Review on colorectal cancer biomarkers

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Abstract

Abstract— The integration of artificial intelligence (AI) into healthcare holds significant potential for enhancing colon cancer detection, prediction, and patient care. AI can significantly improve decision-making processes, particularly in the diagnosis and prognosis of colon cancer. This review focuses on explainable artificial intelligence (XAI), which enhances the interpretability and transparency of AI models, facilitating in-depth disease analysis. By leveraging XAI, this study delves into the complexities of colorectal cancer, emphasizing early detection, risk assessment, and clinical decision-making. The review critically examines existing literature on XAI applications in colorectal cancer, highlighting both the benefits and limitations. It addresses key challenges such as data privacy, model transparency, and regulatory compliance, emphasizing the necessity for robust patient-provider communication to foster trust. Additionally, the study explores ethical and legal considerations, ensuring fair and unbiased AI implementation. Advancements in predictive modeling and interpretive techniques like SHAP (Shapley Additive exPlanations) are discussed, demonstrating their potential in identifying biomarkers and improving patient outcomes through personalized medicine. The review underscores the importance of mitigating biases in AI models, promoting equity in clinical decision-making. Furthermore, this analysis highlights the evolving landscape of AI in healthcare, showcasing significant improvements in areas such as imaging assessment and risk prediction. It also delves into the architecture of various AI models like VGG-16, ResNet50, and InceptionV3, providing a comparative analysis of their accuracy in colorectal cancer detection. Ultimately, this comprehensive analysis of XAI in colorectal cancer aims to bridge the gap between technological innovation and clinical application. By offering insights into the challenges and opportunities presented by XAI, the study seeks to inform future research and policy development, enhancing the overall effectiveness of colon cancer care and contributing to improved patient outcomes.

Introduction

The combination of artificial intelligence and linked healthcare is set to signal a paradigm leap in cancer diagnosis, prognosis, and overall patient management. However, comprehending the logic behind AI measures provides a significant task owing to their inherent ambiguity, especially when human lives are at risk in the detection and treatment of colorectal cancer. This significant study explores the complexities of translational AI in the treatment of colorectal cancer by critically analyzing current tactics, addressing difficult underlying challenges, and forecasting future strategies. It does this by drawing linkages between clinical oncology and technical innovation [1]. Unpacking the complexities of AI, this analysis aims to bridge the gap between sophisticated technology and the impact of the depth it has on humans. The subtleties of the application of interpretive AI in detection and prediction are to be decoded. Insights from this thorough study will not only enrich academic discourse but also inform policy as they are developed and outline the direction AI will take in colorectal cancer management in the coming years [2]. Artificial intelligence (AI) is changing early detection, risk assessment, and clinical decision-making when combined with AI systems, primarily in aspects of colorectal cancer screening and detection like imaging assessment and risk prediction [3]. This is addressed in the rapidly changing landscape of colorectal cancer care. There have been complaints made regarding the box"-nature Because of these models' ambiguity, which makes it difficult to understand the reasoning behind forecasts or recommendations, doctors are unable to use AI models in real-world colorectal cancer treatment situations with confidence. These results make sense in the context of managing colorectal cancer. They highlight the increasing significance of the XAI and its obvious and capable duty to patients' work [4]. The real-life application of explainable artificial intelligence for colon cancer prediction has enhanced the clear vision and ethical consideration of this harmful illness. artificial intelligence plays a vital role in predicting colon disease at its early stages with improved decision-making techniques [5]. It is also essential to carefully deploy the XAI system for the prognosis of colon cancer. Maintaining the privacy of the patients and providing transparency over the XAI is the major challenge for the regulatory landscape surrounding AI [6]. The fair decision for colon cancer is based on a rigorous review and validation process so that no bias or discrimination is made the giving the outcome of the input [7]. This research tells us about the complete consideration of the challenges and the opportunities that came with the use of artificial intelligence in the detection and forecasting of colon cancer. The forecasting is possible just by analyzing the issues that are multifaced and associated with it. Finally, the empathetic knowledge about this colon cancer gave us a structure for future research and preparation for rules in this growing field [8]. Smart technologies that have been utilized in this field that are detecting and predicting colon cancer, hold a high potential to deeply change the finding, forecasting, and managerial process of this malice. As artificial intelligence has become a complex thing in colon detection screening and prognosis, the apprehensions related to their dependability and transparency have gained attention [9]. This serious valuation is determined by the increasing demand for XAI in the area of colon identification and forecasting organization. The basic concerns about the ethics, equality, and consistency of decision-making systems that are used for the identification of colon cancer as well as the forecasting of colon cancer [10]. Additionally, the rapidly growing field and the technological advances in XAI give a thorough examination of how the system used for prediction and identification works. By exploring this field, the goal of the project is to address the ethical and responsible concerns and the application associated with the XAI for detecting and predicting colon cancer should have a transparent process, should promote equity, and must be trustworthy in the process of patientcare's delivery and increase the overall outcomes in the healthcare sector [11].

