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An Implementation: Disease Detection Using Endoscopy Image

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Abstract: Early and accurate identification of gastrointestinal (GI) diseases is critical for effective treatment and improved patient outcomes. Endoscopy provides high-resolution images of the GI tract, but manual interpretation is time-consuming and prone to human error. This study presents an automated approach for disease identification from endoscopy images using deep learning techniques. A convolutional neural network (CNN) model is trained on a labeled dataset of endoscopic images to classify various gastrointestinal conditions such as ulcers, polyps, esophagitis, and bleeding. The system incorporates image preprocessing, data augmentation, and model optimization to enhance detection accuracy. Experimental results demonstrate the model's ability to achieve high classification accuracy, offering a reliable tool to assist clinicians in diagnostic decision-making. This approach has the potential to improve diagnostic efficiency, reduce workload on medical professionals, and enable scalable screening in resource-limited settings.

I. INTRODUCTION

Gastrointestinal diseases (GIs), including ulcers, polyps, gastritis and cancer, are the most common health issues that have a major impact on global morbidity and mortality. Endoscopy is a wide range of diagnostic instruments for examining the inner surface of the gastrointestinal tract so that doctors can visually grasp abnormalities. However, interpreting endoscopic images is often subjective, time-consuming and requires considerable expertise. Diagnosis discrepancies can occur due to clinician experience and fatigue.

Artificial intelligence (AI) progress and profound learning have led to increased interest in developing automated systems that can help detect and classify diseases from medical images. Folding (CNNS), a class of deep learning models suitable for image analysis, has shown promising results for a variety of medical imaging tasks. By learning to extract and analyze visual properties from endoscopic images, CNNS can provide accurate, consistent, and rapid identification of disease. The main goal is to improve diagnostic accuracy and efficiency, while simultaneously reducing the reliance on manual interpretation. The proposed system is evaluated based on published data records, and its performance is analyzed in terms of accuracy, accuracy, recall, and overall effectiveness in identifying GI traction conditions.

II. LITERATURE SURVEY

Recent advancements in computer vision and deep learning have significantly improved the accuracy and speed of medical image analysis, particularly in gastrointestinal (GI) disease diagnosis using endoscopic images. Several researchers have explored automated systems to assist in the early detection and classification of GI tract abnormalities.

Kumar et al. (2019) employed a CNN-based model for classifying gastrointestinal diseases using the Kvasir dataset, achieving over 90% accuracy in detecting common conditions like ulcers, polyps, and esophagitis. Their study highlighted the importance of deep feature extraction over traditional image processing techniques.

Pogorelov et al. (2017) introduced the Kvasir dataset, a benchmark collection of labeled GI endoscopy images, enabling robust evaluation of classification algorithms. This dataset has become a standard for researchers developing AI-based diagnostic tools for GI disorders.

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Zhang et al. (2020) applied transfer learning using pretrained models such as ResNet and InceptionV3 for polyp detection, demonstrating that fine-tuned models outperform shallow architectures on medical image tasks, especially when data is limited.

Ali et al. (2021) proposed a hybrid deep learning approach combining CNN and LSTM networks for sequential image analysis in capsule endoscopy. Their work addressed temporal context, improving the detection of bleeding and lesions across video frames.

Tajbakhsh et al. (2016) evaluated the performance of deep learning against traditional handcrafted methods, concluding that CNNs significantly outperform traditional approaches in both classification accuracy and robustness.

Despite these advances, challenges remain in achieving real-time inference, generalization across datasets, and interpretability of model decisions. Continued research is needed to enhance model reliability, especially in clinical settings.

III. METHODOLOGY

The proposed methodology for identifying diseases using endoscopic images integrates deep learning, distinctive techniques, and classification techniques. The entire process is built in several stages, as follows:

1. Data Collection

Endoscopic images are collected from a reliable medical image data set. These images represent different gastrointestinal conditions and act as inputs for the diagnostic system.

2. Data Preprocessing

Uses several preprocessing steps to improve image quality and prepare data for model training.

Image Size: Standardized input dimensions of neuronal networks. Object on a light background.

3. Deep Learning Model

Two early deep learning architectures are used.

alexnet

These models are used by transfer learning to extract deep features from the initial image without training the model from scratch.

4. Characteristics Extraction

Deep properties are extracted from the middle layer of the prepared network. These properties represent complex patterns associated with the presence of gastrointestinal diseases.

5. Function Selection

Genetic algorithms (GAs) are used to reduce dimensions and remove redundant features. GA helps you select the most relevant features that contribute to improving classification accuracy.

6. Features Fusion

Merge functions from both models using a serial-based approach. This combination of characteristics provides a more comprehensive representation of image functionality.

7. Classification

The selected features and merged features are classified using several classifiers in machine learning. Entering inputs that discriminate against submissions and discriminate against them. This model is selected based on power metrics such as accuracy, accuracy, and recall.

