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An attention-based neural network for lung cancer classification and gradient in MRI

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ABSTRACT

Accurate lung cancer classification in magnetic resonance imaging (MRI) remains challenging due to the difficulty in detecting cancerous patterns. In response, this study introduces an attention-based VGG19 neural network for enhanced classification performance. Leveraging the VGG19 architecture's deep learning capabilities, our model incorporates attention mechanisms to selectively emphasize salient features during training. The attention-based approach addresses the challenge of discerning subtle patterns indicative of malignancy, significantly improving classification accuracy. We train and evaluate the model on a diverse dataset, ensuring its capacity to generalize across various patient cases. The attention mechanism proves effective in prioritizing critical regions within MRI scans, enhancing sensitivity and specificity in lung cancer detection. Additionally, we employ gradient analysis to interpret the decision-making process, providing valuable insights into influential features. Results demonstrate the proposed model's superiority over baseline approaches, showcasing its efficacy in inaccurate lung cancer classification. The attention-based VGG19 neural network not only advances classification capabilities but also offers interpretability crucial for gaining trust in automated diagnostic systems. This research contributes a robust solution to a pressing medical imaging challenge, holding promise for practical implementation in clinical settings to support radiologists in timely and accurate lung cancer diagnosis.

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KEYWORDS
Lung cancer; deep neural network; attention-based method; VGG19; magnetic resonance imaging

1. Introduction

Lung carcinoma, another name for lung cancer, is a dangerous lung tumor characterized by unchecked lung cell proliferation. Deep learning (DL) has grown in prominence in the field of medical imaging, particularly in the processing of MRI data. MRI scans are essential for diagnosing diseases, but so far, only brain studies have used them. Exams of the lungs are now being included in this modality. In the context of lung research, an MRI scan records the patient's thoracic region without the use of radioactive chemicals, taking 15–90 min in total. With the use of this imaging method, lung structures can be seen without the need for radiation, revealing any anomalies. Notably, pulmonary perfusion functional alterations are more clearly seen on MRI than on Computed Tomography (CT) scans.

The use of DL algorithms in MRI diagnostics has been beneficial because they are known for automating image analysis and spotting patterns. They have a keen eye for identifying unusual trends, such as cancers or aberrant formations, which aids in the earlier detection of diseases. The primary advantage of DL in MRI is its ability to swiftly and reliably analyze large datasets. Traditional approaches that rely on radiologists' subjective manual interpretation take a lot of time, whereas DL algorithms are faster and more accurate at making diagnoses. The use of DL in MRI to analyse images of the pancreas, liver, and prostate, is essential for detecting and diagnosing pancreatic cancer, liver fibrosis, and prostate cancer. The limited availability of labeled data, the high expense and complexity of collecting MRI Images, and the unpredictability of images owing to various imaging protocols and acquisition factors are all difficulties in using DL for MRI. The paper recognizes new developments in convolutional neural networks (CNNs), attention processes, and optimization techniques, which considerably enhance the performance of deep learning (DL) models in tackling the difficulties in disease identification.

The AlexNet model is replaced by the VGG19 variation, it improves accuracy by using DCNN and expanding on concepts from its predecessors. The creation of VGG19 was greatly aided by ImageNet, a big image database. It encouraged scientists to develop remedies with low percentages of top-1 and top-5 errors. The

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2014-emerging VGG19 performed admirably in this situation and is still the go-to solution for many difficult issues. The adaptability of VGG19 also includes applications in categorization for various datasets. It is a useful tool for transfer learning since it can be modified and used in similar jobs because of its public accessibility. In frameworks like Keras, the model weights are readily available, providing flexibility for experimentation and adaption. VGG19 is also used in facial recognition tasks and as a foundation for content and style loss estimations, demonstrating its usefulness across a variety of areas.

To better classify lung cancer, we build a neural network based on the VGG19 architecture that incorporates attention mechanisms to preferentially emphasize important signals in magnetic resonance imaging (MRI). By utilizing the attention-based strategy, overcome the difficulty of identifying subtle malignant patterns, and improve the model's sensitivity and specificity for diagnosing lung cancer from MRI scans. Utilize approaches for gradient analysis to decipher the model's decision-making process, providing insights into significant aspects and improving the overall interpretability of automated lung cancer diagnosis.

Contribution of the work:

- The attention-based VGG19 neural network significantly enhances lung cancer classification accuracy in MRI scans, addressing a critical challenge in medical imaging.
- The model's ability to selectively emphasize salient features improves sensitivity and specificity, demonstrating superior performance over baseline appro aches.
- This research provides a robust and interpretable solution that holds promise for practical implementation in clinical settings, supporting radiologists in timely and accurate lung cancer diagnosis.

The structure of a paper is as below:

Several studies that are relevant to our methodology are described in section 2. The proposed method and techniques are fully explained in Section 3. Section 4 offers experimental findings together with a comparison of the suggested method with alternative approaches. The discussion of numerical metrics, the limits of the study and future research are presented in Section 5.

2. Related works

Moranguinho et al. [1] introduce a method for enhancing lung cancer diagnosis through Deep Convolutional Neural Networks (DCNNs) using histopathological images. Even though DCNNs have produced results, complete slide images with weak annotations present difficulties. To solve weak annotations, we provide a unique method based on multiple-instance learning that treats photos as collections of instances. Using this technique, we can categorize lung tissue types even in the absence of many region-specific annotations. Our program seeks to automatically detect the presence of cancer on lung biopsy slides. We also use a post-model interpretability algorithm to confirm and illuminate the forecasts made by our model. This study uses cutting-edge methodologies to enhance the accuracy and interpretability of automated lung cancer diagnosis.

