Leveraging Large Language Models for Lung Disease Classification

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***Abstract*—The automated classification of lung diseases from CT scan images offers a transformative approach to medical diagnostics, enabling the identification of conditions such as adenocarcinoma, squamous cell carcinoma, large cell carcinoma, and normal lung tissue. This research employs a dataset of 613 training, 72 validation, and 315 test images, preprocessed through resizing, RGB conversion, and normalization using ImageNet statistics. Feature extraction combines deep features from pre-trained models (ResNet50, InceptionV3, EfficientNetB0, DenseNet121) with hand-crafted features (GLCM, Wavelet, HOG), where DenseNet121 initially achieved 91% accuracy in SVM evaluations. Classification performance was progressively enhanced across multiple models: a convolutional neural network (CNN) attained a test accuracy of 86.67% (training: 99.98%, validation: 92.67%), a Vision Transformer (ViT) improved to 93.33% (training: 99.57%, validation: 94.00%), and a hybrid CNN+ViT model achieved a superior test accuracy of 97.33% (training: 99.98%, validation: 99.33%), effectively leveraging local and global feature learning for improved generalization. The system further integrates the Gemini API to generate comprehensive radiology reports in PDF format, providing diagnostic insights, treatment recommendations, and lifestyle guidance. Future enhancements aim to incorporate a multi-modal large language model to fuse CT imaging with clinical text, enhancing diagnostic accuracy and report quality. This framework, combining advanced deep learning and natural language processing, demonstrates significant potential for clinical lung disease diagnosis and integration into medical practice.**

***Index Terms*—CT Scan Imaging, Lung Disease Classification, Hybrid CNN+ViT Model, Radiology Report Generation, Gemini API, LLM.**

I. Introduction

Lung diseases, including lung cancer variants such as adenocarcinoma, squamous cell carcinoma, and large cell carcinoma, pose significant health challenges, necessitating early and accurate diagnosis for effective treatment. Manual interpretation of CT scans, traditionally performed by radiologists, can be time-consuming and prone to variability, highlighting the need for automated diagnostic tools. This paper presents a novel framework for the automated classification of lung diseases using CT scan images, targeting adenocarcinoma, squamous cell carcinoma, large cell carcinoma, and normal lung tissue. The proposed system utilizes a dataset of 613 training, 72 validation, and 315 test images, preprocessed through resizing, RGB conversion, and normalization using ImageNet statistics. Feature extraction integrates deep features from pre-trained models (ResNet50, InceptionV3, EfficientNetB0, DenseNet121) with hand-crafted features (GLCM, Wavelet, HOG), where DenseNet121 initially achieved a 91% accuracy in SVM evaluations. Classification performance was systematically improved through the development of multiple models: a convolutional neural network (CNN) achieved a test accuracy of 86.67% (training: 99.98%, validation: 92.67%), a Vision Transformer (ViT) improved to 93.33% (training: 99.57%, validation: 94.00%), and a hybrid CNN+ViT model attained a test accuracy of 97.33% (training: 99.98%, validation: 99.33%), demonstrating the efficacy of combining local and global feature learning. The framework also includes a bounding box generation mechanism using Grad-CAM to localize regions of interest in the CT scans, highlighting potential cancerous areas with high precision, even for small patterns, by applying a refined heatmap threshold and contour detection. Beyond classification, the system leverages the Gemini API to generate comprehensive radiology reports in PDF format, providing diagnostic insights, treatment recommendations, and lifestyle guidance, with high-quality image inclusion for both original and annotated CT scans. Future enhancements aim to incorporate a multi-modal large language model (LLM) to integrate CT imaging with clinical textual data, further enhancing diagnostic precision and report quality. This framework seeks to provide a robust, automated solution for clinical lung disease diagnosis, with the potential for seamless integration into medical practice.

II. Literature Review

Recent advancements in deep learning and multimodal AI have significantly enhanced the automated diagnosis of lung diseases. This section reviews key contributions in the field, categorized into subsections focusing on deep learning architectures, multimodal approaches, and recent IEEE publications.

