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Research Article

Towards Reliable Lung Cancer Diagnosis: A Novel CNN-RNN Hybrid Model For CT-Based Detection

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ABSTRACT

To improve the classification accuracy of lung cancer utilizing the LIDC and Chest CT datasets, this study presents the LungNet-RC model, a hybrid CNN-RNN architecture. With data pre-processing techniques like box filtering and contour enhancement, the model achieves exceptional accuracy, specificity, sensitivity, and AUC scores. Specifically, LungNet-RC attains overall accuracy as 0.9878, training accuracy as 0.9937, test accuracy as 0.9937 and validation accuracy as 0.87 on the LIDC dataset and 0.9988 overall accuracy on the Chest CT dataset with train accuracy as 0.9926, test accuracy as 0.9975 and validation accuracy as 0.7656. When compared with recent deep learning and fusion models, LungNet-RC's superior performance demonstrates its reliability for clinical applications. This study's findings underscore the robustness of the model in differentiating between malignant and benign cases, presenting LungNet-RC as a promising tool for early lung cancer detection.

Keywords: Lung Cancer Detection, Deep Learning, CNN, RNN, AUC, Accuracy.

INTRODUCTION

Among the most common and fatal malignancies in the world, lung cancer makes a substantial contribution to the death rates associated with cancer. Early detection is crucial, as lung cancer often progresses without noticeable symptoms until advanced stages. Although lung nodules and tumors are frequently detected with conventional imaging-based diagnostic techniques like chest X-rays and CT scans, radiologists' interpretation of these pictures is largely dependent on their experience. This dependence increases the risk of variability in diagnosis, especially in high-volume settings where the cognitive load on medical professionals is substantial. Thus, automation and optimization of diagnostic accuracy have become critical in lung cancer research, spurring the development of advanced Machine Learning (ML) and Deep Learning (DL) representations to support radiological assessments.

Since Convolutional Neural Networks (CNNs) can interpret complicated visual input, DL has shown considerable promise in the field of medical imaging. CNNs excel at detecting spatial patterns, making them well-suited for identifying cancerous regions in CT scans. However, in lung cancer detection, merely capturing spatial features is often insufficient. Sequential information, such as variations across CT image slices, is essential for differentiating between malignant and benign patterns more accurately. This capacity may be offered by Recurrent Neural Networks (RNNs), which are efficient at dealing out consecutive records. RNNs do this by examining spatial attributes from several picture slices in order to identify more detailed contextual information. This paper proposes a hybrid model, LungNet-RC, which combines CNNs and RNNs to exploit both spatial and sequential information in lung CT scans, aiming for improved classification performance.

LITERATURE REVIEW

A hybrid system that combines deep learning (DL) and quantum computing was suggested by Martis, Jason Elroy, et al. to improve the detection accuracy of lung cancer from computed tomography (CT) and chest radiographs (CXR). By using quantum circuits for classification and pre-trained models for feature extraction, the suggested system achieves state-of-the-art performance across a range of criteria. In addition to achieving an overall accuracy of

92.12%, the suggested method performs exceptionally well in other critical performance metrics, including sensitivity (94%), specificity (90%), F1-score (93%), and precision (92%). These findings show that, in comparison to conventional techniques, the hybrid strategy is more accurate in identifying lung cancer signals. Additionally, the system's scalability and processing speed are improved by the use of quantum computing, which makes it a viable tool for early lung cancer detection and screening. Utilizing the advantages of quantum computing, the method outperforms conventional techniques in terms of efficiency, accuracy, and speed. With the use of hybrid computational technologies, early cancer diagnosis might be revolutionized, opening the door to more extensive clinical applications and better patient outcomes [1].

A thorough Systematic Literature Review (SLR) employing deep learning techniques for lung cancer research was carried out by R. Javed et al., who also provided a detailed review of the methodology, state-of-the-art advancements, quality evaluations, and tailored deep learning methodologies. Although there are several deep learning techniques for lung cancer classification in this study, the Convolutional Neural Network (CNN), the most widely used technique, is the main emphasis. CNN's multi-layer structure, automated weight learning, and ability to transmit local weights allow it to reach the highest accuracy. Performance metrics such as precision, accuracy, specificity, sensitivity, and AUC are displayed for several algorithms; CNN consistently exhibits the highest accuracy. The results demonstrate how DCNN improves lung cancer detection and classification, which makes them a helpful tool for researchers who want to understand more about how deep learning works in medical applications [2].

