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AI-POWERED GASTRO-INTESTINAL DISEASE CLASSIFICATION WITH EXPLAINABLE INSIGHTS

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Abstract : This project presents a Flask-based web application for automated classification of gastrointestinal endoscopy images using deep learning techniques. The system integrates a convolutional neural network model trained on annotated datasets to identify various gastrointestinal conditions, including polyps, esophagitis, ulcerative colitis, and normal anatomical structures. A role-based authentication mechanism enables secure access for technicians, doctors, and administrators, supporting efficient patient data management and clinical workflows. The application allows image upload, real-time prediction, and visualization of results through Grad-CAM heatmaps, enhancing interpretability and trust in AI-driven decisions. Additionally, the platform includes features such as prediction history tracking and doctor-patient communication. The backend is implemented using Flask, SQLAlchemy, and TensorFlow, while the frontend utilizes standard web technologies. This system aims to assist healthcare professionals in early diagnosis and decision-making, demonstrating the practical integration of explainable artificial intelligence in medical imaging applications.

***IndexTerms* - Gastrointestinal Endoscopy, Image Classification, Deep Learning, Explainable AI, Grad-CAM, Flask, Medical Imaging, Clinical Decision Support.**

I. INTRODUCTION

Gastrointestinal diseases are among the most common health concerns worldwide, requiring accurate and timely diagnosis for effective treatment. Endoscopy is a widely used diagnostic procedure that allows visualization of the gastrointestinal tract; however, manual interpretation of endoscopic images is time-consuming and highly dependent on the expertise of medical professionals. With the rapid advancement of artificial intelligence, particularly deep learning, automated image analysis has emerged as a powerful tool to assist clinicians in identifying abnormalities such as polyps, esophagitis, and ulcerative colitis. Integrating AI into clinical workflows can significantly enhance diagnostic efficiency and reduce human error.

The main aim of this project is to develop an intelligent and user-friendly web-based system that automates the classification of gastrointestinal endoscopy images while providing explainable results. The goal is to support healthcare professionals by offering accurate predictions, visual explanations through Grad-CAM, and efficient patient data management. Additionally, the system aims to facilitate seamless interaction between technicians, doctors, and administrators through role-based access and communication features, thereby improving overall clinical decision-making processes.

To achieve the best results, the system leverages a deep learning model trained on a well-structured dataset of endoscopic images, ensuring robust feature extraction and classification performance. Image preprocessing techniques and standardized input dimensions are used to maintain consistency in predictions. The integration of Grad-CAM enhances transparency by highlighting important regions influencing the model's decisions. Furthermore, the use of a Flask-based architecture, combined with a structured database and secure authentication mechanisms, ensures efficient data handling, scalability, and reliable system performance in real-world scenarios.

II. NEED OF THE STUDY.

The increasing prevalence of gastrointestinal disorders such as polyps, esophagitis, and ulcerative colitis has created a significant demand for accurate and early diagnostic methods. Traditional endoscopic analysis relies heavily on the expertise and experience of clinicians, making the process subjective, time-consuming, and prone to variability. In high-volume clinical settings, this can lead to delayed diagnosis or missed abnormalities, which may result in severe health complications. Therefore, there is a critical need for an automated and reliable system that can assist medical professionals in analyzing endoscopy images with higher consistency and efficiency.

Moreover, the integration of artificial intelligence in healthcare has opened new possibilities for improving diagnostic accuracy and decision-making. However, many AI-based systems lack interpretability, making it difficult for clinicians to trust their predictions. This study addresses the need for an explainable and user-friendly platform that not only classifies gastrointestinal images but also provides visual explanations through techniques like Grad-CAM. By combining deep learning with a web-based interface and role-based access, the system aims to enhance clinical workflows, support better patient management, and bridge the gap between advanced technology and practical medical applications.

III. RELATED WORKS

Recent research in gastrointestinal endoscopy image classification has shown significant advancements with the adoption of deep learning techniques. Early approaches relied on handcrafted features and rule-based methods; however, these were limited in handling complex visual patterns. With the emergence of convolutional neural networks (CNNs), models such as VGG16, ResNet, and GoogLeNet have demonstrated high accuracy in detecting gastrointestinal diseases from endoscopic images . Large-scale datasets like Kvasir and Hyper-Kvasir have further accelerated research by providing annotated medical images for multi-class classification tasks. Studies have reported classification accuracies exceeding 90%, highlighting the effectiveness of deep learning models in clinical diagnosis. Additionally, recent works have focused on improving performance using techniques such as attention mechanisms, self-supervised learning, and hybrid architectures combining CNN and RNN models . Despite these advancements, challenges such as data variability, lack of interpretability, and dependency on labeled datasets remain key research gaps in the field .

