A Comprehensive Survey on IoMT-Based Gastrointestinal Disease Diagnosis Combining Data Security and Automated Classification

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Abstract

The integration of the Internet of Medical Things (IoMT) in gastrointestinal (GI) disease diagnosis from wireless capsule endoscopy (WCE) images introduces both innovative diagnostic capabilities and significant data security challenges. This survey initially focuses on the critical importance of data security in IoMT-based healthcare systems, where the transmission of highly sensitive medical data requires robust encryption, secure communication protocols, and advanced cybersecurity measures to prevent data breaches and ensure patient privacy. It examines various approaches to safeguarding data integrity and secure solutions, which are essential for maintaining trust in IoMT deployments. Furthermore, the survey delves into the classification of GI diseases using WCE images, highlighting the latest advancements in automated diagnostic technologies. These include sophisticated image processing techniques and machine learning algorithms that improve the accuracy and reliability of detecting GI conditions, such as tumors, polyps, and ulcers. By integrating advanced data security measures with cutting-edge classification methods, this survey underscores the dual focus on enhancing diagnostic precision while safeguarding patient information, presenting a holistic approach to future developments in IoMT-based healthcare systems.

Keywords: gastrointestinal diseases, wireless capsule endoscopy, data security, image classification, data privacy, encryption, healthcare systems, automated diagnosis.
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1. Introduction

Over the past few years, the incidence of gastrointestinal disorders has significantly increased worldwide, affecting millions of people annually. Conditions such as inflammatory bowel disease (IBD) [1], colorectal cancer, Crohn's disease, and peptic ulcers have become more prevalent due to factors such as changes in diet, lifestyle, and environmental influences. According to recent statistics, GI diseases are among the leading causes of morbidity and healthcare costs, particularly in developed countries. For instance, colorectal cancer is the third most common cancer globally, with an estimated 1.9 million new cases diagnosed in 2020 alone. Additionally, diseases like Crohn's and IBD are showing a rising trend, especially among younger populations[2], highlighting the urgent need for effective diagnostic and management strategies to address these growing health concerns.

Gastrointestinal diseases often come with a range of debilitating side effects that can significantly impact a patient's quality of life. Symptoms such as chronic abdominal pain, bloating, diarrhea, and fatigue is common among those suffering from GI conditions. In severe cases, these disorders can lead to malnutrition, weight loss, and complications like gastrointestinal bleeding or perforation[3]. The side effects not only cause physical discomfort but also lead to psychological distress, including anxiety and depression. The chronic nature of many GI disorders means that patients often require long-term management strategies, which can include medications, lifestyle modifications, and sometimes surgical interventions[4]. Managing these side effects effectively is critical to improving patient outcomes and reducing the overall burden of GI diseases.

To diagnose and monitor gastrointestinal diseases effectively, several imaging methods have been developed to capture detailed images of the GI tract. Traditional methods such as endoscopy and colonoscopy remain the gold standards for visualizing the upper and lower parts of the GI tract[5]. However, these procedures are invasive, uncomfortable, and often require sedation. To address these limitations, newer, less invasive techniques have been developed, such as WCE[6], which allows for comprehensive imaging of the small intestine without the need for invasive procedures. Other advanced imaging modalities, including computed tomography (CT) enterography, magnetic resonance imaging (MRI) enterography, and ultrasound, provide non-invasive options for assessing different parts of the GI tract, each with its own strengths and limitations. These imaging techniques play a crucial role in the early detection, diagnosis, and management of GI disorders, helping to guide treatment decisions and monitor disease progression.

2. Wireless Capsule Endoscopy

The WCE is a non-invasive diagnostic tool designed to visualize the interior of the GI tract. The device, which is roughly the size of a vitamin pill, is equipped with several components essential for capturing high-quality images as it traverses through the GI tract. Figure 1 shows the basic WCE device working process flowchart. It is a minimally invasive procedure that begins with the ingestion of the patency capsule by the patient. Once swallowed, the capsule travels naturally through the digestive system, powered by the body's peristaltic movements[7]. As it moves, the capsule’s camera continuously captures images of the intestinal walls, illuminated by the LED light source. These images are transmitted wirelessly via the antenna to an external receiver, typically worn on a belt by the patient. The receiver then sends the data to a real-time viewer or computer, where the images are displayed and analyzed by healthcare professionals[8]. After completing its journey through the digestive tract, the capsule is naturally excreted from the body, eliminating the need for retrieval and allowing for a complete, non-invasive examination of the small intestine. This innovative technology provides a comprehensive view of the GI tract, enabling early detection and diagnosis of various gastrointestinal diseases.

