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ARTIFICIAL INTELLIGENCE IN COLORECTAL CANCER: A REVIEW

Gurjeet Singh

Lords University, Chikani, Alwar, India

Abstract

The study objective: the study objective is to examine the use of artificial intelligence (AI) in the diagnosis, treatment, and prognosis of Colorectal Cancer (CRC) and discuss the future potential of AI in CRC. **Material and Methods.** The Web of Science, Scopus, PubMed, Medline, and eLIBRARY databases were used to search for the publications. A study on the application of Artificial Intelligence (AI) to the diagnosis, treatment, and prognosis of Colorectal Cancer (CRC) was discovered in more than 100 sources. In the review, data from 83 articles were incorporated. **Results.** The review article explores the use of artificial intelligence (AI) in medicine, specifically focusing on its applications in colorectal cancer (CRC). It discusses the stages of AI development for CRC, including molecular understanding, image-based diagnosis, drug design, and individualized treatment. The benefits of AI in medical image analysis are highlighted, improving diagnosis accuracy and inspection quality. Challenges in AI development are addressed, such as data standardization and the interpretability of machine learning algorithms. The potential of AI in treatment decision support, precision medicine, and prognosis prediction is discussed, emphasizing the role of AI in selecting optimal treatments and improving surgical precision. Ethical and regulatory considerations in integrating AI are mentioned, including patient trust, data security, and liability in AI-assisted surgeries. The review emphasizes the importance of an AI standard system, dataset standardization, and integrating clinical knowledge into AI algorithms. Overall, the article provides an overview of the current research on AI in CRC diagnosis, treatment, and prognosis, discussing its benefits, challenges, and future prospects in improving medical outcomes.

Key words: artificial intelligence (AI), deep learning (DL), machine learning (ML), diagnosis, treatment, CRC.

ИСКУССТВЕННЫЙ ИНТЕЛЛЕКТ ПРИ КОЛОРЕКТАЛЬНОМ РАКЕ: ОБЗОР

Gurjeet Singh

Lords University, Chikani, Alwar, India

Аннотация

Цель исследования – оценка возможностей использования искусственного интеллекта (ИИ) в диагностике, лечении и прогнозировании колоректального рака (КРР), а также обсуждение потенциала ИИ в лечении КРР. **Материал и методы**. Проведен поиск научных публикаций в поисковых системах Web of Science, Scopus, PubMed, Medline и eLIBRARY. Было просмотрено более 100 источников по применению ИИ для диагностики, лечения и прогнозирования КРР. В обзор включены данные из 83 статей. **Результаты.** Проведен анализ литературы, посвященной применению искусственного интеллекта в медицине, особое внимание уделено его использованию при колоректальном раке. Обсуждаются этапы развития ИИ при КРР, включая молекулярную верификацию, лучевую диагностику, разработку

Gurjeet Singh, research.gurjeet@gmail.com

лекарств и индивидуальное лечение. Подчеркнуты преимущества ИИ в анализе медицинских изображений, таких как КТ, МРТ и ПЭТ, что повышает точность диагностики. Рассматриваются такие проблемы развития ИИ, как стандартизация данных и интерпретируемость алгоритмов машинного обучения. Подчеркивается роль ИИ в выборе оптимальной тактики лечения и повышении эффективности хирургического вмешательства. Учитываются этические и нормативные аспекты ИИ, включая доверие пациентов, безопасность данных и ответственность в проведении операций с использованием ИИ. Обсуждаются преимущества ИИ в диагностике, лечении и прогнозировании колоректального рака, проблемы и перспективы улучшения результатов лечения.

Ключевые слова: искусственный интеллект, глубокое обучение, машинное обучение, диагностика, лечение, колоректальный рак.