3.1Literature Review

The application of artificial intelligence in medical imaging has gained significant attention in recent years, particularly in the field of gastrointestinal endoscopy. Traditional diagnostic approaches relied on manual inspection by clinicians, which is often time-consuming and subject to human error. Early computational methods attempted to assist diagnosis using handcrafted features such as texture, color, and shape descriptors. However, these methods lacked robustness and failed to generalize effectively across diverse datasets, limiting their clinical applicability.

With the advancement of deep learning, convolutional neural networks (CNNs) have become the dominant approach for medical image classification. Architectures such as VGGNet, ResNet, and Inception have demonstrated remarkable performance in identifying gastrointestinal abnormalities from endoscopic images. These models automatically learn hierarchical feature representations, enabling more accurate detection of conditions like polyps, esophagitis, and ulcerative colitis. The availability of publicly accessible datasets such as Kvasir and Hyper-Kvasir has further facilitated the development and evaluation of high-performing classification models.

Recent studies have focused on improving model performance and generalization through advanced techniques such as transfer learning, data augmentation, and ensemble learning. Transfer learning allows pre-trained models to be fine-tuned on medical datasets, reducing the need for large amounts of labeled data. Data augmentation techniques, including rotation, scaling, and flipping, help improve model robustness by increasing dataset diversity. Ensemble methods combine predictions from multiple models to achieve higher accuracy and stability in classification results.

Another important area of research is explainable artificial intelligence (XAI), which aims to enhance the transparency of deep learning models. Techniques such as Grad-CAM (Gradient-weighted Class Activation Mapping) are widely used to visualize the regions of an image that influence model predictions. This is particularly crucial in the medical domain, where interpretability is essential for gaining clinicians' trust. By providing visual explanations, XAI methods help bridge the gap between complex AI models and practical clinical decision-making.

Despite significant progress, several challenges remain in the field of gastrointestinal image classification. Variability in image quality, differences in patient anatomy, and limited availability of labeled medical data continue to impact model performance. Additionally, integrating AI systems into real-world clinical workflows requires addressing issues related to scalability, data security, and user acceptance. Therefore, ongoing research is focused on developing more robust, interpretable, and clinically deployable AI solutions to support healthcare professionals in accurate and efficient diagnosis.

3.2 Comparison with Previous Methodology

Previous methodologies for gastrointestinal endoscopy image analysis primarily relied on manual examination or traditional machine learning techniques using handcrafted features such as color, texture, and shape descriptors. These approaches required significant domain expertise and were often limited in their ability to generalize across diverse datasets. Even with the introduction of deep learning models like CNNs, many existing systems focused solely on classification accuracy without integrating user interaction, explainability, or real-time clinical usability. Additionally, earlier systems lacked structured data management, role-based access, and seamless communication between healthcare stakeholders, making them less practical for real-world deployment.

In contrast, the proposed methodology offers a comprehensive and integrated solution by combining deep learning-based image classification with a Flask-based web application. The system not only performs automated diagnosis using a trained CNN model but also incorporates explainable AI through Grad-CAM to provide visual insights into model predictions. Unlike previous approaches, it includes role-based authentication for technicians, doctors, and administrators, enabling secure and efficient workflow management. Furthermore, the system supports patient record management, prediction history tracking, and a messaging module for doctor-patient communication. This holistic approach enhances usability, transparency, and scalability, making the proposed system more suitable for practical healthcare applications compared to traditional methods.