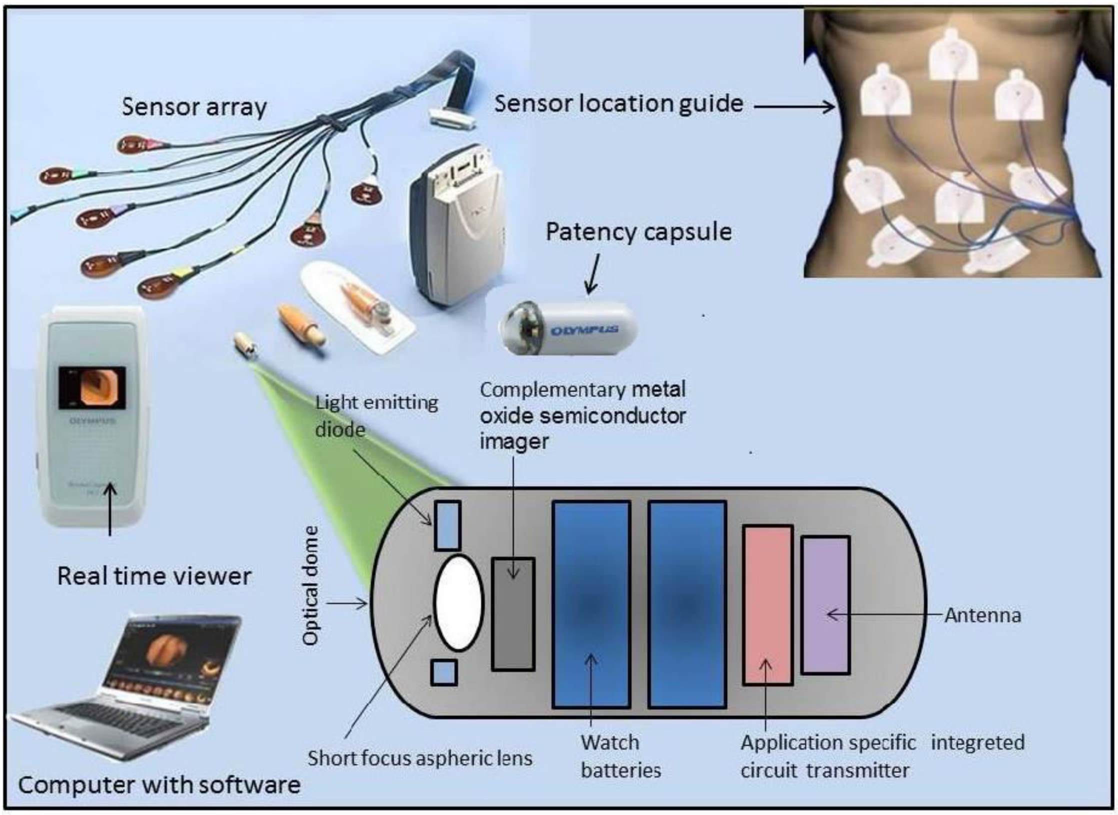

Figure 1. WCE operational procedure.

2.1 Patency Capsule

The patency capsule is a key component of WCE and is the main device swallowed by the patient to facilitate internal imaging of the GI tract, particularly the small intestine. This capsule is a small, pill-sized device equipped with a tiny camera, a light source, and a transmitter. Once ingested, the capsule travels through the digestive system, capturing thousands of high-resolution images of the internal mucosal surfaces. These images help diagnose various GI disorders, such as bleeding, polyps, Crohn's disease, and small bowel tumors. The capsule's design ensures it can navigate through the intestines smoothly without causing discomfort to the patient. As it moves naturally with peristalsis, the onboard camera captures a comprehensive visual record of the GI tract, providing valuable diagnostic information without the need for invasive procedures.

Optical Dome: The optical dome is a critical component of the capsule that houses the camera and light source. It is designed to protect the delicate electronics inside the capsule while maintaining a clear view for the camera. The optical dome is typically made from a transparent, biocompatible material that is resistant to the harsh environment of the GI tract, including stomach acids and digestive enzymes. This component ensures that the camera lens remains unobstructed and clean, allowing for high-quality image capture throughout the duration of the procedure. The dome's shape and materials are optimized to minimize light reflection and refraction, ensuring that the images captured are as clear and accurate as possible.

