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Enhancement of Postoperative Surgery and Interventional Healthcare using Surgical Data Science(SDS)

Abstract: - This paper addresses the challenge of colorectal cancer recurrence despite its preventability, emphasizing the critical need for effective endoscopic interventions. Existing approaches often fail to classify polyps, hindering accurate prediction and timely treatment sufficiently. This paper proposes leveraging AI and machine learning, particularly supervised learning techniques, to enhance polyp classification across eight categories and improve prediction accuracy. The methodology involves a comprehensive review of AI applications in endoscopic surgery, evaluating their clinical effectiveness. Additionally, the paper introduces Surgical Data Science (SDS) as a solution for optimizing postoperative care in colorectal surgery. SDS utilizes machine learning and detailed data analysis to personalize preoperative planning, monitor surgical outcomes in real time, and enhance disease surveillance at a population level. This approach offers a promising pathway to significantly improve colorectal surgery outcomes through precise diagnostics and proactive intervention strategies. In our study, we achieved a diagnostic and prediction accuracy of 99% using a combination of Convolutional Neural Networks (CNN) and Support Vector Machine (SVM) for the 8-class classification of colorectal polyps. Additionally, we obtained a 95% accuracy rate using CNN and Multilayer Perceptron (MLP). This demonstrates the potential of AI-driven techniques in advancing the effectiveness of colorectal cancer treatment.

Keywords: Colorectal Cancer, Endoscopic Surgery, Interventional Healthcare, Surgical Data Science (SDS).

I. Introduction

Cancer causes an estimated 8.9 million deaths globally, making it the second most prevalent infectious disease and accounting for approximately one in six deaths worldwide as in Fig 1. Colorectal cancer is the third most common type of cancer, following lung and breast cancers. Effective treatment requires the timely detection [1][2] and classification of cancer cells. According to the American Cancer Society, 56% of colorectal cancer (CRC) patients, or 4,444 individuals, are diagnosed at a local or advanced stage when the cancer has spread beyond the primary tumor to other body parts [3]. Recent advances in graphics processing and machine learning have introduced numerous affordable computer-assisted diagnostic methods. Traditional techniques aim to implement a pattern recognition-based system for rapid and automatic cancer diagnosis. This involves extracting a fixed set of manually created features from tissue scans based on morphological characteristics and training a classifier to identify these cancers. More recently, deep learning neural networks have been employed to automate feature extraction and classification within an integrated learning framework [4][5]. Segmentation methods have wide-ranging applications, from artificial vision systems to medical diagnostics and mechanical engineering. In mechanical engineering, segmentation techniques are used to analyze materials at the microstructural level. In medical applications, soft tissue segmentation is essential for developing computer-aided diagnostic (CAD) systems, particularly those using computed tomography (CT) scans. Segmentation of soft tissues, such as in colon dissection, is increasingly utilized in modern medical practice to create 3D visualizations of organ structures [6][7][8]. Artificial intelligence (AI) and image analysis have advanced significantly in recent years, facilitating various medical processes. These technologies play a crucial role in clinical decision-making by analyzing medical images and detecting symptoms and diseases. Epidemiological data indicate that colorectal cancer poses a significant burden in many European countries and is associated with a high mortality rate [8]

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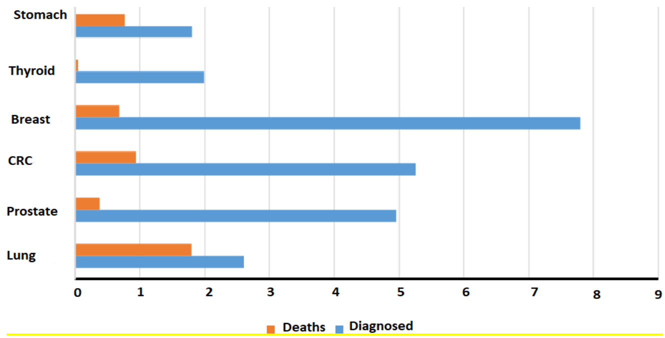

Fig 1 Diagnosed cases and mortality rates for the five most prevalent cancers according to GLOBOCAN 2020[3]

II. Literature Review

Early colorectal cancer (ECC) is cancer confined to the mucosa or submucosa of the colon or rectum. More cases of ECC and precancerous lesions are being diagnosed with increased use of screening colonoscopies. Advances in optical technologies and endoscopic treatment techniques, such as endoscopic submucosal dissection (ESD), have revolutionized ECC management, making endoscopic treatment a viable alternative to surgical resection. Innovative endoscopic diagnostic tools, such as magnifying endoscopy with narrow-band imaging (NBI), enable real-time histologic diagnosis and assessment of invasion depth. However, discrepancies exist between Western and Eastern diagnostic criteria for ECC, with active exchanges needed to harmonize these approaches. Endoscopic resection aims to remove cancer cells to cure ECC completely. Intramucosal cancers rarely metastasize to lymph nodes (LNs), and complete endoscopic removal is often curative. However, submucosal invasion increases the risk of LN metastasis; with current guidelines highlighting and emphasizing the critical importance of the postoperative phase, the study highlights the need to prevent adverse effects such as disease recurrence to improve patient outcomes [9].