N.Divya et.al introduced a novel approach to lung cancer prediction by leveraging CNN on lung X-ray images. The CNN model was trained to identify four types of lung X-rays: normal, squamous cell carcinoma, big cell carcinoma, and adenocarcinoma. The methodology involves preprocessing of lung X-ray images, feature extraction using CNN layers, and classification through a carefully designed NN architecture. The representation's training was based on a set of data encompassing a diverse range of cases, facilitating robust learning and accurate predictions. The possibility for improving early detection and expediting diagnosis, which would result in prompt medical treatments, is what makes this research significant. By automating the categorization of lung cancer types through CNN analysis of chest X-rays, this system aims to contribute to the efficiency of healthcare services and improve patient outcomes[3].

V. Kalpana et.al. intended to determine the best effective strategy for early cancer detection by meticulously pre-processing the dataset and comparing multiple DL models, for example ResNet152V2, Inception V3, ANN then FNN. By shedding light on these models' diagnostic accuracy and performance metrics, such as Precision, Accuracy, Compassion, Specificity, and Part below the ROC curve, our research advances the field by offering a comparative analysis and practical application of these models [4].

D. Mane et.al. research focuses on preparing a heterogeneous dataset that includes both cancerous and non-cancerous lung pictures rigorously separated into test, validation, and training sets. Augmentation techniques including zooming, shearing, flipping, and normalization improve the representation’s capability to identify significant structures in the mixed dataset. The CNN architecture built using Keras comprises convolutional, maxpooling, and dropout layers designed to detect detailed patterns within lung images. To avoid overfitting, early halting and model checkpointing procedures are used during training, assuring optimal performance and generalization. The trained CNN model achieves an impressive 95% accuracy on the given dataset, demonstrating its efficiency in detecting lung cancer. [5].

Through the use of several datasets of lung cancer pictures, such as CT scans and X-rays, M. Grace et al. assesses the efficacy of deep learning algorithms for lung cancer detection. CNNs were used to produce the findings, which were distinguished by their great sensitivity and accuracy. Keras was selected as the development tool because of its effectiveness in completing jobs rapidly. Following a thorough evaluation of the literature, the study produced recommendations for further research and the incorporation of findings into therapeutic applications [6].

S.K. Shah et.al. offers an extensive approach for detecting stages of lung cancer as early as possible from CT scan images using Deep learning. Elastic transformation is used as preprocessing to address class imbalance. Data augmentation is applied to improve model generalization after splitting the data into training, testing and validation. Three pre-trained convolutional neural network architecture (DenseNet201, VGG16, EfficientNetB7) are employed, with transfer learning utilized to fine-tune the models for lung cancer multi-class classification. In the end, weighted CNN ensemble is implemented to combine the predictions of individual models. Final result showcases effectiveness

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of proposed deep learning model, with the weighted ensemble method achieving an accuracy of 98.19% on the test data [7].

Z. Sultana et.al. proposed an ensemble DL method for identifying and classifying lung cancers that greatly impact the Computer Aided Diagnosis (CAD) system. Initially, three deep convolutional neural networks (CNN) Transfer Learning Approaches, MobileNetV2, VGG19, and Resnet50, were used individually to perform classification. Then, these models are combined to perform better in lung cancer diagnosis using the fusion of chest CT and PET-CT images. This method makes use of the pretrained weights of MobileNetV2, VGG19, and ResNet50 to extract features. Then, the extracted features are concatenated and utilized for classification using the weighted average ensemble methodology. The suggested ensemble model outperformed the individual models (98.67% in MobileNetV2, 98.20% in VGG19, and 97.67% in ResNet50) with a test precision of 98.93% following a thorough experimental investigation [8].

T. Singh et.al. presents an optimized approach for early-stage lung cancer detection, utilizing the VGG-16 convolutional neural network (CNN). Achieving a final accuracy of 99%, the study focuses on refining and optimizing VGG-16, a deep learning model, to distinguish between malignant, benign, and normal conditions in CT- scan images. The application of various optimization techniques, such as Gaussian blur, SMOTE (Synthetic Minority Over-sampling Technique), transfer learning, and early callback, significantly enhances the model's performance. These techniques address issues like overfitting and class imbalance, contributing to the overall robustness of the VGG-16 model. The study categorizes CT-scan images cancerous (malignant), non- cancerous (benign), or normal across diverse datasets like IQ- OTH/NCCD-Lung Cancer Dataset, showcasing the model's adaptability to varied patient demographics [9].