Light Emitting Diode: The LED is a vital part of the capsule's imaging system, providing the necessary illumination for the camera to capture clear images inside the dark environment of the GI tract. The LED is designed to emit a bright, yet safe light that illuminates the intestinal walls without causing discomfort or harm to the patient. Proper illumination is crucial for the accurate visualization of the intestinal mucosa, helping to reveal subtle changes in tissue structure and color that may indicate the presence of disease. The LED's light is carefully calibrated to ensure it is bright enough to provide clear images but not so intense as to cause glare or obscure important details.

Complementary Metal-Oxide-Semiconductor (CMOS) Imager: The CMOS imager is the camera sensor embedded within the capsule that captures the images of the GI tract. This sensor is highly sensitive and capable of capturing high-resolution images with excellent color fidelity and low noise, even in low-light conditions provided by the LED. The CMOS technology is chosen for its low power consumption and small size, which are critical for the capsule's operation, as the entire device must function on a small, internal battery. The CMOS imager converts the light reflected from the GI tract tissues into electronic signals, which are then processed into digital images by the capsule's onboard electronics.

Short Focus Aspheric Lens: The short-focus aspheric lens is an optical component that focuses the light onto the CMOS imager, ensuring that the images captured are sharp and clear. This lens is designed to correct for optical aberrations that can distort images, such as spherical aberration. By using an aspheric design, the lens provides a wider field of view and better image quality, which is essential for capturing the complex and varied surfaces of the GI tract. The short focus of the lens allows for detailed close-up images of the intestinal walls, which is crucial for detecting small lesions, polyps, or areas of inflammation that could indicate disease.

Antenna: The antenna is an integral part of the capsule that enables the wireless transmission of the captured images and the capsule's location data to the external receiver worn by the patient. It operates in conjunction with the capsule's transmitter to send the data through the body's tissues to the external data recorder or sensor belt. The design of the antenna must ensure that the signal is strong enough to penetrate the body's tissues and reach the external receiver without significant loss of data quality. The antenna is also responsible for ensuring that the transmission is continuous and reliable, even as the capsule moves and rotates within the GI tract.

Batteries: The batteries are the power source for the capsule's electronics, including the camera, LED, CMOS imager, transmitter, and other internal components. These batteries are small yet powerful, designed to provide a consistent power supply throughout the duration of the WCE procedure, which can last from several hours to a full day, depending on the patient's digestive transit time. The battery life is a critical factor in the design of the capsule, as it must be sufficient to cover the entire period of image capture and transmission. The use of low-power components, such as the CMOS imager and LED, helps to maximize battery life and ensure the procedure is completed successfully.

Application-Specific Integrated Circuit (ASIC) Transmitter: The ASIC transmitter is a specialized circuit within the capsule responsible for processing the captured images and transmitting them wirelessly to the external receiver. The ASIC is designed to handle the specific requirements of image compression, processing, and transmission efficiently, ensuring minimal power consumption and high data integrity. The ASIC transmitter converts the digital images generated by the CMOS imager into a format suitable for wireless transmission, compressing the data to reduce the amount of information that needs to be sent while maintaining image quality. This efficient processing is vital for the successful operation of the WCE system, as it ensures that high-quality images are transmitted in real-time for accurate diagnosis.

2.2 Sensor Belt

The sensor belt is worn by the person, which contains the multiple sensor arrays. It also contains the sensor location guide for identifying sensor position.

Sensor Array: The sensor array consists of several sensors strategically placed on the patient's abdomen to track the capsule's location as it travels through the digestive system. These sensors are external devices that detect the signals emitted by the capsule's transmitter. By receiving these signals, the sensor array can triangulate the capsule's position, helping healthcare professionals understand where within the GI tract the images are being taken. This spatial tracking is crucial for correlating the captured images with specific anatomical locations, allowing for precise localization of abnormalities or areas of interest. The sensor array contributes to the accuracy and effectiveness of WCE by ensuring the comprehensive coverage of the intestinal tract during the examination.

Sensor Location Guide: The sensor location guide is a device used to accurately position the sensors on the patient's abdomen. Proper placement of these sensors is essential for the effective tracking of the capsule’s movement throughout the digestive system. The guide assists healthcare providers in placing the sensors at predefined positions, ensuring optimal signal reception and minimizing the potential for errors in tracking the capsule’s trajectory. Accurate sensor placement enhances the reliability of the data collected, allowing for more accurate mapping of the intestinal images and improving the overall diagnostic accuracy of the WCE procedure.

2.3 Data Gathering Environment

The capsule transmitted are monitored and observed using data gathering environment.