Table.1. Comparison Table

Aspect	Previous Methodology	Proposed Methodology
Technique	Traditional ML / Manual analysis	Deep Learning (CNN)
Accuracy	Moderate	High
Feature Handling	Handcrafted features	Automatic feature extraction
Explainability	Not available	Grad-CAM visualization
System Type	Standalone / Offline	Web-based Flask application
User Access	No role management	Role-based (Technician, Doctor, Admin)
Data Handling	Limited	Structured database with history

3.3 Proposed framework

The proposed framework is designed as an integrated, web-based intelligent system for gastrointestinal endoscopy image classification and clinical workflow support. It combines deep learning techniques with a Flask-based backend to deliver automated diagnosis along with user-friendly interaction. The architecture follows a modular approach, consisting of components for user authentication, image processing, prediction generation, explainability, and data management. This structured design ensures scalability, maintainability, and efficient handling of medical data.

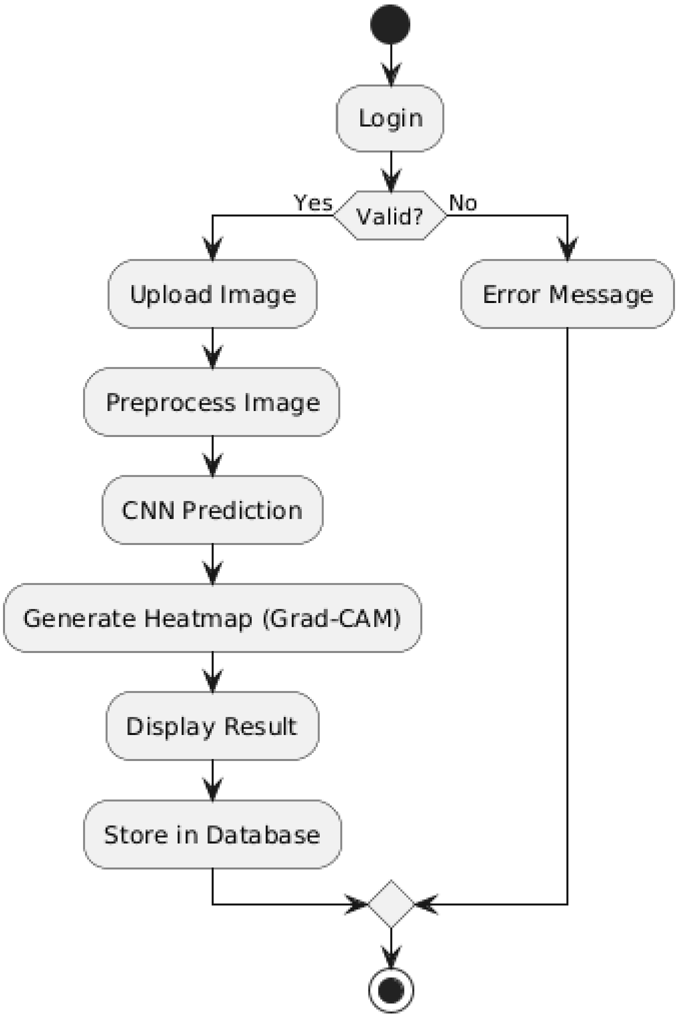

Fig.1.Methodology

The first component of the framework is the role-based authentication system, which manages access for technicians, doctors, and administrators. Each user type is provided with a dedicated dashboard tailored to their responsibilities. Technicians are responsible for uploading patient data and medical images, doctors can review diagnosis results and communicate with patients, and administrators oversee system-level operations such as user management. This separation of roles enhances security and ensures proper workflow organization.

The core of the framework lies in the image classification module, which utilizes a convolutional neural network (CNN) model trained on gastrointestinal endoscopy datasets. When an image is uploaded, it undergoes preprocessing steps such as resizing, normalization, and format conversion before being passed to the model. The trained model then predicts the class label along with a confidence score, enabling automated detection of conditions like polyps, esophagitis, and ulcerative colitis.

To improve trust and interpretability, the framework integrates an explainable AI component using Grad-CAM. This module generates heatmaps that highlight the regions of the image contributing most to the prediction. The visualization is overlaid on the original image and presented to the user, allowing clinicians to understand and validate the model's decision-making process. This feature is particularly important in medical applications where transparency is critical.

The system also includes a robust database management layer implemented using SQLAlchemy and SQLite. It stores user details, patient records, prediction history, and communication data. Each prediction is linked to a specific patient and user, ensuring traceability and easy retrieval of past results. Additionally, the messaging module enables direct communication between doctors and patients, facilitating better follow-up and clinical interaction.