By analyzing CT scan pictures, Khattab M. Ali Alheeti et al. investigate how transfer learning models affect the efficiency of deep learning models in lung cancer classification. Furthermore, it looks into how well different machine learning and deep learning models—including Support Vector Machine (SVM) and convolutional neural networks (CNN) like InceptionV3, VGG16, Xception, ResNet50, and MobileNetV2—perform in the early detection of lung cancer from CT scan images. Following preprocessing, the SVM model's overall accuracy was 89%. The suggested method was used with the following dataset on five pre-trained models: ResNet50, In-ceptionV3, VGG16, Xception, and MobileNetV2: chest CT scan; The Mo-bileNetV2 model fared the best among the pre-trained CNN models, with the greatest accuracy of 98% and the lowest test loss. With an accuracy of 97%, the Xception model came in second. In terms of enhancing picture contrast and speeding up processing, the image pre-processing stage is crucial to system performance [10].

G. Lavanya et.al. aims to develop, an effective customized Convolutional Neural Network model that can accurately identify areas on CT scans that have lung nodules and those that do not. The study utilizes two datasets, the LUNA-16 dataset for training and the IQ-OTH/NCCD dataset for testing. Additionally, author employed a U-Net model for precise lung nodule segmentation. This segmentation approach aimed to achieve a comprehensive characterization of nodules based on their spatial characteristics. The testing phase involves evaluating the performance of the trained models on the dataset IQ-OTH/NCCD, particularly focusing on localizing nodules in malignant cases. Overall, the research highlights the effectiveness of DL in early recognition and analysis of lung cancer [11].

The goal of M. Jaeyalakshmi et al.'s study on lung cancer diagnosis using deep learning models and radiomics techniques is to improve cancer detection and extract tumor characteristics from chest CT images. The study concentrated on how deep learning and radiomics techniques may be seamlessly combined to improve cancer diagnosis and fully extract tumor traits [12].

Using the LeNet-5 algorithm, Dhayalini, M. et al. presented a unique method for the early and precise detection of lung cancer. Initially, a median filter is used for preprocessing. Cancerous nodules in lung images were segmented using a hybrid fuzzy with a genetic algorithm (GA). The dataset gathered by the Image Database Resource Initiative and the Lung Image Database Consortium is used to create the suggested LeNet-5 in MATLAB. Various performance parameters are compared and evaluated with existing algorithms and cutting-edge methods. The experimental outcomes demonstrate that the suggested algorithm has higher classification accuracy (99.2%) than other methods[13].

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By analyzing CT scan pictures, Karthikeyan, N. et al. presented a specific CNN framework that was painstakingly created for the early identification of lung cancer. Through rigorous comparative analyses with alternative models, the research highlights the CNN's superior performance, marking a substantial improvement over conventional diagnostic technique. The results accentuate the efficacy of the proposed deep learning model, solidifying its position as a more robust and potent diagnostic tool compared to prevailing approaches for the lung cancer early detection [14].

In this study, M.N. Satyanarayana et al. address the difficulties in detecting lung cancer early by putting forward an automated method that makes use of a variety of ML and image processing approaches. This study has utilized a collection of images including different lung cancer types and healthy lung tissue. By analyzing this data, deep understanding has gained on its properties. Then, this study has tested various machine learning models and selected the most accurate one for real-time implementation. The proposed system's effectiveness in lung cancer detection is finally analyzed by using performance evaluation. Finally, the system is deployed with a user-friendly interface to aid healthcare professionals in diagnosing lung cancer[15].

Genç, Muhittin and Akar, Funda highlights the benefits of AI in early lung cancer detection. This study used Gabor and Histogram Equalization+CLAHE filters to create 6 datasets. Two categories are used to evaluate CNN and YOLO lung cancer diagnostic outcomes. Image preprocessing evaluation is one of these kinds. The other looks at how success is impacted by dataset partitioning into training, testing, and validation. In dataset partitioning, the CNN model gets the highest F1 Score (70%-20%-10% and 60%-20%-20%) while employing the Histogram Equalization+CLAHE filter. 99% was the outcome. The YOLO model had the highest success rate with a 96% F1 Score using the identical preprocessing and dataset partition [16].