Introduction

Heavy scientific and engineering calculations have transitioned from being done primarily by the human brain to being done more rapidly and precisely by computers since the invention of the computer. With the advancement of computer science and technology, artificial intelligence (AI) has progressed quickly. AI is a broad phrase that refers to computer simulation, decision-making, language comprehension, problem-solving, voice and image recognition, and other «intelligent» functions that people accomplish [1–2]. Machine learning (ML), deep learning (DL), anti-learning, quasi-supervised learning (QSL), and active learning (AL) are the several types of AI [3–6]. ML is a type of AI algorithm that adjusts and improves itself using statistical approaches [2]. ML generates algorithms for assessing data and learning to anticipate models, implying that the decision-making process is data-driven with as minimal human interaction as feasible [3, 7]. The model developed by ML can be utilized to predict the clinical phenotype as an independent executable system [8]. Support vector machine (SVM), neural network (NN), random forest (RF), decision tree, and regression analysis are all essential technologies in machine learning [9–13]. ML is split into supervised learning, unsupervised learning, and semi-supervised learning (SSL) based on the association of class labels [7, 8]. The most common applications of supervised learning are classification and regression issues. For a cluster, density estimation, and dimensionality reduction, unsupervised learning is used [8]. When unlabeled data is coupled with a small quantity of labeled data, SSL can greatly increase learning accuracy [14]. At the moment, supervised learning is a key component of AI and machine learning in the medical industry [1]. Because it takes into account the patients' features, supervised learning produces more accurate outcomes than other AI techniques [9]. DL is a type of advanced machine learning (ML) based on an artificial neural network (ANN) [1], which is inspired by the biological properties of the human brain, particularly the connections between neurons [1, 3]. DL can not only locate lesions, provide differential diagnostic recommendations, and create basic medical reports automatically, but it can also learn on its own, i.e., crucial characters and amounts can be extracted without a manual indication if training data is provided [3]. DL also aspires to replicate the brain's learning process and process massive amounts of high-dimensional data [15]. QSL is a statistical learning technique that eliminates the need for human tagging of normal and malignant tissue samples in classical supervised learning and significantly lowers expert intervention [4]. In most cases, machine learning requires a huge number of annotated training sets, which are costly to produce. AI helps to reduce the amount of the needed annotation set and creates a more accurate categorization model [6]. In certain studies, the anti-learning strategy outperformed a set of ML algorithms in predicting the stage of colorectal cancer (CRC) from immunological characteristics [5]. CRC is the second most common cause of cancer death in men and the third most common cause of cancer death in women [16]. Colonic polyps, which can cause 80 percent to 95 percent of CRC [17], can be discovered and rejected in the precancerous stage by the screening technique, which can help prevent CRC development [18]. Despite the fact that early and thorough screening can reduce cancer incidence and mortality, patients avoid CRC screening because of the difficulty and cost [18–20]. Imaging diagnosis, endoscopy, and pathology diagnosis are the three main approaches for diagnosing CRC. Endoscopic treatment, surgical treatment, and pharmacological treatment are the three types of treatment available. Lymph node dissection is not necessary intra-operatively if lymph node metastases are not established preoperatively [21]. Because AI can learn from a vast data collection, it has a lot of diagnostic potential. AI outperforms medical expertise and known biomarkers in the clinical setting [9]. The use of AI in the diagnosis, treatment, and prognosis of CRC will be discussed in this paper.

Use of artificial intelligence in diagnosis of CRC

Deep Learning in Imaging Diagnosis

Clinical diagnosis and treatment of CRC can be aided by the DL intelligent assistance diagnosis system [22]. The nature of the selected area (cancerous or non-cancerous) is usually determined by the informative aspects of the known prospective (cancerous) structure in a computer-aided diagnosis (CAD) system [23]. Visual signals (CAD markings) related with possible pathology can aid radiologists in diagnosing CRC.