Finally, the framework is deployed as a Flask web application, integrating frontend technologies such as HTML, CSS, and JavaScript for an interactive user interface. The system supports real-time image upload, instant prediction, and visualization, making it suitable for practical use in clinical environments. Overall, the proposed framework effectively combines deep learning, explainable AI, and web technologies to deliver a comprehensive and scalable solution for gastrointestinal disease diagnosis.

3.4 Main Methodology

- The system begins with user authentication, allowing secure login for technicians, doctors, and administrators.
- Role-based access control is implemented to provide separate dashboards for each user type.
- Technicians create and manage patient records including basic details like name, age, and contact information.
- Endoscopy images are uploaded through the web interface for analysis.
- The uploaded image is read and converted into a numerical array format for processing.
- Image preprocessing is performed, including resizing, normalization, and channel adjustment.
- The processed image is fed into a pre-trained Convolutional Neural Network (CNN) model.
- The model performs feature extraction and classification to identify gastrointestinal conditions.
- A probability score (confidence) is generated for each class prediction.
- The system selects the final predicted class based on the highest probability.
- Grad-CAM is applied to generate a heatmap visualization highlighting important regions in the image.
- The prediction result, confidence score, and Grad-CAM image are stored in the database.
- The results are displayed on the dashboard with diagnosis details and visual explanation.
- Doctors can review patient history and send messages for further consultation.
- The system maintains prediction history and data records for future reference and analysis.

3.4.1 Implementation

The implementation of the proposed system begins with setting up the development environment and configuring the Flask framework. Required libraries such as TensorFlow, Keras, OpenCV, SQLAlchemy, and Flask-Login are installed and integrated. The project structure is organized into modules for models, forms, routes, and templates to ensure maintainability. The SQLite database is configured, and initial tables are created using SQLAlchemy to store user, patient, prediction, and message data.

The next step involves implementing the user authentication system. Flask-Login is used to manage user sessions, while Flask-WTF handles form validation. Registration and login functionalities are developed with secure password hashing using Werkzeug. Role-based access control is implemented to differentiate between technicians, doctors, and administrators, ensuring that each user can only access their respective dashboard and functionalities.

Following authentication, the database models are defined and linked using SQLAlchemy relationships. Separate tables are created for users, patients, predictions, and messages. Foreign key relationships ensure proper mapping between entities, such as linking predictions to specific patients and users. This structured schema enables efficient data retrieval and management throughout the application.

The core functionality is implemented by integrating the deep learning model for image classification. The pre-trained model is loaded using TensorFlow/Keras with compatibility handling. Image preprocessing functions are developed to resize images, normalize pixel values, and convert them into the required input format. Upon uploading an image, the system processes it and feeds it into the model to generate predictions and confidence scores.

To enhance interpretability, the Grad-CAM visualization module is implemented. This component generates heatmaps that highlight the regions of the image influencing the model's prediction. The heatmap is overlaid on the original image and saved as a static file. This visual output is then displayed alongside the prediction result, helping users understand the reasoning behind the classification.

