 participants were retrospectively analyzed, while 150 were surveyed prospectively. The deep learning model achieved industry-leading performance, with a sensitivity of 97.09% and a specificity of 97.01% when tested on the designated dataset. The hyperparameter-optimized classification model performed exceptionally well, attaining an AUC of 99.89%. External validation further confirmed the model's robustness, yielding a specificity of 97.20% and a sensitivity of 95.16% for lesion and frame-based polyp detection. Additionally, the model demonstrated an AUC of 95.21% in polyp classification. With its high accuracy and reliability, this deep learning-based system has the potential to be integrated into clinical practice, enabling endoscopists and physicians to make timely and effective diagnostic decisions.

Tang et al. (2023) developed an artificial intelligence system that leverages image analysis to detect and classify polyps. To minimize the miss rate, they incorporated additional polyp images into the YOLO training process by applying conditional GAN and data augmentation techniques. After five iterations of testing, the proposed model achieved its highest performance, with an average precision (AP) of approximately 55% for SSA and 73% for TA. When GAN 300 was not used, the results for IoU, mAP, and AP were lower. Notably, implementing DeclurGAN-v2 led to an approximate 5% increase in mAP, indicating that this technique significantly improved the model’s accuracy.

Aish et al. (2022) explored five different methods for classifying gastrointestinal (GI) tract disorders. Their approaches included three techniques utilizing Convolutional Neural Networks (CNN) with transfer learning and two methods based on global feature extraction. The authors proposed a hybrid approach that integrated transfer learning with a pre-trained CNN and global feature extraction. Notably, they discovered that combining two neural networks—ResNet-152 and DenseNet-161—along with an additional Multi-Layer Perceptron (MLP) yielded superior performance. This ensemble approach achieved remarkable results, with an accuracy of 95.80%, precision of 95.87%, and an F1-score of 95.80% on the validation and test datasets provided by the task organizers.

Komeda et al. (2021) developed an image classification model based on ResNet to classify colorectal polyps. They used a dataset of approximately 127,610 images collected from Kindai University Hospital, categorizing them into three classes: adenoma (62,510 images), non-adenoma (hyperplastic) (30,443 images), and standard (34,657 images). The study employed ten-fold cross-validation to evaluate model performance. The model demonstrated excellent performance across various metrics, including sensitivity, specificity, positive predictive value (PPV), diagnostic accuracy, and negative predictive value (NPV) for adenoma detection using white-light imaging (WLI), narrow-band imaging (NBI), and chromoendoscopy imaging (CEI). Sensitivity scores were 98.8% for WLI, 98.2% for NBI, and 94.9% for CEI. Notably, NPV and PPV for NBI and CEI outperformed those for WLI. Additionally, the model achieved a substantial diagnostic accuracy of approximately 93% for WLI.

Hsu et al. (2021) developed a CNN-based model for classifying and detecting colorectal polyps using grayscale imaging and deep learning (DL). The classification task focused on distinguishing between neoplastic and hyperplastic polyps. Their dataset included 1,000 colorectal polyp images collected from Linkou Chang Gung Medical Hospital, along with images from the public CVC Clinic dataset. To ensure robustness, they applied five-fold cross-validation by dividing the dataset into five groups. The study also examined the effect of grayscale transformation, which converts RGB images to a 0–255 grayscale range. When using RGB and NBI images, the model achieved a polyp identification accuracy of 94.1%, which improved to 95.1% after converting the images to grayscale. This finding suggests that grayscale imaging enhances classification accuracy. However, accuracy decreased when polyp image dimensions fell below 1,600 pixels. Based on these results, the study recommends adjusting the distance between the polyps and the lens to improve diagnostic precision and image quality. For NBI images, the model achieved an accuracy of approximately 83%, a precision of 82%, and a recall of 95%.

In their recent study, Liew et al. (2021) proposed an integrated approach combining Principal Component Analysis (PCA), a modified deep residual network, and AdaBoost ensemble learning to distinguish between endoscopic images with and without polyps. To optimize efficiency, they modified the ResNet-50 architecture, reducing computation time while maintaining strong performance. The model was trained using three datasets: ETIS-LaribPolypDB, Kvasir, and CVC-ClinicDB. It achieved outstanding performance, with a Matthews Correlation Coefficient (MCC) of 98.19%, an accuracy of 99.1%, a sensitivity of 98.82%, a precision of 99.37%, and a specificity of approximately 99.38%.