Computer with Software: The computer with specialized software is used to receive, analyze, and store the images captured by the capsule. The software provides a user-friendly interface for healthcare providers to review the images, make annotations, and generate diagnostic reports. Advanced image processing algorithms, including AI and machine learning tools, can be integrated into the software to assist in identifying abnormalities and classifying diseases. This capability enhances the diagnostic process by providing automated assistance and reducing the time required for manual image review. The computer also stores the captured data securely, allowing for future reference and comparison with subsequent WCE procedures.

Real-Time Viewer: The real-time viewer is an external device, typically a computer, tablet, or specialized monitor, that displays the images captured by the capsule in real-time. As the capsule moves through the GI tract, the images are transmitted wirelessly to the viewer, allowing healthcare providers to monitor the progress of the capsule and review the images as they are captured. This real-time monitoring capability enables the immediate identification of any areas of concern, such as bleeding, inflammation, or lesions, facilitating timely clinical decisions. Additionally, the real-time viewer provides a platform for adjusting the examination process if needed, such as repositioning the patient to help the capsule navigate more effectively through the intestines.

2.4 Advantages

The WCE offers several advantages over conventional endoscopy, CT, and MRI. Unlike conventional endoscopy, which requires sedation and involves the insertion of a long, flexible tube with a camera, WCE is minimally invasive and does not require sedation, making it more comfortable for patients. It provides direct visualization of the entire gastrointestinal tract, including areas that are difficult to reach with traditional endoscopy. Compared to CT and MRI, WCE avoids the exposure to ionizing radiation and is often less expensive and more convenient, as it involves swallowing a small capsule equipped with a camera. This capsule captures images as it naturally moves through the digestive system, allowing for detailed examination of mucosal surfaces and identification of abnormalities such as bleeding, polyps, or tumors.

3. GI based IoMT Framework

The IoMT significantly enhances the process of GI disease classification through the integration[9] of WCE with advanced digital and connectivity technologies. In this IoMT framework, a miniature capsule embedded with a camera, sensors, and communication modules is ingested by the patient, allowing for non-invasive exploration and imaging of the GI tract as shown in Figure 2. The capsule contains several components, including a communication module, battery, processor, image sensor, and illumination source, all of which work in tandem to capture and transmit high-resolution images of the GI tract. As the capsule moves naturally through the digestive system, it continuously captures images that are transmitted to an external data recorder via a sensor belt worn by the patient. This approach enables continuous monitoring and real-time data acquisition, making it possible to detect various GI conditions, such as tumors, polyps, bleeding, and inflammation.

The data captured by the WCE capsule is stored on an SD card within the data recorder. The integration of IoMT allows for seamless transmission of this data to a centralized system, such as a standalone workstation or a mobile device, where it can be further analyzed. Physicians can access the data on their workstations to inspect the images and videos in detail, identifying any abnormalities or pathological changes indicative of GI diseases. The use of IoMT in this context enables remote monitoring and diagnostics, reducing the need for physical presence and enhancing the accessibility of healthcare services, especially for patients in remote or underserved areas. Additionally, the data can be analyzed using machine learning algorithms and artificial intelligence (AI) models to improve diagnostic accuracy and provide automated disease classification, thus supporting clinical decision-making[10].

A significant advantage of IoMT-based GI disease classification is its ability to leverage machine learning and deep learning techniques for automated image analysis. The images captured by the WCE are processed using advanced AI algorithms, such as convolutional neural networks (CNNs), which are trained to recognize patterns and features associated with specific GI diseases. By employing these algorithms, the system can classify different types of GI conditions with high accuracy, providing physicians with a reliable second opinion and reducing the risk of human error. Moreover, the use of IoMT allows for continuous improvement of these models through iterative learning, where new data collected from different patients can be used to retrain and refine the algorithms, enhancing their predictive power and robustness over time.

Data security and privacy are critical considerations in IoMT-based GI disease classification due to the sensitive nature of the medical data being captured and transmitted. The IoMT framework incorporates several layers of security to ensure data integrity and confidentiality. This includes encryption of data transmitted between the WCE capsule, the data recorder, and the external devices, as well as secure access protocols to prevent unauthorized access. Ensuring robust data security is essential not only for protecting patient privacy but also for maintaining trust in the IoMT-enabled healthcare ecosystem.

