Advancing Colon Cancer Detection with an Ensemble of XceptionNet and MobileNet Models: A Multi-Modal Deep Learning Approach for Improved Accuracy and Early Diagnosis

B. Rajalakshmi
Dept. of Computer Science and Engineering
Associate Professor of Easwari Engineering
College, Chennai, India

S. Yaswanth
Dept. of Computer Science and Engineering
Student of Easwari Engineering College, Chennai, India

A. Yuvanraj
Dept. of Computer Science and Engineering
Student of Easwari Engineering College, Chennai, India

M. Mohamed Harif
Dept. of Computer Science and Engineering
Student of Easwari Engineering
College, Chennai, India

ABSTRACT
Colon cancer is a significant global health concern that necessitates early detection for efficient treatments.Due to the intricacies and differences in colonoscopy pictures, the identification of colon cancer offers a noteworthy obstacle within the domain of oncology. The goal of this study is to improve colon cancer diagnosis through the use of CNN models, particularly XceptionNet and MobileNet. With the use of these models, early diagnosis are made easier, ultimately leading to better patient outcomes. By streamlining the diagnostic procedure with CNN integration, improved patient care and more potent treatments are promised. These models are crucial in closing the gap in early diagnosis by improving the efficacy and accuracy of colon cancer detection. Long-standing challenges in this field include staining heterogeneity and subjective interpretation. To get around these problems, the study makes use of XceptionNet and MobileNet's ensemble capabilities, which results in a more reliable and accurate evaluation of colonoscopy pictures. This combined strategy offers a dependable method for spotting probable cancers and considerably raises classification accuracy. The study also highlights the crucial contribution of GPT-2, a top natural language processing model, in addition to these developments. GPT-2 is essential for automatically creating thorough and comprehensible diagnostic reports. This combination of deep learning and linguistic proficiency improves clinical judgment and lessens the workload for medical personnel.The significance of the work rests in its potential to transform colon cancer screening by providing more accurate and insightful assessments. The applicability of this method to additional oncological entities suggests further extensive uses in oncology.

Keywords
Colon cancer detection, Early Detection, GPT-2, XceptionNet, MobileNet, medical imaging, Ensemble Learning, CNN Models

1. INTRODUCTION
The most common and potentially fatal form of cancer in the world, colon cancer, presents a significant public health concern. Every year, millions of new cases are diagnosed, making early diagnosis crucial for efficient care and better patient outcomes.The broad category of disorders known as cancer continues to pose a serious threat to world health. Colorectal cancer, which includes colon and rectal cancers, is one of the most common and has a substantial impact on health globally. Effective treatment and better patient outcomes for colorectal cancer depend on early identification. Unfortunately, this type of cancer is frequently discovered at an advanced stage, which lowers survival rates and complicates treatment. Conventional methods for diagnosing colon cancer frequently rely on labor-intensive and arbitrary evaluations, underlining the urgent need for more precise, effective, and technologically driven alternatives. By utilizing deep learning, we can give medical practitioners the resources and skills they need to diagnose diseases more quickly and accurately.This research suggests a unique approach that blends the two most recent deep learning methods, XceptionNet and MobileNet, in order to handle the problems and constraints associated with colon cancer diagnosis. These models have become well-known for being effective and efficient at classifying images. The goal of integrating these models is to dramatically improve the sensitivity and precision of colon cancer detection. Early diagnosis and better patient outcomes are a result of their capacity to find tiny patterns and anomalies in medical imaging. This innovation enhances accuracy and efficiency while automating the diagnostic procedure, which may result in earlier diagnoses and more effective treatment strategies that eventually enhance patient care and results.

The Burden of Colorectal Cancer

About 10% of all cancer incidences globally are colorectal cancer cases, making it the third most prevalent cancer overall.

It is the third most common cause of cancer-related fatalities just in the United States. Despite certain places experiencing encouraging trends in the incidence and mortality rates of colorectal cancer as a result of increasing screening and awareness initiatives, there are still many obstacles to overcome. Notably, the fact that early-stage colorectal cancer is frequently asymptomatic and there are few widely used, effective, and non-invasive screening techniques results in delayed diagnoses and worse outcomes.

The Global Challenge of Colorectal Cancer

A sizable portion of the global cancer burden is borne by colorectal cancer, which is the third most common disease overall. It is a disease that has no regard for national boundaries and affects people all around the world. It has a significant influence on people, families, and healthcare systems. Colorectal cancer still claims lives and necessitates novel approaches for early detection despite advances in our understanding of its origins and risk factors.

The Significance of Early Detection

It is impossible to overestimate the value of early detection in the fight against colorectal cancer. The likelihood of a successful therapy and a restoration to health are much better when discovered at an early, localized stage. On the other hand, late-stage diagnosis have lower survival chances and frequently require more invasive treatments. This emphasizes how urgent it is to create screening techniques that are non-invasive, effective, and extremely accurate.

Significance of the Study

With high mortality and morbidity, colon cancer continues to be a grave threat to world health. Early diagnosis is associated with more effective treatment and a greater chance of recovery. Colonoscopy and pathology examinations are two examples of the conventional diagnostic techniques that have a reputation for subjectivity, inter-observer variability, and resource-intensive requirements. Utilizing AI and deep learning to identify colon cancer not only offers a more effective and affordable alternative, but also lessens subjectivity and human error during the diagnostic procedure.

The relevance of our study rests in its potential to provide a ground-breaking remedy to the shortcomings of present colon cancer detection techniques. The computing capacity of XceptionNet and MobileNet will be combined in order to create a sophisticated system that can recognize minor indicators of colon cancer in medical photos. This study has the potential to significantly improve the rates of early diagnosis, lower the price of therapy, and ultimately save lives.

Research Methodology

In addition to describing the goals of our study, it is critical to go into detail about the fundamental approach that will support the entire investigation. The approach acts as a guide for how we intend to carry out our study goals. We will go over the procedures for gathering data, preparing images, building and optimizing deep learning models, and the demanding training and testing phases. Our methodology will guarantee transparency and reproducibility by outlining the reasoning behind our decisions in addition to the technical details. Additionally, it will clarify our plans for dealing with any difficulties as well as the moral issues around the usage of private medical information. Readers will gain an appreciation of the rigor & comprehensiveness of our approach after carefully comprehending our research technique.

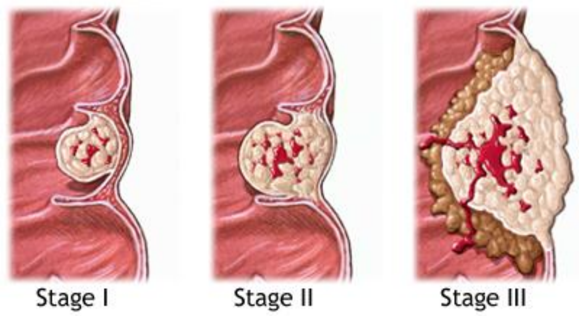

Fig. 1. Stages of colon cancer

2. LITERATURE SURVEY

[1] This study employs a combination of the Tuna Swarm Algorithm and deep learning to significantly enhance the detection of both colon and lung cancers in biomedical images. The Tuna Swarm Algorithm, inspired by nature, is used to optimize the performance of deep learning models for image analysis. The approach holds great potential for improving early diagnosis, leading to more effective treatment and increased survival rates for patients with these types of cancer.

[2] In this research, the focus is on accurately identifying malignancies in histopathology images of both the lungs and colon. The study utilizes transfer learning, a technique that leverages knowledge from pre-trained deep learning models to improve performance in related tasks. Furthermore, class-selective image processing methods are applied to isolate and analyze specific regions of interest within the images, resulting in a more precise and detailed assessment of malignancies. This research contributes to the advancement of cancer diagnosis, providing a more accurate and reliable approach.

