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Machine Learning Techniques for Diagnosis of Lower Gastrointestinal Cancer: A Systematic Review

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Abstract

Background: Nowadays, it can be seen that changes have taken place in the process of diseases and their clinical parameters. Accordingly, in some cases, general medical science and the use of clinical statistics based on the experiences of the physicians are not enough for the provision of sufficient tools for an early and accurate diagnosis. Therefore, medical science increasingly seeks to use unconventional methods and machine learning techniques. The issue of diagnosis in the medical world and the error rate of physicians in this regard are among the main challenges of the condition of patients and diseases. For this reason, in recent years, artificial intelligence tools have been used to help physicians. However, one of the main problems is that the effectiveness of machine learning tools is not studied much. Due to the sensitivity and high prevalence of diseases, especially gastrointestinal cancer, there is a need for a systematic review to identify methods of machine learning and artificial intelligence and compare their impact on the diagnosis of lower gastrointestinal cancers.

Objectives: This systematic review aimed to identify the machine learning methods used for the diagnosis of lower gastrointestinal cancers. Moreover, it aimed to classify the presented methods and compare their effectiveness and evaluation indicators.

Methods: This systematic review was conducted using six databases. The systematic literature review follows the Preferred Reporting Items for Systematic Reviews and Meta-Analyses statement for systematic reviews. The search strategy consisted of four expressions, namely "machine learning algorithm", "lower gastrointestinal", "cancer", and "diagnosis and screening", in that order. It should be mentioned that studies based on treatment were excluded from this review. Similarly, studies that presented guidelines, protocols, and instructions were excluded since they only require the focus of clinicians and do not provide progression along an active chain of reasoning. Finally, studies were excluded if they had not undergone a peer-review process. The following aspects were extracted from each article: authors, year, country, machine learning model and algorithm, sample size, the type of data, and the results of the model. The selected studies were classified based on three criteria: ١) machine learning model, ٢) cancer type, and ٣) effect of machine learning on cancer diagnosis.

Results: In total, ٤٤ studies were included in this systematic literature review. The earliest article was published in ٢٠١٠, and the most recent was from ٢٠١٩. Among the studies reviewed in this systematic review, one study was performed on the rectum (rectal cancer), one was about the small bowel (small bowel cancer), and ٤٢ studies were on the colon (colon cancer, colorectal cancer, and colonic polyps). In total, ١٩ out of the ٤٤ (٤٣٪) articles from the systematic literature review presented a deep learning model, and ٢٥ (٥٧٪) articles used classic machine learning. The models worked mostly on image and all of them were supervised learning models. All studies with deep learning models used Convolutional Neural Network and were published between ٢٠١٦ and ٢٠١٩. The studies with classic machine learning models used diverse methods, mostly Support Vector Machine, K-Nearest Neighbors, and Artificial Neural Network.

Conclusion: Machine learning methods are suitable tools in the field of cancer diagnosis, especially in cases related to the lower gastrointestinal tract. These methods can not only increase the accuracy of diagnosis and help the doctor to make the right decision, but also help in the early diagnosis of cancer and reduce treatment costs. The methods presented so far have focused more on image data and more than anything else have helped to increase the accuracy of physicians in making the correct diagnosis. Achievement of the right method for early diagnosis requires more accurate data sets and analyses.

Keywords: Diagnosis, Lower gastrointestinal cancer, Machine learning

١. Background

Colorectal cancer is the third most common cancer in males and the second most common cancer in females. Unfortunately, a large number of patients with the final segment of the gastrointestinal (GI) system cancers die each year due to late diagnosis and overgrowth of cancer. One of the main reasons for this is that the symptoms of cancer do not appear until its later stages.