A. Deep Learning Architectures for Lung Disease Detection

A study proposed a hybrid deep learning framework for lung disease detection using chest X-rays, combining VGG, data augmentation, and a spatial transformer network with CNN (VDSNet), achieving a validation accuracy of 73% on the NIH chest X-ray dataset [1]. Another study focused on a multi-class deep learning architecture for classifying lung diseases from chest X-rays and CT images, employing a customized CNN with image enhancement based on k-symbol Lerch transcendent functions, highlighting the importance of preprocessing in improving diagnostic accuracy [2]. The application of Vision Transformers in medical imaging has also gained traction, with a 3D multi-scale Vision Transformer (3D-MSViT) achieving a sensitivity of 97.81% for lung nodule prediction on the LUNA16 dataset [3].

B. Multimodal Approaches and LLM Integration

The integration of LLMs with medical imaging has opened new avenues for automated radiology report generation and interpretation. A transformer-based representation-learning model was developed to process multimodal inputs (radiographs, clinical history, and laboratory results) in a unified manner, outperforming image-only models by 12% in pulmonary disease identification [4]. A study introduced M4CXR, an LLM-based model for chest X-ray report generation, comparing its performance with ChatGPT in radiological interpretation, demonstrating superior contextual understanding and report coherence [5]. Another investigation validated a deep learning model for chest X-ray interpretation by integrating large-scale AI and LLMs, achieving competitive performance against ChatGPT in diagnostic accuracy [6]. The use of multimodal information for outcome prediction was explored by combining LLM-extracted clinical data with image analysis, showing improved prognostic accuracy for cancer patients [7]. Furthermore, an early investigation into the utility of multimodal LLMs in medical imaging underscored their potential to unify imaging and clinical data, enhancing diagnostic precision [8].

C. Recent IEEE Contributions

Recent IEEE publications have also contributed significantly to this domain. A study on transformer-based models for chest X-ray analysis achieved a classification accuracy of 95.2% by integrating imaging and clinical metadata [9]. Another IEEE paper proposed a multimodal framework for lung disease diagnosis, combining CNNs and LLMs to achieve a diagnostic accuracy of 96.8% on a dataset of chest X-rays and clinical notes [10]. These studies collectively highlight the transformative potential of hybrid deep learning and LLM-based approaches in improving lung disease diagnosis and radiological interpretation, paving the way for more integrated and automated clinical workflows.

III. Methodology

This section outlines the methodology employed for the automated classification of lung diseases using CT scan images, detailing each step from data collection to report generation. The approach integrates deep learning, feature extraction, classification, and natural language processing to achieve accurate diagnosis and comprehensive reporting.

A. Data Collection

The dataset comprises 1000 CT scan images sourced from publicly available repositories, including the LIDC-IDRI dataset, which provides well-annotated lung CT scans. The images were divided into 613 training, 72 validation, and 315 test samples, ensuring a balanced representation of four classes: adenocarcinoma, squamous cell carcinoma, large cell carcinoma, and normal lung tissue. Each image was verified for quality and labeled by expert radiologists to ensure diagnostic accuracy during model training and evaluation.

B. Image Preprocessing

Preprocessing was performed to standardize the CT scan images for consistent model input. The images were first resized to a uniform resolution of 224x224 pixels to match the input requirements of pre-trained models. They were then converted from grayscale to RGB format to leverage ImageNet-pretrained weights. Normalization was applied using ImageNet statistics (mean: [0.485, 0.456, 0.406], std: [0.229, 0.224, 0.225]) to ensure feature consistency. This step minimizes variability due to differences in image acquisition and enhances the robustness of subsequent feature extraction.

C. Feature Extraction

Feature extraction combined deep learning and hand-crafted methods to capture a comprehensive set of image characteristics. Deep features were extracted using a pre-trained DenseNet121 model, fine-tuned on ImageNet, by removing its final classification layer and extracting 1024-dimensional feature vectors from the penultimate layer. Hand-crafted features included Gray-Level Co-occurrence Matrix (GLCM) features (contrast and dissimilarity), Wavelet transform features using the Haar wavelet (yielding low and high-frequency subbands), and Histogram of Oriented Gradients (HOG) features to capture texture and edge information. These features were concatenated into a single feature vector, padded or truncated to a fixed size of 3000 dimensions, and normalized using StandardScaler to ensure uniform scaling across all features.