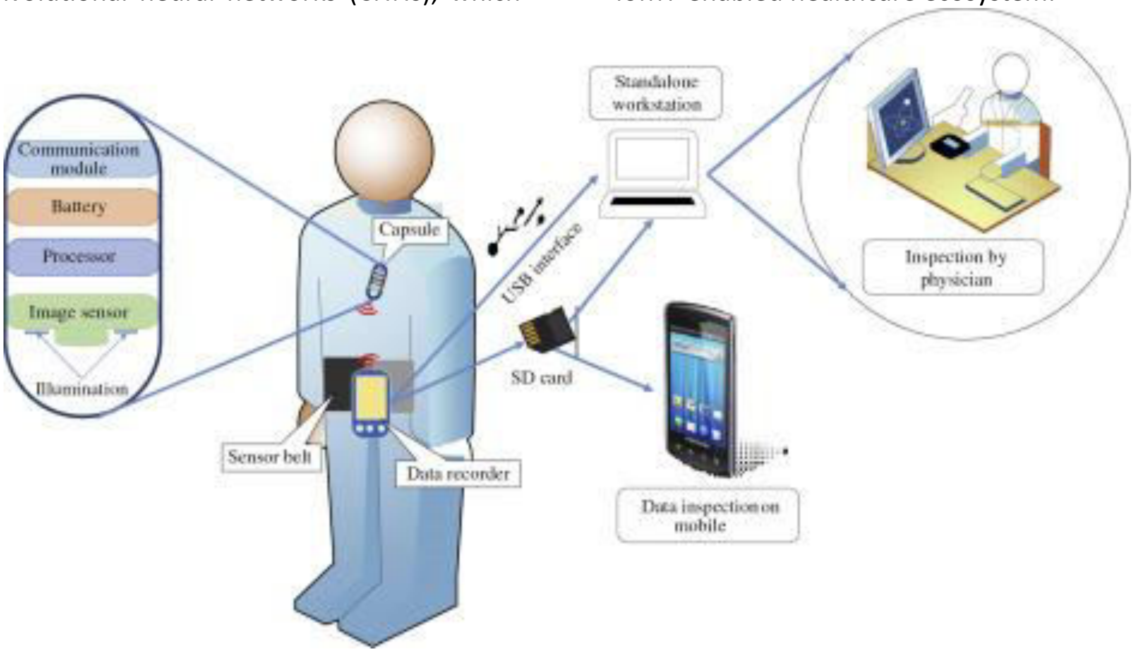

Figure 2. GI based IoMT Framework.

4. Literature Survey

4.1 Survey on IoMT Security Protocols

In [11], the authors proposed the use of electronic devices within the framework of Artificial Intelligence of the IoMT (AIoMT). Their method involved integrating advanced electronic devices to enhance AI capabilities in medical IoT applications, aiming to improve the efficiency of healthcare delivery through real-time monitoring and data analysis. This approach sought to advance the overall security and functionality of AIoMT systems by leveraging specialized electronic devices. In [12], the authors discussed advanced enabling technologies in IoMT for personalized healthcare. They focused on various technologies that enhance the capabilities of IoMT systems, such as advanced sensors and data processing techniques, to offer more tailored healthcare solutions. The methodology highlighted the role of these technologies in improving the precision and personalization of healthcare services through better data collection and analysis.In [13], the authors analyzed threats and security measures associated with IoMT. Their methodology involved a comprehensive study of potential security threats and proposed various measures to mitigate these risks. This included the implementation of advanced security protocols and strategies to protect sensitive health data transmitted across IoMT networks.

In [14], the authors conducted a systematic review of IoMT research, identifying trends and challenges. They reviewed existing research to map the evolution of IoMT systems and highlight significant research trends and challenges. The study aimed to provide a comprehensive overview of the current state of IoMT research and its future directions. In [15], the authors provided insights into IoMT, focusing on data fusion and security issues. They proposed methods for integrating and analyzing data from various IoMT devices to improve healthcare outcomes while addressing security concerns. The methodology involved exploring solutions to enhance the security of data fusion processes within IoMT frameworks.In [16], the authors reviewed security issues and attack detection methods in IoMT. Their methodology included evaluating different security threats and developing techniques for detecting and responding to attacks on IoMT systems. The review aimed to enhance understanding of the security landscape and improve attack detection mechanisms.

In [17], the authors proposed a security enhancement scheme for IoMT applications using fuzzy logic processing and lightweight encryption. Their methodology focused on improving access control schemes within IoMT systems by applying fuzzy logic and lightweight encryption techniques to strengthen security and privacy measures.In [18], the authors discussed the evolution of IoMT, integrating machine learning and addressing security and interoperability challenges. Their methodology involved examining how machine learning technologies can be incorporated into IoMT systems to address various challenges related to security and system interoperability.In [19], the authors proposed a privacy-preserving Brakerski-Gentry-Vaikuntanathan (BGV) homomorphic encryption scheme for IoMT data security. The methodology aimed to enhance data security by employing homomorphic encryption techniques to protect sensitive IoMT data while allowing for secure computations.