The research led by Soumya Vats et.al. leverages lung nodule images extracted from CT scans within the Lung 1 dataset, classifying them into adenocarcinoma and small-cell carcinoma categories. While the Support Vector Machine (SVM) learning technique is used for the classification job, the transfer learning algorithm VGG16 is used for feature selection. Notably, this approach yields a commendable accuracy of 98%, underscoring its potential significance in the realm of early lung cancer detection and patient care[17].

The goal of the study by D. Tai et al. was to create a method for diagnosing lung cancer using deep learning and radiomics. 1012 patients were gathered from an open-source database, while 86 patients were enlisted from Bach Mai Hospital. Initially, deep learning has been used in the U-NET segmentation process and the DenseNet model for cancer classification. Second, size, surface area, and volume were measured and computed using radiomics. Lastly, the hardware was created to read data from the tag by connecting the Arduino Nano to the MFRC522 module. Training accuracy was 0.98, validation loss was 0.498, train loss was 0.27, and validation loss for cancer classification was 0.78 using the segmentation model that was used [18].

A comprehensive and comparative framework for Identification of lung cancer using CNN is proposed to improve early diagnosis and increase survival rates. The CNN with PCA approach as a promising solution to address these challenges. By combining the strengths of CNNs for image analysis and PCA for feature extraction, the plan seeks to grow a robust and effective lung cancer detection system. The suggested technique is contrasted with the baseline method (SVM). The method SVM achieved accuracy upto 75.0%. Finally, the results also show that CNN outperforms the other ML algorithms. The proposed model gives high accuracy upto 98.548%[19].

Sirisha, J et.al. presents an in-depth investigation into the application of CNN models for lung cancer prediction using medical imaging data. Leveraging insights from previous ANN-based approaches, the author proposed novel CNN architectures and explore advanced techniques to enhance predictive performance. Through thorough testing and analysis, the study shows how well CNN models detect lung cancer from Computed Tomography (CT) scan pictures. Author finally also discussed the potential clinical implications and future directions for leveraging deep learning methods in lung cancer prediction and diagnosis[20].

METHODS

This study aims to develop a robust lung cancer classification model called **LungNet-RC** (Lung Cancer Detection using Recurrent-Convolutional Architecture) using a hybrid CNN-RNN architecture. The following sections describe

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the datasets, image preprocessing techniques, and model training strategies used in this research. The following diagram illustrates the system architecture.

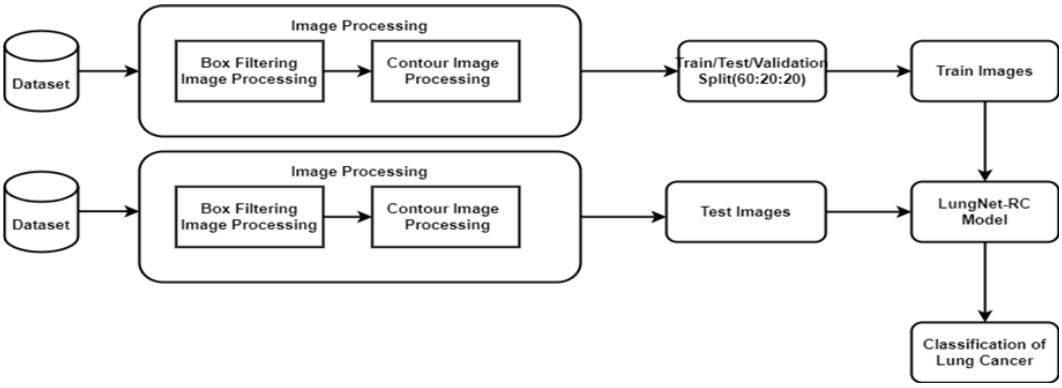

Figure 1: System Architecture

3.1. Datasets

In this work, two datasets were utilized to classify lung cancer from chest CT scan pictures:

- **LIDC-IDRI Dataset:** A sizable publicly accessible dataset created especially for lung nodule analysis and lung cancer research is the Lung Image Database Consortium Image Collection (LIDC-IDRI). This dataset contains 2,066 thoracic CT scans, totaling approximately 150 GB. After applying data augmentation techniques, the dataset size increased to 14,488 images. In a 60:20:20 ratio, the photos were separated into preparation, authentication, and challenging sets.
- **Chest CT Scan Dataset:** This dataset initially consisted of 1,000 chest CT pictures in JPEG format. By means of data amplification, 1,400 photos were added in total. Additionally, these photos were segmented using the same 60:20:20 ratio into preparation, authentication, and analysis sets.

