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DEEP LEARNING-BASED LUNG CANCER DETECTION USING HYBRID VGG16 AND RESNET50 ENCODER–DECODER

S. Jeyakumar

Professor&Principal

Computer Science and Engineering,

Jayaraj Annapackiam CSI College of Engineering, Nazareth, India.

S. Jenolin Aiswarya

PG Scholar

Computer Science and Engineering,

Jayaraj Annapackiam CSI College of Engineering, Nazareth, India.

Abstract **- Lung cancer remains one of the leading causes of cancer-related deaths worldwide, making early and accurate diagnosis critical for improving patient survival and treatment outcomes. Traditional manual analysis of Computed Tomography (CT) scan images is time-consuming, prone to human error, and highly dependent on the expertise of radiologists. To address these challenges, this study proposes a hybrid deep learning framework that combines the strengths of the VGG16 and ResNet50 models for automated lung cancer detection. The proposed model analyzes CT scan images and classifies them into three categories: benign, malignant, and normal. In this hybrid architecture, VGG16 is utilized to capture fine-grained spatial features, while ResNet50 learns deeper abstract representations, improving the overall classification performance and reliability. Additionally, the model integrates the interpretability technique Grad-CAM to highlight important lung regions that influence the prediction results. This visualization capability enhances transparency and allows medical professionals to better understand and trust the model's decisions. The proposed approach aims to support radiologists by providing an efficient and reliable automated system for early lung cancer detection**

Keywords - Deep Learning, Lung Cancer Detection, CT Scan Image Analysis, VGG16, ResNet50, Grad-CAM, Medical Image Classification

I. INTRODUCTION

Lung cancer is one of the most common and deadly cancers worldwide, accounting for a significant number of cancer-related deaths each year. Early detection plays a vital role in improving patient survival rates and enhancing treatment effectiveness. However, the manual analysis of Computed Tomography (CT) scan images is time-consuming, requires highly skilled radiologists, and is often prone to human errors. Recent advancements in deep learning have shown promising results in medical image analysis, enabling automated detection and classification of diseases from imaging data. In this study, a hybrid deep learning framework is proposed by combining the capabilities of VGG16 and ResNet50 to improve the accuracy of lung cancer detection. The proposed system classifies lung CT scan images into three categories: benign, malignant, and normal. In addition, the model performs segmentation of lung regions affected by cancer and provides visual explanations using Grad-CAM to highlight important areas influencing the prediction. This interpretability helps medical professionals better understand the model's decision-making process. The developed system aims to support radiologists in clinical diagnosis, reduce diagnostic errors, and enhance overall medical decision-making.

II LITERARURE SURVEY

Lung-EffNet: Lung Cancer Classification Using EfficientNet from CT-Scan Images

The study "Lung-EffNet: Lung Cancer Classification Using EfficientNet from CT-Scan Images" presents a deep learning approach for automated lung cancer detection using CT scan images. The method employs the EfficientNet model to extract important features and classify lung images. EfficientNet improves model performance by optimizing network depth, width, and image resolution, allowing accurate classification with fewer parameters. The results of the study show that this approach can effectively detect lung cancer patterns from CT images and assist radiologists in early diagnosis and decision-making.

Lung Cancer Detection Model Using Deep Learning Technique

The study "Lung Cancer Detection Model Using Deep Learning Technique" proposes a deep learning-based approach for detecting lung cancer from CT scan images. The model uses convolutional neural networks to automatically extract features from medical images and classify them into different categories. Deep learning techniques improve the accuracy and efficiency of lung cancer detection compared to traditional manual methods. The proposed system helps in identifying cancerous patterns in CT scans at an early stage and supports radiologists in making faster and more reliable diagnostic decisions.

A CAD System for Lung Cancer Detection Using Hybrid Deep Learning Techniques

The study "A CAD System for Lung Cancer Detection Using Hybrid Deep Learning Techniques" proposes a computer-aided diagnosis (CAD) system for detecting lung cancer from CT scan images. The approach combines multiple deep learning models to improve feature extraction and classification performance. Hybrid deep learning techniques help capture both detailed and high-level features from medical images, leading to more accurate detection results. The system assists radiologists in identifying cancerous regions in lung CT scans and supports early diagnosis and clinical decision-making.