The ultimate goal of this study is to clarify the working, methods, and how XAI works in the area of identification and prediction of colon cancer by doing in-depth and important research. Employing a meticulous method, the look evaluates technical reports, convention lawsuits, and cutting-edge studies literature to offer insightful insights into the software of XAI for colon cancer diagnostics and prognostic evaluation. The paper is structured as follows: Section II offers a synopsis of XAI and its importance within the realm of colon cancer prediction and analysis. Section III delves into the architectural frameworks, programs, demanding situations, and future potentialities of XAI technology particularly tailor-made for colon cancer control. Finally, Section IV summarizes the salient findings of the review, alongside their theoretical and sensible implications for reinforcing cancer screening and prediction methodologies.

Literature Review

The author[11] reviewed a range of topics including the factors that are responsible for the low civic activity in polish society such as psychological norms, and societal attitudes and also the importance of vaccination in preventing disease to combat the rise in unvaccinated individuals.

The author [12] gives the brief about the distortion of knowledge value by misinformation to combat it effectively. The focus is on key Audit Matters(KAM) disclosures , liability and client management reactions. The research also provides the valuable insights but there is a need for further research to address specific drawback and limitation in each respective field.

The author [13] provides the insight to topics such as diabetes management, tax compliance and e-learning. The methodology used in the article is the randomized control trials and analysis of research results. This review efficiently helps in establishing credibility and identifying gaps in research.

The author [14] review the process involves surveying sources to establish familiarity with current research in a specific field. The study describes the type 2 diabetes mellitus patients, single and combined exercises to reduce blood levels that improves health indicators. comparative analysis methodology is used to find the outcome of the research topics.

Table 1: Show the Literature Review of the Papers Related to the Colon Cancer Detection

S.No	Conclusions	Results	Methods Used
[17]	- AI plays a crucial role in predicting MSI status from WSIs. - Immune cell quantification is vital in predicting survival in CRC. - Studies highlight the importance of immune cell densities for patient survival.	- Review of AI-based studies, immunotherapy in colorectal cancer, and predictive models. - Accuracy analysis of techniques predicting MSI status from HE images.	- Deep learning for MSI prediction from HE images. - Literature review of AI-based studies on immunotherapy in colorectal cancer.

[18]	- Identified obstacles in XAI for healthcare. - Classified XAI in healthcare into five categories.	- Identified obstacles in XAI for healthcare: System, Legal, and Communication. - Reviewed applications of AI in healthcare: Diagnosis, Prognosis, and Medication discovery. - Classified XAI in healthcare into five categories: Dimension reduction, Feature selection. -Provided a comprehensive examination of XAI methodologies.	- Example-based, attribution-based, and model-based explanations are evaluated. - Interpretability, simplicity, clarity, soundness, and completeness are key qualities. - XAI methods include keeping interpretability while enhancing performance.

[19]	- GPT-4 exhibits racial and gender bias in clinical tasks. - The study lacks actionable recommendations for safe technology integration.	- GPT-4 exhibits racial and gender bias in medical tasks. - Amplifies harmful societal biases and stereotypes in clinical decision-making. - Falls short of providing actionable recommendations for safe technology integration.	- Study highlights racial and gender bias in GPT-4. - Recommendations for the safe integration of technology into clinical workflows lacking.
[20]	- Reviews AI-based ML and DL techniques for colorectal cancer prediction. - Identifies medical and technical challenges in predicting colorectal cancer using AI. - Emphasizes the importance of early diagnosis for colorectal cancer.	- Lack of real-world systems for standard healthcare practice. - Challenges in predicting colorectal cancer using AI: medical and technical. - Lack of algorithms for diverse dataset types like text and images.	- Machine learning (ML) and deep learning (DL) techniques - ML and DL algorithms for predicting colorectal cancer