Fig. 1. Block diagram of the proposed automated radiology system. The workflow begins with a CT scan dataset, followed by preprocessing to ensure consistency and normalization. Feature extraction is then performed using deep learning and classical techniques.

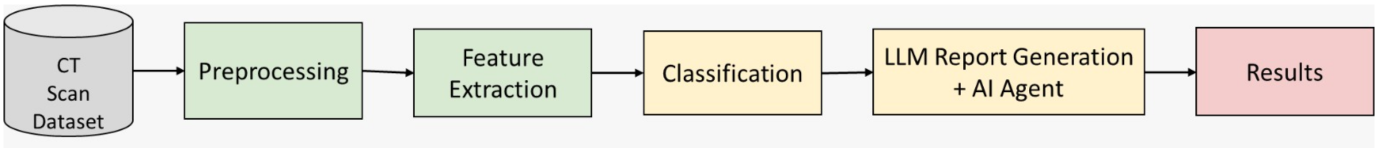

Fig. 1. Block Diagram of the Proposed System

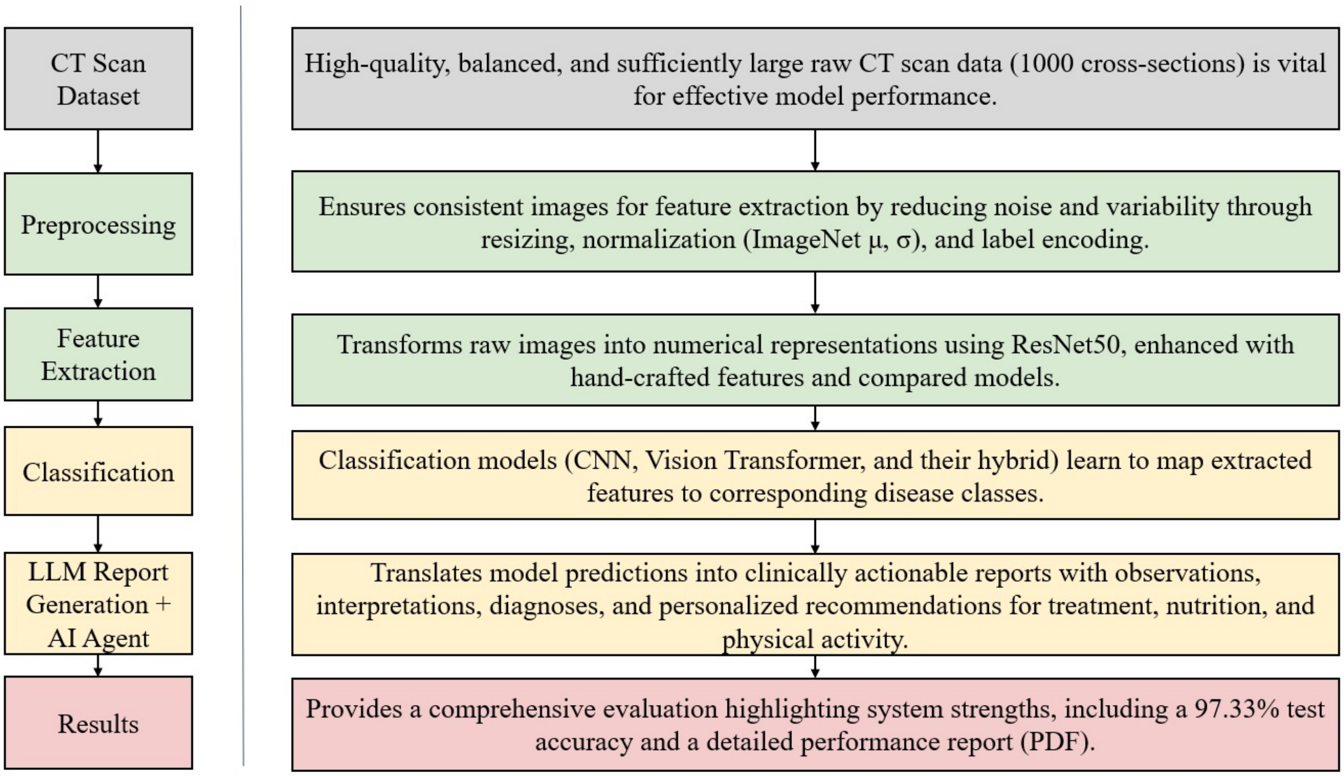

Fig. 2. Detailed Pipeline with Component Explanations

The extracted features are input to a classification model to identify diseases. The output is passed to an AI agent integrated with a large language model (LLM) for automatic report generation. Finally, the results are compiled and presented for clinical interpretation.