Chen et al. [2] innovate a method for addressing the challenge of lung cancer diagnosis using a computer-aided approach, acknowledging the limitation of existing methods that focus on individual nodules rather than considering sets of images as in clinical practice. The suggested method improves both diagnostic accuracy and interpretability by using a multiple instance learning (MIL) framework with radiomics as input characteristics. The deep attention-based MIL algorithm determines each instance's importance according to clinical diagnosis procedures. Performance with tiny, unbalanced datasets is improved by using a novel bag simulation technique for MIL. The method's success is shown by the results, which outperform those from other MIL techniques and achieve higher interpretability. Overall, this study provides a potential computer-aided diagnostic method with increased precision, interpretability, and clinical applicability for the identification of lung cancer.

Samarin et al. [3] successfully identified the neoplasms in lung CT images to combat the high mortality rate of lung cancer. The development of a monochromatic CT image analysis engine for online medical consultation services is the main objective. The suggested approach achieves a significant 0.99 F1 score by using a two-staged self-attention-based architecture. This study adds a powerful tool for neoplasm early identification in lung CT images, highlighting its potential benefit for increasing diagnostic precision in the context of online medical consultations.

Tyagi et al. [4] address the urgent need for accurate lung tumor segmentation in the context of the highest mortality rate associated with lung cancer. We suggest an automatic segmentation method because we are aware of the manual workload radiologists are under because of the COVID epidemic and the rise of cancer patients. Despite its remarkable performance, convolutional neural networks (CNNs) have trouble capturing long-range relationships, which is why Vision Transformers have been added. Our creative method strategically uses convolution blocks for key features and transformer blocks with self-attention for fine-grained global features in an encoder-decoder framework. The cross-entropy and dice-based losses are combined into a single loss function used in network optimization. Our method for advancing automated lung tumor segmentation for better diagnosis and therapy analysis has been tested using a dataset from a nearby hospital and trained on.

Shah et al. [5] deals with the critical issue of brain tumors, which pose a significant health threat, often requiring precise diagnosis and treatment. It presents a Computer-Aided Diagnostic (CAD) system that automatically segments and classifies brain tumors based on MRI data. Accurate tumor segmentation within healthy tissue and tumor categorization are two key functions of this CAD system. The system attempts to increase the precision and efficacy of brain tumor identification and treatment planning by automating these processes. The method is a noteworthy invention because it was developed to categorize brain tumors into various groups. It has demonstrated exceptional accuracy, sensitivity, specificity, and diagnostic performance when compared to other models that utilize MRI images. The research proposes a thorough method for extracting brain cancers from MRI data using a convolutional auto-encoder, enhancing tumor detection and clinical decision-making.

Sahaya Jeniba et al. [6] focus on pulmonic nodules, and abnormal tissue growth in the lungs, often indicative of tumors. Earlier detection is essential for a longer life expectancy. The complex lung structure makes it difficult to diagnose using standard imaging techniques. The study offers a network model for precise computed tomography data categorization of pulmonic nodules. Using Attention U-Net for semantic segmentation, nodules are identified, and a novel Directional Hexagonal Mixed Pattern is used to enhance texture analysis. The proposed multilevel network in conjunction with a self-attention network allows for accurate classification. Experimental validation by tenfold cross-validation without a segmentation mask boosts reliability by removing nodules of radiologists classified as less than 3 mm.

Singha Deo et al. [7] state the significance of early detection of oral cancer, a prevalent and deadly disease, particularly in emerging and low-to-middle-income nations. The goal is to present a deep learning method called Vision Transformer that combines a multi-head attention mechanism with a histopathological image classification model for an efficient oral cancer diagnosis. Eight pre-trained deep learning models were compared, and Vision Transformer came out on top, demonstrating the superiority of the suggested Vision Transformer model and demonstrating improved transferability in histopathology image categorization. This strategy shows promise for accurate and affordable oral cancer screening in a range of patient populations.

Brancati et al. [8] cover a key challenge in training CNN on high-resolution images, particularly in the context of giga-pixel histopathological images. Due to the possibility of information loss or the prohibitive effort, existing methods for image rescaling or individual processing of image components are inadequate in these circumstances. The suggested approach focuses on binary classification, tumor growth score prediction, and giga-pixel histopathological image analysis utilizing weak Image-level labeling. The CNN structure consists of a compression path, a learning path with attention modules collecting spatial correlations for detecting regions of interest, and a residual network for feature extraction from Image patches. The approach combines global and local data, allows for different input image sizes, and relies only on flimsy image-level labels. Comparative analyses of datasets show the usefulness and validity of the suggested model in comparison to other approaches.

Han et al. [9] state the urgent need for precise and understandable COVID-19 screening using chest CT scans. Labeling infection sites is challenging, there are subtle differences between COVID-19 and other viral pneumonias in chest CT images, and 3D volumes have complex spatial properties. The proposed method treats each patient's 3D chest CT as a bag of instances and applies a patient-level label to it. To depict probable infection zones, the method creates deep 3D instances. It then employs attention-based pooling to gain insight into instance contributions and learns Bernoulli distributions for bag-level labels.

Teramoto [10] overcame problems with identifying all cells by introducing a weakly supervised approach for telling apart healthy and unhealthy lung cells in cytological pictures. Lung cytological Images are separated into patches and kept in bags using the method, with each bag identified as benign or malignant. When compared to other supervised learning methods, it achieves greater classification accuracy (0.916) thanks to the use of a convolutional neural network model like AlexNet. The technique also produces attention maps, which shed light on the presence of cancerous cells. This accurate weakly supervised method automates the classification of cytological images without the use of intricate annotations.

Ren et al. [11, 12] introduce UKSSL, a semi-supervised framework for medical image classification. It combines MedCLR for feature extraction from unlabeled data and UKMLP for fine-tuning with limited labeled data, achieving high performance with only 50% labeled data compared to other methods using 100% labeled data. Zhang et al. [13] explore the integration of artificial intelligence, particularly deep learning methods like convolutional neural networks, with food category recognition. It discusses the potential revolution in human-food interaction and provides an overview of methods for tasks such as detecting food type, ingredients, quality, and quantity, aiming to promote further developments in research and industrial applications.