[21]	- Texture analysis effectively differentiates tissue types in colorectal cancer histology. - Automation of tissue classification in histological images is feasible. - Multiclass texture analysis can quantify tissue regions and aid prognosis.	- Achieved accuracy in multi-class texture analysis comparable to other studies. - Released comprehensive image set for colorectal cancer tissue classification. - Automated tasks like tissue region classification and invasion depth quantification. - Potential applications in tumor grading, antigen distribution classification, and survival prognosis.	- Ensemble of decision trees - Perception-like features - GLCM features - multi-channel visualization - Implementation in Matlab

[22]	- Machine learning models predict survival with 77% accuracy. - Random Forest and XGBoost models outperformed Naive Bayes. - Clinical staging, surgery, and age are key predictors of survival.	- Machine learning models predicted colorectal cancer patients' survival with 77% accuracy. - The XGBoost model outperformed neural networks in survival prediction accuracy. - Random Forest and XGBoost models showed the best performance in predictions. - Important features for predictions included clinical staging, age, and surgery.	- Evaluated 31,916 colorectal cancer cases in Sao Paulo state. - Used Naive Bayes, Random Forest, and XGBoost classifiers for predictions. - Extracted data from Hospital Based Cancer Registries of São Paulo.

[23]	- The SHAP method identifies personalized CRC biomarkers and distinct CRC probabilities. - Local explanations provide more interpretable results than global explanation methods. - SHAP values allow clear separation between healthy and CRC subjects.	- The SHAP method identifies personalized CRC biomarkers and separates subjects into subgroups. - SHAP values show a clear separation between healthy and CRC subjects. - Local explanations provide more interpretable PCA results than global explanations.	- SHAP for personalized CRC biomarker identification across datasets. - SHIPMENT with TreeExplainer for SHAP value calculation in microbiome research.

Table 2: Show the Dataset used and Summary of the papers

S.No	Dataset used	Summary
[24]	TCGA dataset was used for training and validation.	AI-based studies in immunotherapy for colorectal cancer. Role of AI in predicting MSI status from digital WSIs.
[25]	Kaggle colon cancer Dataset is used	AI approaches, contributions, limitations, and future research directions discussed. Exploration of immune cell infiltrates and alternate data modalities.

[26]	TCGA dataset was used.	Classified XAI in healthcare into five categories: Dimension reduction, Feature selection. Provided a comprehensive examination of XAI methodologies.
[27]	UCI ML repository Dataset is used	Future research areas, constraints, contributions, and methodologies in AI are reviewed.
[28]	TCGA dataset was used.	Examines ML and DL methods powered by AI for the prediction of colorectal cancer.
[29]	TCGA dataset was used for training and validation.	Finds the scientific and medical obstacles to utilising AI to forecast colorectal cancer.
[30]	Kaggle colon cancer Dataset is used	Highlights how crucial an early diagnosis is for colorectal cancer.

Results And Discussions

This analysis of translational artificial intelligence (XAI) in colon cancer, looks at important conclusions and viewpoints from current works, emphasizing the difficulties, advancements, and consequences of applying AI in clinical settings

Challenges and Opportunities in Healthcare XAI

Policy, regulatory, and communication challenges pose significant obstacles to implementing Explainable Artificial Intelligence (XAI) in healthcare. The integration of AI systems with existing healthcare infrastructures must navigate complex regulatory landscapes to ensure compliance, data protection, and interoperability. Regulatory frameworks vary across regions, necessitating adaptable AI solutions that meet diverse legal requirements. Moreover, issues surrounding liability, transparency, and patient consent remain critical concerns, influencing the acceptance and adoption of AI technologies in clinical settings.

Effective communication between AI systems and healthcare providers is crucial for fostering trust and promoting informed decision-making. Poor communication can hinder the acceptance of AI-driven recommendations, leading to skepticism among clinicians and patients alike. Therefore, efforts to enhance communication channels and educate stakeholders about AI capabilities and limitations are essential for successful integration into healthcare workflows. Despite these challenges, AI presents numerous opportunities to revolutionize healthcare practices. AI applications have demonstrated significant advancements in medication development, diagnostics, and predictive analytics, surpassing traditional methods in accuracy and efficiency. For instance, machine learning algorithms can analyze vast datasets to identify patterns and correlations that aid in early disease detection and personalized treatment strategies. XAI techniques, such as feature selection and dimensionality reduction, provide systematic approaches to address specific healthcare challenges, enhancing decision support systems and clinical outcomes.