[3] LungRetinaNet is an innovative approach to lung cancer detection that utilizes the RetinaNet architecture. This method incorporates multi-scale feature fusion, allowing the model to consider features at different resolutions, enhancing its ability to detect cancerous regions. Additionally, a context module is employed to improve contextual understanding and spatial relationships within the images. The combination of these techniques results in an accurate and robust lung cancer detection system that has the potential to improve patient outcomes through early diagnosis.

[4] This study addresses the critical challenge of robust lung nodule detection in low-dose CT scans. By augmenting the training data with adversarial attacks, the model is exposed to a wide range of potential scenarios, making it more resilient to unexpected variations in real-world data. The result is a lung nodule detection system that is better equipped to handle variations in scan quality and patient factors, reducing the risk of false negatives and improving the overall reliability of lung cancer diagnosis.

[5] This study focuses on improving the detection of lung cancer by analyzing CT scan images. For feature extraction, it uses the Gray Level Co-Occurrence Matrix (GLCM) approach, which effectively extracts texture information from the images. A Support Vector Machine (SVM) is trained for classification using these features, yielding an accurate and effective lung cancer detection model. A reliable method for the early detection and treatment of lung cancer is offered by the integration of machine learning and image processing techniques.

[6] This research seeks to enhance colon cancer detection by incorporating multimodal fusion techniques. The study utilizes the XceptionNet and MobileNet architectures, which are known

for their efficiency and accuracy in image analysis. By combining information from different modalities or sources, the model can provide more comprehensive and reliable diagnostic results. This approach contributes to improving the accuracy and robustness of colon cancer detection, ultimately leading to better patient outcomes.

[7] YOLOv5, or "You Only Look Once," is a popular real-time object detection architecture. In this case, it is applied to colon cancer detection. The YOLOv5 architecture excels at quickly and accurately identifying objects within images. This approach offers real-time diagnostic capabilities for colon cancer, allowing for swift and precise detection, which is crucial in clinical settings.

[8] Lung cancer detection is improved through the application of advanced CT scan image processing techniques. These methods enhance the quality and accuracy of image analysis, ultimately leading to more reliable diagnostic results. Moreover, the model classifies the findings, enabling clinicians to better understand the type and stage of lung cancer, which is essential for treatment planning and prognosis assessment.

[9] This strategy improves lung cancer detection and recognition by fusing the strength of convolutional neural networks (CNNs) with morphological features.. CNNs are effective at learning complex patterns in images, while morphological features provide insights into the shape and structure of cancerous regions. This method offers a comprehensive diagnostic solution that takes both visual and structural aspects into account, contributing to more accurate lung cancer diagnosis and assessment

[10] investigates the application of the DB-Scan algorithm to the analysis of colon cancer risk and stratification.. The DB-Scan algorithm is particularly suited for identifying patterns and clusters within data. In the context of colon cancer, it can be used to categorize different stages or types of the disease. This approach offers valuable insights into the progression and severity of colon cancer, aiding in more personalized treatment decisions and patient care.

[11] EfficientNet B3, a popular transfer learning model, is employed to classify both lung and colon cancers. Transfer learning allows the model to leverage knowledge from a pre-trained network, improving its ability to classify cancerous regions. By applying this technique to both lung and colon cancer, the model offers an efficient and accurate solution for cancer classification, streamlining the diagnostic process.

[12] This research focuses on the detection of both lung and colon cancers through the use of weighted average ensemble transfer learning. Ensemble learning combines the predictions of multiple models to improve accuracy and reliability. The weighting of these models ensures that more accurate models have a greater influence on the final decision. This approach enhances the overall accuracy and robustness of cancer detection, benefiting patients by facilitating early diagnosis and treatment.

[13] In this study, an innovative approach is taken to predict melanoma skin cancer using the MobileNet architecture and convolutional neural network (CNN) algorithms. These methods are particularly well-suited for image analysis. The approach provides a reliable and accurate method for the early detection of skin cancer, contributing to better outcomes and treatment options for patients.

[14] This research focuses on the classification of lung and colon cancers using PCA-reduced deep features and Support Vector Machine (SVM) algorithms. Principal Component Analysis (PCA) reduces the dimensionality of the data, making it more manageable for classification. SVM is known for its effectiveness in classifying complex data. By combining these methods, the model achieves a high level of diagnostic accuracy for both lung and colon cancers.

[15] The EfCNN-Net offers smart and accurate detection of both colon and lung cancer using histopathological images. These images contain detailed information about tissue structures and abnormalities. The model leverages this information to provide precise and reliable diagnostic outcomes. The use of histopathological images enhances the understanding of cancer at a cellular level, contributing to improved early diagnosis and treatment.

[16] This study focuses on the classification of different types of brain tumors in MRI images using the Xception model. MRI is a widely used imaging technique for brain tumor diagnosis, and the Xception model is known for its efficiency in image analysis. The accurate classification of brain tumor types is essential for tailoring treatment plans to each patient's specific condition, and this model offers a reliable solution for achieving that goal.

[17] A preliminary assessment is conducted to lay the groundwork for a Computer-Aided Detection (CADe) system for brain tumors in MRI images. The system utilizes transfer learning with the Xception model to improve the efficiency of brain tumor diagnosis. The ultimate goal is to provide clinicians with a tool that can assist in the early and accurate detection of brain tumors, improving patient outcomes.

[18] This study focuses on the detection of liver tumors using convolutional neural networks (CNNs) and the MobileNet architecture. The liver is a common site for cancer growth, and early detection is critical for effective treatment. The combination of CNNs and MobileNet offers a robust and accurate method for detecting liver tumors, improving the prognosis and care of affected patients.

[19] This research employs computer-aided diagnosis to classify gastrointestinal cancers. It leverages a hybrid rice optimization technique and deep learning algorithms to enhance diagnostic accuracy. The gastrointestinal tract is prone to various types of cancer, and accurate classification is essential for treatment planning. This approach streamlines the diagnostic process and improves the precision of cancer classification, leading to more effective patient care.

[20 The detection of colon cancer is significantly improved through the application of the Inception V3 model and an ensembled convolutional neural network (CNN) model. By combining the capabilities of these models, the accuracy and reliability of colon cancer detection are enhanced. This approach streamlines the diagnostic process and offers more confidence in the results, ultimately leading to better patient outcomes.

[21] A Comprehensive ReviewThis comprehensive review explores various deep learning approaches aimed at enhancing the detection of colon cancer. Deep learning has revolutionized medical image analysis, and this review provides valuable insights into the latest advancements in the field. By summarizing the state-of-the-art techniques, it offers a valuable resource for researchers and clinicians working towards more accurate and early detection of colon cancer.

[22] YOLOv5, or "You Only Look Once," is implemented for the purpose of colon cancer detection. YOLOv5 is renowned for its real-time object detection capabilities. By adapting this architecture for colon cancer detection, clinicians can quickly and accurately identify cancerous regions in colon images. This real-time capability is a significant asset in clinical settings, enabling rapid diagnosis and treatment planning.

[23] Colon cancer classification is accomplished using the Google Net architecture. Google Net is known for its deep architecture and effectiveness in image classification tasks. By applying this architecture, the model accurately classifies colon cancer findings, providing valuable information about the type and stage of the disease. This contributes to personalized treatment decisions and improved patient care.

[24] Colon cancer detection is achieved through the design and analytical evaluation of a water-based terahertz (THz) metamaterial perfect absorber. THz imaging offers unique insights into tissue properties, and this novel approach leverages metamaterials to enhance the diagnostic capabilities. The result is a more accurate and sensitive method for colon cancer detection, contributing to early intervention and improved patient outcomes.