3.2. Image Processing

Each image from the datasets underwent a series of pre-processing steps to enhance feature extraction and prepare them for model training. The steps included:

- **Box Filtering:** This initial step reduces image noise and enhances the clarity of the structures within each CT scan. Box filtering is particularly effective in smoothing the images while preserving essential details, which increases the model's capacity to identify features relevant to lung cancer classification.
- **Contour Image Processing:** After box filtering, contour processing was applied to highlight the boundaries of lung nodules and other relevant structures. This method improves the pictures' edge information, which is essential for differentiating between lung malignant and non-cancerous areas.

3.3. Data Augmentation

Methods of data augmentation were used to expand both datasets and enhance the model's generalizability. Random rotations, flips, zooming and brightness modifications were some of these methods. Data augmentation was essential to create a diverse dataset, which is particularly important given the variability in CT scan images among different patients.

3.4. Dataset Splitting

A 60:20:20 ratio was used to separate the two datasets into preparation, authentication, and analysis sets. This split ensures a balanced distribution across the datasets and enables the model to learn effectively while providing a means for unbiased performance evaluation.

3.5. Model Architecture: LungNet-RC

A hybrid model combining CNN and RNN was employed to classify lung cancer. The CNN component extracts altitudinal structures from the images, effectively capturing the spatial patterns associated with lung nodules. After

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the features were collected, they were sent to the RNN component, which improves the model's capacity to distinguish between malignant and non-cancerous instances by capturing contextual information and sequential patterns over several layers.

3.6. Training And Evaluation

The LungNet-RC hybrid model was trained using training photos, and the validation images were utilized to adjust the hyperparameters and track the representation's performance to avoid overfitting. The final evaluation was conducted on the test dataset, which provided an unbiased assessment of the model's classification accuracy.

This structured methodology ensures a robust and effective approach for lung cancer classification founded on chest CT scans, leveraging both the spatial and sequential patterns in the images to enhance predictive accuracy.

RESULTS

The findings from the dataset we utilized for our lung cancer detection research study will be covered in this part.

Dataset	Accuracy				Specificity	Sensitivity	AUC
	Train	Test	Validation	Overall			
LIDC	0.9937	0.9937	0.8700	0.9878	0.9888	0.9868	0.9878
Chest CT	0.9926	0.9975	0.7656	0.9988	0.9992	0.9976	1

Table 1: Train, test and Validation accuracy, specificity, sensitivity and AUC using LungNet-RC model

We have applied our proposed LungNet-RC model on both dataset LIDC and Chest CT Scan lung cancer dataset and results are encouraging. The results demonstrate high performance across all metrics for both the LIDC and Chest CT datasets. For the LIDC dataset, the model's total accuracy was 0.9878 and train accuracy as 0.9937, test accuracy as 0.9937 whereas validation accuracy was 0.8700, which is closely aligned with its specificity (0.9888) and sensitivity (0.9868). With no discernible bias toward false positives or false negatives, this balance indicates that the model is consistently successful in accurately recognizing both positive and negative situations. The model performs exceptionally well in class distinction, as seen by its strong discriminatory ability for the LIDC dataset and its AUC score of 0. 9878.With an overall accuracy of 0.9988 for the Chest CT dataset, the model outperformed the others, with train, test, and validation accuracy of 0.9926, 0.9975, and 0.7656, respectively. The specificity and sensitivity ethics of 0.9992 then 0.9976, correspondingly, reveal that the model is exceptionally reliable in differentiating between classes, with minimal misclassification of either type. Additionally, an AUC score of 1 highlights the model's near-perfect performance, underscoring its robustness and reliability on the Chest CT dataset.

These results suggest that the model is highly effective and could be considered for clinical or diagnostic applications, given its consistent and high-level performance across both datasets. The performance of proposed LungNet-RC model on the LIDC and Chest CT datasets demonstrates impressive accuracy, specificity, sensitivity, and AUC scores, placing it among the top-performing approaches in recent studies. Specifically, LungNet-RC model's overall accuracy on the LIDC dataset (0.9878) and Chest CT dataset (0.9988) surpasses the 93-95% accuracy range commonly achieved by recent models using similar datasets. For instance, recent algorithms integrating radiomics, CNNs, and Graph Convolutional Networks (GCNs) have reached accuracies around 94.57%, sensitivity of 93.69%, and AUC of approximately 0.9629 on LIDC datasets. These values highlight substantial performance yet fall slightly below your model's scores, particularly in sensitivity and AUC, where your model achieved 0.9868 and 0.9878, respectively, for the LIDC dataset[21]. Figure 2 show the accuracy and loss curve comparison for the proposed LungNet-RC model on both datasets i.e. LIDC and Chest CT Scan.