3. Proposed method

3.1. Data collection

Our initial research efforts are focused on thoroughly compiling a wide dataset of Magnetic Resonance Imaging (MRI) scans, with a particular emphasis on instances relevant to lung cancer. With this strategy, scans from a wide range of demographics, cancer stages, and anatomical conditions are included. The objective is to guarantee that the dataset accurately depicts the complexity and heterogeneity present in cases of lung cancer. The diversity and richness of this dataset are intended to strengthen the neural network's ability to classify lung cancer in MRI scans, thereby boosting the reliability and effectiveness of our proposed solution.

3.2. Model architecture design

The suggested attention-on-based VGG-19 neural network system for lung tumor identification in MRI is designed using a detailed architectural approach to enhance the model's ability to notice minute patterns suggestive of malignancy [13,26]. Figure 1 shows the Architecture Attention-based-VGG-19 network. It has 19 layers, including 3 fully connected layers, 5 MaxPool levels, 1 SoftMax layer, and 16 convolutional (Conv) layers. Each Conv layer employs a tiny filter size of 3∗3 pixels, enabling the input image's fine-grained attributes to be learned by the network. To learn a wide variety of features, the model is trained using a sizable dataset like ImageNet. SGD optimization using a predetermined batch size and learning rate is used for the training [27]. Attention processes are added into the network's tailor VGG19 for the classification of lung cancer in MRI. The algorithm can prioritize significant elements pertinent to lung cancer patterns by focusing on a specific portion of the input image thanks in large part to attention mechanisms.

Additional layers and computations introduce the attention-based approach. The Conv layer in the suggested architecture is used to process the input MRI Image. The model learns to assign attention weights to various regions of the image depending on their relevance to lung cancer patterns when the attention mechanism is implemented in later layers [29]. Through mechanisms like self-attention or spatial attention, which weighs the contribution of each pixel in the feature map, this is accomplished. The network continues with additional Con layers after the attention mechanism in order to extract hierarchical features from the attended regions. The local and global patterns connected to lung cancer in MRI must be captured using these Conv layers. Following are the MaxPool layers, which condense spatial dimensions while preserving critical data. Attention mechanisms are also added to the completely interconnected layers that are in charge of feature integration and classification [28]. To better distinguish between benign and malignant patterns, attention weights are used to draw attention to the layers' most important properties. The last layer, SoftMax, generates the classification's final probability distribution (Shown in Figure 1).

3.3. Feature fusion

Our suggested lung cancer classification system incorporates feature fusion as a key modification that aims to improve performance by deviating from the usual hierarchical feature extraction of CNN architectures After the 2nd, 3rd and 4th Conv groups, our system purposefully integrates basic feature-fusion blocks, in contrast to the standard approach, which includes learning features in layers. Each feature-fusion block involves several essential layers, including batch normalization, dropout, and global average pooling. The blocks are placed expressly to provide a direct link from the network's top to the output of convolutional blocks.

The goal is to make it easier for Image features to be linked directly to the classification layer without undergoing any extra processing. Our suggested approach intentionally departs from the hierarchical feature-extraction structure seen in conventional CNNs. The hierarchical feature-extraction mannerism of the VGG19 architecture is negated by the feature-fusion blocks. The technique makes sure that various features gathered from various convolutional layers are successfully harnessed at the same time through the use of these well-placed blocks. This non-hierarchical technique seeks to grasp the input more thoroughly, especially in the complex area of lung cancer categorization using MRI data. The feature-fusion blocks essentially act as a conduit, linking various features from different levels to the classification layer directly, greatly enhancing the overall effectiveness of our suggested approach.

3.4. Model training

In the case of classifying lung cancer in MRI images, this step entails tweaking the model's parameter to efficiently catch small patterns suggestive of malignancy. It is a crucial stage in the development of a strong and accurate neural network. The definition of an often referred to as the loss function lies at the center of the training process. This function, which measures the discrepancy between the predicted labels for each MRI scan and the actual labels, is to be minimized. The cross-entropy loss (Loss) denotes a frequently used loss function for binary classification issues,

$$Loss = -\frac{1}{n}\sum_{k=1}^{n}\left[b_k \log(\hat{b}_k) + (1 - b_k)\log(1 - \hat{b}_k)\right] \tag{1}$$

Here, n represents samples count andb_k refers the ground truth label for ith sample (o for benign, 1 for