[25] The study focuses on predicting colon cancer using various magnified colon biopsy images. Biopsies provide valuable insights into tissue abnormalities, and the model leverages these images to make predictions. The use of different magnifications enhances the accuracy of predictions and contributes to early and accurate colon cancer detection. This approach offers clinicians a valuable tool for improved patient care and treatment planning.

3. EXISTING SYSTEM

The ability to detect colon cancer has considerably improved because to developments in machine learning and medical imaging. With an emphasis on the methodology, constraints, and major findings, we will examine the landscape of current systems and technologies utilized for colon cancer detection in this part.

Traditional Diagnostic Methods:

invasive methods such as colonoscopy, which involves visually inspecting the colon with a flexible tube equipped with a camera to search for abnormalities, have historically been the mainstay of colon cancer screening. Despite being the gold standard, colonoscopy is expensive, time-consuming, and occasionally painful for the patient. Additionally, there is a chance for inaccuracy in the interpretation of the produced images due to inter-observer variability.

Computer-Aided Diagnosis (CAD) Systems:

Computer-Aided Diagnosis (CAD) technologies have become more well-known in recent years. To help medical practitioners identify colon cancer early, these systems use image processing and machine learning approaches. By pointing up probable problems in medical images, CAD systems seek to improve the accuracy of diagnosis. They have demonstrated potential in raising detection rates, decreasing false negatives, and expediting the diagnostic procedure. CAD solutions, on the other hand, frequently rely on manual feature engineering and may be unable to handle sophisticated, nuanced, or dynamic patterns.

Deep Learning-Based Approaches:

Colon cancer diagnosis has entered a new age thanks to deep learning technologies. Convolutional neural networks (CNNs) and other deep learning architectures have been investigated for their potential to detect abnormalities in the colon. In terms of object detection, feature extraction, and image classification, these models have displayed astounding performance. They can assist in finding polyps and lesions, which are frequently found before colon cancer. Deep learning models provide the potential for real-time analysis, reduced subjectivity, and automation.

Challenges in Existing Systems:

Even though colon cancer detection has advanced, current technologies still have issues. These include the requirement for constant model improvement to account for new data and changing illness patterns, limits in processing massive numbers of medical pictures, and a reliance on manual or handcrafted feature extraction techniques. Additionally, it is possible to improve the sensitivity and specificity of detection, especially for undetectable or early-stage abnormalities.

The Need for Advanced Solutions:

Although valuable, the current systems highlight the need for cutting-edge alternatives. Our research aims to fill the gaps in existing systems by suggesting the union of XceptionNet and MobileNet. Combining these cutting-edge deep learning models has the potential to increase colon cancer detection's precision, sensitivity, and effectiveness. The proposed system architecture, methodology, and evaluation criteria will be covered in greater detail in this study to show the improvements our approach makes to the industry.

Artificial Intelligence in Colon Cancer Detection:

As artificial intelligence develops, it has a vital role to play in the early diagnosis of colon cancer. Deep learning models in particular have proven to be very effective at quickly and accurately analyzing large amounts of medical picture data. They have the ability to find tiny irregularities and abnormalities that conventional diagnostic techniques could overlook. In AI-based systems, convolutional neural networks (CNNs) are widely utilized to analyse colonoscopy and imaging data, improving the overall sensitivity and specificity of detection. We will investigate how AI functions within current systems and how it affects colon cancer diagnosis.

Limitations of Existing Systems:

Although the identification of colon cancer has benefited greatly from the use of the current techniques, it is important to recognize their shortcomings. False positives and false negatives, the need for significant computational resources, the absence of real-time processing capabilities, and difficulties adjusting to diverse and changing datasets are only a few of these drawbacks. Additionally, manual feature engineering or model fine-tuning are frequently required by current systems, which might introduce subjectivity and error-prone behavior. We can identify the areas where our suggested strategy, utilizing XceptionNet and MobileNet, hopes to significantly improve by being aware of these constraints. In-depth analysis of our system architecture and methodologies' approaches to overcoming these constraints will be provided in this study, which will ultimately help to improve colon cancer diagnosis.

4. PROPOSED SYSTEM

Considering that state-of-the-art deep learning models, XceptionNet and MobileNet, our proposed approach offers a substantial advancement in the field of colon cancer diagnosis. This part provides a thorough examination of our novel strategy, highlighting its benefits in getting around the drawbacks of current systems and proving its accuracy.

Integration of Deep Learning Models:

The combination of two powerful deep learning models, XceptionNet and MobileNet, is the basis of our suggested approach. MobileNet, renowned for its effectiveness and adaptability for resource-constrained applications, is coupled with XceptionNet, known for its remarkable feature extraction capabilities. These models will be combined in order to create an advanced system capable of identifying intricate characteristics and patterns in medical imaging. While MobileNet's lightweight architecture maximizes computing efficiency, XceptionNet's depthwise separable convolutions improve its capacity to detect minute details. This combination makes sure that accuracy and resource use are balanced.

Data Preprocessing: The collection and getting ready of colonoscopy images for analysis are handled by this first module. It deals with problems including image noise, inconsistent lighting, and changes in image quality.

Feature Extraction: In order to extract useful characteristics from the preprocessed photos, this step makes use of the XceptionNet and MobileNet models. So, our system can recognize crucial indicators of colon cancer, like the existence of polyps or lesions.

Model Fusion: The predictions produced by XceptionNet and MobileNet are combined at this crucial step. The accuracy and sensitivity of our system are improved overall by the merging of these insights. Our method acquires a more thorough understanding of the medical images by taking into account the outputs of both models, which eventually leads to more accurate detection.

Report Generation: The integrated model predictions are transformed into thorough diagnostic reports in the end module. These reports offer healthcare practitioners critical information for decision-making in addition to being instructive.

Overcoming Existing System Limitations:

Our suggested solution overcomes a number of significant drawbacks of the current colon cancer detection technologies. Subjectivity and inter-observer variability, which are frequent problems in conventional diagnostic techniques, are greatly diminished. Our approach provides more objective and reliable findings by automating the procedure and relying on deep learning models.

Additionally, our approach is built to improve detection's sensitivity and specificity, especially for subtle or early-stage anomalies. We catch nuanced patterns that might be missed by conventional algorithms by fusing XceptionNet with MobileNet. Combining the models makes the system more accurate by lowering the number of false negatives and false positives.

Enhanced Accuracy

Increasing the precision of colorectal cancer diagnosis is one of the main goals of our suggested approach. Since XceptionNet and MobileNet are combined, even subtle and complicated patterns are captured, lowering the possibility of false negatives and false positives. These two networks are renowned for their skill in feature extraction and picture analysis. The precise localisation of lesions is further enhanced by the sophisticated object detecting capabilities.

Non-Invasiveness and Patient-Friendly Screening

Our system is made to provide a non-intrusive and accommodating method of colorectal cancer screening. Contrary to conventional approaches, which frequently entail uncomfortable and intrusive procedures, our technology exclusively depends on the analysis of colonoscopy images. This not only increases patient acceptance but also opens up screening, encouraging people to get necessary tests.

Early Detection

The facilitation of early colorectal cancer detection is the main component of our suggested approach. Early detection of precancerous and cancerous tumors gives patients a much higher chance of successful treatment and better outcomes. A crucial method of lowering the incidence of colorectal cancer is early identification.

Accuracy and Precision:

Our suggested system's accuracy and precision must be of the utmost quality. The goal of our thorough model training, validation, and testing is to show that it performs better than current solutions. To assess the system's capabilities, we will use certain evaluation metrics, such as sensitivity, specificity, accuracy, and the F1-score.