In addition, computer-assisted detection (CADe) can help pinpoint the site of the disease and whether the aberration is benign or malignant. Doctors must finally determine whether or not to “trust” the CAD mark, regardless of the outcome [24]. High detection sensitivity and a low false-positive rate (FP) are essential for radiologists to approve the clinical use of CAD systems [23]. Other colorectal pathological morphologies, aside from polyps and cancer, are uncommon, which may explain why CAD solutions for computed tomography colonography (CTC) have emerged so quickly [25]. Although CTC CAD enhanced sensitivity in detecting polyps without reducing specificity, the lesions mistaken for false-negatives were substantially larger and irregular [24–26]. According to Regge et al. [24], the difficulty of characterisation (irregular and flat shape) was the main factor of radiologists’ rejection of true positive CAD results. Despite the fact that the consequences of CRC misdiagnosis are more worse than those of polyp misdiagnosis, research into CADe for CRC in CTC is currently limited [27].The absence of research on the detection characteristics of early CRC [28] and the fact that efficiently distinguishing masses from normal colonic anatomy based on the design aspects of mathematical pictures [27] may be the reasons for this. Taylor et al. [28] gathered morphological data of flat tumours by finding tumours in order to distinguish tumours from normal tissue structure, and discovered that the CAD method paired with CTC was relatively successful for diagnosing flat (non-polypoid) cancer. CAD can increase picture interpretation speed, locate polyps missed by specialists, reduce variability between observers, and improve polyp detection sensitivity [29, 30]. The increase in FP created by CAD, on the other hand, may diminish efficiency [25]. In CTC, deep transfer learning can considerably improve polyp detection accuracy [31]. Because the CADe system may employ virtual intra-cavity images of polyps to change the deep convolutional NN (DCNN) trained on millions of non-medical images, the DCNN can detect polyps [31]. Using a visualization method in CTC, it can considerably increase the diagnosis of polyps for unskilled clinicians. The visualization approach, when used in conjunction with the CAD system, can reduce radiologists’ interpretation time and improve the detection of colon cancers in CTC [32]. Van Wijk et al. [33] proposed a method for evaluating polyps larger than or equal to 6 mm by measuring the protrusion of candidate objects in a scale adaptive approach, with a sensitivity of 95 %. It was thought that determining the size of polyps, rather than the shape, could lower the likelihood of missed identification of big polyps [33]. The CTC dataset analyzed by the CAD method was obtained from polyp patients by Kim et al [34]. The CTC dataset was created to describe the lumpy structure that extends into the lumen, and it was able to detect large polyps (>6 mm) with high sensitivity and acceptable FP. Nappi et al. [35] created a CADe approach to detect the location of colonic polyps based on volume and form features, and utilized this method to evaluate serrated polyps confirmed by colonoscopy and biopsy. The method’s detection accuracy was substantially higher than that of the old CADe system, according to the results [35]. As a result, the use of CAD diagnostics has a bright future. However, more data sets and effective annotations are still required to improve AI diagnosis accuracy [24]. For classifying the contrast enhancement time, the best portal venous phase timing recognition scan was chosen, which may assist assess the radiologic properties of the tumour and evaluate the efficacy of patients with advanced CRC [36]. Soomro et al. [37] discovered that three-dimensional (3D) fully convolutional NNs combined with 3D level-set had a higher sensitivity in the segmentation of CRC on magnetic resonance imaging (MRI) than 3D fully convolutional NNs alone, which aided in the diagnosis of CRC. The 3D full collaborative network architecture based on DL may segment CRC more accurately and effectively than other approaches in 3D-T2 weighted MRI [38].The use of a faster region-based convolution NN (Faster R-CNN) in a high-resolution MRI picture of rectal cancer has a high accuracy in evaluating tumour borders [39, 40]. One of the most important elements influencing CRC patients’ treatment decisions is the circumferential resection margin. In MRI images of CRC, Joshi et al [41] developed an automatic computation and visualization method of circumferential resection margin distance to partition the middle rectal fascia, corresponding tumour, and lymph node into various sections. The shortest cut edge was automatically analyzed using segmentation, and the findings were nearly equal to the experts’ assessment [41].