Today, due to the changes that have taken place in the process of diseases and their clinical parameters, in some cases, general medical science and the use of clinical statistics based on physician experience alone cannot provide sufficient tools for accurate and accurate diagnosis (١). Therefore, medical science increasingly seeks to use unconventional methods and machine learning techniques (٢,٣). Based on the nature and the type of the problem that needs to be solved, as well as the used clinical data, supervised and unsupervised approaches to machine learning can be employed to diagnose diseases (٤). Machine learning is one of the branches of artificial intelligence that enables a machine to study existing data without explicit planning to learn to discover patterns and make decisions based on existing data (٥,٦). In other words, this technology allows the machine, like physicians, to describe and diagnose diagnostic data to discover and present meaningful structural features and determine which features are related to the results of the defined cases. This tool is very useful for processing the bulk of unstructured biometric data, such as radiological images (٧). The issue of diagnosis in the medical world and the error rate of physicians in this regard is one of the main challenges due to the conditions of patients and diseases, and in recent years, artificial intelligence tools have been used to help physicians in this regard.

٢. Objectives

One of the main issues is that the effectiveness of these tools is not much studied. Meanwhile, due to the sensitivity and high prevalence of diseases, especially gastrointestinal tract cancer, the need is felt for a systematic review to identify methods of machine learning in artificial intelligence and compare their impact on the diagnosis of lower gastrointestinal cancers.

٣. Methods

٣,١. Protocol

This systematic review follows the PRISMA statement for systematic reviews. Moreover, the Critical Appraisal Skills Program checklist was used to help the readers make sense of this qualitative research.

٣,٢. Paper sources

Publications from Google Scholar, Scopus, ProQuest, PubMed, Web of Science, Cochrane, and SID as a Persian database, were searched in September ٢٠١٩ to identify articles that described and discussed the role of machine learning algorithms in the diagnosis of lower gastrointestinal cancers.

٣,٣. Search strategy

Due to the different terminologies of the selected databases in indexing papers, in an attempt to include all relevant articles, we used thesauruses, a systematic record in databases of subject headings used to index articles. To organize the search systematically, we grouped the search terms around four expressions: “Machine Learning”, “Lower Gastrointestinal Cancers”, “Cancer”, and “Diagnosis and Screening”. Further elaboration of the four expressions used to find eligible articles can be seen in Table ١. The search strategy consisted of four expressions: expression one (Machine Learning), expression two (Lower Gastrointestinal), expression three (Cancer), and expression four (Diagnosis and Screening). The terms within each expression were a mix of Medical Subject Headings (MeSH) terms and synonyms. We applied AND operator Between each expression and OR operator between each MeSH term and its synonyms. There were only a few exclusion criteria, such as being written in languages other than English and Persian, publication before ٢٠١٠, and being performed during treatment and follow-up of patients.

٣,٤. Inclusion and exclusion criteria of papers

The focus of this study was on machine learning models used for diagnosing and screening lower gastrointestinal cancers. The focus was on studies that presented machine learning algorithms, models which were relevant for lower gastrointestinal cancers diagnosis. It should be mentioned that the studies which focused on treatment and diagnosis of non-cancer problems were excluded from this research. The studies that were published before ٢٠١٠ and whose full text was unavailable or was not in English or Persian were excluded as well. Finally, studies were excluded if they had not undergone a peer-review process.

٣,٥. Study selection and data extraction

The OneNote ٢٠١٦ was used to handle the articles. To remove duplicates in the identified references, the functions ‘Find Duplicates’ and ‘Remove Duplicates’ were applied. Titles and abstracts of the selected papers were read to find the eligible articles based on the inclusion and exclusion criteria. The full texts of the remaining articles were studied to extract the required data. The extracted data included authors, year, country, machine learning model and algorithm, sample size, type of data, and results of the model. To reduce bias during the selection and reviewing process, the author and one of the co-authors, went through each article systematically, discussed the scope of each article, and decided whether an article was relevant in proportion to the present systematic literature review. The inter-rater reliability was not calculated

Table ١. The four expressions below show the search strategy applied in the systematic literature review. Each expression consists of Medical Subject Headings (MeSH) terms and synonyms. Between each MeSH term and its synonym, the Boolean operator OR is used, and between each expression the Boolean operator AND is applied.