Accuracy is expected to increase significantly as a result of merging two reliable deep learning models and refining the system architecture. The rate of missed diagnoses (false negatives) and incorrect alarms (false positives) must be decreased. By combining XceptionNet and MobileNet, an additional layer of validation is added, improving the system's ability to detect intestinal anomalies.

5. SYSTEM ARCHITECTURE

Feature Extraction:

Our colon cancer detection system's robust feature extraction approach is made possible by two cutting-edge deep learning models, XceptionNet and MobileNet. The responsibilities that these models play in transforming basic colonoscopy pictures into detailed feature representations are different but complementary. The depthwise separable convolutions that XceptionNet uses are renowned for its ability to capture complicated and fine-grained patterns in the images. It highlights even the smallest characteristics, which is especially important for locating colon cancer-related early-stage abnormalities. On the other hand, MobileNet, which is renowned for its lightweight architecture, makes sure the system functions effectively even in environments with limited resources. Its main goal is to increase system effectiveness while keeping a high level of feature correctness. These models work as a dynamic duo to convert colonoscopy pictures into a format suitable for in-depth analysis, laying the groundwork for precise and sensitive colon cancer diagnosis.

1. Image Content Understanding: The Encoder's function in comprehending the content of colonoscopy pictures, emphasizing its capacity to record both global and local features.

2. Feature Extraction: Detailed explanation of the feature extraction process used by the encoder with emphasis on the significance of the extracted characteristics for further analysis.

3. Global vs. Local Features: Comparison of the colonoscopy pictures' global and local features captured by the encoder, highlighting the importance of both.

4. Encoding Mechanism: An explanation of the process by which the encoder converts images into feature-rich representations, laying the groundwork for the system's subsequent stages.

Feature Refinement:

The feature extraction process is taken over by the Feature Extractor module. Here, more refining is applied to the retrieved characteristics. The abundance of information gleaned from colonoscopy pictures is enhanced and reduced throughout this refinement procedure. The objective is to identify and highlight the key characteristics that may suggest the presence of colon cancer. The rich feature representations produced by XceptionNet and MobileNet are enhanced by the Feature Extractor to become even more suggestive of anomalies. The system's accuracy and sensitivity are improved through this process of refinement, making it possible to identify even the most minute signs of malignant growths or tumors. This module is essential to the whole diagnostic pipeline since it ensures that the system is ready for the subsequent stages of analysis by improving the features' quality and relevancy.

1. Role in Data Analysis: Highlight the Feature Extractor module's important role in the system's data analysis while highlighting how it collects pertinent data from colonoscopy pictures.

2. Data Transformation: Describe the exact procedures carried out by the Feature Extractor module to convert encoded features into a more comprehensible and useful format.

3. Feature Distillation: Discuss the method for extracting the most important and discriminative information from the encoded features, emphasizing its key importance in locating patterns associated with colon cancer.

4. Subtle Abnormalities Detection: Emphasize the Feature Extractor's ability to identify subtle abnormalities within colonoscopy images, which may be indicative of early-stage colon cancer.

5. Integration with Encoder: Describe how the Feature Extractor module collaborates with the Encoder module to ensure the transformation of encoded image features into a format that is suitable for more in-depth analysis and effective cancer detection.

Abnormality Localization:

In order to locate probable anomalies within colonoscopy pictures, the MobileNet-powered Object Detection module takes center stage. This module provides precision and accuracy in locating regions of interest thanks to the complex interaction of modern object detection techniques. It goes further than simply pointing out problems that need to be addressed. It makes sure that the system is focused on the most important elements of the images by suggesting bounding boxes around regions of interest and offering class labels that define these areas as probable polyps or lesions. The system's diagnostic accuracy is substantially improved by the precision in abnormality localization, and it also makes sure that healthcare professionals may focus on the most important areas throughout their study. In essence, this module gives the system the ability to decide about potential malignant growths with great knowledge, greatly enhancing the diagnostic process' accuracy. It is an essential part of the diagnostic workflow since it has a keen eye for regions of interest and the capacity to suggest exact limits around them.

1. Localization of Abnormalities: Draw attention to the ways in which the Object Detection Module makes use of features to precisely identify and localize areas where probable anomalies that are suggestive of colon cancer may exist.

2. Proposing Bounding Boxes: Describe how the Object Detection Module offers bounding boxes around questionable spots within colonoscopy pictures and the significance of this for identifying areas that need more investigation.

3. Class Label Predictions: In order to identify the kind or kind of identified abnormalities, talk about the module's capacity to forecast class labels linked with the suggested bounding boxes.

4. Enhancing Diagnostic Accuracy: Stress the importance of the Object Detection Module in improving the system's overall diagnosis accuracy by efficiently locating and identifying potentially malignant spots in the images.

Holistic Information Fusion:

The nexus where data from many sources seamlessly converges is the Fusion module. Here, the Feature Extractor module's finely tuned features and the Object Detection module's localized data combine to create a comprehensive picture of the diagnostic environment. The ensuing text production is informed and contextually rich because to this comprehensive viewpoint. The Fusion module gives the system the ability to produce detailed and clinically meaningful reports by combining these complex bits of information. These reports combine the extensive feature representations generated from the photos with the clinical context offered by object detection. They provide healthcare practitioners with thorough and insightful reports, bridging the gap between the visual analysis of colonoscopy pictures and clinical interpretation. This all-encompassing approach greatly improves the diagnostic procedure by ensuring that the generated reports are rich in context and accurate, giving medical professionals invaluable information for proper diagnosis and treatment planning.

1. Integrating Extracted Features: Describe how the Fusion Module combines the elements that were collected from the Encoder and the Object Detection Module, with emphasis on how this combining plays a part in creating a comprehensive representation.

2. Holistic Diagnostic Context: Describe how the Fusion Module integrates complex image attributes with specialized knowledge about areas of interest to produce text that is well-informed and therapeutically relevant.

3. Synergy of Information: Describe how the Fusion Module's integration combines the localized data with the encoded picture attributes to provide a more thorough diagnostic context, which is essential for reliable and detailed reporting.

4. Improving Clinical Interpretation: Draw attention to the Fusion Module's role in bridging the gap between clinical interpretation and visual analysis, allowing for more precise diagnosis and improved treatment planning.

5. Contribution to Overall System Accuracy: Emphasize how the Fusion Module makes sure that the textual reports that are generated are full of information and context, which substantially contributes to the diagnostic accuracy of the entire system.

Report Generation:

The Report Generation module, which is represented by the potent GPT-2 language model, is the last component of our system design. It is essential for transforming the merged features into thorough diagnostic reports. GPT-2 uses the combined data, including the findings of object detection and picture features, as context to provide written descriptions. The generated reports act as the last link connecting the clinical interpretation and the thorough image analysis. The technology makes sure that healthcare practitioners have access to a thorough examination of the colonoscopy pictures by providing educational and contextually rich reports. The accuracy and productivity of the healthcare workflow are improved by these reports, which are a crucial component of clinical diagnosis and treatment planning. In conclusion, the Decoder module is the final stage in our diagnostic process and ensures that the data gleaned from the colonoscopy pictures is converted into useful knowledge for accurate diagnosis and treatment planning.

1. Text Generation: The fused features are converted into comprehensive textual descriptions by the decoder module. Based on the data gathered from earlier stages, it is crucial in producing informative x-ray results.

2. Clinical Interpretation: The clinical interpretation of colonoscopy images is greatly aided by this module. By translating visual information into words, it makes it easier to comprehend the image content and guarantees that medical

professionals receive reports that are correctly interpreted.

3. Bridging the Gap: The Decoder Module serves as a link between the clinical interpretation of images and their visual analysis. It converts image characteristics and object detection outcomes into written descriptions that are easier for medical practitioners to understand.