Given the preventability of colorectal cancer despite its high mortality rate, the study underscores the significance of endoscopic interventions. AI and machine learning, mainly supervised learning techniques, are employed to enhance polyp classification from 8 classes and prediction accuracy, thereby reducing the incidence of colon cancer through precise diagnostics and timely interventions. The study reviews current AI applications in endoscopic surgery and evaluates their effectiveness in clinical settings. The narrative concludes optimistically, envisioning widespread accessibility to these advancements to ensure equitable healthcare outcomes globally. Surgical Data Science (SDS) offers promising advancements in postoperative care for colorectal surgery. Through machine learning and comprehensive data analysis, SDS aims to enhance surgical outcomes and minimize complications. It enables personalized preoperative planning by identifying high-risk patients and tailoring interventions accordingly. SDS also facilitates real-time monitoring of surgical data and patient outcomes, allowing for early detection of complications and prompt intervention. Furthermore, SDS has the potential to revolutionize population-level disease detection in colorectal surgery by analyzing extensive healthcare data. In summary, SDS provides a data-driven approach to improve postoperative care and outcomes in colorectal surgery significantly [9].

Hari et al. explored substantial advancements in machine learning (ML) and deep learning (DL) models for cancer detection. They stressed the critical importance of early diagnosis due to the high mortality rates linked with late detection. The study evaluates the effectiveness of ML and DL models in detecting four significant types of cancer: brain, lung, skin, and breast cancer. Their analysis draws from a review of 130 peer-reviewed studies published between 2018 and 2023, with 56 focusing on ML and 74 on DL techniques. These studies were assessed based on various parameters, including cancer type, features used, top-performing models, datasets, and accuracy. The results indicate that DL models typically outperform ML models in terms of accuracy, with DL models achieving up to 100% accuracy, compared to 99.89% for ML models. However, the study noted that both ML and DL methods still have room for improvement, particularly in overcoming model accuracy and generalizability challenges. The study concluded that while ML and DL models hold significant potential for enhancing cancer diagnostics, specific challenges must be addressed for these models to be effectively integrated into clinical practice. These challenges include the need for more comprehensive and diverse datasets, the development of models capable of generalizing across different populations, and the seamless integration of these models into existing healthcare systems. The study offers an in-depth analysis of the current landscape of cancer detection using ML and DL, emphasizing the progress made in recent years. The comparison between ML and DL techniques is particularly insightful, highlighting the strengths and limitations of each approach.

III. METHODOLOGY

Data augmentation is required for medical datasets for several reasons, including limited patient availability for certain diseases, patient reluctance to provide images, and the need to safeguard privacy and sensitivity concerns associated with such data. In this research, the ERCPMP dataset [21] is utilized. The ERCPMP dataset is an endoscopic image and video collection designed to aid in recognizing and studying colorectal polyps' morphology and pathology [12] [13]. Compiled from 191 patients, it includes 796 images and 21vedios.

We developed and validated a novel artificial intelligence (AI) deep learning model intended as an adjunctive tool for screening colonic malignancies in colorectal specimens. The aim is to enhance cancer detection and classification, allowing pathologists to allocate their attention to more complex decision-making endeavors amidst their demanding schedules. As described in Fig 3, creating an automated polyp detection system using machine learning follows a consistent workflow, typically involving sample normalization, augmentation, model fine-tuning, and evaluation [10] [11]. Our workflow starts with collecting the data as in gastroenterology classifications such as Paris, Pit, and JNET. In contrast, the pathological data covers diagnoses including Tubular, Villous, Tubulovillous, Hyperplastic, Serrated, Inflammatory, and Adenocarcinoma with detailed dysplasia grades. This robust training resource addresses the significant challenge of developing accurate AI algorithms for medical applications, thus enhancing the detection, diagnosis, and treatment of colorectal cancer. The dataset's availability on Elsevier Mendeley Dataverse and its ongoing development highlights its potential impact on medical research and AI-driven medical diagnostics [11] [13]. See Fig 6 for a visualization of a convolutional neural network architecture [14].