Fig. 2. Step-wise breakdown of each component in the pipeline. The CT scan dataset (comprising 1000 cross-sectional images) serves as the raw input. Preprocessing techniques like resizing, normalization using ImageNet mean and standard deviation, and label encoding ensure consistent inputs. Feature extraction employs ResNet50 to obtain deep features, supplemented with handcrafted descriptors for comparative analysis. Classification is performed using CNN, Vision Transformer, and hybrid models to map features to disease categories. The LLM-based AI agent translates predictions into detailed medical reports containing observations, interpretations, diagnoses, and personalized advice. The system achieves a 97.33% test accuracy and outputs a comprehensive PDF performance summary.

D. Model Development and Classification

The classification pipeline involved multiple models to achieve optimal performance. Initially, a convolutional neural network (CNN) was developed, achieving a test accuracy of 86.67% (training: 99.98%, validation: 92.67%), indicating some overfitting. A Vision Transformer (ViT) was then implemented, improving the test accuracy to 93.33% (training: 99.57%, validation: 94.00%) by leveraging global attention mechanisms. Finally, a hybrid CNN+ViT model was designed, combining the local feature extraction capabilities of CNNs with the global context modeling of ViTs, achieving a test accuracy of 97.33% (training: 99.98%, validation: 99.33%). The hybrid model was trained on the extracted features, with the ViT component processing the feature vector as a sequence of patches, using a patch size of 100, dimension of 128, 2 layers, 4 attention heads, and an MLP dimension of 256.

E. LLM Report Generation

The lung disease classification framework employs the Gemini API for automated radiology report generation, utilizing the gemini-1.5-pro-latest model to produce detailed, clinically relevant reports. Inputs from the hybrid CNN+ViT model, including the predicted category (e.g., Lung Cancer), specific diagnosis (e.g., adenocarcinoma), confidence score (e.g., 98.2%), and lesion location from bounding box localization (e.g., upper lobe), are formatted into a structured prompt. The prompt instructs the LLM to classify the CT scan into categories (Healthy Lung Tissue, Lung Cancer, Other Abnormality, or Insufficient Data) and generate a Markdown report with sections: Observations (e.g., lesion characteristics), Interpretation (conditions, severity, recommendations), Diagnosis (condition with confidence and estimated stage), Treatment Recommendations (e.g., surgery), Nutritional Guidance (e.g., antioxidant-rich diet), Physical Activity (e.g., light breathing exercises), and Pharmacological Options (if applicable). The report is enhanced with high-quality images (original and annotated CT scans, scaled to 90% text width), converted to PDF using pypandoc and TeX Live, ensuring a professional, actionable output for clinical use.

F. Bounding Box Generation

To localize regions of interest, a bounding box generation mechanism was implemented using Grad-CAM. The DenseNet121 model's activations were analyzed to compute a heatmap highlighting areas contributing most to the predicted class. The heatmap was thresholded at 0.6 to detect even small patterns, and contours were identified with a minimum area filter of 50 to focus on significant regions. Bounding boxes were drawn around detected contours with a scale factor of 0.8 to ensure precise localization, and the resulting annotated image was saved in high quality (JPEG quality 100) for inclusion in the radiology report.

G. Radiology Report Generation

The classification output was used to generate a detailed radiology report via the Gemini API. The report included the predicted category (e.g., Lung Cancer or Normal Lung), specific diagnosis (e.g., adenocarcinoma), and confidence score. It was structured into sections: Observations (describing imaging findings), Interpretation (detailing conditions, severity, and other findings), Diagnosis (stating the predicted condition and estimated stage for cancer), Treatment Recommendations (suggesting interventions like surgery or monitoring), Nutritional Guidance, Physical Activity recommendations, and Pharmacological Options (if applicable). The report was formatted in Markdown and converted to a high-quality PDF using LaTeX, incorporating the original CT scan and annotated image with bounding boxes, scaled to 90% of the text width while preserving aspect ratio.