Expression ١ (Machine Learning)	Expression ٢ (Lower Gastrointestinal)	Expression ٣ (Cancer)	Expression ٤ (Diagnosis and Screening)
Machine Learning OR Artificial Intelligence OR Deep Learning OR Neural Networks OR Data Mining OR Text Mining	ileum OR large intestine OR jejunum OR colon OR rectum OR cecum OR anal canal OR Intestine Small OR Duodenum	Neoplasm OR cancer OR tumor	Prediction OR diagnosis OR detection OR screening OR predict

in this study. The included machine learning models from the studies were subsequently described and classified according to the selected variables. The studies were classified in three ways: ١) type of machine learning model, ٢) type of cancer, and ٣) effect of machine learning on cancer diagnosis.

٤. Results

٤,١. Study Selection

Figure ١ shows the flowchart of the selection process of articles included in the systematic literature review. Systematic searches led to the identification of ٧٧٤ articles. Before starting the preliminary screening process of titles and abstracts, ١٥٨ duplicates were removed; hence, ٦١٦ records remained to be screened. The screening process followed the inclusion and exclusion criteria as explained in the method section, leaving ٧٤ articles for full-text review. There were ٣٠ articles excluded based on the full-text review process; hence, the final number of studies included in the systematic review was ٤٤. The earliest relevant article was published in ٢٠١٠, and the most recent was from ٢٠١٩.

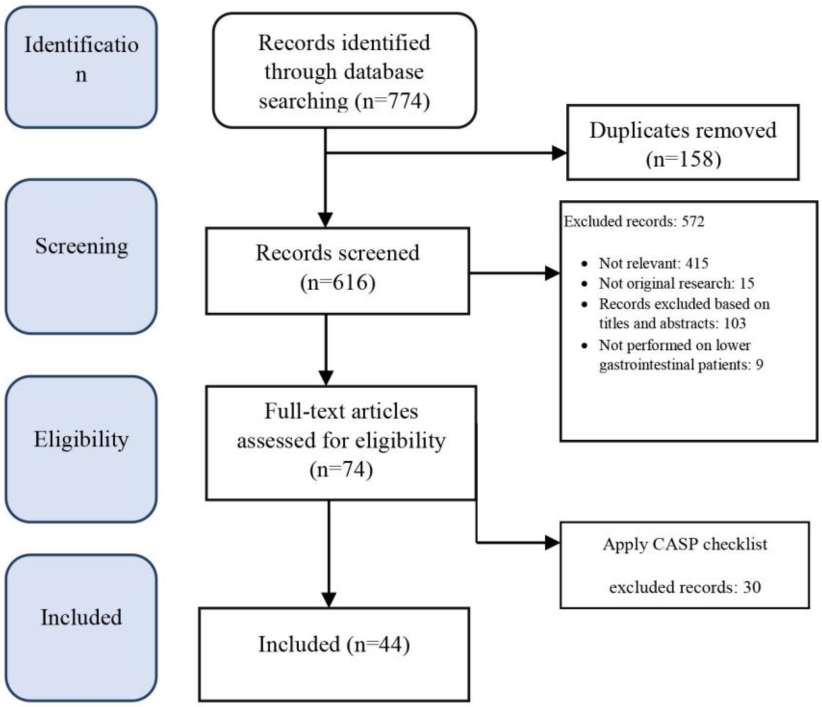

Figure ١. Flowchart of the selection process of the articles included in the systematic literature review. CASP: Critical Appraisal Skills Program