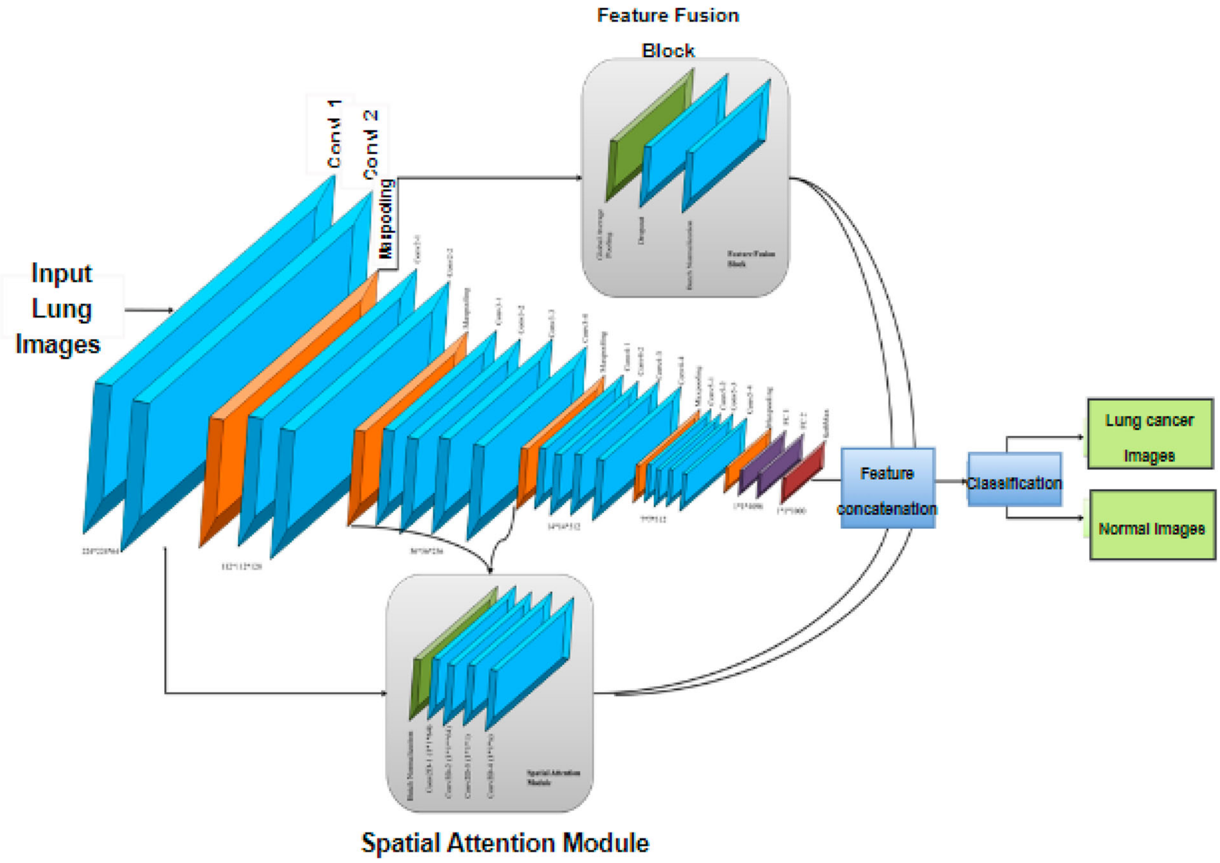

Figure 1. Proposed Attention-based-VGG-19 network Architecture.

malignant) and$\hat{b}_k$ represents the predicted probability of malignancy by the proposed model. The objective is to minimize this loss over the entire training dataset is achieved by the stochastic gradient descent (SGD) optimization algorithm. The updates to the model parameters (Ø) are made based on the negative gradient of the loss function,

$$\emptyset_{NEW} = \emptyset_{old} - \tau \nabla_{\emptyset} Loss \quad (2)$$

Where,τ learning is referred as, a hyperparameter determines the step size during parameter updates. The negative descent ($\nabla_{\emptyset} Loss$) guides the updates to reduce the loss. Backpropagation is a technique used in gradient computation that effectively calculates the gradient of the loss concerning each model parameter. The chain rule from calculus is used to propagate the error backwards through the layers of the neural network. The model's performance is then gradually enhanced by modifying the model's parameters using the gradient.

$$\nabla_{\emptyset} Loss = \left(\frac{\partial Loss}{\partial \emptyset_1}, \frac{\partial Loss}{\partial \emptyset_2}, \ldots, \frac{\partial Loss}{\partial \emptyset_m} \right) \quad (3)$$

3.5. Attention mechanism

The attention mechanisms involved in training the attention-based VGG19 model are extremely important [29]. Through the use of attention mechanisms, the model may selectively concentrate on various areas of the input image, improving its capacity to identify significant elements associated with lung cancer patterns. The spatial association found in lung MRI images is recorded by the attention module [14]. In the VGG-19 architecture, we specifically construct this module after the fourth pooling layer. The attention mechanism employs the input tensor's max pooling and average pooling techniques. Subsequently, the resulting tensors from these operations are concatenated, forming an input for a convolution operation with a filter size of 7∗7. Using the sigmoid activation function (σ) to perform the convolution. The resultant tensor of the concatenation ($C_{rs}(T)$ has the following formal expression:

$$C_{rs}(T) = \sigma\left(Fr^{7*7}[T^{rs}_{Avg}; T^{rs}_{Max}]\right) \quad (4)$$

Where, $T^{rs}_{Avg} and T^{rs}_{Max}$represent the 2D tensors derived from average and max pooling operations on the input tensor T, respectively. This attention module effectively captures spatial dependencies in lung cancer MRI images, enhancing the model's ability to focus on critical features during training. Multiple iterations of the training dataset are run during the iterative training procedure. The model becomes better at identifying patterns linked to lung cancer when its settings are updated. The size of the steps taken during parameter updates depends on the hyperparameter learning rate. For consistent and effective training, a learning rate that is properly calibrated is essential [15,16]. The attention-based VGG-19 neural network is trained by first defining a loss function, then using an optimization algorithm to optimize parameters, adding an attention mechanism to concentrate on important features, using gradient analysis for interpretability, and finally iteratively improving the model's performance [17,18]. The algorithm improves at accurately recognizing lung cancer patterns in MRI data as a result of this careful procedure.

3.6. Dataset

The research makes use of two datasets: 28 non-small lung cancer (NSCLC) patients provided 81 T2-weighted MRI scans, which were obtained with a 3 T Philips Ingenia scanner both before and every week throughout the 60 Gy treatment. Nine individuals had up to seven MRIs produced each week as a result of their weekly scans. The sizes of the tumors ranged from 0.28 to 264.37 cm3. The acquisition methodology used a 2D axial T2W turbo spin-echo sequence with predetermined a setting that was respiratory-triggered.