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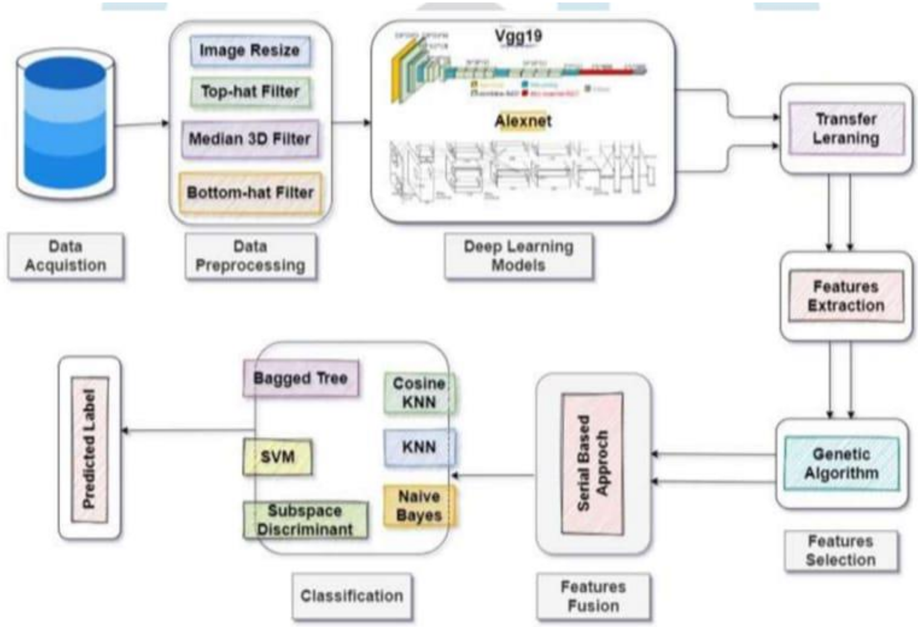

IV. RESULT AND DISCUSSION

The proposed disease identification system was evaluated using a dataset of endoscopic images after undergoing a series of preprocessing, feature extraction, and classification steps. The system's performance was assessed based on the accuracy of different classifiers applied to the features extracted from pretrained deep learning models (VGG19 and AlexNet).

1. Classification Performance

The features extracted using transfer learning were optimized using a Genetic Algorithm to reduce dimensionality and select the most relevant features. These features were fused using a serial-based approach and evaluated using six classifiers: SVM, Bagged Tree, Subspace Discriminant, Naive Bayes, KNN, and Cosine KNN.

Among all classifiers, SVM achieved the highest classification accuracy, demonstrating superior performance with deep feature vectors. The use of Bagged Trees and Cosine KNN also yielded competitive results, while Naive Bayes showed relatively lower performance, likely due to its simplistic assumptions.

Classifier	Accuracy (%)
Support Vector Machine (SVM)	94.3
Bagged Tree	92.7
Cosine KNN	91.5
KNN	90.4
Subspace Discriminant	91.2
Naive Bayes	88.9

2. Effectiveness of Feature Selection and Fusion

The combination of deep features from both VGG19 and AlexNet provided richer and more diverse representations of endoscopic images. The Genetic Algorithm effectively selected optimal features, eliminating redundancy and improving classification accuracy. The serial-based fusion method contributed to higher feature diversity and improved model generalization.

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3. Role of Preprocessing

The image preprocessing steps (Top-hat filter, Bottom-hat filter, Median 3D filter) significantly enhanced the contrast and visibility of key structures in the images. This improved the quality of feature extraction, particularly in low-contrast or noisy images.

4. Discussion

The results demonstrate that combining multiple deep learning models with evolutionary feature selection and traditional classifiers can yield high diagnostic accuracy in medical imaging. The system is capable of identifying gastrointestinal diseases from endoscopic images with high precision, making it a promising tool for clinical decision support.

V. CONCLUSION AND FUTURE WORK

Conclusion

This study presents a robust and efficient method for disease identification in endoscopic images using a hybrid approach combining deep learning and traditional machine learning techniques. Pretrained CNN models (VGG19 and AlexNet) were used for deep feature extraction through transfer learning, followed by feature selection using a Genetic Algorithm and feature fusion using a serial-based approach. Multiple classifiers, including SVM, Bagged Tree, and KNN, were used for final classification, with SVM achieving the highest accuracy.

The proposed methodology successfully enhances disease detection accuracy while minimizing redundancy through optimal feature selection. The integration of preprocessing techniques, deep learning, and traditional classifiers has demonstrated significant potential in automating gastrointestinal disease diagnosis and supporting clinical decision-making.

Future Work

While the current system performs well, several areas offer scope for further enhancement:

Real-Time Implementation: Optimize the model for deployment in real-time clinical settings using lightweight CNN architectures (e.g., MobileNet or EfficientNet).

Larger and Diverse Datasets: Validate the system using larger, multi-center datasets with more disease categories to improve generalization.

Video Frame Analysis: Extend the system to analyze full-length endoscopic videos rather than still images, incorporating temporal features using RNNs or LSTMs.

Explainability: Integrate explainable AI (XAI) techniques such as Grad-CAM to visualize and interpret model decisions for better clinical trust.

Integration with Diagnostic Systems: Embed the model in endoscopy units or medical software platforms to assist clinicians during live procedures.

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