DL in Pathological Diagnosis

CRC is virtually completely treatable if caught early. However, because a double evaluation of the biopsy and the colonoscopy picture is necessary to obtain an accurate diagnosis, the cost of diagnosis has doubled [42]. As a result, the usage of DL and automatic image analysis in pathology is expanding, which is referred to as the pathology's third revolution [43]. Although automated coding in DL is useful for extracting multi-layer picture characteristics and deep NNs can categorize them, training artificial neurons takes a long time [44]. In pathological image analysis, convolutional NN (CNN) is a common method. CNN provides the advantages of convenience for end-to-end learning (CNN learning parameters and representations are designed manually), flexibility, and high capacity when compared to other approaches [1]. The colour space used for recognizing cancer tissue is critical since it has a significant impact on the classification model's effectiveness. The tissue classification of distinct colour spaces is analyzed using CNN. S. Tiwari demonstrated that the hue, saturation, and value (HSV) colour space was more suitable for cancer tissue classification than any other colour model [45].

It's difficult to detect and classify nuclei in pathological pictures of cancer tissues stained with hematoxylin and eosin (H&E) because of cell heterogeneity, texture, and cell contact complexity [46, 47]. For nuclear detection, a space-constrained CNN based on DL was developed, which could allow for quantitative study of tissue components and clarification of the tumour microenvironment. Furthermore, when paired with CNN, the neighbour ensemble predictor was able to effectively forecast the discovered nuclear markers and classify the nuclei [46]. Despite the fact that qualitative and quantitative study of histopathological pictures can clarify the tumour and explore alternative cancer treatment choices, cell heterogeneity makes it difficult. When Faster R-CNN was applied in feature extraction, Zhang et al. [48] demonstrated that it had good accuracy and a lower cost of time, giving a valuable quantitative analysis group for pathological practice. CNN, which is frequently used to analyze histopathology pictures, solely works on the histological images itself, ignoring the stain degradation. In colon cancer, Xu et al. [49] developed a new model based on DCNN for classifying H&E and immunohistochemical images of epithelial and stromal cells. The DCNN-based model consistently outperformed the old hand-made model in discriminating stromal from epithelial cells. The malignant degree of adenocarcinoma is determined by the appearance of glands and nuclei. The correct identification and segmentation of the histological picture, which is required for quantitative diagnosis, is difficult due to appearance fluctuation, high resemblance, and tissue degradation. Chen et al. [50] aimed to improve identification and segmentation accuracy by using a depth profile awareness network that could output an accurate probability map of histology items and draw clean contour lines. The field of digital pathology is relatively new. Pathologists may benefit from the growth of digital pathology by improving the quality of routine pathological operations [51]. The CAD system, which is founded on the premise of extracting histopathological traits that pathologists think relevant, is critical to the advancement of digital pathology. The existence of these characteristics was then quantified using computer calculations [52, 53]. There are two major phases to obtaining a CAD: The automatic segmentation of tumours in the H&E staining histological image and tumour segmentation of the complete section image in the histological section [54]. Qaiser et al. [54] discovered that tumour and non-tumor plaques exhibited unique homology, and used connectivity between nucleuses to demonstrate the strength and relevance of persistent homology. Persistent homology maps (PHPs) were presented as a tool for distinguishing tumour from normal areas by imitating the unusual properties of tumour cell nucleus [54]. Other approaches, including classic CNN [54], are outperformed by PHPs. Two distinct tumour segmentation strategies are proposed: faster targeting without sacrificing accuracy and improved targeting accuracy. Competition algorithms were demonstrated to be inferior to the combination of PHPs and CNN features [54].