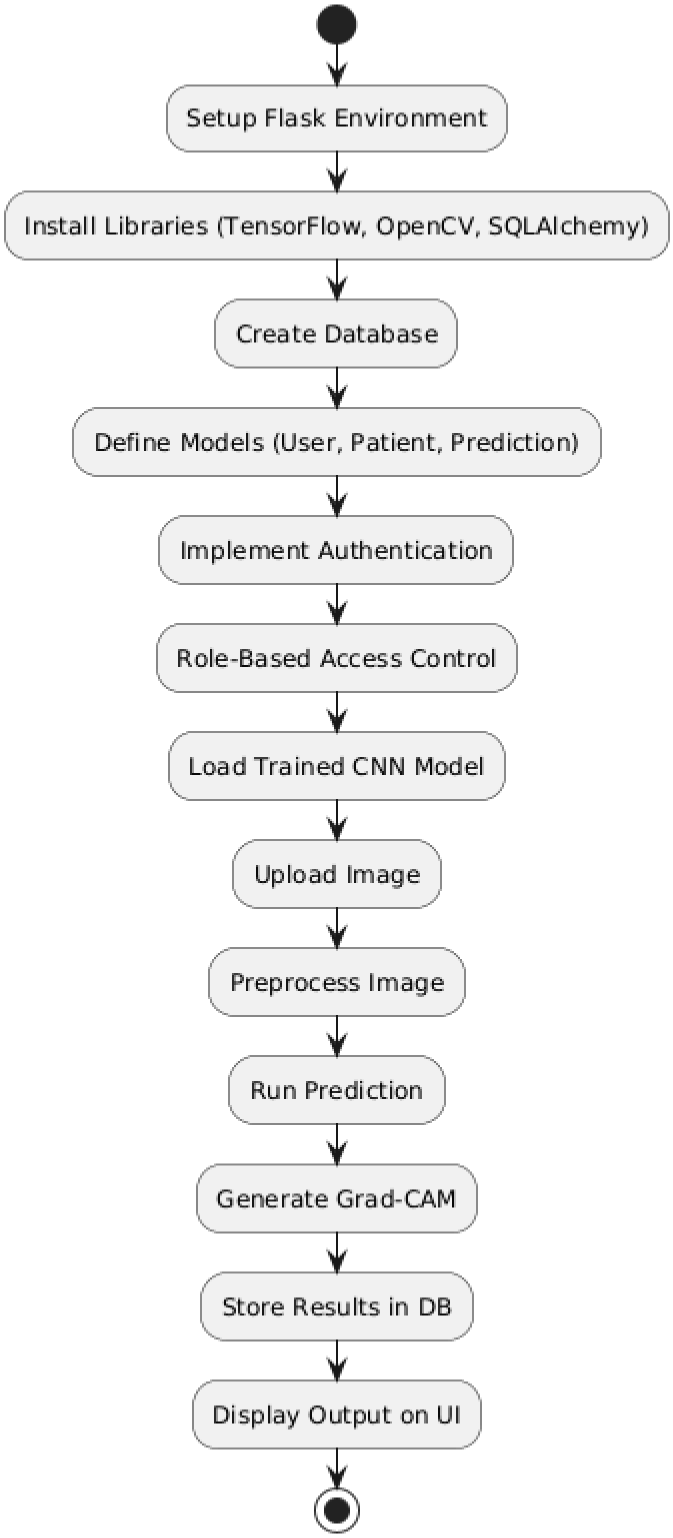

Fig.2.Implementation

The user interface is developed using HTML, CSS, and JavaScript, providing interactive dashboards for different roles. Technicians can create patients and upload images, doctors can review predictions and communicate with patients, and administrators can manage users and monitor system activity. Forms and templates are designed to ensure smooth navigation and usability across all functionalities.

Finally, the system is tested and deployed locally using the Flask development server. Various test cases are executed to validate image upload, prediction accuracy, database operations, and user interactions. Debugging and error handling mechanisms are implemented to ensure system stability. The application is then made ready for deployment, demonstrating a complete and functional AI-based web system for gastrointestinal image classification.

IV. RESULTS AND DISCUSSION

4.1 System output screenshots and explanation

The developed system was tested using a set of gastrointestinal endoscopy images to evaluate its classification performance and overall functionality. The deep learning model successfully classified images into multiple categories such as polyps, esophagitis, ulcerative colitis, and normal anatomical structures. The system demonstrated consistent prediction capability, providing outputs along with confidence scores, which indicates the reliability of the trained model in handling real-time image inputs.