AI-Powered Lung Cancer Detection: Assessing VGG16 and CNN Architectures for CT Scan Image Classification

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The study "AI-Powered Lung Cancer Detection: Assessing VGG16 and CNN Architectures for CT Scan Image Classification" investigates the use of deep learning models for automated lung cancer detection from CT scan images. The research evaluates the performance of VGG16 and Convolutional Neural Network (CNN) architectures in classifying lung images. These models automatically extract important features from CT scans to identify cancerous patterns. The results show that deep learning-based approaches can improve classification accuracy and assist medical professionals in early lung cancer diagnosis.

Deep Learning Techniques to Diagnose Lung Cancer the study "Deep Learning Techniques to Diagnose Lung Cancer" explores the application of deep learning methods for detecting lung cancer from medical imaging data. Convolutional Neural Networks (CNNs) are used to automatically extract meaningful features from CT scan images and classify them into cancerous and non-cancerous categories. Deep learning techniques improve diagnostic accuracy by learning complex patterns in medical images. The study demonstrates that automated deep learning systems can support radiologists in early detection and enhance the reliability of lung cancer diagnosis.

III PROBLEM STATEMENT

Lung cancer is one of the leading causes of cancer-related deaths worldwide, and early detection is essential to improve patient survival rates. However, early-stage lung cancer is often difficult to detect, which can lead to delayed diagnosis and reduced treatment success.

The manual analysis of CT scan images by radiologists is time-consuming and may be affected by human errors or variations in expertise. In addition, there is a lack of reliable automated systems capable of accurately classifying and segmenting lung CT images.

These limitations can result in delays or inaccuracies in diagnosis, which may lead to incorrect treatment decisions and poorer patient outcomes. Therefore, there is a need for an efficient and automated system that can support the early and accurate detection of lung cancer.

IV EXISTING SYSTEM

In the existing system, lung cancer detection is primarily performed through the manual analysis of CT scan images by experienced radiologists. This process requires significant expertise and is often time-consuming due to the large number of medical images that need to be examined. Additionally, manual interpretation may lead to variations in diagnosis because different radiologists may interpret the same image differently.

Some existing automated methods use traditional machine learning and basic deep learning models for lung cancer detection. However, these systems often rely on single neural network architectures, which may not effectively capture complex features present in CT scan images. As a result, the accuracy and reliability of these systems may be limited. Therefore, there is a need for more advanced and efficient deep learning approaches to improve the detection and classification of lung cancer from CT images.

V PROPOSED METHODOLOGY

A. Data Collection

The dataset used in this study consists of lung CT scan images collected from publicly available medical imaging datasets. These images include three categories: benign, malignant, and normal lung conditions. The dataset provides sufficient samples for training and evaluating the deep learning model. Proper organization of the dataset into training, validation, and testing sets ensures effective model development and reliable performance evaluation.

B. Data Preprocessing

Data preprocessing is an essential step to improve the quality and consistency of the input images. All CT scan images are resized to a fixed dimension of 224 × 224 pixels to match the input requirements of the deep learning models. Image normalization is performed by scaling pixel values between 0 and 1. Data augmentation techniques such as rotation, zooming, horizontal flipping, and shifting are applied to increase dataset diversity and reduce the risk of overfitting during training.

C. Hybrid Encoder–Decoder Model Architecture

The proposed system utilizes a hybrid encoder–decoder deep learning architecture combining VGG16 and ResNet50. In this architecture, VGG16 acts as the encoder to extract detailed spatial features from lung CT images, while ResNet50 functions as the decoder to learn deeper feature representations and improve classification performance. This hybrid design helps capture both fine-grained and high-level features from the medical images, enhancing the model's ability to detect lung cancer accurately.

D. Transfer Learning and Fine-Tuning

Transfer learning is applied to improve model performance by using pretrained weights from large image datasets. The initial layers of the model are kept frozen to retain previously learned features, while the later layers are fine-tuned to adapt to lung CT scan images. Fine-tuning allows the model to learn domain-specific patterns related to lung cancer detection, leading to better classification accuracy and faster convergence during training.