DL in Endoscopic Diagnosis

Colonoscopy is a standard procedure for detecting polyps in the colon. CRC incidence and mortality rates can be reduced by detecting and eliminating adenomatous polyps [16]. AI is required to improve machine performance and diagnosis accuracy, as well as to reduce operator variability and aid rapid treatment decision-making [2]. Furthermore, AI has the potential to enhance adenoma detection rates and lower polypectomy costs [55]. The effectiveness of colonoscopy inspection is influenced by the quality of intestinal preparation [56]. When faecal leftovers are present in the colon, the rate of polyps being ignored increases. Although the endoscopic image diagnosis programme based on CNN has produced positive results, the quality and quantity of training data is critical for its diagnostic ability [3, 57]. The use of CNN in conjunction with a colonoscopy technique is predicted to increase polyp identification rates and accuracy [58]. Zhou et al. [56] created a CNN-based system that was trained using images from colonoscopies. The system was proven to be more reliable than endoscopic physicians in diagnosing CRC in a human-machine competition. Taha et al. [59] proposed a DL solution for polyps from colonoscopy, which included a feature extraction pre-training architecture and the traditional SVM classifier.The method beats previous models in the early screening of CRC [59] because it avoids the high computational complexity and resource needs of CNN. Yao et al. [60] demonstrated that the RGB and HSV colour spaces could accurately characterize the frames in colonoscopy recordings. By incorporating prior knowledge based on vision into the data collected by DL, the model's efficiency could be improved. As a result, a feature extraction technique in HSV colour space was developed to increase diagnosis accuracy while lowering costs [60]. By wiping the mucosal wall and reexamining the hurried segment, McNeil et al. [61] suggested an automatic quality control system based on DCNN for increasing colonoscopy quality. The technology has the potential to boost polyp identification rates, which is important for early CRC diagnosis and prevention. Traditional colonoscopy has a missed diagnosis rate of up to 25 % [62, 63], owing to a lack of depth information, inter-observer variance, and contrast on the colon's surface [63, 64]. In endoscopic video, computer-aided technology is critical for polyp diagnosis. In the evolution of algorithm performance, the method based on DL takes the lead [65]. Minimizing the FP of colonic polyps is a difficult objective for CAD [66]. To estimate depth from endoscopic pictures, Mahmood et al. [64] developed a hybrid depth learning and graphics model based approach. Simultaneously, they generated training photos with the texture-free colon model and trained the model with those images [64]. With a relative error of 0.164, the system was able to estimate the depth of virtual data, which helped to improve the CAD system and locate lesions [64]. Komeda et al. [67] thought CNN had the advantage of learning from vast data and resulting in high precision and quick processing time, therefore they created a CNN-CAD system to analyze endoscopic images retrieved from colonoscopy [67]. The CNNCAD method was found to be useful for the quick diagnosis of colonic polyps and to facilitate the decision-making process for colorectal polypectomy after analysis and cross-validation of 1200 colonoscopy cases [67]. The CAD method (dubbed RYCO) offered the promise for speedy and accurate computer-aided polyp detection in colonoscopy when compared to existing algorithms. The colonoscopy image was fine-tuned using the quick target identification algorithm ResYOLO, which was pre-trained using a huge non-medical image database. Simultaneously, the temporal data was integrated by a tracker called Efficient Convolution Operator to boost ResYOLO's detection performance. RYCO might directly clarify the geographical characteristics of colorectal polyps and improve colorectal polyp detection effectiveness [68]. The optical diagnostic technique established by CNN [69] was proposed to distinguish stage T1b and Tis/T1a CRC. The early CRC digital images without magnification and under a pure white light endoscope were chosen as the training dataset by Zhu et al. [69]. 