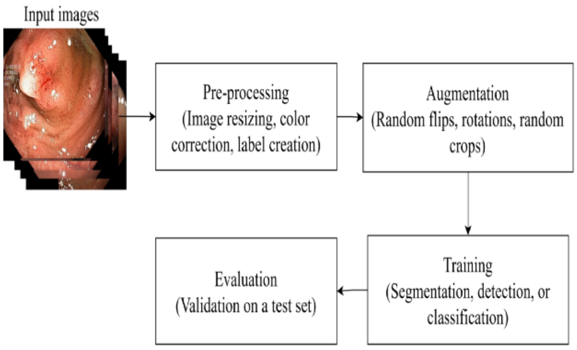

Fig 2 The process for developing an automated polyp detection system using SVM and MLP.

Table 1 Outline of the ERCPMP dataset, which includes patient demographics, anatomical characteristics, morphological details, and pathology findings [1]

Patient Demographic				Anatomical Features				Morphology		Surface Pattern		Pathology	
Patient Code	Image & Video	Sex	Age	Polyp Location	Size (mm)	Circum	Cross Two Folds	Paris	LST Type	Pit	JNET	Diagnosis	Dysplasia Grade & Differentiation
23001	+	F	35	Rectum	2*2	<1/3	Neg	0-IIa	LST-G HT	III	2A	Tubular	LGD
23002	+	M	76	Rectum	3*3	<1/3	Pos	0-IIa	LST-G HT	III, IV	2A	T+V	LGD
23003	+	F	66	Rectum	4*3	<1/3	Pos	0-IIa	LST-G HT	IV, V	2B	Villous	HGD
23004	-	F	50	Rectum	3.5*1.5	<1/3	Pos	0-IIa + Is	LST-G MN	III, IV, V	2B	T+V	HGD
23005	+	F	73	Rectum	4*3	<1/3	Pos	0-IIa + Is	LST-G MN	IV, V	2B	Villous	HGD
23006	+	M	82	Rectum	4*3	<1/3	Pos	0-IIa + IIc	LST-NG PD	III, IV	2A	T+V	LGD
23007	+	F	42	Rectum	3.5*2	<1/3	Pos	0-IIa + Is	LST-G MN	IV	2A	Villous	LGD
23008	+	F	48	Rectosigmoid	4*4	<1/3	Pos	0-IIa	LST-G HT	III, IV	2A	Serrated	T+V
23009	Image	M	68	Rectosigmoid	5*3	>1/3	Pos	0-IIa	LST-G HT	III, IV, V	3	T+V	HGD
23010	Image	F	64	Rectum	2*1.5	<1/3	Neg	0-Ips	-	III, V	2B	Tubular	HGD
23011	-	F	53	Rectum	1.5*1	<1/3	Neg	0-Is	-	III	2A	Tubular	LGD
23012	Image	M	47	Rectum	1.5*1	<1/3	Neg	0-Ips	-	III, IV	2A	T+V	LGD
23013	Image	F	73	Rectum	2*2	<1/3	Neg	0-IIa	LST-G HT	III, IV, V	2B	T+V	HGD
23014	Image	F	60	Rectum		<1/3	Neg	-	-	-	-	Adenocarcinoma	N/A
23015	Image	F	44	Rectum	2.5*2	<1/3	Neg	0-IIa + Is	LST-G HT	III, IV, V	2B	T+V	HGD
23016	+	F	57	Rectum	1	<1/3	Neg	0-Is	-	I	1	Hyperplastic	-
23017	Image	F	43	Rectum	1	<1/3	Neg	0-Is	-	I	1	Hyperplastic	-
23018	Image	M	67	Rectum	1*1	<1/3	Neg	0-Is	-	I	1	Hyperplastic	-
23019	+	F	34	Rectum	1*1	<1/3	Neg	0-Is	-	III	2A	Tubular	LGD
23020	Image	M	69	Rectum	1.5*1	<1/3	Neg	0-Ip	-	III	2A	Tubular	LGD
23021	Image	F	64	Rectum	1*1	<1/3	Neg	0-Is	-	I	1	Hyperplastic	-
23022	-	M	44	Rectum	1*1	<1/3	Neg	0-Is	-	I	1	Hyperplastic	-
23023	Image	F	32	Rectum	3*3	<1/3	Pos	0-IIa	-	III, IV, V	2B	T+V	HGD
23024	-	F	37	Rectum	1.5*2	<1/3	Neg	0-IIa	-	-	-	Inflammatory	-