E. Model Training

The model is trained using the prepared dataset with a defined batch size and number of training epochs. During training, the network learns to extract relevant features and classify the images into benign, malignant, and normal categories. An optimization algorithm such as Adam is used to update the model parameters, while early stopping and checkpoint techniques are applied to prevent overfitting and save the best-performing model.

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F. Performance Evaluation

The performance of the proposed model is evaluated using several standard classification metrics, including accuracy, precision, recall, and F1-score. In addition, confusion matrices and ROC curves are used to analyze the classification results in detail. These evaluation metrics help measure the effectiveness and reliability of the proposed lung cancer detection system for medical diagnosis applications.

VI FLOWCHART

The flow chart represents the overall workflow of the proposed lung cancer detection system based on deep learning techniques. The process begins with data collection, where lung CT scan images are gathered from the dataset. These images are then passed to the data preparation stage, which includes preprocessing steps such as resizing, normalization, and data augmentation to improve image quality and increase dataset diversity.

After preprocessing, the system moves to model development, where the hybrid deep learning architecture is designed using VGG16 and ResNet50 in an encoder–decoder framework. The developed model is then trained using the prepared dataset during the model training phase, allowing the network to learn important features from CT scan images.

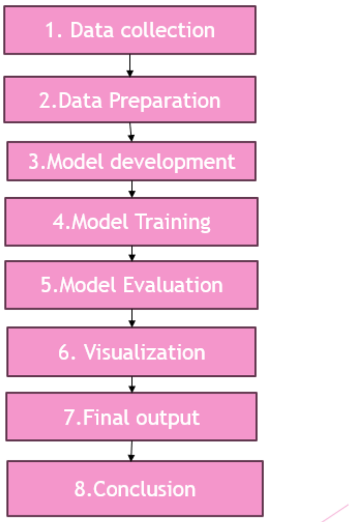

Fig 1. Flow Chart for Proposed Method

Next, model evaluation is performed using performance metrics such as accuracy, precision, recall, and F1-score to measure the effectiveness of the model. The visualization stage applies techniques like Grad-CAM to highlight the important regions in the CT images that influence the prediction results. Finally, the system produces the final output, which classifies the CT scan images into benign, malignant, or normal categories, of the proposed approach for lung cancer detection.

VII ARCHITECTURE DIAGRAM

The proposed system uses a hybrid encoder–decoder deep learning architecture for lung cancer detection from CT scan images. The process begins with the input layer, where CT scan images are provided with a size of 224 × 224 × 3. These images first undergo a preprocessing stage, which includes resizing, normalization, and data augmentation to improve the quality and diversity of the dataset for better model training.

After preprocessing, the images are passed to the encoder, which is based on the VGG16 architecture. The encoder consists of five convolutional blocks that extract hierarchical features from the CT images. Each block contains convolution and max-pooling layers that gradually reduce the spatial dimensions while capturing important visual patterns related to lung abnormalities.

The extracted feature maps are then fed into the decoder, which is built using the bottleneck layers of ResNet50. The decoder progressively reconstructs and refines the learned features through multiple stages using convolution, upsampling, and batch normalization layers. Skip connections from the encoder blocks are also utilized to retain important spatial information and improve feature reconstruction.

Following the decoder, the architecture includes fully connected layers with dense and dropout operations to enhance feature learning and prevent overfitting. The output layer uses a softmax activation function to classify the CT images into three categories: Normal, Benign, and Malignant.

Finally, the model integrates the visualization technique Grad-CAM to highlight the important regions of the CT scan that influence the model's prediction. This improves the interpretability of the system and helps medical professionals understand the decision-making process of the model.

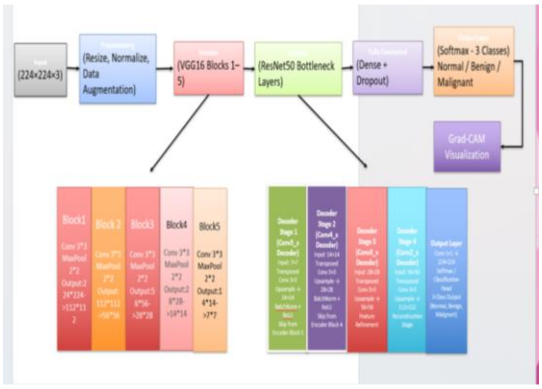

Fig 2 Architecture for proposed lung cancer detection using VGG16 – ResNet 50

VIII RESULT AND DISCUSSION

Deep learning models were implemented and compared to evaluate their effectiveness in lung cancer detection from CT scan images. The baseline model using VGG16 achieved an accuracy of 95%, demonstrating strong performance in classifying lung CT images.