Patino-Barrientos et al. (2020) developed a convolutional neural network (CNN) model to classify colorectal polyps as malignant or benign using the Kudo classification system, which comprises five categories: I, II, III, IV, and V. Types I to IV were categorized as nonmalignant, while type V represented malignant polyps with a prospective classification rate of 56%. The dataset consisted of 600 images collected by the University of Deusto, sourced from colonoscopy videos of 142 patients treated at Biodonostia Health Research Institute and Urduliz Hospital. To ensure generalizability, images were captured under various conditions and resolutions, ranging from low resolution (150 × 150 pixels) to high resolution (1024 × 1280 pixels). Initially, a basic CNN model was tested for feature extraction, followed by VGG-16. After splitting the dataset into training (68%), validation (16%), and testing (16%), the model achieved an optimal accuracy of approximately 83%.

Urban et al. (2018) trained a deep convolutional neural network (D-CNN) model using 8,641 images from 2,000 patients. To evaluate the model, they analyzed 20 colonoscopy recordings spanning approximately five hours, supplemented by nine archived videos. When compared to assessments by experienced colonoscopists, the CNN model demonstrated an accuracy of 96.4%, with a false-positive rate of 7%. This study highlighted the potential of CNN models as reliable diagnostic tools in colorectal polyp detection.

Byrne et al. (2017) introduced an AI model to distinguish between adenomatous and hyperplastic diminutive colorectal polyps using a deep convolutional neural network (DCNN) trained exclusively on narrow-band imaging (NBI) video data. The model was tested on 125 videos; however, 15% of the cases (19 polyps) exhibited insufficient confidence in classification. Among the remaining 106 polyps, the model achieved an accuracy of 94%, sensitivity of 98%, specificity of 83%, a negative predictive value (NPV) of 97%, and a positive predictive value (PPV) of 90%.

3. Objective

To develop Convolutional Neural Networks (CNNs) for classifying the shape of colorectal polyps in endoscopic images, the following steps can be implemented:

Model Development:

- Design and implement CNN architectures tailored for colorectal polyp shape classification.
- Ensure the model can handle various polyp shapes (e.g., sessile, flat, and pedunculated) and distinguish between subtle differences in their appearances.

Training the CNNs:

- Use annotated datasets of endoscopic images, ensuring that the data includes diverse examples of polyps with different shapes and characteristics.
- Preprocess the images for input into the CNN, including resizing, normalization, and augmentation techniques to improve model robustness.
- Utilize transfer learning when necessary to leverage pre-trained models for enhanced feature extraction, particularly in the medical domain.

Model Evaluation:

- Evaluate the model's performance using key metrics, including accuracy, sensitivity (also known as recall), specificity, and F1-score.
- Utilize a validation and test set to evaluate the model's generalization capabilities and its effectiveness in detecting polyps across different image conditions.

Handling Challenging Cases:

- Optimize the CNNs to address common challenges in polyp shape classification, such as sessile, flat, or pedunculated polyps that might be difficult to detect using traditional diagnostic methods.
- Apply techniques like multi-scale detection, attention mechanisms, or advanced image enhancement to aid in detecting such cases.

Continuous Refinement:

- Regularly refine the model by incorporating feedback from clinical use and updating it with new annotated data.
- Fine-tune hyperparameters, model layers, and data preprocessing steps to minimize errors and improve detection rates over time.

Elevating Convolutional Neural Network-Based Models:

- Focus on enhancing CNN-based models through innovation by testing different architectures, exploring hybrid models, or combining CNNs with other machine-learning techniques for better performance.
- Aim for continuous model development to stay at the forefront of colorectal polyp shape classification, ultimately improving clinical outcomes in early diagnosis.

By following these steps, CNN models can be effectively developed and optimized to provide high-quality, real-time assistance in detecting and classifying colorectal polyps, leading to improved early diagnosis and prevention strategies for colorectal cancer.

Alkhatib et al. (2024) noted the swift progression of healthcare services, which is anticipated to keep advancing. The adoption of cutting-edge technologies, including modern sensors, networks, and cloud computing, has transformed conventional healthcare systems. These advancements have significantly enhanced efficiency, improved patient care, and enabled more accurate diagnostics, fostering a more cohesive and connected healthcare environment. Utilizing machine learning and deep learning for disease detection plays a key role in minimizing time and effort (Alkhatib et al., 2024; Alzoubi et al., 2024).

4. Methodology

Dataset

The present Kvasir dataset, comprising images captured from within the gastrointestinal (GI) system, was utilized. The files are classified and annotated by physicians and experienced endoscopists.

Kvasir is vital in examining computer-aided detection for both individual and complex disorders. The dataset comprises authenticated and annotated endoscopic images of the gastrointestinal (GI) tract, carefully selected by certified endoscopists. In the autumn of 2017, MediaEval released this dataset to the public as part of their Medical Multimedia Challenge, a project that presents scientific objectives for benchmarking purposes .

Both deep learning and machine learning can leverage the vast repository of images. The pathological findings consist of polyps, ulcerative colitis, and esophagitis. The image resolution varies from 720x576 to 1920x1072 pixels. The dataset consists of

1,500 images classified as usual and 1,500 images showing colorectal polyps **.**

A physician has classified the images; a Jordanian doctor who works at KAUH is a specialist in diagnosing diseases of the digestive system. The classification of images was based on their shape.