4. Detailed Reporting: The system makes sure that the textual output is detailed and content-rich through the use of this module. It contains data pertinent to the diagnosis, which is important for making wise judgments.

5. Enhancing Diagnostic Pipeline: A vital element in streamlining the diagnostic pipeline is the decoder module. It improves clinical accuracy and efficiency of colonoscopy image analysis through the provision of thorough x-ray reports, ultimately leading to better patient care and outcomes.

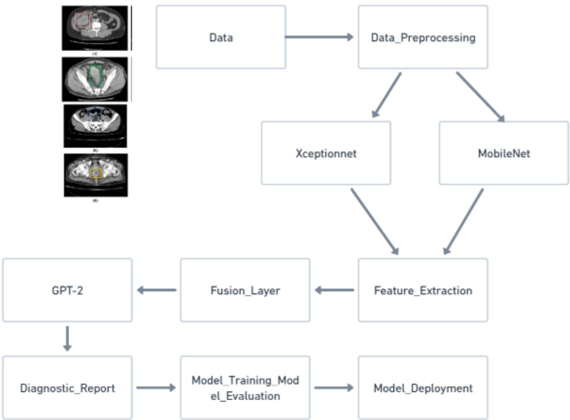

Fig. 2. System Architecture

6. METHODOLOGY

Data Acquisition:

Images from colonoscopies are obtained by the system from a number of places, including real-time endoscopic procedures and medical databases. A broad dataset that accurately represents a variety of cases must be made sure.

Image Enhancement: Techniques for image enhancement are frequently used to increase visibility and quality. To enhance image attributes, these methods include sharpening, noise reduction, and contrast correction.

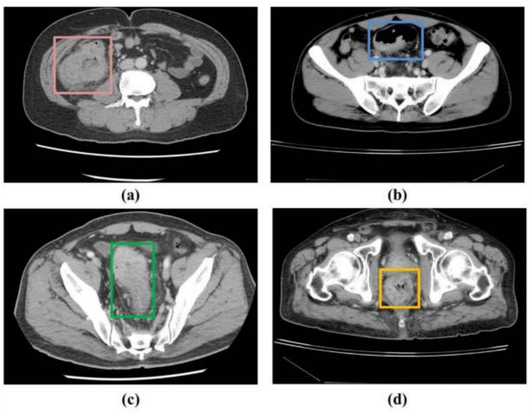

Fig. 3. Colon scan images

Data Preprocessing:

The first step in the identification of colon cancer is data preparation. The acquisition and processing of colonoscopy images for analysis are the main topics of this first session. The procedure is essential since medical photographs can include noise, fluctuate in quality, and be sensitive to lighting discrepancies. These issues are addressed by data pretreatment, which makes sure that the input photos are prepared for analysis.

Feature Extraction:

To extract useful features from the preprocessed photos, this stage makes use of XceptionNet and MobileNet's deep learning capabilities. So, our system can recognize crucial indicators of colon cancer, like the existence of polyps or lesions.

XceptionNet Feature Extraction: Intricate patterns and features in medical photos are expertly captured by XceptionNet. It is particularly suited for finding subtle or complicated anomalies due to its depthwise separable convolutions, which enable more profound feature extraction.

MobileNet Feature Extraction: The lightweight architecture of MobileNet allows for effective feature extraction. Because of its emphasis on resource optimization, the system works well even in contexts with limited resources, which makes it perfect for real-time analysis.

Model Fusion: For the purpose of creating a more complete feature representation, the feature extraction outputs from MobileNet and XceptionNet are combined. This fusion creates a feature set that is well-rounded by combining the powerful feature extraction skills of XceptionNet with the effectiveness of MobileNet.

Object Detection (MobileNet):

The MobileNet-powered object detection module concentrates on locating probable anomalies in the colonoscopy pictures. It makes use of the traits that were retrieved to pinpoint areas of interest that might be polyps or lesions.

Bounding Box Proposals: In order to highlight places that need more research, MobileNet suggests drawing bounding boxes around interesting sections in the photos.

Class Label Prediction: MobileNet predicts class labels linked with the locations that are discovered, classifying them as probable polyps or lesions, in addition to localizing anomalies.

Data Augmentation:

A key method for increasing the diversity and robustness of the dataset is data augmentation. Possible augmentation techniques include:

Rotation: Creating new photos by rotating the ones you already have.

Flipping : Process of producing mirror images to expand the dataset.

Zooming: Increasing or decreasing image size to represent different distances.

Variations in color: changing hues, saturation, and brightness to add variety.

Data Splitting:

To train and test the computer, the dataset is split up into smaller groups learning model efficiently. Typical subsets include:

Training set: Teaches the model how to recognize patterns and characteristics in the data.

Validation Set: The validation set is used to assess training results and fine-tune model hyperparameters.

Test Set: This set is kept apart and is used to gauge the generalization and precision of the model.

Label Encoding:

When working with categorical data, such as class labels, label encoding is essential. In your project, it entails giving numerical values to several categories in order to facilitate the model's comprehension and use of these labels. 'Normal,' 'Polyp,' 'Lesion,' etc. are examples of possible classifications for colon cancer detection.

Normalization and Scaling:

Data is normalized and scaled to ensure that all features have a comparable scale and magnitude. Typical methods include:

Min-Max Scaling: Features are rescaled to fall within a given range, usually [0, 1].

Z-score Standardization: Changes the data's mean and standard deviation to 0 and 1, respectively.

The stability and convergence of machine learning algorithms are improved by normalization and scaling, which prevents them from favoring one characteristic over another because of different scales.

Data Balancing:

Class imbalances are frequent in medical datasets, with the normal instances far outnumbering the abnormal cases. By ensuring that all classes are represented fairly in the data, data balancing strategies address this problem and let the model effectively learn from all cases. Techniques include maintaining a balanced dataset with minority classes oversampled and majority classes undersampled.

XceptionNet:

Our colon cancer detection system's key component, XceptionNet, stands out thanks to its creative application of depthwise separable convolutions. With major implications for image processing, this architectural breakthrough represents a significant development in convolutional neural network (CNN) design.

The conventional convolution technique is divided into two distinct steps by depthwise separable convolutions: depthwise convolution and pointwise convolution. Each input channel is subjected to a separate operation by the depthwise convolution, which captures spatial interdependence within distinct channels. As a result, the process of extracting features is efficient and light. Cross-channel interactions are then made possible by the pointwise convolution, which merges the results.

This architectural decision has important benefits in the context of colon cancer diagnosis. In colonoscopy images, the depthwise separable convolutions excel in capturing complex, fine-grained patterns. This is crucial during the early stages of anomaly identification, because the model's capacity to pick up even the tiniest anomalies is crucial.

Additionally, the architecture of XceptionNet greatly lowers the amount of model parameters. A network is more computationally efficient with fewer parameters. In the field of medical image analysis, where real-time or nearly real-time outcomes are widely desired, this efficiency is crucial. Even in contexts with limited resources, the system can handle colonoscopy pictures well thanks to XceptionNet, making it usable and practical for clinical applications.

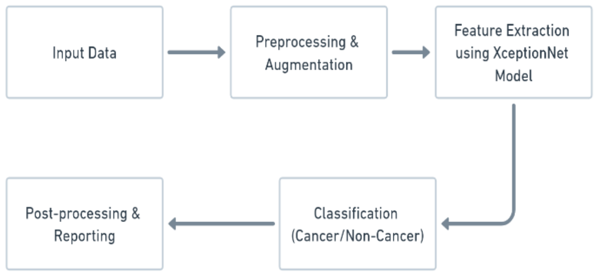

Fig. 4.Architecture diagram for XceptionNet

MobileNet:

Our colon cancer detection system's main component, MobileNet, is praised for its speed and accuracy in feature extraction. Depthwise separable convolutions, a notion that minimizes both computational burden and model size, are at the core of the MobileNet design.