Addressing Bias and Interpretability

The identification and mitigation of bias in AI models used in healthcare settings are critical for ethical and equitable patient care. Recent studies have highlighted the presence of biases, including gender and racial biases, in AI algorithms, which can perpetuate disparities in clinical decision-making. For example, biases in training data can lead to skewed predictions or recommendations, affecting diagnostic accuracy and treatment outcomes across different demographic groups. Ensuring the interpretability of AI models is essential for understanding how decisions are made and detecting potential biases. Interpretability techniques, such as model-agnostic approaches and visualization tools, enable healthcare professionals to scrutinize AI-generated insights and validate their clinical relevance. Transparent AI systems empower clinicians to trust AI recommendations, fostering collaboration between human expertise and machine intelligence in healthcare delivery. Moreover, ethical considerations in AI development and deployment are paramount. Ethical AI frameworks emphasize principles such as fairness, accountability, and transparency (FAT) to guide responsible AI implementation. Stakeholders must collaborate to establish guidelines and standards that uphold patient rights, mitigate risks, and promote ethical practices in AI-driven healthcare applications.

Additional Challenges in Healthcare XAI

In addition to policy, regulatory, communication, bias, and interpretability challenges, several other obstacles hinder the widespread adoption of XAI in healthcare:

1. **Data Privacy and Security:** Protecting sensitive patient information is crucial in AI-driven healthcare systems. Compliance with data protection regulations (e.g., GDPR, HIPAA) is mandatory to prevent unauthorized access or breaches that could compromise patient confidentiality and trust in AI technologies.

2. **Data Quality and Availability:** AI algorithms heavily rely on high-quality, diverse datasets to generate reliable predictions and recommendations. However, healthcare data often suffer from incompleteness, inconsistency, and bias, posing challenges for training robust AI models that generalize well across diverse patient populations.

3. **Interoperability and Integration:** Integrating AI solutions into existing healthcare IT infrastructures requires seamless interoperability with electronic health records (EHRs), medical imaging systems, and other clinical data repositories. Standardized formats and protocols are essential to ensure data compatibility and facilitate data exchange across different healthcare settings.

4. **Resource Constraints:** Implementing and maintaining AI technologies require significant investments in infrastructure, training, and ongoing support. Healthcare organizations must allocate resources effectively to overcome financial and technical barriers associated with adopting AI-driven solutions.

5. **Regulatory Uncertainty:** Rapid advancements in AI technology outpace regulatory frameworks, creating uncertainties around legal liabilities, licensing requirements, and reimbursement policies for AI-based healthcare services. Clear guidelines and collaborations between policymakers, regulators, and industry stakeholders are essential to navigate regulatory challenges and promote innovation responsibly.

Opportunities for Advancement

Despite these challenges, ongoing research and development initiatives continue to propel the evolution of XAI in healthcare:

1. **Advanced AI Algorithms:** Innovations in deep learning, natural language processing, and reinforcement learning enhance AI's capabilities in complex medical tasks, such as disease prognosis, treatment planning, and patient monitoring.

2. **Multimodal Data Integration:** Integrating diverse data sources, including genomic data, wearable sensor data, and social determinants of health, enables comprehensive patient profiling and personalized healthcare interventions.

3. **Collaborative Research Initiatives:** Cross-disciplinary collaborations between AI researchers, clinicians, bioinformaticians, and policy experts facilitate knowledge exchange and accelerate the translation of AI innovations into clinical practice.

4. **Patient-Centric Solutions:** Designing AI technologies with patient-centered principles ensures that healthcare interventions prioritize individual preferences, values, and treatment goals, enhancing patient engagement and adherence to therapeutic regimens.

5. **Global Health Initiatives:** Addressing healthcare disparities and improving access to AI-driven diagnostics and treatments in underserved communities through international partnerships and public health interventions.

EAdvancements in Predictive Modelling

Recent advancements in AI-powered predictive modeling have substantially enhanced health outcomes, particularly for cancer patients. Machine learning models, trained on diverse datasets, have demonstrated high accuracy in predicting survival rates among colorectal cancer patients. These models incorporate a wide range of clinical variables, allowing for precise prognostication and personalized treatment planning.