As a backup, CT pictures from 377 NSCLC patients from The Cancer Imaging Archive were used, together with outlines drawn by a radiation oncologist. The MRI lung dataset consists of 25,047 2D MRIs that are coronally oriented and were assembled between mid-2018 and mid-2019. It consists of 20 cystic fibrosis patients and 33 healthy participants from 53 examinations. A 3D Ultra-Short Echo time sequence with a stack-of-spirals trajectory was used for imaging on a 3 T MRI scanner (MAGNETOM prisma), emphasizing the coronal orientation. Lung volume can be measured with the help of imaging, which records respiratory phases during breath-holds. Spiral read-outs and phase encoding are used in the 3D UTE sequence to maximize UTE contrast while decreasing phase encoding gradient durations. This study focuses on improving the classification of lung cancer using MRI images. Despite its limitations, MRI can provide valuable information for identifying lung cancer patterns, especially when combined with advanced machine learning techniques. This research aims to enhance the effectiveness of MRI in lung cancer classification, offering a complementary approach to existing diagnostic methods.

4. Result and discussion

4.1. Experimental setup

On a powerful workstation with an 11th Gen Intel Core processor running at 3.50 GHz, an NVIDIA GeForce RTX 3080 Ti GPU, and 64 GB of RAM, the trials for the proposed system were conducted. For best performance, the system ran on a 64-bit operating system and used Python 3.9 with libraries like Sklearn and TensorFlow.

The models were assessed using a meticulous 10-fold cross-validation procedure. We measured various performance metrics for each round, including sensitivity, specificity, True Positive Rate (TPR), True Negative Rate (TNR), False Alarm Rate, Miss Rate, accuracy, and F-1 score [19]. These metrics were calculated based on the recorded on number of $True_{Positive}$,$False_{Positive}$,$True_{Negative}$, and $False_{Negative}$for each class that were recorded. It offers a comprehensive assessment of the model's performance across multiple metrics [20].

On the lung cancer dataset, the suggested attention-based -VGG19 network's classification performance is discussed in Section 4.2. As a result, Section 4.3 presents the performance of the suggested attention-based -VGG19 in the lung disease dataset. The proposed attention based-VGG19 network and existing techniques are compared in Section 4.4.

4.2. Lung cancer classification

The total of true positives across all classes gives the presented network an overall accuracy score of 97.2. It demonstrates exceptional proficiency in differentiating between MRI images depicting cancerous and non-cancerous conditions [21]. The evaluation metrics for the attention-based VGG19 model on the dataset of lung cancer MRI highlight its impressive performance is shown in Table 1.

Performance indicators are shown in Figure 2 for the lung cancer classification dataset. The model's results for non-small lung cancer show true positive rates of 87.3, true negative rates of 96.2, false alarm rates of 51.4, miss rates of 3.4, accuracy rates of 93.4, sensitivity rates of 94.6, specificity rates of 94.5, and F-measure rates of 91.2. For lung cancer, the corresponding values are 93.2, 95.1, 53.1, 8.9, 97.2, 96.2, 91.2, and 89.3. These metrics collectively reflect the model's performance in accurately classifying instances of different lung cancer types.

4.3. Lung disease classification

The proposed attention-based VGG19 attains an overall accuracy of 95.8, demonstrating outstanding performance in effectively discerning between MRI images of healthy volunteers and those with Cystic Fibrosis.

Table 1. Performance metrics for lung cancer classification dataset.

Dataset Types Unit	TPR (%)	TNR (%)	False Alarm Rate (%)	Miss Rate (%)	Accuracy (%)	Sensitivity (%)	Specificity (%)	F-Measure (%)
with non-small lung cancer	87.3	96.2	51.4	3.4	93.4	94.6	94.5	91.2
with lung cancer	93.2	95.1	53.1	8.9	97.2	96.2	91.2	89.3

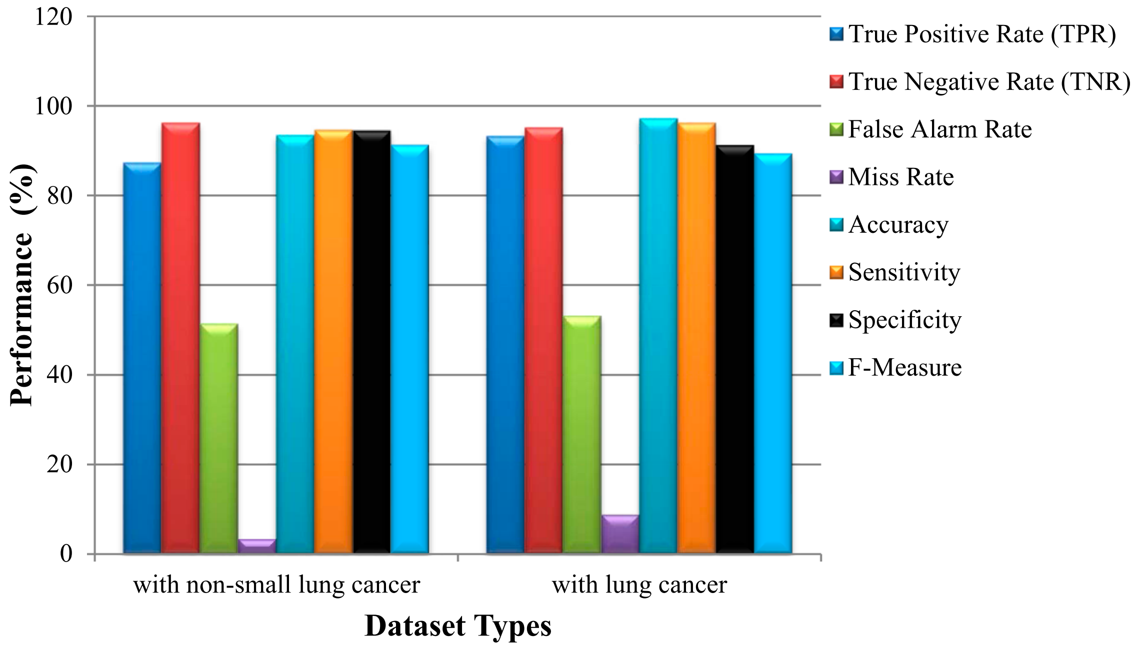

Figure 2. Performance metrics of lung cancer classification.