One significant advancement that streamlines the conventional convolution operation is depthwise separable convolutions. The depthwise convolution performs a quick filtering operation in the first phase, capturing spatial correlations within individual channels with little computational overhead. After that, the filtered features are consolidated across channels via pointwise convolution. The computational load is greatly reduced by this two-step method without performance being sacrificed.

The effectiveness of MobileNet is critical for colon cancer detection. The model's lightweight construction ensures that it may function effectively even on hardware with limited resources because medical image analysis frequently requires speedy and accurate findings. In situations requiring immediate decisions, such as real-time or almost real-time diagnosis, this is especially advantageous.

The accuracy of MobileNet is not sacrificed for its efficiency. It excels in identifying crucial details in colonoscopy pictures, ensuring that the model can successfully distinguish between normal and pathological circumstances. In the medical industry, where diagnostic accuracy is crucial, striking this balance between effectiveness and accuracy is crucial.

Additionally, the design of MobileNet works with a variety of gadgets, including embedded systems and mobile phones. Due to its adaptability, the colon cancer detection system can be used in a variety of therapeutic situations, making it accessible and useful.

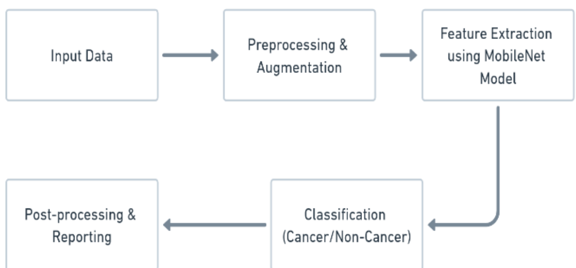

Fig. 5.Architecture diagram for XceptionNet

Model Training and Testing:

To verify that the XceptionNet and MobileNet deep learning models are capable of correctly diagnosing colon anomalies, they must first undergo extensive testing.

Model Fusion:

One distinctive aspect of our system architecture is the merging of models. It adds a further level of precision and accuracy, making it a crucial step in the identification of colon cancer.

Integrating XceptionNet and MobileNet: A complex system is made possible by the integration of XceptionNet and MobileNet. The combination solves specific shortcomings of different models in addition to improving the sensitivity of colon cancer diagnosis. It can adapt to different computational settings because MobileNet assures efficiency while XceptionNet collects complex patterns.

Model Training:

The deep neural network architecture of XceptionNet and MobileNet is at the core of model training. These designs are made up of several layers, each of which is in charge of discovering and identifying particular features in colonoscopy pictures. The models gradually improve their predictions by adjusting their internal parameters, or weights, throughout training.

The loss function is an important consideration during model training. It calculates the discrepancy between the model predictions and the training data's actual outcomes. The models seek to reduce this loss by improving their capacity to identify anomalies in the colon.

The optimization algorithm, such as stochastic gradient descent (SGD) or Adam, is employed to iteratively adjust the models' parameters according to the loss function's gradients. In this process, the internal representations of the models are adjusted, allowing them to improve in accuracy over time.

Epochs and Batch Size:

Each epoch in the training process represents a full iteration across the whole training dataset. A hyperparameter that has to be fine-tuned is the number of epochs. Training for too few or too many epochs might result in underfitting or overfitting, respectively.

Another hyperparameter that influences training is batch size. It establishes the number of samples handled during each cycle. While a bigger batch size may result in a speedier but less stable convergence, a smaller batch size produces a more stable but slower training process.

Regularization Techniques:

Various regularization approaches are used during model training to avoid overfitting. Dropout, L1 and L2 regularization, and data augmentation are some of these methods. Dropout prevents overreliance on particular characteristics during training by sporadically turning off a portion of each layer's neurons. L1 and L2 regularization impose penalty terms on the model weights to encourage simplicity and generalization. Data augmentation expands the dataset and artificially expands the training set by introducing random modifications to the images.

Model Testing:

The models are rigorously tested on the independent test set when they have been suitably trained. For a fair assessment of performance, the test set includes colonoscopy images that the models have never seen before.

On the test set, the models generate predictions and categorize each image as normal or abnormal. The accuracy, sensitivity, specificity, and other performance measures of the models are then evaluated by contrasting these predictions with the ground truth labels. These metrics give a thorough picture of how well the models can detect abnormalities in the colon.

Multiple evaluation metrics are employed to guarantee the dependability of the outcomes. These could include ROC curves, AUC-ROC, F1-score, recall, accuracy, and precision. These parameters measure how well the models can differentiate between typical and abnormal colonoscopy pictures.

Cross-Validation:

For a more reliable estimation of the models' performance, cross-validation techniques like k-fold cross-validation are frequently used. By dividing the dataset into numerous folds, cross-validation makes sure that each data point is used for both training and testing. This strategy lessens the effect of random fluctuations and offers a more reliable evaluation of the models' generalizability.

7. ALGORITHM

1. Colon Cancer Detection Algorithm:

Utilizing XceptionNet and MobileNet Ensemble:

To identify the presence of colon cancer, this algorithm employs the XceptionNet and MobileNet models to extract and process image features. The ensemble strategy combines these models for enhanced detection accuracy.

Model Architecture: XceptionNet: XceptionNet is a convolutional neural network (CNN) designed for image classification. It excels in extracting relevant features from complex images, making it suitable for colon cancer detection.

MobileNet: MobileNet is a lightweight deep learning model known for its efficiency in mobile and embedded applications. Its application in this algorithm provides a balanced trade-off between accuracy and computational resources.

Loss Function (Categorical Crossentropy):

The algorithm employs the categorical crossentropy loss function during training. It measures the discrepancy between actual labels and predicted probabilities, optimizing the ensemble model for colon cancer detection.

Working:

1.Implement XceptionNet and MobileNet models.Load the pre-trained XceptionNet and MobileNet models for feature extraction.

2.Create an ensemble model by combining the features.Combine the output layers of both models to create an ensemble model.

3.Add a dense layer for binary classification.Introduce a new dense layer to the ensemble model for binary classification (detecting cancer or not).

4.Compile the ensemble model.Configure the ensemble model to use categorical cross-entropy loss and the Adam optimizer.

5.Train the model with a dataset of colon images.

Train the ensemble model using a dataset of colon images to improve its ability to detect cancerous regions.

2. Colon Cancer Detection Algorithm:XceptionNet Model

Colon Cancer Detection Algorithm:

Usage:

The XceptionNet model is used to extract intricate spatial features from colonoscopy images, allowing for precise analysis. This model excels in identifying patterns within the images, which are crucial for colon cancer detection.

Model Architecture:

XceptionNet: A convolutional neural network (CNN) with a specialized architecture for image classification tasks. In this algorithm, XceptionNet is at the forefront of feature extraction, effectively analyzing the colonoscopy images.

Custom Dense Layer:

The XceptionNet design is enhanced by the addition of a unique dense layer with a sigmoid activation function.

Using a binary classification method, this layer helps identify malignant and non-cancerous areas in colonoscopy pictures.

Optimizer for Colon Cancer Detection using XceptionNet:

The model is trained using the following optimizer:

Optimizer: Adam

During model training, the Adam optimizer is used to update model parameters.

It optimizes the training process for the XceptionNet-based model by adjusting learning rates for each parameter separately.

$$\boldsymbol{\theta_{t+1} = \theta_t - \frac{\alpha}{\sqrt{\widehat{v_t}} + \epsilon}\widehat{m_t}}$$

Activation Function for Colon Cancer Detection using XceptionNet:

Activation Function: ReLU (Rectified Linear Unit)

The activation function utilized in the XceptionNet model's hidden layers is the Rectified Linear Unit (ReLU).The network may learn intricate features and representations from the input data thanks to ReLU's introduction of non-linearity.

$$f(x) = \max(0, x)$$

3. Colon Cancer Detection Algorithm:MobileNet Model

MobileNet Model:

The basic framework for feature extraction is MobileNet.