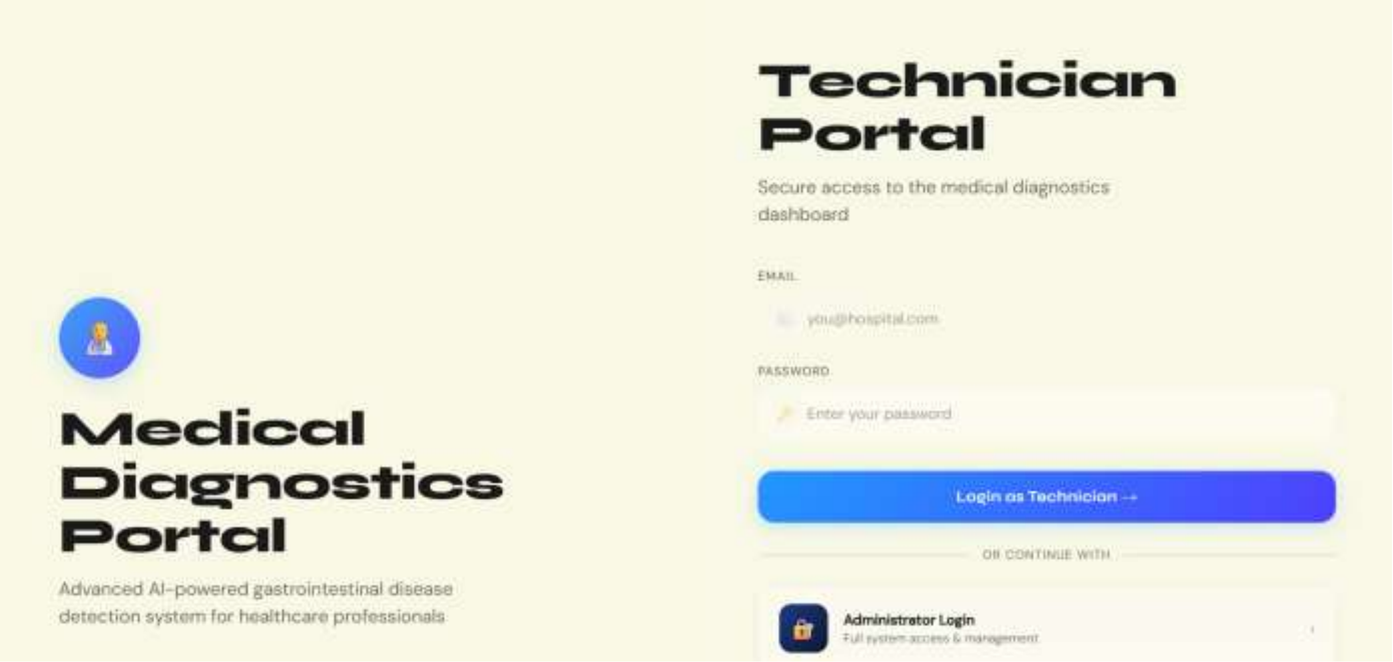

Fig.3.Main Interface

The classification results show that the model is capable of identifying distinct visual patterns present in endoscopic images. Conditions like polyps and ulcerative colitis were detected with relatively high confidence due to their prominent structural features. Normal anatomical regions such as the cecum, pylorus, and z-line were also correctly identified, highlighting the model's ability to differentiate between healthy and abnormal tissues. This demonstrates the effectiveness of convolutional neural networks in medical image analysis tasks.

The integration of Grad-CAM visualization significantly enhanced the interpretability of the system. The generated heatmaps provided clear insights into the regions of the image that influenced the model's predictions. This feature helps users, especially medical professionals, to validate whether the model is focusing on clinically relevant areas. As a result, the system builds trust and improves transparency, which are critical factors in healthcare applications.

From a system perspective, the web-based interface performed efficiently in handling user interactions such as image uploads, prediction display, and data retrieval. The response time for predictions was minimal, making the system suitable for real-time usage. The role-based dashboards ensured smooth navigation and appropriate access control, allowing different users to perform their respective tasks without conflicts.

The database component effectively managed patient records, prediction history, and communication data. Each prediction was stored with relevant details, enabling easy tracking and retrieval of past results. This feature is particularly useful for longitudinal analysis and follow-up consultations. Additionally, the messaging system facilitated communication between doctors and patients, enhancing the overall usability of the application.