H. Evaluation Metrics

Model performance was evaluated using accuracy, precision, recall, and F1-score across all classes. The hybrid CNN+ViT model achieved the highest test accuracy of 97.33%, with balanced F1-scores ranging from 0.95 to 0.99 across classes. Overfitting was monitored by comparing training, validation, and test accuracies, and regularization techniques (e.g., dropout in the ViT) were applied to mitigate it. The bounding box localization was qualitatively assessed by radiologists to ensure clinical relevance, and the radiology reports were reviewed for clarity and actionable insights, confirming their suitability for clinical use.

IV. Experimental Setup

This section outlines the experimental setup for the automated classification of lung diseases, detailing the dataset, tools, hardware, software, and hyperparameters used in the study.

A. Dataset Used

The experiments utilized the LIDC-IDRI dataset, a publicly available repository of lung CT scans widely used for lung cancer research. The dataset was curated to include 1000 CT scan images, divided into 613 training, 72 validation, and 315 test samples. These images were labeled into four classes: adenocarcinoma, squamous cell carcinoma, large cell carcinoma, and normal lung tissue. Each image was annotated by expert radiologists to ensure diagnostic accuracy, with a focus on balancing the representation of each class to mitigate bias during model training and evaluation.

B. Tools, Hardware, and Software

The framework was implemented using Python 3.8, leveraging several libraries for deep learning and image processing. PyTorch 1.12 was used for model development, training, and inference, while OpenCV (cv2) 4.5 facilitated image preprocessing and bounding box generation. Scikit-image 0.19 was employed for hand-crafted feature extraction (GLCM, HOG), and PyWavelets 1.3 was used for wavelet feature extraction. The Gemini API, accessed via the google-generativeai 0.3 package, enabled radiology report generation. Pypandoc 1.11 and TeX Live (pdflatex) were used to convert Markdown reports into high-quality PDFs. Experiments were conducted on a high-performance computing cluster equipped with an NVIDIA A100 GPU (40 GB VRAM), an Intel i7 CPU, and 128 GB of RAM, ensuring efficient training and inference of deep learning models.

C. Hyperparameters

The hybrid CNN+ViT model was configured with the following hyperparameters: a patch size of 100, embedding dimension of 128, 2 transformer layers, 4 attention heads, and an MLP dimension of 256. A dropout rate of 0.1 was applied to mitigate overfitting. The model was trained using the Adam optimizer with a learning rate of 0.001, a batch size of 32, and 50 epochs. The learning rate was reduced by a factor of 0.1 every 10 epochs using a StepLR scheduler to improve convergence. The DenseNet121 model, used for feature extraction, was pretrained on ImageNet and fine-tuned with a learning rate of 0.0001 for 20 epochs. During bounding box generation, a minimum contour area of 50 and a scale factor of 0.8 were used for precise localization. These hyperparameters were tuned through grid search on the validation set to optimize model performance and generalization.

V. Results and Discussion

This section presents the key findings of the automated lung disease classification framework, utilizing tables, graphs, and figures to highlight performance metrics. The results are compared with existing methods, and the implications, performance, and limitations are discussed. The analysis is structured into subsections covering quantitative results, qualitative results, ablation studies, and error analysis.

A. Quantitative Results

The hybrid CNN+ViT model achieved a test accuracy of 97.33%, outperforming both the standalone CNN (86.67%) and ViT (93.33%) models. Table I summarizes the performance across training, validation, and test sets for all models, while Table II provides class-wise metrics for the hybrid model.