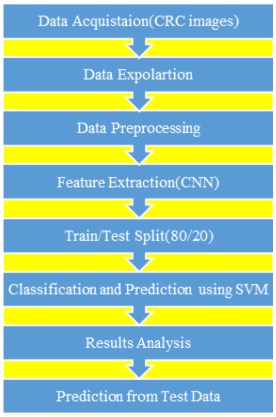

Fig 3 Workflow of our Proposed Work

A. Implementation

This section details the steps in implementing the machine learning model for polyp classification [22]. We employed a pre-trained VGG16 model to extract features from endoscopic images. An attention mechanism was incorporated to highlight essential features within the extracted feature maps (Fig 6). The images were loaded, resized to a standard dimension (224x224 pixels), and preprocessed to match the input requirements of the VGG16 model [23] [24]. Feature vectors were extracted from the preprocessed images using the pre-trained VGG16 model enhanced with the attention mechanism. Patient information, including diagnosis and corresponding image paths, was collected. Labels were extracted and encoded for machine-learning purposes. Finally, the dataset was split into training 80% and 20 % testing sets, respectively [25] [26] [27]. A Multilayer Perceptron Model (MLP) is a type of neural network that consists of multiple layers of neurons, including an input layer, hidden layers, and an output layer, and it has been used because it effectively handles high-dimensional data, captures complex patterns, and can generalize well to unseen data. MLPs are suitable for multi-class classification tasks, offering flexibility and integration with other models, such as SVM and CNN, to enhance prediction accuracy in medical applications. The equation for MLP can be represented as in Equation 1:

$$y = \sigma(Wn \cdot \sigma(Wn - 1 \cdot \ldots \cdot \sigma(W1 \cdot x + b1) + bn - 1) + bn) \qquad (1)$$

where:

X is the input feature vector,

Wi and bi are the weight matrices and bias vectors for each layer iii,

σ\ is the activation function (e.g., ReLU, sigmoid),

Y is the output vector representing the class probabilities.

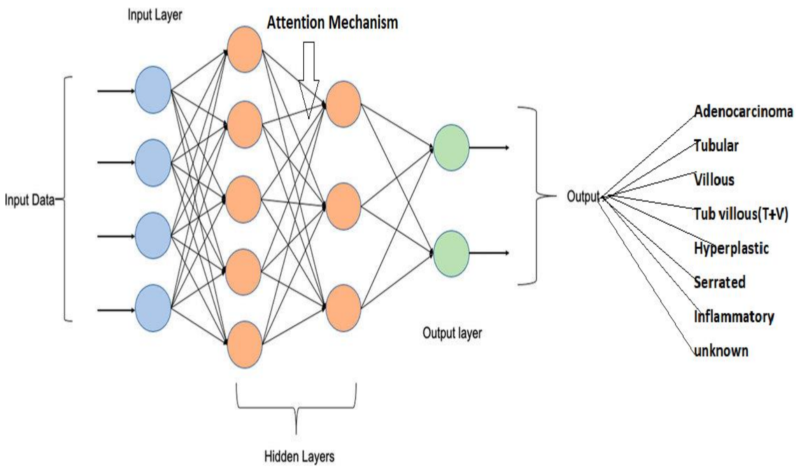

Fig 4 The Workflow for the MLP

The MLP learns to map input features to class labels through backpropagation, adjusting weights and biases to minimize the classification error. [20] [21] [22] A Multi-Layer Perceptron (MLP) classifier was trained on the extracted features and corresponding labels. The model's performance was evaluated using the testing set. Predictions were made on the test set, and the model's accuracy was calculated. [18] [19] Finally, the features, actual

diagnoses, and predicted diagnoses were saved for further analysis as described in Fig 4 [28] [29]. We also used SVM for the task of predicting and diagnosing colorectal cancer across eight classes; SVM was chosen over other models, including Multi-Layer Perceptron (MLP) [30] [31] [32] due to its superior accuracy and performance.
Accuracy: SVM achieved a 99% accuracy rate, outperforming MLP, which had a 95% accuracy. This difference was crucial; as higher accuracy is essential in medical diagnoses.
Handling Complexity: SVM effectively captured the complex patterns in the colorectal cancer dataset, particularly with non-linear kernels, providing better results than other models.
Generalization: SVM's strong generalization capability made it more reliable, especially with a smaller dataset, reducing the risk of overfitting compared to MLP.
Efficiency: SVM requires fewer hyper parameters and less fine-tuning than MLP, making it more efficient and easier to implement for this specific application.
The equation for SVM in the context of colorectal cancer diagnosis can be represented as in Equation 2:

$$f(x) = w^t\,x\, +\, b \qquad (2)$$

where:

w is the weight vector,

x is the feature vector representing the characteristics of the colorectal polyps (e.g., morphology, pathology)?