Table 1: Distribution of images by classification (Shape of polyp)

Classification of images	Number of images
Flat	128
Sessile	157
Pedunculated	156

Methodology

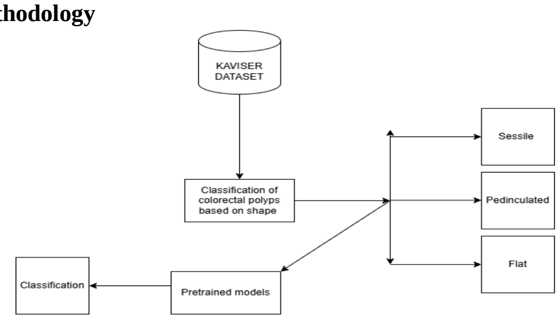


Figure 2: Paper Methodology

Hyperparameter

Table 2: Hyperparameters for training

Class	Shape
Number of Epochs	20
Batch Size	64

Using 75% of the dataset for training and 25% for testing yielded the best results. The learning rate was set to 0.01, and Adam was used as the optimizer.5. Results and Conclusion

Table 3: Shows the results of experiments

Algorithm	# Epoch	Batch	Accuracy	Learning Rate	Recall	Precision	F1-score
VGG19	20	64	0.9333	0.001	0.69	0.71	0.69
VGG16	20	64	0.9485	0.001	0.73	0.76	0.73
Resnet101	20	64	0.9515	0.001	0.73	0.74	0.74
Resnet50	20	64	0.9121	0.001	0.56	0.59	0.55
Xception	20	64	0.8697	0.001	0.58	0.58	0.58
R-CNN	20	64	0.7970	0.001	0.68	0.68	0.68
CNN	20	64	0.9424	0.001	0.72	0.72	0.72
InceptionV3	20	64	0.8030	0.001	0.54	0.54	0.53

Table 3 presents the performance metrics of various deep-learning algorithms evaluated for the classification of colorectal polyps. The models were trained for 20 epochs with a batch size of 64 and a learning rate of 0.001. The results highlight differences in accuracy, recall, precision, and F1-score across the tested architectures. ResNet101 achieved the highest accuracy of 95.15%, along with recall, precision, and F1-score values of 0.73, 0.74, and 0.74, respectively. This suggests its robustness in extracting relevant features for classification. VGG16 demonstrated strong performance, with an accuracy of 94.85% and an F1-score of 0.73, making it one of the top-performing models. CNN (custom) also performed well, with an accuracy of 94.24% and an F1-score of 0.72, suggesting its effectiveness in the classification task. VGG19 had an accuracy of 93.33%, with a recall of 0.69 and an F1-score of 0.69. ResNet50 demonstrated moderate performance, achieving an accuracy of 91.21%, but exhibited lower recall and F1-score values. Xception, R-CNN, and InceptionV3 exhibited comparatively lower accuracy and F1 scores, with InceptionV3 being the least effective model at 80.30% accuracy and an F1 score of 0.53.

Conclusion

The experimental results indicate that ResNet101 outperforms other models in colorectal polyp classification, making it the most suitable choice for this task. VGG16 and the custom CNN also

Showed promising results, making them viable alternatives. The relatively lower performance of models such as InceptionV3 and Xception suggests that they may not be as effective in capturing key features required for accurate polyp classification. Future work could explore optimizing hyperparameters, integrating ensemble techniques, or employing transfer learning to enhance classification performance further.

Compliance with ethical standards

Disclosure of conflict of interest

No conflict of interest is to be disclosed.

References

1. Cheng, L. K., O'Grady, G., Du, P., Egbuji, J. U., Windsor, J. A., & Pullan, A. J. (2010). Gastrointestinal system. *Wiley Interdisciplinary Reviews: Systems Biology and Medicine*, *2*(1), 65-79.
2. Ferlay, J., Colombet, M., Soerjomataram, I., Mathers, C., Parkin, D. M., Piñeros, M., ... & Bray, F. (2019). Estimating the global cancer incidence and mortality in

2018: GLOBOCAN sources and methods. *International journal of cancer*, *144*(8), 1941-1953.

of colonic polyps vs. Resected polyps. *Journal of Imaging*, *9*(10), 215.