Table ٢. Deep learning models

Reference No.	Data presented in the article	Applied techniques	Year of publication	Country of publication
(٨)	Image	CNN	٢٠١٦	UK
(٢٦)	Video	CNN	٢٠١٦	Hong Kong
(٢٧)	Image	CNN	٢٠١٦	Hong Kong
(٤٥)	Image	CNN	٢٠١٦	USA
(٢٣)	Image	CNN	٢٠١٧	Austria
(٢٨)	Image	CNN	٢٠١٧	Taiwan
(٤٠)	Image	CNN	٢٠١٧	UK
(٤٦)	Image	CNN+SVM	٢٠١٧	China
(٥١)	Image	CNN	٢٠١٧	Japan
(٣٠)	Image	CNN	٢٠١٨	Germany
(٣٣)	Image	CNN	٢٠١٨	USA
(٣٤)	Image	CNN	٢٠١٨	China
(٢٩)	Image	CNN	٢٠١٩	Japan
(٣٢)	Image	R-CNN	٢٠١٩	USA
(٣٦)	Image & Video	CNN	٢٠١٩	Denmark
(٣٨)	Image	CNN	٢٠١٩	Korea
(٣٩)	Image	CNN	٢٠١٩	India
(٤٣)	Image	CNN	٢٠١٩	France
(٤٤)	Image	CNN	٢٠١٩	UK

CNN: convolutional neural network, SVM: support vector machine, R-CNN: region-based convolutional neural networks

Table ٣. Classic machine learning models

Reference No.	Data presented in the article	Applied techniques	Year of publication	Country of publication
(١١)	Image	SVM	٢٠١٠	USA
(٤٧)	Image	Fourier Filters	٢٠١٠	Austria
(١٢)	Image	SVM	٢٠١١	USA
(١٣)	Image	GrayRLM	٢٠١١	Turkey
(١٤)	Image	SVM	٢٠١١	Netherlands
(٤٨)	Image	SVM+KNN+ANN	٢٠١١	China
(١٥)	Image & Table	ANN	٢٠١٢	Iran
(١٦)	Image	RMM	٢٠١٢	Turkey
(١٨)	Image	ANN	٢٠١٢	Italy
(١٠)	Image	SVM+KNN	٢٠١٣	Korea
(١٧)	Image	ANN	٢٠١٣	USA
(٩)	Image	SVM	٢٠١٤	Pakistan
(١٩)	Image	SVM	٢٠١٤	Taiwan
(٢٠)	Image	SVM	٢٠١٥	Korea
(٢١)	Image	Ensemble classifiers	٢٠١٦	Spain
(٤٩)	Image	J٤٨, nearest neighbor, backpropagation based on multilayer perceptron, Naive Bayes, and SVM	٢٠١٦	Brazil
(٥٠)	Image	ANN	٢٠١٦	Romania
(٢٢)	Image	Binary pattern approach with genetic fuzzy based improved kernel SVM classifier	٢٠١٧	USA
(٢٤)	Image	Regression neural network enhanced with the augmented Lagrangian genetic algorithm	٢٠١٧	India
(٢٥)	Image	SVM, MLP	٢٠١٧	Turkey
(٣٥)	Image	Sparse autoencoder+SVM+image processing methods	٢٠١٧	China
(٣١)	Image	SVM+dictionary learning	٢٠١٨	Norway
(٣٧)	Image	Random forest	٢٠١٩	China
(٤١)	Image	SVM, deep belief network	٢٠١٩	Turkey
(٤٢)	Image	SVM	٢٠١٩	India

SVM: support vector machine, KNN: k-nearest neighbors, ANN: artificial neural network, RMM: resampling-based Markovian model, MLP: multilayer perceptron

٤,٢.Types of Machine learning models

٤,٢,١.Deep learning models

In total, ١٩ out of the ٤٤ (٤٣٪) articles included in the systematic literature review presented a deep learning model. The oldest and newest of these studies were published in ٢٠١٦ and ٢٠١٩, respectively. The applied techniques in these ٢٠ studies covered cancer diagnosis using the convolutional neural network (CNN). The data sets applied in these models encompassed various sizes and all of their data sets involved image and video (Table ٢).