$w^t\,x$ is the dot product of w and x.

b is the bias term.

The decision boundary is determined by the sign of f(x), and the SVM aims to maximize the margin between different classes (e.g., tubular, villous, hyperplastic). In colorectal cancer polyp prediction, the SVM decision function is a powerful tool to classify polyps based on their features. By learning the optimal weights and bias from training data, the SVM model can accurately distinguish between different types of polyps, aiding in early diagnosis and treatment planning.

B. Results

We achieved high accuracy in classifying colorectal cancer polyps into eight types using two machine learning techniques: Support Vector Machine (SVM) and Multi-Layer Perceptron (MLP). A pre-trained convolutional neural network (CNN) model (VGG16) was used for feature extraction, followed by applying an attention mechanism to the dataset. The accuracy achieved using SVM was 99%, while the MLP attained an accuracy of 95%. Based on these results, SVM appears to be the preferred method for polyp classification in this study, as represented in Table 2.

IV. Conclusion

Our study highlights the inherent limitations of traditional methods for colorectal cancer prediction and postoperative care. Without the integration of surgical data science, predictive accuracy is limited, personalized care is less precise, and postoperative management tends to be more reactive than proactive. These limitations underscore the need for more advanced approaches. Potential improvements through surgical data science are significant. Advanced predictive models utilizing machine learning algorithms can enhance the accuracy of colorectal cancer risk assessments. Integrating genomic data into these models provides a comprehensive risk profile, enabling more precise interventions.

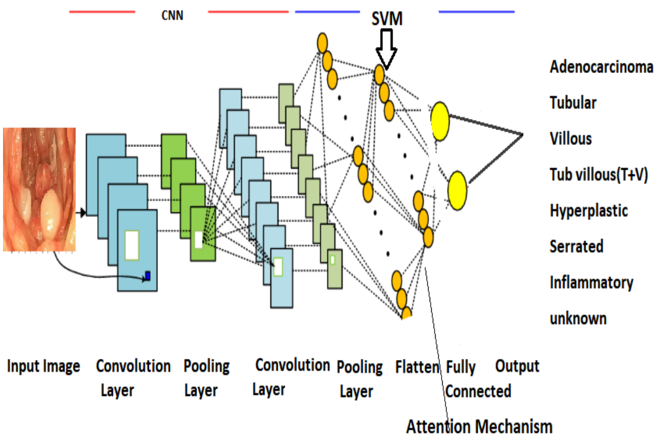

Fig 5 A convolutional neural network (CNN) architecture for the categorization of colorectal polyps and prediction using SVM and MLP [15]

Table 2 Comparison Between Our Work and Previous Work

Aspect	Forootan et al. (2023)	Ponzio et al. (2018)	Mitsala et al. (2021)	Proposed Methodology
Dataset	ERCPMP Dataset	Custom Dataset	Review Paper	ERCPMP Dataset
Methodology	Deep Learning (CNN)	Deep Learning (CNN)	AI Techniques Review	SVM, MLP, VGG16, Attention Mechanism
Performance Metrics	Accuracy, Precision, Recall	Accuracy, Precision	N/A	Accuracy, Precision, Recall, F1-score
Accuracy	96.8%	91.5%	N/A	SVM: 98.7%, MLP: 94.6%
Precision	95.6%	90.1%	N/A	SVM: 98.3%, MLP: 93.2%
Recall	97.2%	91.0%	N/A	SVM: 98.9%, MLP: 94.8%
F1-score	96.4%	90.5%	N/A	SVM: 98.6%, MLP: 94.0%
Unique Contribution	Comprehensive Dataset	Deep Learning Techniques	Overview of AI in Colorectal Cancer	Integration of SDS, Attention Mechanism

Moreover, data science facilitates enhanced surgical planning through preoperative simulations and risk stratification, leading to optimized surgical approaches. In postoperative care, predictive analytics tools can foresee complications, allowing for proactive management and reducing adverse outcomes. Personalized recovery plans, informed by data-driven insights, ensure that care is tailored to individual patient needs, optimizing recovery times and outcomes. Continuous analysis of surgical outcomes and integration of feedback loops further refine predictive models and treatment protocols, driving continuous improvement in surgical practice. Moreover, Data science can help surgeons refine minimally invasive surgical techniques, leading to faster recovery and fewer patient complications.

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