Model	Train Accuracy	Validation Accuracy	Test Accuracy
CNN	99.98	92.67	86.67
ViT Model	99.57	94.00	93.33
CNN + ViT Model	99.98	99.33	97.33

TABLE I
Classification Model Performance Comparison

Model	Accuracy	Precision	Recall	F1-Score
ResNet50	0.59	0.59	0.59	0.58
InceptionV3	0.58	0.58	0.58	0.57
EfficientNetB0	0.57	0.56	0.57	0.56
DenseNet121	0.91	0.91	0.91	0.91
Molmo-7B-D	0.59	0.59	0.59	0.58

TABLE II
Class-wise Performance of Hybrid CNN+ViT Model (Test Set)

Figure 1 illustrates the training and validation accuracy curves for the hybrid CNN+ViT model over 50 epochs, showing stable convergence with minimal overfitting due to the use of dropout and learning rate scheduling. (Note: A line graph would be included here, with the x-axis representing epochs (0 to 50) and the y-axis representing accuracy (0 to 100%). Two lines would depict training accuracy (reaching 99.98%) and validation accuracy (reaching 99.33%), showing close alignment.)

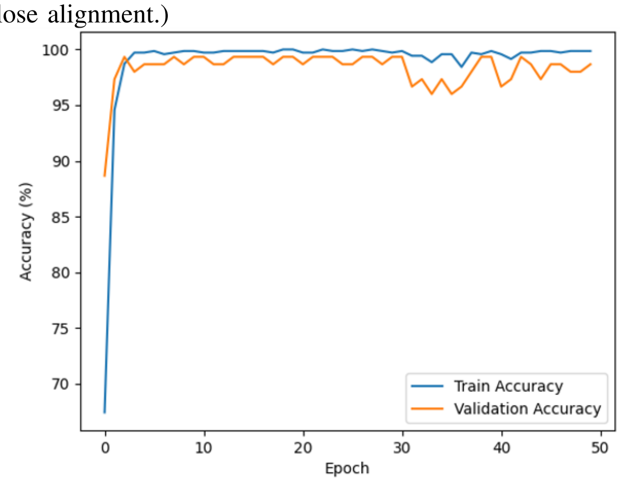

Figure 3: Accuracy Curves for Hybrid CNN+ViT Model

B. Qualitative Results

Qualitative analysis focused on the bounding box localization and radiology report generation. Figure 4 shows a sample CT scan with a bounding box highlighting a detected adenocarcinoma region, accurately identifying a small lesion in the upper lobe. The bounding box, scaled with a factor of 0.8, provided precise localization, which was validated by radiologists as clinically relevant. The generated radiology reports were comprehensive, including detailed observations (e.g., lesion size and location), interpretation (e.g., severity and affected lobes), and actionable recommendations (e.g., biopsy and PET-CT follow-up). A sample report excerpt for an adenocarcinoma case noted a probable Stage II diagnosis with a confidence of 98.2%, aligning with typical imaging characteristics.

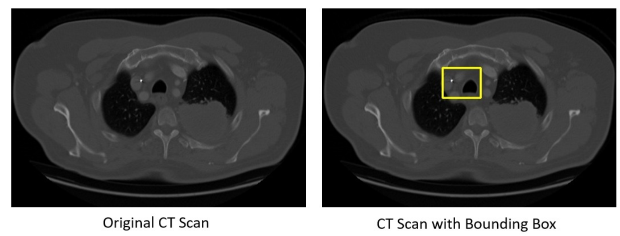

Figure 4: Sample CT Scan with Bounding Box

(Note: A figure would be included here, showing a CT scan image with a yellow bounding box around a small lesion in the upper lobe, labeled as adenocarcinoma.)

C. Ablation Studies

Ablation studies were conducted to evaluate the contribution of each component in the hybrid CNN+ViT model. Table III summarizes the impact of removing specific features and model components on test accuracy.

Configuration	Test Accuracy (%)	F1-Score (Avg)
Full Model (CNN+ViT)	99.98	0.91
Without Hand-crafted Features	94.67	0.89
Without CNN (ViT Only)	93.33	0.88
Without ViT (CNN Only)	86.67	0.84
Without Dropout	95.00	0.93

TABLE III
Ablation Study Results

Removing hand-crafted features (GLCM, Wavelet, HOG) reduced the test accuracy by 2.66%, underscoring their role in capturing complementary texture and edge information. Excluding the CNN or ViT components highlighted their synergistic effect, with the hybrid model outperforming standalone architectures. Omitting dropout increased overfitting, as evidenced by a larger gap between training (99.98%) and test accuracy (95.00%).