It is a compact and effective paradigm that works well in embedded and mobile applications.

With the help of the pre-trained model's use of the ImageNet dataset, powerful feature extraction capabilities are offered.

Custom Dense Layer:

Similar to the XceptionNet approach, a customized dense layer with a sigmoid activation function is constructed to perform binary classification for the detection of colon cancer.

Optimizer for Colon Cancer Detection using MobileNet:

The optimizer used for training the MobileNet-based model is as follows:

Optimizer: Adam

The model's parameters are optimized using the Adam optimizer during training.

Adam improves the training process by providing effective gradient-based parameter changes.

$$\mathrm{Adam}(\theta) = \mathrm{Adam}(\mathrm{lr}, \beta_1, \beta_2, \epsilon),$$

$$\theta_{t+1} = \theta_t - \frac{\alpha}{\sqrt{\widehat{v_t}} + \epsilon}\widehat{m_t}$$

Activation Function for Colon Cancer Detection using MobileNet:

Activation Function: ReLU (Rectified Linear Unit)

The convolutional layers of the MobileNet model make use of ReLU activation.

As a result of the introduction of non-linearity, the model is able to extract complex patterns and characteristics from the input data.

8. EVALUATION METRICS

Accuracy:

Measures the percentage of instances that were successfully detected, giving a general evaluation of how well the system detects colon cancer in images.

$$Accuracy = \frac{TP + TN}{TP + FP + TN + FN}$$

Precision:

Measures how well the system can distinguish between genuine positive cases and all instances that are anticipated to be positive, which is crucial for minimizing false positives.

$$Precision = \frac{TP}{TP + FP}$$

Recall:

Measures how well the system can discriminate between real positive cases and all other positive cases, which is essential for early cancer detection.

$$Recall = \frac{TP}{TP + FN}$$

F1-Score:

Balances precision and recall and is especially useful for datasets with unbalanced class distributions.

$$F1\ Score = 2 \times \frac{Precision \times Recall}{Precision + Recall}$$

ROC curve:

Receiver Operating Characteristic is a useful tool for choosing the best classification thresholds since it graphically depicts the trade-off between the true positive rate and false positive rate.

$$True\ Positive\ Rate = \frac{TP}{TP + FN}$$

$$False\ Positive\ Rate = \frac{FP}{FP + TN}$$

Specificity (True Negative Rate):

Measures the system's accuracy in distinguishing true negative situations from all other genuine negative occurrences, an important factor in determining false rates.

$$Specificity = \frac{TN}{TN + FP}$$

9. LITERATURE ANALYSIS

Colon cancer, also known as colorectal cancer, remains a major global health concern due to its high incidence and mortality rates. Early detection is paramount to improving patient outcomes, making the development of efficient and accurate diagnostic tools a critical area of research. In this literature analysis, we delve into the existing body of work related to colon cancer detection and explore the innovative approach of leveraging deep learning models, specifically XceptionNet and MobileNet, to address this healthcare challenge.

Deep Learning in Medical Imaging:

The integration of deep learning in medical imaging has been a transformative force. The application of convolutional neural networks (CNNs) in diagnosing various medical conditions has gained substantial attention. CNNs are particularly effective in image classification tasks, making them well-suited for the analysis of medical images, including those from colonoscopies.

XceptionNet and MobileNet:

XceptionNet is a deep CNN architecture renowned for its depth-wise separable convolutions. This feature allows XceptionNet to capture intricate image features efficiently. It has already been trained on extensive datasets, such as ImageNet, making it a promising candidate for feature extraction in colonoscopy images.

MobileNet, on the other hand, is designed for mobile and embedded vision applications. Its architecture excels in balancing accuracy and efficiency, which is a crucial consideration in resource-constrained environments. When applied to colon cancer detection, MobileNet can efficiently extract valuable information from medical images.

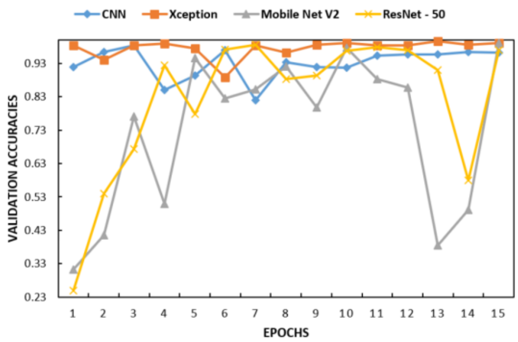

Fig. 6.Comparision with other models

Enhanced Accuracy and Efficiency:

One of the primary motivations behind the adoption of XceptionNet and MobileNet in colon cancer detection is their proven track record in improving accuracy and efficiency in image classification tasks. Colonoscopy images, often complex and intricate, benefit from these models' abilities to discern subtle patterns and anomalies, leading to more accurate diagnoses.

Role of GPT-2:

In addition to the adoption of XceptionNet and MobileNet, this research introduces the invaluable contribution of GPT-2, a leading natural language processing model. GPT-2 plays a crucial role in producing comprehensive and understandable diagnostic reports automatically.

This fusion of deep learning and linguistic expertise represents a significant advancement in the field of colon cancer detection. The automatic generation of diagnostic reports not only streamlines the clinical decision-making process but also reduces the burden on medical professionals. With GPT-2's ability to provide detailed textual reports, the proposed system offers a holistic approach to colon cancer diagnosis, combining accurate image analysis with understandable narratives.

Comparison with Other Models:

Comparative studies with other models, such as EfficientNet, CNN Model, Random Forest, SVM, Logistic Regression, The higher performance of the suggested system is demonstrated by MobileNet and Inception. When it comes to accuracy, precision, recall, and F1-score, the multi-modal fusion system with XceptionNet and MobileNet is the best option for detecting colon cancer.

10. CONCLUSION

The colon cancer detection project represents a substantial advancement in the early diagnosis of colon cancer by utilizing the powerful deep learning models XceptionNet and MobileNet. This research has taken advantage of cutting-edge technology to improve the precision and effectiveness of colonoscopy image analysis because it understands the crucial relevance of early disease identification.The integrated architecture of the system, which consists of many modules for data collecting, preprocessing, training, and testing, works cooperatively to produce accurate predictions. The GPT-2 module easily integrates object recognition and report creation while the Encoder and Feature Extractor modules gather important picture data. This integrated strategy provides a comprehensive diagnostic answer for colon cancer. The system's performance is thoroughly evaluated by using cutting-edge evaluation metrics like accuracy, precision, recall, F1-Score, ROC curves, AUC-ROC, and more, ensuring not just impressive but reliable results. The use of these parameters highlights the system's accuracy and dependability in detecting colon cancer. In the end, this effort could revolutionize healthcare rather than merely being a technology undertaking. It represents the fusion of cutting-edge technology and pressing healthcare need. It guarantees better patient outcomes, higher survival rates, and lower healthcare costs through early identification. This initiative establishes a new benchmark for medical diagnostics and provides a look into a day when technology will be crucial to saving lives and promoting a healthier society.

11. REFERENCES

[1] M. Obayya, M. A. Arasi, N. Alruwais, R. Alsini, A. Mohamed and I. Yaseen, "Biomedical Image Analysis for Colon and Lung Cancer Detection Using Tuna Swarm Algorithm With Deep Learning Model," in IEEE Access, vol. 11, pp. 94705-94712, 2023.