In [20], the authors enhanced IoMT security using meta-learning for ensemble intrusion detection systems. Their methodology involved developing a meta-learning approach to improve the performance of ensemble intrusion detection systems in identifying and mitigating security threats within IoMT environments.In [21], the authors proposed a 3D chaos-based medical image cryptosystem for secure cloud-IoMT communication. Their methodology focused on using chaos theory to develop a cryptographic system for securing medical images transmitted over cloud-based IoMT platforms.In [22], the authors introduced SmartHealth, an intelligent framework for securing IoMT service applications using machine learning. The methodology involved leveraging machine learning algorithms to enhance the security of IoMT applications by detecting and preventing unauthorized access and data breaches.

In [23], the authors proposed an approach to securing IoMT applications by enhancing the reliability of security policies within cloud databases. Their methodology focused on improving the robustness of security policies to ensure reliable protection of IoMT data stored in cloud databases.In [24], the authors developed iSecureHealth, a technique for secure health data exchange using IoMT devices. Their methodology involved implementing secure protocols and mechanisms to facilitate safe data transfer between IoMT devices, ensuring the confidentiality and integrity of health information.In [25], the authors introduced a user-authenticated IoMT security model that utilizes blockchain authorization with data indexing and analysis. The methodology involved employing blockchain technology to provide a secure and transparent authorization framework for IoMT data management and analysis.

In [26], the authors proposed a privacy-preserving multi-factor authentication scheme for cloud-assisted IoMT with post-quantum security. Their methodology aimed to enhance data security by incorporating multi-factor authentication and post-quantum cryptographic techniques to protect IoMT data in cloud environments.In [27], the authors conducted a comprehensive study on security protocols in AI-enabled IoMT systems. Their methodology involved reviewing and analyzing various security protocols to improve the protection of AI-driven IoMT applications from potential threats.In [28], the authors proposed a time-based authentication framework for privacy-preserving IoMT sensor monitoring, leveraging blockchain technology. The methodology focused on using time-based authentication mechanisms combined with blockchain to enhance the security and privacy of IoMT sensor data.

In [29], the authors introduced a fast and lightweight image cryptosystem designed for IoMT applications. Their methodology involved developing a cryptographic system that balances security and performance, ensuring rapid and secure encryption of medical images in IoMT environments.In [30], the authors proposed a confidentiality and privacy approach for IoMT-based embedded systems using key generation and steganography. Their methodology involved implementing key generation techniques and steganographic methods to protect the confidentiality and privacy of data within IoMT embedded systems.

4.2 Survey on GI Classification Methods

In [31], the authors proposed using Explainable Artificial Intelligence (XAI) for diagnosing gastrointestinal diseases within the context of telesurgery. Their methodology involved integrating XAI techniques to provide transparent and interpretable decision-making processes, which enhanced the reliability and accuracy of disease diagnosis during remote surgical procedures.In [32], the authors explored self-supervised pretraining for vision problems in gastrointestinal endoscopy. They proposed a self-supervised learning framework that improves feature extraction and classification performance by pretraining models on large, unlabeled endoscopic datasets before fine-tuning on specific diagnostic tasks.In [33], the authors introduced CG-Net, convolutional neural network (CNN) framework for classifying gastrointestinal tract diseases. Their approach involved designing a specialized CNN architecture that enhances feature extraction and classification accuracy for various gastrointestinal conditions.In [34], the authors applied deep CNNs for accurate classification of gastrointestinal tract syndromes. Their methodology focused on leveraging deep CNN models to analyze and classify endoscopic images, aiming to improve diagnostic precision for gastrointestinal disorders.

In [35], the authors developed a multi-module attention-guided deep learning framework for identifying gastrointestinal diseases in endoscopic imagery. Their methodology utilized attention mechanisms within a deep learning framework to enhance feature extraction and improve the accuracy of disease identification.In [36], the authors proposed a spatial-attention ConvMixer architecture for classifying and detecting gastrointestinal diseases using the Kvasir dataset. Their methodology involved incorporating spatial attention mechanisms into the ConvMixer architecture to improve the detection and classification performance of gastrointestinal conditions.