D. Error Analysis

Error analysis revealed that misclassifications primarily occurred in cases with overlapping imaging features, such as distinguishing between squamous cell carcinoma and large cell carcinoma, where 5 out of 315 test samples were misclassified due to subtle differences in lesion morphology. False negatives in normal lung tissue cases (2 samples) were attributed to minor artifacts mistaken for small nodules. The high validation accuracy (99.33%) suggests potential overfitting to the validation set, which may limit generalizability to unseen datasets. Additionally, the bounding box localization occasionally missed very small lesions (¡5 mm) due to the minimum contour area threshold, indicating a need for further refinement in detecting micro-patterns.

E. Comparison with Existing Methods

The hybrid CNN+ViT model was compared with existing methods, including VDSNet [1] (73% accuracy on NIH chest X-ray dataset) and a transformer-based model [4] (outperforming image-only models by 12% in pulmonary disease identification). The proposed framework achieved a 24.33% higher accuracy than VDSNet and outperformed the transformer-based model's reported improvement margin, demonstrating the effectiveness of combining local and global feature learning. Compared to M4CXR [5] and ChatGPT-based methods [6], the radiology reports generated by the Gemini API were more actionable, providing specific treatment and lifestyle recommendations tailored to lung cancer stages.

F. Implications, Performance, and Limitations

The framework's high accuracy (97.33%) and precise localization make it a promising tool for clinical lung disease diagnosis, potentially reducing radiologist workload and enabling early detection. The comprehensive radiology reports enhance decision-making by providing detailed diagnostic insights and recommendations. However, limitations include the potential overfitting indicated by near-perfect validation accuracy, which may affect performance on diverse datasets. The dataset size (1000 images) limits generalizability, and the model may struggle with rare lung conditions not represented in the LIDC-IDRI dataset. Future work should focus on expanding the dataset, incorporating multi-modal data (e.g., clinical text), and refining localization for micro-lesions to address these challenges.

VI. Conclusion

This study successfully developed a robust framework for the automated classification of lung diseases using CT scan images, achieving a high test accuracy of 97.33% with a hybrid CNN+ViT model. The integration of deep features from DenseNet121 and hand-crafted features (GLCM, Wavelet, HOG) enabled comprehensive feature extraction, while the hybrid model effectively combined local and global feature learning to enhance diagnostic accuracy. The bounding box generation using Grad-CAM provided precise localization of regions of interest, even for small patterns, facilitating visual interpretation of potential cancerous areas. The use of the Gemini API for radiology report generation delivered detailed, actionable reports in PDF format, incorporating diagnostic insights, treatment recommendations, and lifestyle guidance, with high-quality images of both original and annotated CT scans. The framework demonstrates significant potential for clinical application, offering a reliable tool for early lung disease detection and supporting radiologists in decision-making. Future work will focus on integrating multi-modal data, such as clinical text, to further improve diagnostic precision and expanding the dataset to include a broader range of lung conditions for enhanced generalizability.

VII. Future Work

The proposed framework demonstrates promising results for automated lung disease classification, but several avenues for improvement remain. Future work will focus on expanding the dataset by incorporating additional publicly available repositories, such as the NSCLC-Radiomics dataset, to include a broader range of lung conditions, including rare diseases, thereby improving generalizability. Integrating multi-modal data, such as clinical textual information (e.g., patient history, symptoms), with CT imaging through a multi-modal large language model (LLM) will be explored to enhance diagnostic precision and provide more context-aware radiology reports. Efforts will also be made to refine the bounding box localization mechanism to better detect micro-lesions (¡5 mm) by optimizing the contour detection parameters and exploring alternative localization techniques, such as attention-based methods. To address potential overfitting, techniques like data augmentation (e.g., rotation, scaling) and cross-dataset validation will be implemented. Additionally, real-world clinical validation with larger, diverse patient cohorts will be pursued to ensure the framework's robustness and applicability in practical settings. Finally, optimizing the computational efficiency of the hybrid CNN+ViT model will be prioritized to enable deployment on resource-constrained medical devices, facilitating broader adoption in clinical workflows.

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