Table 2. Performance metrics for lung disease classification dataset.

Dataset Types Unit	TPR (%)	TNR (%)	False Alarm Rate (%)	Miss Rate (%)	Accuracy (%)	Sensitivity (%)	Specificity (%)	F-Measure (%)
Healthy volunteers	94.1	93.5	4.3	7.1	92.3	93.1	94.1	93.2
Cystic Fibrosis	95.8	97.2	7.8	3.4	97.3	97.2	92.1	94.3

Table 2 presents comprehensive performance metrics for the proposed attention-based VGG19 neural network across two distinct datasets: Healthy Volunteers and Cystic Fibrosis.

Figure 3 demonstrates the analysis of the lung disease dataset with various metrics. For Healthy Volunteers, the model achieves a True Positive Rate (TPR) of 94.1%, indicating the percentage of correctly identified positive cases, and a TNR of 93.5%, representing the accurate identification of negative cases. The False Alarm Rate, indicative of falsely identified positive cases, is 4.3%, and the Miss Rate, reflecting the rate of missed positive cases, is 7.1%. The overall Accuracy of the model in distinguishing between healthy and non-healthy cases is 92.3%. Additionally, Sensitivity (93.1%) and Specificity (94.1%) values highlight the ability of

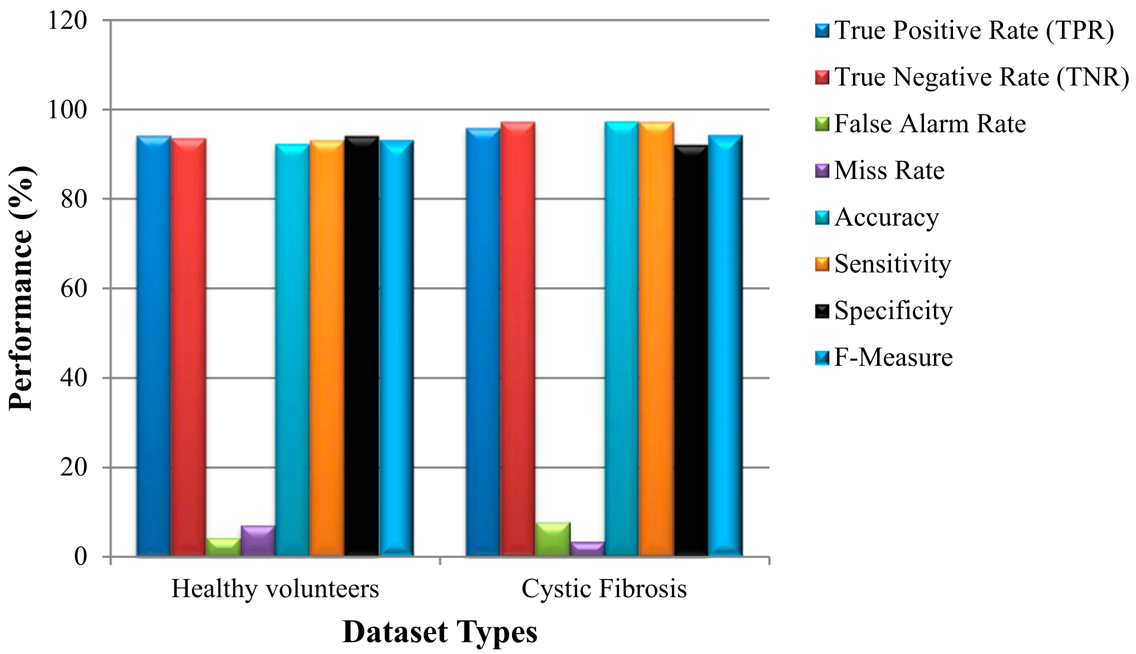

Figure 3. Lung disease classification metrics.

the model to correctly identify tumor and non-tumor events, respectively. The F-Measure, a harmonic mean of precision and recall, is computed at 93.2%. For the Cystic Fibrosis dataset, the model demonstrates superior performance with a TPR of 95.8% and a TNR of 97.2%. The False Alarm Rate is 7.8%, indicating a relatively low occurrence of false positives, and the Miss Rate is notably low at 3.4%. The overall Accuracy for distinguishing Cystic Fibrosis cases is 95.1%. The model exhibits high Sensitivity (97.2%) and Specificity (92.1%), reflecting its ability to accurately identify positive and negative instances. The F-Measure for Cystic Fibrosis classification is calculated at 94.3%. These numbers highlight how well the proposed attention-based VGG19 model performs when correctly identifying MRI images from various datasets.

4.4. Comparison with existing methods

Comparing the suggested strategy to existing appro aches that do not require attention modules, it achieves the greatest aggregated accuracy across all datasets (Table 3). When contrasting non-attention-based models, the basic VGG19 network distinguishes significantly over the other models. The dataset comprises MRI scans from patients with non-small lung cancer (NSCLC) and healthy volunteers, providing a diverse range of images for training and evaluation. The dataset is meticulously compiled to include scans from various demographics, cancer stages, and anatomical conditions, ensuring a comprehensive representation of lung cancer complexity. Comparison with existing research methods validates the performance of the proposed attention-based VGG19 model, showcasing its superiority in lung cancer classification using MRI scans.