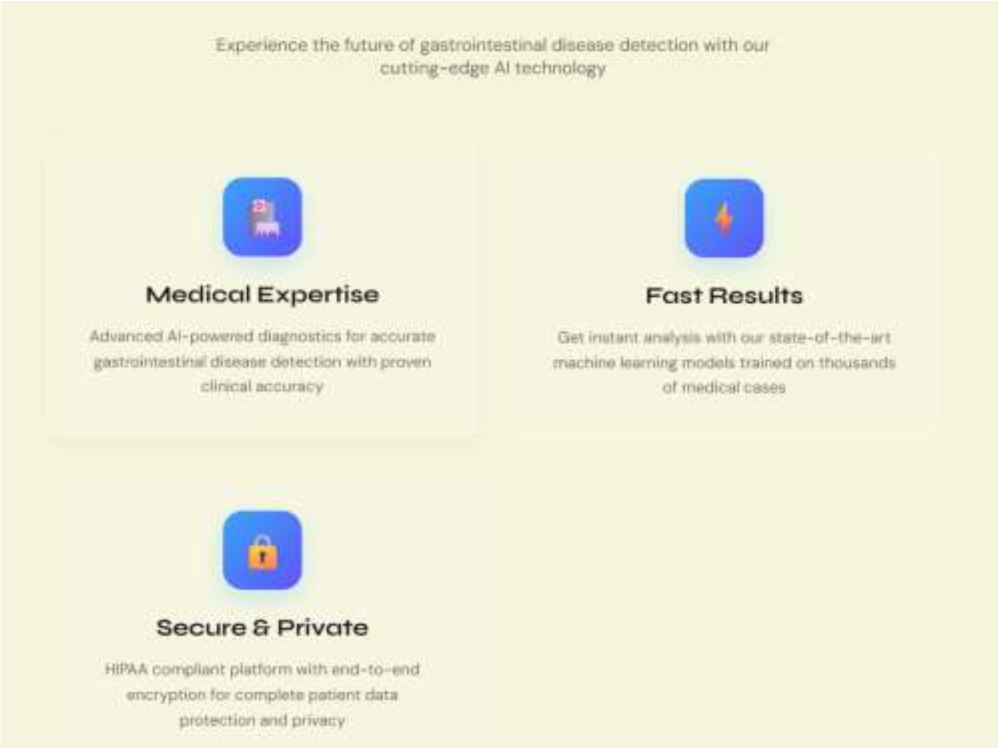

Fig.4.Features

Despite these positive outcomes, certain limitations were observed during testing. The model's performance is dependent on the quality and diversity of the training dataset. Variations in image resolution, lighting conditions, and noise can affect prediction accuracy. Furthermore, the current Grad-CAM implementation, while useful for visualization, can be further improved for more precise localization of features.

Another challenge lies in the scalability and deployment of the system in real-world clinical environments. While the application performs well in a local setup, handling large-scale data and concurrent users may require more robust infrastructure, such as cloud deployment and advanced database systems. Security and privacy of medical data are also important considerations that need to be addressed before real-world adoption.

Overall, the results indicate that the proposed system is effective in automating gastrointestinal image classification and supporting clinical decision-making. The combination of deep learning, explainable AI, and web-based technologies provides a comprehensive solution for medical image analysis. With further improvements in model optimization, dataset expansion, and system deployment, the framework has strong potential for practical use in healthcare settings.

4.2 Conclusion

The proposed system successfully demonstrates the integration of deep learning and web technologies for automated classification of gastrointestinal endoscopy images. By leveraging a convolutional neural network, the system is capable of accurately identifying various gastrointestinal conditions and presenting results in a user-friendly manner. The inclusion of explainable AI through Grad-CAM enhances the transparency of predictions, making the system more reliable and suitable for clinical support. Additionally, the role-based architecture and database management ensure efficient handling of patient data and streamlined workflow among technicians, doctors, and administrators.

Overall, the project highlights the potential of AI-driven solutions in improving diagnostic efficiency and supporting medical decision-making. While the system performs effectively in its current form, further enhancements such as improved model accuracy, real-time deployment, and stronger data security measures can make it more robust for real-world applications. This work serves as a foundation for developing advanced, scalable, and interpretable healthcare systems that bridge the gap between artificial intelligence and practical medical use.

4.3 Future Scope

- Improve model accuracy by training on larger and more diverse gastrointestinal datasets.
- Implement a real Grad-CAM algorithm for more precise and clinically reliable explanations.
- Integrate advanced deep learning architectures such as ResNet or EfficientNet for better performance.
- Deploy the application on cloud platforms for scalability and real-time access.
- Replace SQLite with robust databases like PostgreSQL or MongoDB for handling large-scale data.

- Develop a mobile application for easier access by doctors and patients.
- Add support for video-based endoscopy analysis instead of only static images.
- Incorporate multi-disease detection and severity grading for better clinical insights.
- Enhance security by implementing data encryption and HIPAA-compliant standards.
- Integrate electronic health records (EHR) systems for seamless clinical data exchange.
- Add multilingual support to make the system usable in different regions.
- Implement continuous learning mechanisms to update the model with new medical data over time.

V. Acknowledgement

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