Comparative Effectiveness of Machine Learning Techniques

Comparative studies have highlighted the efficacy of various machine learning techniques in predictive modeling. For instance, clustering techniques such as Random Forest and XGBoost have shown superior performance in handling complex and high-dimensional datasets. Random Forest, an ensemble learning method, constructs multiple decision trees during training and outputs the mode of the classes for classification tasks. Its ability to reduce overfitting and handle missing values makes it particularly suitable for medical datasets. XGBoost, another powerful ensemble technique, enhances predictive performance through gradient boosting, which sequentially builds trees to correct errors made by previous models. This method's flexibility and robustness have made it a preferred choice in many predictive modeling tasks. By leveraging these techniques, researchers have achieved remarkable accuracy in predicting survival rates for colorectal cancer patients, providing valuable insights into factors influencing patient outcomes.

Importance of Clinical Variables in Predictive Models

Incorporating crucial clinical variables such as age, surgical history, and clinical stage significantly enhances the predictive power of these models. Age, for instance, is a well-established prognostic factor, with older patients generally exhibiting poorer outcomes. Surgical history, including the type and extent of surgery, provides critical information about disease management and its impact on survival. Clinical stage, which indicates the extent of cancer spread, remains a fundamental determinant of prognosis.

Moreover, integrating additional variables such as genetic markers, lifestyle factors, and treatment regimens can further refine predictive models. For example, genetic mutations in oncogenes and tumor suppressor genes play a crucial role in cancer progression and response to therapy. By incorporating these genetic markers, predictive models can offer more personalized prognostic information and guide tailored treatment strategies.

SHAP Approach in Personalized Medicine

The SHAP (SHapley Additive exPlanations) approach has demonstrated significant potential in personalized medicine by identifying distinct biomarkers associated with subgroups of colorectal cancer patients. SHAP values provide a unified measure of feature importance, explaining the contribution of each feature to the model's predictions. This approach not only enhances the transparency of predictive models but also advances our understanding of disease mechanisms.

By using SHAP values, researchers can identify specific biomarkers and pathways that differentiate patient subgroups, enabling more precise classification and risk stratification. For instance, SHAP analysis might reveal that certain genetic mutations are strongly associated with poor prognosis in a specific patient subgroup, guiding clinicians towards more aggressive treatment options for these patients.

Enhancing Patient Outcomes through Local Interpretation

Local interpretation of SHAP evaluation offers clinicians practical information to enhance patient outcomes through targeted therapies. By understanding the individual contributions of each feature to a patient's risk profile, clinicians can make informed decisions about treatment options. For example, if SHAP analysis indicates that a patient's age and specific genetic markers significantly increase their risk, clinicians can prioritize treatments that address these risk factors.

Furthermore, SHAP values can facilitate the identification of patients who are likely to benefit from novel therapies or clinical trials. By pinpointing key biomarkers and clinical characteristics, SHAP analysis helps match patients with the most appropriate therapeutic interventions, improving overall treatment efficacy and patient outcomes.

Integration of Multimodal Data

The integration of multimodal data sources, such as genomic data, medical imaging, and electronic health records, represents a significant advancement in predictive modeling. Combining these diverse data types provides a comprehensive view of patient health, enabling more accurate and personalized predictions. For instance, integrating genomic data can uncover molecular alterations driving cancer progression, while imaging data can provide detailed information about tumor morphology and response to treatment.

Advanced machine learning techniques, such as deep learning, are particularly well-suited for handling multimodal data. Convolutional neural networks (CNNs), for example, excel at analyzing medical images, identifying subtle patterns that may be missed by traditional methods. When combined with clinical and genomic data, these models can generate more precise predictions and offer new insights into disease biology.

Challenges and Future Directions

Despite these advancements, several challenges remain in predictive modeling for cancer outcomes. Ensuring data quality and consistency across diverse datasets is crucial for model reliability. Standardizing data collection and preprocessing methods can help mitigate these issues. Additionally, addressing biases in training data is essential to avoid perpetuating health disparities in predictive models.

Future research should focus on developing more robust and interpretable models, integrating cutting-edge AI techniques with domain-specific knowledge. Collaborations between data scientists, clinicians, and bioinformaticians are essential to drive innovation and ensure the clinical relevance of predictive models. Furthermore, ongoing efforts to validate and refine these models through real-world clinical trials are necessary to demonstrate their utility in improving patient outcomes.

Advancements in AI-powered predictive modeling hold great promise for transforming cancer care. By leveraging sophisticated machine learning techniques, incorporating diverse clinical variables, and utilizing interpretable methods like SHAP, researchers and clinicians can develop precise, personalized prognostic tools. These innovations pave the way for more effective and targeted therapies, ultimately enhancing patient outcomes and advancing the field of oncology.