A hybrid architecture combining VGG16 as the encoder and ResNet50 as the decoder was also implemented. This model achieved an accuracy of 92%,

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showing that the hybrid approach can effectively extract both detailed and deep features from the CT images. However, its performance was slightly lower than the standalone VGG16 model.

Another hybrid model using ResNet50 as the encoder and VGG16 as the decoder achieved an accuracy of 64%, which indicates that this architecture was less effective for the given dataset. The comparison of these models shows that the VGG16-based architecture performs better for lung cancer classification in this study. These results highlight the importance of selecting an appropriate architecture for medical image analysis tasks.

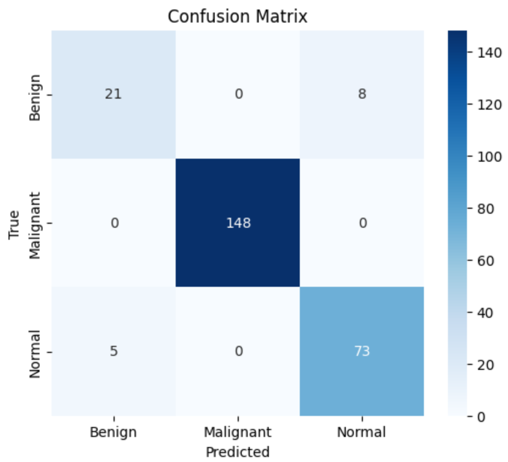
IX CONCLUSION

This study presented a deep learning-based approach for lung cancer detection using CT scan images. The proposed system utilized a hybrid encoder–decoder architecture combining VGG16 and ResNet50 to improve feature extraction and classification performance. The model was trained and evaluated to classify CT scan images into three categories: normal, benign, and malignant.

Experimental results showed that the baseline VGG16 model achieved the highest accuracy of 95%, while the hybrid VGG16 encoder–ResNet50 decoder model achieved 92% accuracy. The ResNet50 encoder–VGG16 decoder model showed lower performance with 64% accuracy. These results indicate that VGG16-based architectures are effective for lung cancer classification in this study.

Overall, the proposed deep learning framework demonstrates the potential of automated systems in assisting radiologists for early lung cancer detection. Such systems can help reduce diagnostic errors, improve clinical decision-making, and support efficient medical image analysis.

Confusion Matrix



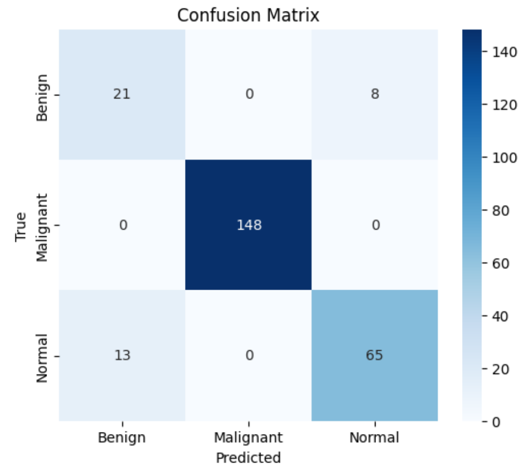


Fig3 Confusion Matrix for VGG16 model

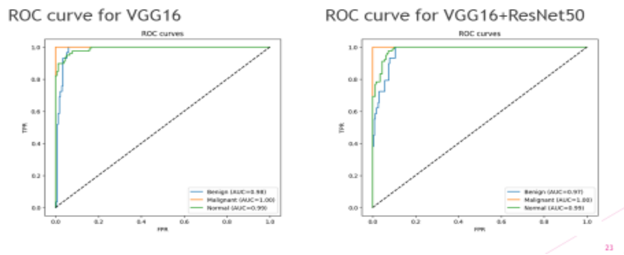


Fig 4 Confusion Matrix for Vgg16_ResNet50 Model

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