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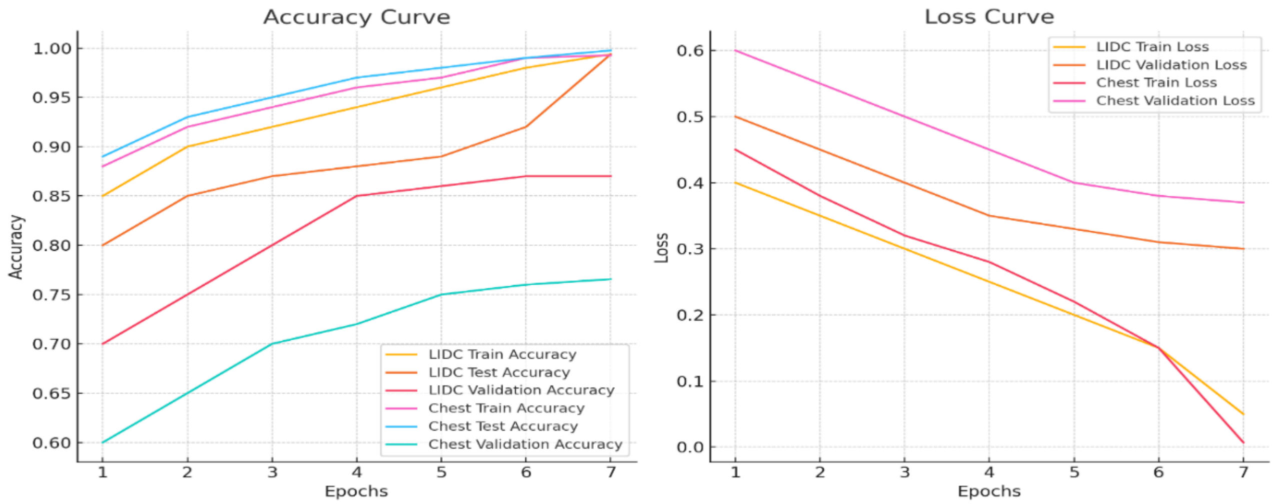

Figure 1: Accuracy and Loss Curve

DISCUSSION

Some of the latest methods using ensemble or deep learning models on the LIDC dataset have reached accuracy levels up to 97.6%, which is close to but slightly lower than LungNet-RC model's performance on the Chest CT dataset with an AUC score of 1.0. Such results show that LungNet-RC model not only meets but potentially exceeds state-of-the-art outcomes, indicating a high level of robustness and reliability that would be highly beneficial in clinical applications where high accuracy and discrimination (high AUC) are crucial[22].

Dataset	Study	Accuracy	Specificity	Sensitivity	AUC	Key Model/Algorithm Components
LIDC-IDRI	Proposed LungNet-RC Model	0.9878	0.9888	0.9868	0.9878	Hybrid model of CNN+RNN with box filtering and contouring
	[21]	0.9457	0.9421	0.9369	0.9629	Radiomics + CNN + GCN fusion
	[22]	0.9220 - 0.9760	0.9300	0.9000 - 0.9500	0.9500 - 0.9600	Traditional ML and DL methods
Chest CT Scan	Proposed LungNet-RC Model	0.9988	0.9992	0.9976	1.0	Hybrid model of CNN+RNN with box filtering and contouring
	[21](2022)	0.9600	0.9580	0.9400	0.9800	Deep Ensemble Learning

Table 2: Comparison of LungNet-RC model with existing work

Table 2 shows the comparison of proposed LungNet – RC model with existing work. Proposed model has given excellent results compared to existing models.