In [37], the authors utilized Probailistic-CNNs with transfer learning for classifying gastrointestinal diseases from endoscopic images. Their approach involved fine-tuning pre-trained CNN models on endoscopic image datasets to enhance diagnostic accuracy for gastrointestinal disorders.In [38], the authors developed a multi-fusion CNN(MF-CNN) to improve the diagnosis of gastrointestinal diseases in endoscopy image analysis. Their methodology combined multiple CNN models to leverage diverse features and enhance the overall diagnostic performance.In [39], the authors combined CNNs with a 2-D visualization method for classifying gastrointestinal tract lesions. Their approach aimed to integrate CNN-based feature extraction with 2-D visualization techniques to enhance the classification accuracy of gastrointestinal lesions.In [40], the authors proposed GIEnsemformerCADx, a hybrid ensemble learning approach for recognizing gastrointestinal cancer. Their methodology combined multiple machine learning models to form an ensemble, improving the accuracy and robustness of gastrointestinal cancer detection.

In [41], the authors employed an ensemble extreme learning machine (ELM) method along with explainable AI for detecting various gastrointestinal tract diseases. Their approach integrated deep learning with ELM and explainable AI techniques to enhance diagnostic accuracy and provide interpretable results.In [42], the authors optimized the EfficientNet model for detecting gastrointestinal disorders using transfer learning and wireless capsule endoscopy images. Their methodology involved fine-tuning EfficientNet on capsule endoscopy images to improve the detection and classification of gastrointestinal disorders.In [43], the authors developed GastroVRG, an advanced transfer feature-based method for early screening of gastrointestinal health. Their approach focused on using transfer learning to enhance feature extraction and improve the early detection of gastrointestinal conditions.In [44], the authors introduced GastroFPN, an advanced deep segmentation model with an enhanced feature pyramid network decoder for gastrointestinal disease classification. Their methodology aimed to improve segmentation accuracy and feature extraction for better disease diagnosis.

In [45], the authors proposed a patch-and-amplify capsule network for recognizing gastrointestinal diseases. Their methodology involved using a capsule network combined with a patch-and-amplify strategy to enhance the accuracy and robustness of disease recognition in gastrointestinal images.In [46], the authors developed a CBAM-integrated CNN for precise multi-class anatomical landmark identification in gastrointestinal diagnosis. Their approach combined Convolutional Block Attention Modules (CBAM) with CNNs to improve the precision and accuracy of anatomical landmark identification in gastrointestinal endoscopy images.In [47], the authors proposed an optimal CapsNet model-based computer-aided diagnosis system for gastrointestinal cancer classification. Their methodology focused on enhancing the CapsNet model to improve classification accuracy and diagnostic performance for gastrointestinal cancer.

In [48], the authors used deep learning techniques for early gastric cancer detection and lesion segmentation based on gastroscopic images. Their approach combined deep learning models with image segmentation techniques to improve the early detection and classification of gastric cancer.In [49], the authors employed deep learning to detect and localize gastrointestinal diseases using wireless capsule endoscopic images. Their methodology involved using advanced deep learning techniques to enhance the detection and localization of diseases in capsule endoscopy images.In [50], the authors introduced lightweight relational embedding in task-interpolated few-shot networks for enhanced gastrointestinal disease classification. Their methodology focused on using relational embedding techniques within few-shot learning frameworks to improve classification performance for gastrointestinal diseases.

5. Problem Statement

Manual disease classification methods, such as traditional diagnostic practices, often face significant challenges that impact their effectiveness and efficiency. These methods are typically time-consuming, requiring manual examination and interpretation of diagnostic data, which can lead to subjective errors and variability in results. The reliance on human expertise introduces inconsistencies, as different practitioners may have varying levels of experience and diagnostic skills. Additionally, manual classification methods may struggle with handling large volumes of data and complex cases, leading to delays in diagnosis and potentially impacting patient outcomes. The need for manual analysis also limits the scalability of these methods, making them less suitable for high-throughput environments.

Conventional endoscopy methods, while effective in visualizing internal organs, present several challenges for patients. These procedures can be invasive, often requiring sedation or anesthesia, which carries inherent risks and discomfort. The preparation and recovery time can be lengthy and burdensome, impacting patient compliance and overall experience. Conventional endoscopy also has limitations in terms of accessibility and availability, as the procedure often requires specialized equipment and trained personnel. Additionally, there is a risk of complications such as bleeding, infection, or damage to internal tissues, which can further exacerbate patient concerns and affect their health outcomes.

In the realm of the IoMT, data security presents a critical concern, especially in GI applications. Despite the advancements in IoMT technology, there is a notable lack of literature specifically addressing the security of GI-based IoMT systems. These systems generate and transmit sensitive health data, making them vulnerable to various cybersecurity threats, including unauthorized access, data breaches, and tampering. The absence of robust security measures can lead to potential misuse or loss of patient information, jeopardizing patient privacy and trust in IoMT solutions. Ensuring secure communication, data integrity, and access control within IoMT platforms is essential to mitigate these risks and protect patient data.