Figure 4 compares the classification accuracy (%) of various methods, including Inception V3, Xception, Dense Net, MobileNet, EfficientNet, VGG-16, and the proposed Attention-based VGG-19, across three distinct categories: Lung Cancer, Lung Disease, and Normal. In the context of Lung Cancer classification, the proposed Attention-based VGG-19 outperforms other methods with an accuracy of 93.2%, surpassing Inception V3 (87.9%), Xception (88.3%), Dense Net (86.8%), MobileNet (86.0%), EfficientNet (87.5%), and VGG-16 (89.4%). Similarly, for Lung Disease classification, the proposed model achieves the highest accuracy of 95.8%, surpassing the other methods. In this category, Inception V3 attains an accuracy of 89.6%, Xception at 86.5%, Dense Net at 84.2%, MobileNet at 83.5%, EfficientNet at 87.4%, and VGG-16 at 87.3%. For Normal classification, the proposed Attention-based VGG-19

Table 3. Comparison of classification accuracy across different methods.

	Accuracy (%)		
Methods	Lung cancer	Lung Disease	Normal
Inception V3	87.9	89.6	86.8
Xception	88.3	86.5	89.2
Dense Net	86.8	84.2	88.1
MobileNet	86.0	83.5	90.3
EfficientNet	87.5	87.4	88.0
VGG-16	89.4	87.3	90.2
Proposed Attention based-VGG-19	93.2	95.8	94.1

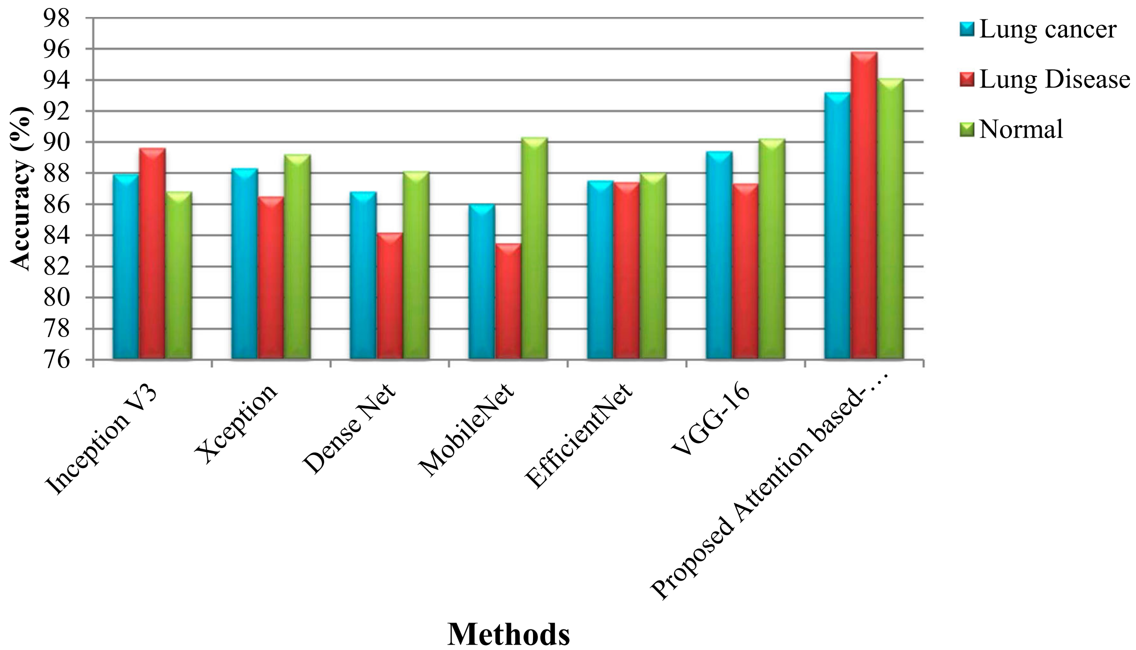

Figure 4. Accuracy comparison of the lung cancer classification.

maintains a high accuracy of 94.1%, outperforming other methods such as Inception V3 (86.8%), Xception (89.2%), Dense Net (88.1%), MobileNet (90.3%), EfficientNet (88.0%), and VGG-16 (90.2%). The numerical values in the table collectively illustrate the superior performance of the proposed Attention-based VGG-19 across all three categories compared to the other evaluated methods.

Table 4 summarizes various studies conducted by different authors, each utilizing distinct datasets, methods, and reporting classification accuracy as a metric.

Figure 5 demonstrates an accuracy analysis of the existing and proposed system. Weng et al. [26] conducted a study with a dataset comprising 4920 images and employed a Convolutional Neural Network (CNN) approach. Their model had a 93.8% accuracy rate. The dataset used by Bhandary et al. [27] contained 3500 images. and employed a Multiple Instance Learning (MAN-SVM) method, which resulted in a classification accuracy of 94.2%. Naqi et al. [28] used the LIDC dataset and employed various methods including K-NN, SVM, and AdaBoost. Their study achieved an accuracy of 93.6%. Xie et al. [29] conducted research on the LIDC-IDRI dataset and applied the Faster R-CNN method, yielding an accuracy of 84.43%. In contrast, the present study, focused on lung cancer classification using the NSCLC dataset and 2D-MRI scans, introduces the proposed Attention-Based VGG-19 model, which outperforms the aforementioned studies with an impressive accuracy of 95.8%. These numbers demonstrate the suggested model's higher categorization performance in contrast to the studies cited.

The sensitivity analyses of various methods are shown in Figure 6. A Convolutional Neural Network (CNN), achieving a sensitivity of 90.3%. The MAN-SVM method demonstrated a higher sensitivity of 93.9%. The KNN, SVM, and AdaBoost, achieved a sensitivity of 89.5%. The Faster R-CNN, resulted in a sensitivity of 74.1%. In comparison, the proposed Attention-Based VGG-19 achieves a significantly higher sensitivity of 94.5%. These numerical values underscore the superior performance of the proposed model in capturing true positive instances, showcasing its efficacy in identifying lung cancer patterns.