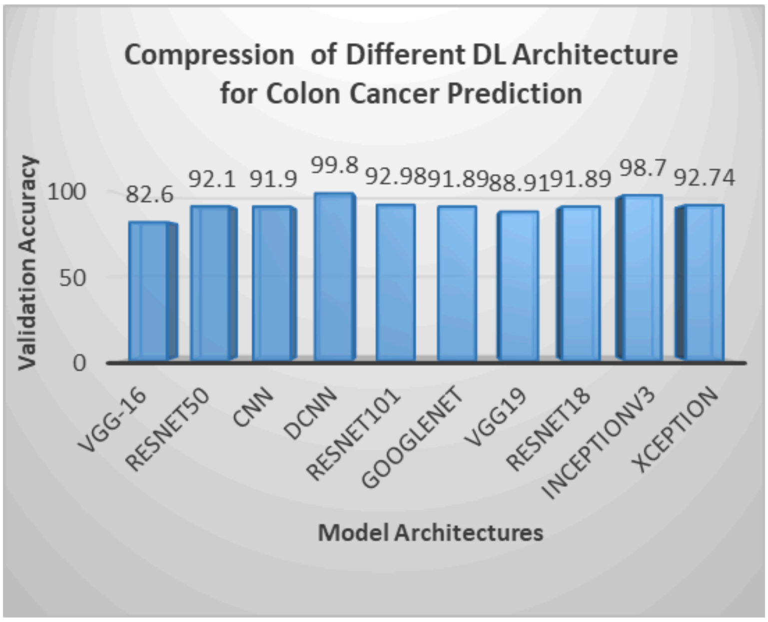

Figure. 2 Compression between the model's accuracy

The above figure 2 shows the compression between the different deep learning architectures for colon cancer prediction and detection the above graphs I drew from the different papers that have been reviewed in the literature where the respective authors used this model of deep learning to predict colon cancer and the best-performed model architecture from above-reviewed paper is DCNN with 99.8 accuracies as there also some limitation present in this model as well but it performs better from any other model architecture that has been used by the authors in their studies.

Table III suggests the different models used to predict colon disease by the different authors with different model architectures and accuracy.

S.No	Disease	Model Architectures	Accuracy
1	Colon Cancer	VGG-16	82.6
2	Colon Cancer	ResNet50	92.1
3	Colon cancer	CNN	91.9
4	Colon Cancer	DCNN	99.8
5	Colon Cancer	ResNet101	92.98
6	Colon Cancer	GoogLeNet	91.89
7	Colon Cancer	VGG19	88.91
8	Colon Cancer	ResNet18	91.89
9	Colon Cancer	InceptionV3	98.7

Conclusion

This vital analysis culminates by underscoring the pivotal effect Explainable Artificial Intelligence (XAI) has exerted in transforming the landscape of colon cancer prediction and analysis. A meticulous examination of posted studies and technical papers has elucidated the position XAI methodologies play in enhancing the reliability and interpretability of colon cancer detection models. Moreover, several demanding situations have been diagnosed, such as the need for sturdy validation frameworks and the resolution of moral concerns, which must be surmounted to harness the capacity of XAI in scientific settings. Despite those obstacles, the promising findings offered on this look illustrate the innovative impact XAI can wield in augmenting early detection rates and prognostic accuracy inside the management of colon most cancers. The insights gleaned from this evaluation keep profound implications for the future trajectory of colon cancer care, paving the manner for more particular and obvious diagnostic and predictive models driven by explainable synthetic intelligence.

This observation identifies numerous avenues for similar studies and improvement inside the domain of XAI for colon cancer detection and prediction. Foremost, there is an urgent want to establish regular assessment standards and benchmarks to assess the efficacy and generalizability of XAI models across diverse patient populations and healthcare settings. Novel XAI procedures, which include interpretable deep gaining knowledge of frameworks and ensemble techniques, warrant research to in addition enhance the interpretability and transparency of colon cancer diagnostic fashions. Furthermore, an extensive opportunity lies in leveraging the total breadth of available data sources, inclusive of genomics, imaging, and scientific statistics, via multimodal facts integration for extra specific and personalized cancer hazard stratification. Finally, longitudinal investigations and actual global validation trials are important to verify the scientific value and effectiveness of XAI-primarily based colon cancer detection and forecasting techniques in improving patient consequences and guiding medical choice-making. By addressing those destiny research instructions, we can pave the way for an extra green and affected person-centric approach to colon cancer care via the appropriate integration of Explainable AI.

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