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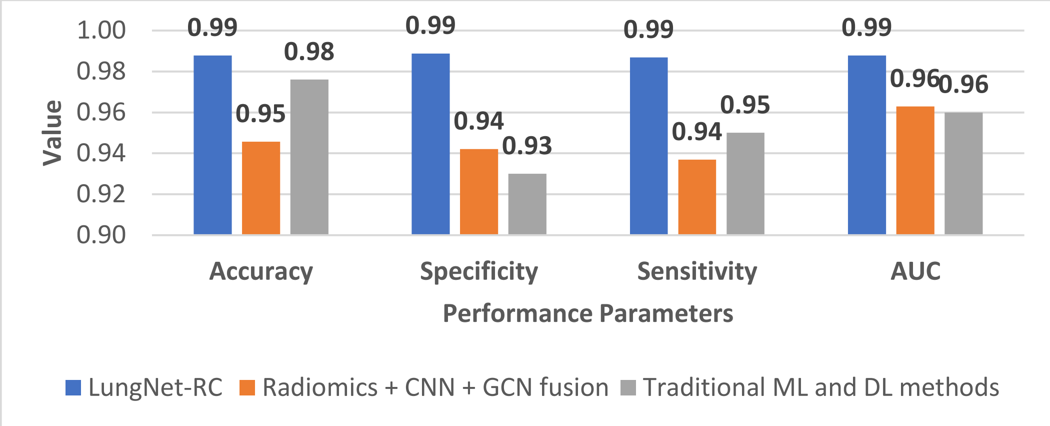

Figure 3: Comparative Analysis on LIDC Dataset

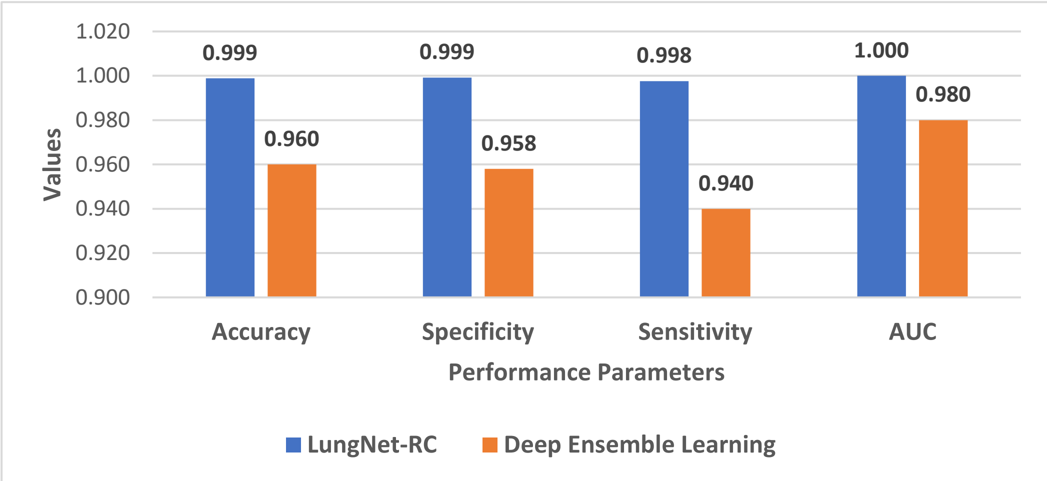

Figure 2: Comparative Analysis on Chest CT Scan Dataset

Figures 3 and 4 show the graphical analysis of comparison of the proposed model with existing model on LIDC and Chest-CT Scan dataset respectively. The proposed LungNet-RC model's performance on both datasets is consistently higher than recent studies, especially in specificity and AUC, where it outperforms other models that utilize complex architectures such as Radiomics-CNN-GCN fusions. The LungNet-RC model's higher sensitivity and accuracy rates, particularly on the Chest CT dataset (achieving a perfect AUC), indicate a potential for robust diagnostic applications.

CONCLUSION

The LungNet-RC model demonstrates robust performance in lung cancer classification, achieving high accuracy and reliability across both LIDC and Chest CT datasets. Its hybrid CNN-RNN architecture and comprehensive pre-processing techniques contribute to a balanced model that excels in differentiating between malignant and benign cases. These results indicate that LungNet-RC can be effectively used in clinical settings, potentially enhancing diagnostic accuracy and contributing to better patient outcomes. Future work could explore additional pre-trained networks and fine-tuning techniques to further enhance model accuracy. Additionally, extending LungNet-RC's application to other cancer types could increase its utility. Integrating radiomic features or incorporating attention mechanisms could provide more granular insights into tumor characteristics, further improving classification accuracy.

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