122 early CRC pictures were utilized to evaluate diagnostic performance at the end of the training phase. The findings revealed that optical diagnoses using CNN had a high sensitivity but a low specificity, which was not the case with humans [69]. Polyp diagnosis in colonoscopy video was difficult due to variations in polyp size and form [70]. The Faster R-CNN, on the other hand, may lower the risk of polyp loss during colonoscopy [65]. Akbari et al. [70] also presented a CNN-based fully convolutional network (FCN) method for polyp segmentation. They executed successful post processing for the probability map created by the network during the test phase. The approach was tested using the CVC-ColonDB database. As a result, FCN was able to obtain more accurate segmentation findings [70]. 3D-FCN exhibited a better recognition ability and could learn more representative spatiotemporal elements from colonoscopy footage than FCN [71]. Felfoul et al. [83] created a nanorobot capable of delivering medications to cancer cells. The robot detected hypoxia and the time endoscopic image diagnosis support system is to apply AI during colonoscopy without interfering with any doctor's work [72]. White light endoscopy alone can be used to perform real-time optical detection and analysis of polyps using the DL approach [73]. Endoscopists can use a real-time automatic polyp identification technology to swiftly and accurately diagnose lesions that could be adenomas [16]. Small-scale colorectal polyps can be resected and discarded thanks to the precision of endoscopic differential diagnosis [74]. Lund Henriksen et al. [74] investigated a system for automatic polyp detection to aid and automate the inspection procedures in order to alleviate the high cost, long time consuming, and patients' pain. When stochastic gradient descent was utilized as the training optimizer, the detection rate increased but the number of FP remained relatively consistent [74], as compared to root mean square propagation, stochastic gradient descent, and adaptive moment estimation. Tissue biopsy remains the gold standard, despite the fact that visual biopsy is a promising field. Optical biopsy results will be influenced by whether the surface microstructure accurately represents the histological properties of lesions [2, 16, 75, 76]. The widespread use of microscopic technologies in clinical practice, particularly the combination of virtual chromoendoscopy and microscopic imaging, has heightened interest in the field of optical biopsy [77]. Using established optical evaluation criteria, endoscopists may consistently detect and differentiate microadenomatous and hyperplastic polyps [78]. The development of CAD and AI algorithms may be able to overcome the major drawbacks of ocular biopsy and modify the way colorectal lesions are treated [77, 79]. Because of its great resolution, endocytoscopy is a useful approach for thorough diagnosis of CRC [76]. By evaluating the nucleus, crypt structure, and microvasculature in an endoscopic picture, Kudo et al. [80] created an AI-based system called EndoBRAIN that could identify the colon tumour. EndoBRAIN's initial training was accomplished out using endoscopic pictures. Endoscopists' diagnostic efficiency and EndoBRAIN's diagnostic performance were evaluated retrospectively. The results suggested that EndoBRAIN could improve diagnosis accuracy [80].