Conventional Artificial Intelligence (AI), Machine Learning (ML), and Deep Learning (DL) methods for GI disease classification face several limitations. One major issue is the requirement for large, labeled datasets to train models effectively, which can be challenging to obtain in sufficient quantities. These methods may also struggle with overfitting, where models perform well on training data but poorly on unseen data, limiting their generalizability. Additionally, the complexity of GI data, including variations in image quality and pathology, can hinder model performance and accuracy. Another challenge is the interpretability of AI and ML models, as their "black-box" nature can make it difficult for clinicians to understand and trust the model's predictions. Addressing these issues is crucial for improving the reliability and adoption of AI, ML, and DL technologies in GI disease classification.

6. Future Directions

To the best of current knowledge, no comprehensive survey has been conducted that specifically addresses the intersection of IoMT security with GI disease classification. This represents a significant gap in the literature, as existing studies primarily focus on IoMT security in a general context or on GI disease classification using traditional AI, ML, and DL methods without integrating security considerations. The novelty of addressing this gap lies in exploring the unique security challenges and requirements of IoMT systems used in GI diagnostics, which involves both securing sensitive health data and improving classification accuracy. By bridging this gap, the research aims to advance the field by proposing integrated solutions that enhance both the security and effectiveness of IoMT-based GI disease classification systems. So, the future directions are defined as follows:

- Future research should explore the incorporation of advanced privacy-preserving techniques into IoMT frameworks, beyond traditional encryption methods. IoMT involves the interconnection of medical devices and systems through network technologies, facilitating remote monitoring, data collection, and healthcare delivery. Given the sensitive nature of medical data, ensuring its security during transmission and storage is paramount. Hybrid encryption combines symmetric and asymmetric encryption techniques to achieve both efficiency and security. In IoMT, this research aims to develop robust encryption methods tailored to the specific requirements and constraints of medical IoT devices, ensuring the confidentiality and integrity of patient data.

- To delves into the realm of medical imaging analysis, particularly focusing on gastrointestinal (GI) diseases detected through Wireless Capsule Endoscopy (WCE) color images. WCE is a minimally invasive diagnostic technique that enables visualization of the gastrointestinal tract using a small capsule-sized camera. The objective here is to develop a binary classification system capable of distinguishing between diseased and healthy segments of the GI tract based on WCE color images. To achieve this, optimal feature extraction techniques will be employed to capture relevant patterns and characteristics from the images, followed by the utilization of deep learning algorithms for classification. By leveraging deep learning, which excels at learning intricate patterns from large datasets, the aim is to enhance the accuracy and efficiency of GI disease diagnosis, thereby aiding clinicians in timely and accurate treatment decisions.
- To builds upon the second by expanding the scope to encompass multi-class classification of gastrointestinal diseases from WCE images. In addition to binary classification, this objective aims to differentiate between various types of GI diseases, enabling more comprehensive diagnostic capabilities. To achieve this, the research proposes the integration of natural-inspired feature selection methods, which mimic biological processes such as evolution or neural activity, to identify the most discriminative features for classification. These selected features, along with optimal feature extraction techniques, will feed into deep learning classifiers to enable accurate multi-class classification of GI diseases from WCE images. By combining advanced feature selection, feature extraction, and deep learning techniques, this research seeks to enhance the diagnostic accuracy and utility of WCE technology in clinical practice, ultimately improving patient outcomes and healthcare efficiency in the realm of gastrointestinal disorders.

7. Conclusion

This survey concludes that while significant progress has been made in the automated classification of GI diseases through advanced machine learning and deep learning algorithms, ensuring the security and privacy of sensitive patient data remains a critical challenge. The adoption of robust encryption techniques, secure communication protocols, and innovative technologies such as blockchain is essential to protect data integrity and patient confidentiality. Looking to the future, the development of more sophisticated AI models with enhanced interpretability, combined with stronger, more flexible cybersecurity frameworks, will be crucial in addressing these challenges. Furthermore, future research should focus on integrating IoMT with other emerging technologies, such as edge computing and federated learning, to enhance real-time diagnostic capabilities while reducing latency and maintaining data security. The continuous evolution of IoMT systems will require a balanced approach that harmonizes technological advancements in automated disease detection with the highest standards of data security, paving the way for safer, more efficient, and patient-centered healthcare solutions.

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