٤,٢,٢. Classic machine learning models

In total, ٢٥ (٥٧٪) of the reviewed studies used classic machine learning models. The oldest and newest studies were performed in ٢٠١٠ and ٢٠١٩, respectively. As it is shown in Table ٣, these models mostly used support vector machine (SVM), artificial neural network (ANN), k-nearest neighbors (K-NN) as their techniques. In some studies, an ensemble model was used.

Table ٤. Colon cancer

Reference No.	Year	Country	Applied techniques	Accuracy (%)	Sensitivity (%)	Specificity (%)	Other (%)
(٤٧)	٢٠١٠	Austria	Fourier filters	٩٦,٩	No	No	No
(١٣)	٢٠١١	Turkey	GrayRLM	٨٧,١	٧٩,٢	٩٠,٧	No
(١٥)	٢٠١٢	Iran	ANN	No	٨٥,٧	٤٤,٤	No
(١٦)	٢٠١٢	Turkey	Resampling-based Markovian model	٩٠,٣٢	No	No	No
(١٠)	٢٠١٣	Korea	SVM K-NN	٩٦,٢	No	No	No
(٩)	٢٠١٤	Pakistan	SVM	٩٨,٨٥	١٠٠	٩٨	No
(٢١)	٢٠١٦	Spain	Ensemble classifiers	٨٢,٦	٨٥,٨٨	٧٢,٧٤	No
(٤٦)	٢٠١٧	China	CNN+ SVM	٩٨	No	No	No
(٣٩)	٢٠١٩	India	CNN	٧٢	No	No	No
(٣٧)	٢٠١٩	China	Random Forest	٩١,٨	No	No	No
(٣٨)	٢٠١٩	Korea	CNN	٩٤	١٠٠	٨٨	No
(٤١)	٢٠١٩	Turkey	SVM, deep belief network	٩٩,٤٤	٨٨,٣٧	No	F Score=٩٣,٦

ANN: artificial neural network, SVM: support vector machine, K-NN: k-nearest neighbors, CNN: convolutional neural network

Table ٥. Colorectal cancer

Reference No.	Year	Country	Applied techniques	Accuracy (%)	Sensitivity (%)	Specificity (%)	Other (%)
(۱۲)	۲۰۱۱	USA	SVM	No	۷۹	۸۳	No
(۱۷)	۲۰۱۳	USA	ANN	No	No	No	RSME=۱,۲٦
(۸)	۲۰۱٦	UK	CNN	۷۸	۸۲	No	F۱ Score=۸۰
(۲۷)	۲۰۱٦	Hong Kong	CNN	۸٥,۹	۸۷,٦	No	F۱ Score=۸۷,۰۱
(٤۹)	۲۰۱٦	Brazil	J٤۸, Nearest neighbor, Backpropagation based on multilayer perceptron, naive Bayes and SVM	No	۹۲,٥٤	۸٥,۰۷	No
(٥۰)	۲۰۱٦	Romania	ANN	۸٤,٥۲	No	No	No
(۲۳)	۲۰۱۷	Austria	CNN	۹٦,٤	No	No	No
(٤۰)	۲۰۱۷	UK	CNN	No	No	No	F۱ Score=۸۹
(۲۹)	۲۰۱۹	Japan	CNN	۸۱,۲	۸۹,۰	٦۷,٥	No
(۳۲)	۲۰۱۹	USA	CNN (R-CNN)	No	No	No	F۱ Score=۹٦,٦
(٤۳)	۲۰۱۹	France	CNN	No	No	No	Dice coefficient= ۰,۹۳
(٤٤)	۲۰۱۹	UK	CNN	No	No	No	Dice coefficient=۰,۹

RMSD: root-mean-square deviation, SVM: support vector machine, ANN: artificial neural network, CNN: convolutional neural network, R-CNN: region-based convolutional neural networks