4. Huang, Y., Liu, Y., Yin, X., Zhang, T., Hao, Y., Zhang, P., ... & Wang, G. (2023). Establishment of clinical predictive model based on the study of influence factors in patients with colorectal polyps. *Frontiers in Surgery*, *10*, 1077175.
5. Bond, J. H., & Practice Parameters Committee of the American College of Gastroenterology. (2000). Polyp guideline: diagnosis, treatment, and surveillance for patients with colorectal polyps. *Official journal of the American College of Gastroenterology| ACG*, *95*(11), 3053-3063.
6. Hao, Y., Wang, Y., Qi, M., He, X., Zhu, Y., & Hong, J. (2019). Risk factors for recurrent colorectal polyps. *Gut and Liver*, *14*(4), 399.
7. Shussman, N., & Wexner, S. D. (2014). Colorectal polyps and polyposis syndromes. *Gastroenterology report*, *2*(1), 1-15.
8. Bour, A., Castillo-Olea, C., Garcia-Zapirain, B., & Zahia, S. (2019, December). Automatic colon polyp classification using convolutional neural network: a case study at basque country. In *2019 IEEE international symposium on signal processing and information technology (ISSPIT)* (pp. 1-5). IEEE.
9. Almo’men Bellah Alawnah. Colorectal polyp detection: Elevation of convolutional neural network-based models. International Journal of Science and Research Archive, 2025, 14(03), 987-993. Article DOI: https://doi.org/10.30574/ijsra.2025.14.3.0754
10. Shen, M. H., Huang, C. C., Chen, Y. T., Tsai, Y. J., Liou, F. M., Chang, S. C., & Phan, N. N. (2023). Deep learning empowers endoscopic detection and polyps classification: a multiple-hospital study. *Diagnostics*, *13*(8), 1473.
11. Tang, C. P., Chang, H. Y., Wang, W. C., & Hu, W. X. (2023). A novel computer-aided detection/diagnosis system for detection and classification of polyps in colonoscopy. *Diagnostics*, *13*(2), 170.
12. Aish, M. A., Abu-Naser, S. S., & Abu-Jamie, T. N. (2022). Classification of pepper using deep learning.
13. Komeda, Y., Handa, H., Matsui, R., Hatori, S., Yamamoto, R., Sakurai, T., Takenaka, M., Hagiwara, S., Nishida, N., Kashida, H., Watanabe, T., & Kudo, M.

3. Abraham, A., Jose, R., Ahmad, J., Joshi, J., Jacob, T., Khalid, A. U. R., ... & Toma, M. (2023). Comparative analysis of machine learning models for image detection (2021). Artificial intelligence-based endoscopic diagnosis of colorectal polyps using residual networks. *PloS one*, *16*(6), e0253585. https://doi.org/10.1371/journal.pone.0253585
14. Hsu, C. M., Hsu, C. C., Hsu, Z. M., Shih, F. Y., Chang, M. L., & Chen, T. H. (2021). Colorectal polyp image detection and classification through grayscale images and deep learning. *Sensors*, *21*(18), 5995.
15. Liew, W. S., Tang, T. B., Lin, C. H., & Lu, C. K. (2021). Automatic colonic polyp detection using integration of modified deep residual convolutional neural network and ensemble learning approaches. *Computer Methods and Programs in Biomedicine*, *206*, 106114.
16. Patino-Barrientos, S., Sierra-Sosa, D., Garcia-Zapirain, B., Castillo-Olea, C., & Elmaghraby, A. (2020). Kudo’s classification for colon polyps assessment using a deep learning approach. *Applied Sciences*, *10*(2), 501.
17. Urban, G., Tripathi, P., Alkayali, T., Mittal, M., Jalali, F., Karnes, W., & Baldi, P. (2018). Deep learning localizes and identifies polyps in real time with 96% accuracy in screening colonoscopy. *Gastroenterology*, *155*(4), 1069-1078.
18. Byrne, M. F., Chapados, N., Soudan, F., Oertel, C., Pérez, M. L., Kelly, R., ... & Rex, D. K. (2019). Real-time differentiation of adenomatous and hyperplastic diminutive colorectal polyps during analysis of unaltered videos of standard colonoscopy using a deep learning model. *Gut*, *68*(1), 94-100.
19. Alkhatib, A. J., AlZoubi, A., Alaiad, A., Aqoulah, A. A., Alawnah, A. M. B., Alharoun, M., & Azar, M. E. (2024). Privacy Issues in Electronic Medical Records: A Systematic Review. *Multicriteria Algorithms with Applications*, *3*, 32-41.
20. Alkhatib, A. J., Alharoun, M., Alzoubi, A., Muqdadi, E., Aqoulah, A. A., & Alawnah, A. M. B. (2024). Diagnosing brain tumors from mri images through a multi-fused CNN with auxiliary layers. *Sustainable Machine Intelligence Journal*, *6*, 2-1.
21. Alzoubi, A., Alaiad, A., Alkhattib, K., Alkhatib, A. J., Aqoulah, A. A., Alawnah, A. M. B., & Hayajnah, O. (2024). Detection of depression from Arabic tweets using machine learning. *Sustainable Machine Intelligence Journal*, *6*, 3-1.