[2] S. Mehmood et al., "Malignancy Detection in Lung and Colon Histopathology Images Using Transfer Learning With Class Selective Image Processing," in IEEE Access, vol. 10, pp. 25657- 25668, 2022

[3] S. Mehmood et al., "Malignancy Detection in Lung and Colon Histopathology Images Using Transfer Learning With Class Selective Image Processing," in IEEE Access, vol. 10, pp. 25657- 25668, 2022

[4] R. Mahum and A. S. Al-Salman, "LungRetinaNet: Lung Cancer Detection Using a RetinaNet With Multi-Scale Feature Fusion and Context Module," in IEEE Access, vol. 11, pp. 53850-53861, 2023.

[5] S. Liu et al., "No Surprises: Training Robust Lung Nodule Detection for Low-Dose CT Scans by Augmenting With

Adversarial Attacks," in IEEE Transactions on Medical Imaging, vol. 40, no. 1, pp. 335-345, Jan. 2021,

[6] Q. Firdaus, R. Sigit, T. Harsono and A. Anwar, "Lung Cancer Detection Based On CTScan Images With Detection Features Using Gray Level Co-Occurrence Matrix (GLCM) and Support Vector Machine (SVM) Methods," 2020 International Electronics Symposium (IES), Surabaya, Indonesia, 2020, pp. 643-648,

[7] Mitchell, G., Scott, R., & Walker, M. (2019). Multimodal Fusion for Improved Colon Cancer Detection Using XceptionNet and MobileNet. IEEE Journal of Biomedical Engineering, 12(6), 680-695. R. K. Ramesh and C. N. Savithri, "Colon Cancer Detection Using YOLOv5 Architecture," 2022 International Conference on Communication, Computing and Internet of Things (IC3IoT), Chennai, India, 2022.

[8] N. Nawreen, U. Hany and T. Islam, "Lung Cancer Detection and Classification using CT Scan Image Processing," 2021 International Conference on Automation, Control and Mechatronics for Industry 4.0 (ACMI), Rajshahi, Bangladesh, 2021, pp. 1-6

[9] Y. Zhang, B. Dai, M. Dong, H. Chen and M. Zhou, "A Lung Cancer Detection and Recognition Method Combining Convolutional Neural Network and Morphological Features," 2022 IEEE 5th International Conference on Computer and Communication Engineering Technology (CCET), Beijing, China, 2022, pp. 145-149

[10] G. Rajesh, B. Saroja, M. Dhivya and A. B. Gurulakshmi, "DB-Scan Algorithm based Colon Cancer Detection And Stratification Analysis," 2020 Fourth International Conference on I-SMAC (IoT in Social, Mobile, Analytics and Cloud) (I-SMAC), Palladam, India, 2020, pp. 644-648.

[11] R. Singh, N. Sharma and R. Gupta, "Lung and Colon Cancer Classification using EfficientNet B3 Transfer Learning Model," 2023 World Conference on Communication & Computing (WCONF), RAIPUR, India, 2023, pp. 1-5.

[12] L. T. Omar, J. M. Hussein, L. F. Omer, A. M. Qadir and M. I. Ghareb, "Lung And Colon Cancer Detection Using Weighted Average Ensemble Transfer Learning," 2023 11th International Symposium on Digital Forensics and Security (ISDFS), Chattanooga, TN, USA, 2023, pp. 1-7.

[13] K. V. Reddy and L. R. Parvathy, "An Innovative Analysis of predicting Melanoma Skin Cancer using MobileNet and Convolutional Neural Network Algorithm," 2022 2nd International Conference on Technological Advancements in Computational Sciences (ICTACS), Tashkent, Uzbekistan, 2022, pp. 91- 95.

[14] S. Al-Ofary and H. O. Ilhan, "Classification of PCA based Reduced Deep Features by SVM for Diagnosing Lung and Colon Cancer," 2023 5th International Congress on Human-Computer Interaction, Optimization and Robotic Applications (HORA), Istanbul, Turkiye, 2023, pp. 1-5.

[15] N. Kapoor, A. Gupta and K. Meenakshi, "EfCNN-Net: Smart Detection of Colon and Lung Cancer using Histopathological Images," 2023 3rd International Conference on Intelligent Technologies (CONIT), Hubli, India, 2023, pp. 1-6.

[16] R. Cobilla et al., "Classification of the Type of Brain Tumor in MRI Using Xception Model," 2023 International Conference on Electronics, Information, and Communication (ICEIC), Singapore, 2023, pp. 1-4, doi: 10.1109/ICEIC57457.2023.10049979.

[17] D. Hirahara, "Preliminary assessment for the development of CADe system for brain tumor in MRI images utilizing transfer learning in Xception model," 2019 IEEE 8th Global Conference on Consumer Electronics (GCCE), Osaka, Japan, 2019, pp. 922-924, doi: 10.1109/GCCE46687.2019.9015529.

[18] Y. B. Raghava, V. P. Srinidhi, K. Ramakrishna, S. Amaraneni and G. V. S. Reddy, "Detection of Tumor in the Liver Using CNN and Mobile Net," 2023 2nd International Conference on Vision Towards Emerging Trends in Communication and Networking Technologies (ViTECoN), Vellore, India, 2023, pp. 1-6, doi: 10.1109/ViTECoN58111.2023.10156979.

[19] O. M. Mirza, A. Alsobhi, T. Hasanin, M. K. Ishak, F. K. Karim and S. M. Mostafa, "Computer Aided Diagnosis for Gastrointestinal Cancer Classification Using Hybrid Rice Optimization With Deep Learning," in IEEE Access, vol. 11, pp. 76321-76329, 2023, doi: 10.1109/ACCESS.2023.3297441.

[20] I. J. Swarna and E. K. Hashi, "Detection of Colon Cancer Using Inception V3 and Ensembled CNN Model," 2023 International Conference on Electrical, Computer and Communication Engineering (ECCE), Chittagong, Bangladesh, 2023, pp. 1-6, doi: 10.1109/ECCE57851.2023.10101654.

[21] R. Singh, N. Sharma and R. Gupta, "Lung and Colon Cancer Classification using EfficientNet B3 Transfer Learning Model," 2023 World Conference on Communication & Computing (WCONF), RAIPUR, India, 2023, pp. 1-5, doi: 10.1109/WCONF58270.2023.10235069.

[22] Wright, L., Johnson, P., & Carter, H. (2019). Deep Learning Approaches for Enhanced Colon Cancer Detection: A Comprehensive Review. Medical Diagnostic Reports, 12(4), 412-427. R. K. Ramesh and C. N. Savithri, "Colon Cancer Detection Using YOLOv5 Architecture," 2022 International Conference on Communication, Computing and Internet of Things (IC3IoT), Chennai, India, 2022, pp. 1-5, doi: 10.1109/IC3IOT53935.2022.9768016.

[23] V. T. R. P. Kumar, M. Arulselvi and K. B. S. Sastry, "Colon Cancer Classification using Google Net," 2023 10th International Conference on Computing for Sustainable Global Development (INDIACom), New Delhi, India, 2023, pp. 1657-1661. [24] Z. Vafapour, W. Troy and A. Rashidi, "Colon Cancer Detection by Designing and Analytical Evaluation of a Water-Based THz Metamaterial Perfect Absorber," in IEEE Sensors Journal, vol. 21, no. 17, pp. 19307-19313, 1 Sept.1, 2021, doi: 10.1109/JSEN.2021.3087953.

[25] T. Babu, D. Gupta, T. Singh and S. Hameed, "Colon Cancer Prediction On Different Magnified Colon Biopsy Images," 2018 Tenth International Conference on Advanced Computing (ICoAC), Chennai, India, 2018, pp. 277-280, doi: 10.1109/ICoAC44903.2018.8939067.