Table ٦. Colonic Polyp

Reference No.	Year	Country	Applied techniques	Accuracy (%)	Sensitivity (%)	Specificity (%)	Other (%)
(۱۱)	۲۰۱۰	USA	SVM	No	۸۳	No	No
(۱۸)	۲۰۱۲	Italy	ANN	۱۰۰	۱۰۰	No	No
(۱۹)	۲۰۱٤	Taiwan	SVM	۹٦	No	No	No
(۲۰)	۲۰۱٥	Korea	SVM	۷۰,٦۷	۷۰,٦	No	No
(۲٦)	۲۰۱٦	Hong Kong	CNN	۸۸,۱	۷۱	No	F۱ Score=۷۸,٦
(٤٥)	۲۰۱٦	USA	CNN	۹۹	No	۹۸	No
(۲۲)	۲۰۱۷	USA	SVM	۹۳,۲	No	No	No
(۲٤)	۲۰۱۷	India	Regression neural network	۹۷,۳۷	۹٦,٥	۹٦,۲٥	No
(۲٥)	۲۰۱۷	Turkey	SVM MLP	No	No	۹٥,۸	No
(۲۸)	۲۰۱۷	Taiwan	CNN	No	۸۷,۱	۹٦,۳	No
(۳٥)	۲۰۱۷	China	SVM	No	No	No	No
(٥۱)	۲۰۱۷	Japan	CNN	۷۲	۸۱	No	No
(۳۰)	۲۰۱۸	Germany	CNN	No	۹۳,۹	۸۹	No
(۳۱)	۲۰۱۸	Norway	SVM	۹٥,۹	۹٥,۸	۹٥,۹	No
(۳۳)	۲۰۱۸	USA	CNN	۹٦,٤	No	No	No
(۳٤)	۲۰۱۸	China	CNN	No	۹٤,۳	۹٥,۹۲	No
(۳٦)	۲۰۱۹	Denmark	CNN	No	No	No	No
(٤۲)	۲۰۱۹	India	SVM	۹٥,۷	۹٥,٤	۹٦	No

SVM: support vector machine, ANN: artificial neural network, CNN: convolutional neural network MLP: multilayer perceptron

٤,۳. Types of cancer and the effect of machine learning

٤,۳,۱. Rectal Cancer

Among the studies reviewed in this systematic review, only one study was conducted on the rectom organ. In the aforementioned study, which predicted rectal cancer and used PET-CT images and the SVM method, in addition to the presence or absence of cancer, its physical characteristics were also identified. It should be mentioned that it was conducted in the Netherlands in ۲۰۱۱ (۱٦). Notable points of this study are its only evaluation index which is the area under the curve, and it is not clear whether it has performed correctly in other possible indicators or not. In addition, there is no comparison with similar works in this study; therefore, its effectiveness cannot be commented on in this study.

٤,۳,۲. Small bowel

Among the studies included in this systematic review, only one study was performed on the small bowel organ. In the above-mentioned study, which diagnosed a small bowel tumor and used endoscopic images and an ensemble method, an attempt was made to accurately identify the tumor in question. It was conducted in ۲۰۱۱ in China (٤۸), and one of its notable points was its evaluation indicators. In the aforementioned study, accuracy, sensitivity, and specificity were used and acceptable results were obtained, compared to other models.

٤.۳,۳. Colon cancer

Among the studies included in this systematic review, there were ٤۲ studies on colon cancers. It is noteworthy that ١٢, ١١, and ١٩ of these studies were related to the diagnosis of colon cancer, colorectal cancer, and cancerous polyps.

٤.٣.٤.Colon cancer

i. According to the accuracy index, the highest value was related to the reference number (٤١) which was ٩٩,٤٤. In this study, published in ٢٠١٩, the SVM method was used. Reviewing the studies, it can be seen that the average accuracy in the studies carried out during ٢٠١٥-١٩ is higher than that of the studies performed during ٢٠١٠-١٥. Moreover, the accuracy of the models implemented with the CNN method (on average) is higher than that of the other models.

ii. In terms of sensitivity index, two studies with reference numbers of (٩) and (٣٨) had the highest value which is ١٠٠٪. The first study was published in ٢٠١٤ and used SVM, and the second one was published in ٢٠١٩ and used CNN.