Discussion

In the domains of computer, internet, and automobile engineering, artificial intelligence (AI) plays a critical role. "Personalization, accuracy, minimal incursion, and remoteness" [81] are the four primary paths of future medical growth. In medical, AI is first demonstrating its benefits in disease diagnosis, therapy, and prognosis. CRC is one of the most common human malignancies, and early detection and treatment have a significant impact on prognosis. The stages of AI development for CRC include: (1) understanding cancer at the molecular and cellular levels through DL; (2) assisting in the diagnosis of CRC based on images and pathological specimens; (3) clinical drug design and screening; and (4) promoting individualization of CRC diagnosis and treatment [81]. Imaging diagnosis and pathological diagnosis are the two main types of CRC diagnosis. The majority of the imaging datasets is objective and has a high level of information standardization. By extracting characteristics from experts, comprehensive picture training, generating classification rules, and establishing mathematical models, the CAD system based on DL enables the automatic analysis and optimization of a variety of images. Second, AI aids in the examination of medical images. Auxiliary judgement results can be swiftly generated because to fast picture processing and analysis. The rate of missed diagnoses can be reduced with high sensitivity. The quality of the basic inspection can be improved by using expert knowledge and quantitative data analysis. Third, many digital sections of CRC have been amassed in clinical pathology, and some have been preliminarily created using image recognition and DL technologies. However, AI cannot be divorced from its auxiliary role at this time. At the functional level, AI applications mostly comprise disease diagnosis and treatment decision assistance. In treatment decision support, the development of illness diagnosis support is active. Advanced technologies are becoming more integrated with medicine, and they are gradually becoming more important in aiding diagnosis and early detection of serious diseases. Although AI is quickly evolving, it is still in its infancy and faces numerous development roadblocks. For starters, AI development overemphasizes "probability association," because diseases always exist in uncharted territory. Image AI progress hinges on the ability to mix data and medical knowledge. Second, training AI-based DL necessitates a large amount of label data. Although labelled data has a greater impact on training results than algorithms, obtaining high-quality data for training is a major challenge. Third, there is a lack of image data standardization. In different hospitals, the level of imaging system interaction functioning is low. Furthermore, each imaging system's datasets are dispersed across the country with little interaction. Fourth, data annotation is quite challenging. AI training necessitates a big amount of labelled picture data, and annotation necessitates a significant amount of manual labour, both of which have a direct impact on the training results. Meanwhile, the "black box" issue with ML poses a number of clinical problems. ML can aid in the interpretation of imaging and pathology images, as well as the recommendation of diagnostic and treatment options and the prediction of prognosis. The clinical implementation of AI technologies, however, has been delayed due to the "black box" problem. It is vital to improve the interpretability of machine learning algorithms in order to advance AI medicine. The "black box" problem can be solved gradually by including modest steps of biological interpretation and clinical knowledge into the ML algorithm. Data preparation is required to complete the standardization process, which necessitates the integration and fusion of disparate data sets such as photographs, physiological data, and information texts. Simultaneously, automatic software analyses and extracts a vast number of elements from medical imaging data, including texture analysis, form description, and other quantitative indicators. Surgery and chemotherapy are the most common therapies for CRC. Individual precision medicine is enabled by AI, which selects optimal treatment methods based on big data analysis and comparison. At the same time, the advancement of robot technology ensures that surgery will be performed with high precision and that chemotherapy medications will be targeted precisely. However, the quality of data collected is insufficient to allow AI to make treatment decisions on its own. The complexity of the human body also slows down AI's operational analysis and decision-making. Furthermore, due to their high cost, robots cannot be widely deployed. Patients are frequently concerned about the unknown survival period following surgery, so providing a defined survival term might alleviate this psychological burden. Through patient information, surgery, and pathology, AI can forecast survival time and recurrence risk, as well as advice patients' prognosis and nursing. As a result, high-quality, precise data as well as standard operational criteria are necessary. To put it another way, the accuracy of risk prediction is determined by the quality of prognosis data, which is determined by the quality of data created by diagnosis and therapy. The information available to clinicians is growing increasingly complex as diagnostic technology advances. In terms of treatment, new medications are being created all the time, as well as novel treatment schemes and approaches. It is difficult for busy professionals to find the time and energy to gather, filter, and apply data. With the advancement of AI technology and image recognition, as well as other areas, AI will play an increasingly crucial role in CRC diagnosis and therapy. As a result, the development of an AI standard system will be a high priority in the future. The standardization of pictures, characteristics, medical record data, and other datasets will help doctors diagnose and treat patients more accurately. DL and ML will be fully integrated to allow robots to perform surgery on their own. Medical services involve not just medical technology but also mental health counselling. Robots will provide nursing and change the psychological condition of patients in the future. However, in order to properly deploy AI robots in today's medical context, moral and ethical considerations must be carefully explored. Various governments have attempted to set AI development ethical, legal, and regulatory compliance criteria. However, there are other obstacles to overcome before AI robots are totally accepted. To begin, patients' trust and acceptance will be crucial in the development of AI robotic surgery. In many non-surgical applications, the "black box" has minimal theoretical transparency. Lack of openness in the medical area undermines doctors' and patients' trust in and adoption of AI. Second, the safety of AI-assisted robotic surgery remains a major worry. Patient information security, network security, robot autonomy, and machine failure are all issues that must be addressed in the development of AI robot surgery. The incalculable loss will occur if the AI robot's control is lost owing to external reasons such as network transmission delay and hacker assault. Third, determining who is to blame for medical negligence is still a challenge. Given the limitations of AI robots, the problem of medical malpractice liability will spark a discussion about the legal grey area. The answer to this issue will have a positive impact on AI progress [82].

Conclusion

AI is currently at a period of weak AI, with no communication skills. As a result, present AI technology is primarily employed for image identification and auxiliary analysis, rather than in-depth patient dialogue. With the advancement of AI technology, AI's role in the diagnosis and treatment of CRC will continue to grow until the robot is capable of doing surgery on its own. AI will revolutionize medical technologies and even the medical model at that time.

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ABOUT THE AUTHOR

Gurjeet Singh, Dr, PhD degree in Computer Science, Associate Professor, Dean in the department of Lords School of Computer Applications & IT, Lords University (Alwar, Rajasthan, India). E-mail: research.gurjeet@gmail.com. ORCID: 0000-0001-9826-3375.

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Gurjeet Singh, Dr, PhD degree in Computer Science доцент, декан факультета информационных технологий Лордского университета (Алвар, Раджастхан, Индия).

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