iii. The specificity index was reported in only five studies, the study with reference number (٩) being the highest. (Table ٤)

٤.٣.٥. Colorectal cancer

i. According to the accuracy index, the highest value is related to reference number (٢٣) which is ٦٩,٤. In this study, published in ٢٠١٧, the CNN method was used. A review of the studies revealed that the accuracy of the models implemented with the CNN method (on average) is higher than that of the other methods.

ii. In terms of sensitivity index, the study with reference number (٤٩) had the highest value which was ٩٢,٥٤٪. The aforementioned study was published in ٢٠١٤ and used K-NN.

iii. The specificity index was reported in only three studies, the highest of which belonged to the study with reference number (١٢) which was published in ٢٠١١ and used SVM.

iv. Some studies have also reported the F١ Score among which the highest value (٩٦٪) was related to the study with reference number (٣٢) published in ٢٠١٩. It should be noted that this study used CNN. (Table ٥)

٤,٣,٦. Colonic Polyp

i. According to the accuracy index, the highest value (١٠٠٪) is related to reference number (١٨). In this study, published in ٢٠١٢, the ANN method was used. A review of the studies indicated that the accuracy of the models implemented with the SVM method (on average) is higher than that of the other models.

ii. In terms of sensitivity index, the highest value (١٠٠٪) was related to the study with reference number (١٨). This study was published in ٢٠١٢ and used ANN.

iii. The specificity index was reported in only three studies, and the study with reference number (٤٥) had the highest index. The aforementioned research was published in ٢٠١٦ and used CNN. (Table ٦)

٥. Discussion

Machine learning techniques are appropriate tools for the diagnosis of cancer, especially in cases involving the lower gastrointestinal tract. They not only increase the accuracy of the diagnosis and help the doctors make a better decision but also help in early cancer detection. The methods presented so far have focused more on the image as their dataset and increased the accuracy of the diagnosis of physicians. Achievement of the right method for early detection requires appropriate data sets and more accurate analysis.

By conducting this review, which has finally included ٤٤ articles, the following has been achieved:

❖ Articles focused on the diagnosis of three types of cancer (Colon cancer, colorectal cancer, and polyp detection). The variety of models used in these studies was high and among them, SVM and CNN tools were the most commonly used methods. The SVM was usually used in the studies with a low volume of data, while CNN was used in situations where the volume of used data was high. Although this choice is closely related to the taste and ability of the researcher, in the case of data constraints, they were forced to choose despite this.

❖ Among the reviewed articles, only one article (١٥) dealt with the issue of early detection. In addition to being a potential for future research work, this can also be a threat. This means that no attempt has been made to create a data set for this issue. It is noteworthy that in the aforementioned study, in addition to image data, tabular data, including demographic data and patient records were used which are necessary for early diagnosis.

❖ It should be noted that the evaluations have not been performed based on a single procedure and each study has used its own indicators. For example, some studies have reported only one indicator; hence, it is not possible to know whether this study performed better in terms of other indicators or not. This can be a weakness but regarding the values reported for the indicators in these studies, accuracy and sensitivity indices were on average better in newer studies and studies that used the CNN method. Moreover, the specificity index was better reported in studies that have used the SVM method.

❖ Most studies concluded that the use of machine learning tools and especially methods based on CNN has contributed significantly to the accuracy and speed of diagnosis of physicians, especially in situations where the physician faces a large amount of video and video data.

٦. Conclusion

Machine learning methods are suitable tools in the field of cancer diagnosis, especially in cases related to the lower gastrointestinal tract. They can increase the accuracy of diagnosis, help the doctor to make the right decision, and also help in early diagnosis of cancer and reduction of treatment costs. The methods presented so far have focused more on image data and helped to increase the accuracy of the diagnosis of the physician more than anything else. Achievement of the right method for early diagnosis requires more accurate data sets and analyses.

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