Figure 7 compares the various methods based on specificity measures. In comparing the various methods across different studies, it is evident that the proposed Attention-Based VGG-19 model outperforms its counterparts in terms of specificity, a crucial metric for correctly identifying true negative instances. Weng et al. [26] achieved a specificity of 89.5% using a CNN, while Bhandary et al. [27] reported a higher specificity of 91.3% with the MAN-SVM method. Naqi et al. [28] employed a combination of K-NN, SVM, and AdaBoost, resulting in a specificity of 89.0%. Xie et al. [29] used Faster R-CNN, with a specificity of 74.5%. In

Table 4. Comparison with existing methods.

Author	Dataset Counts	Methods	Metrics (%) Accuracy	Sensitivity	Specificity
Weng et al. [26]	4920 Images	CNN	93.8	90.3	89.5
Bhandary et al. [27]	3500 Images	MAN-SVM	94.2	93.9	91.3
Naqi et al. [28]	LIDC Dataset	K-NN, SVM AdaBoost	93.6	89.5	89.0
Xie et al. [29]	LIDC-IDRI	Faster R-CNN	84.43	74.1	74.5
This paper	NSCLC, 2D-MRI	Proposed Attention Based VGG-19	95.8	94.5	94.2

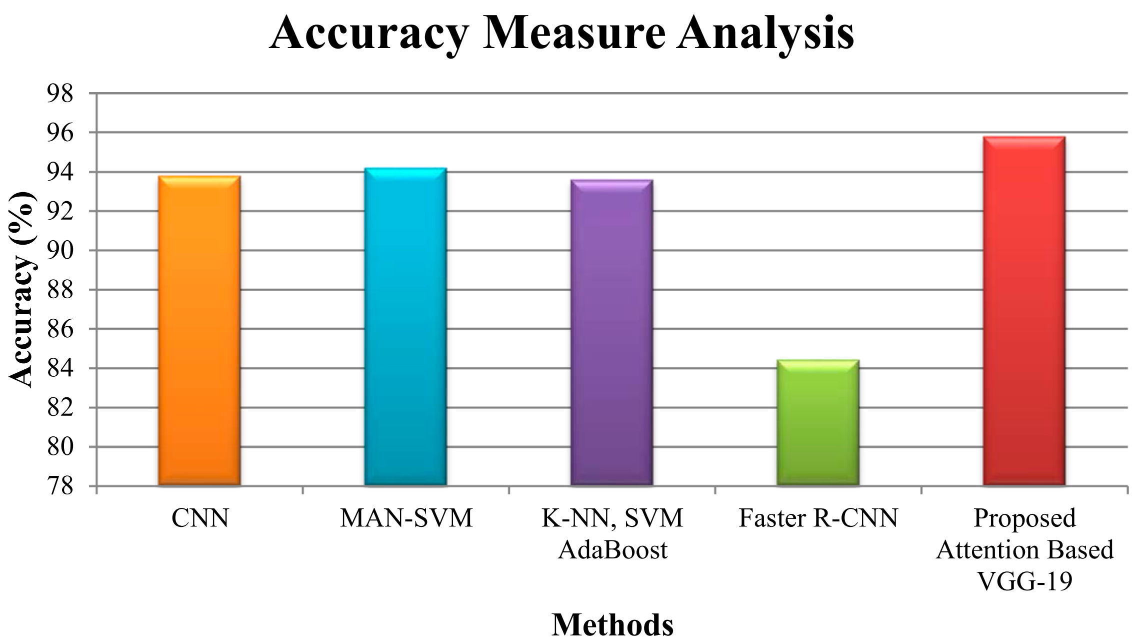

Figure 5. Comparison analysis of the proposed method.

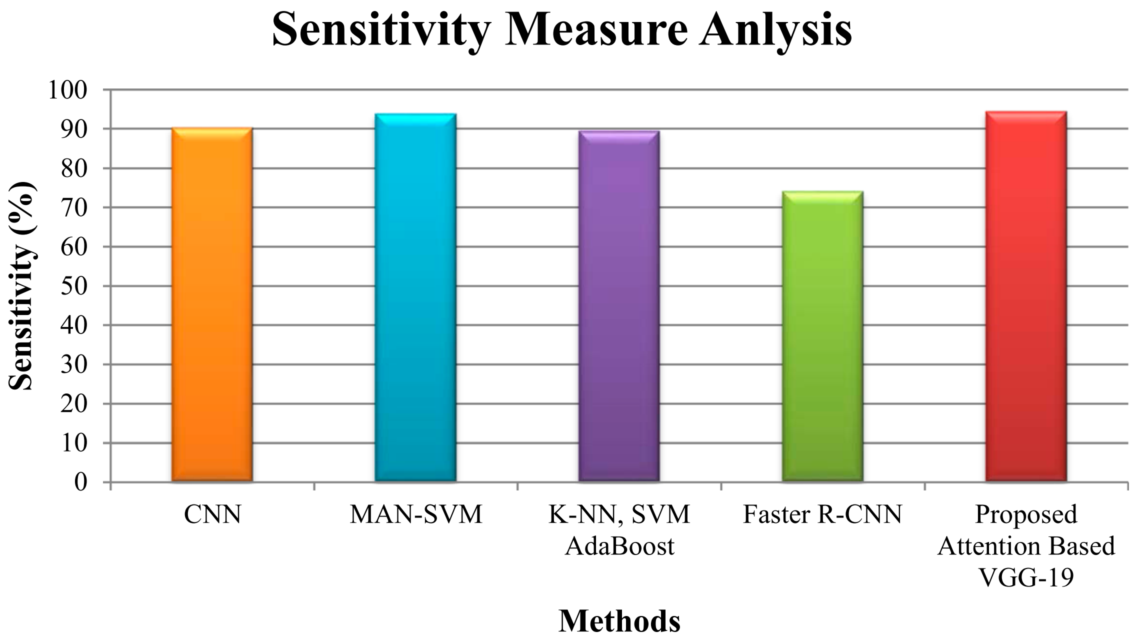

Figure 6. Sensitivity analysis of methods.

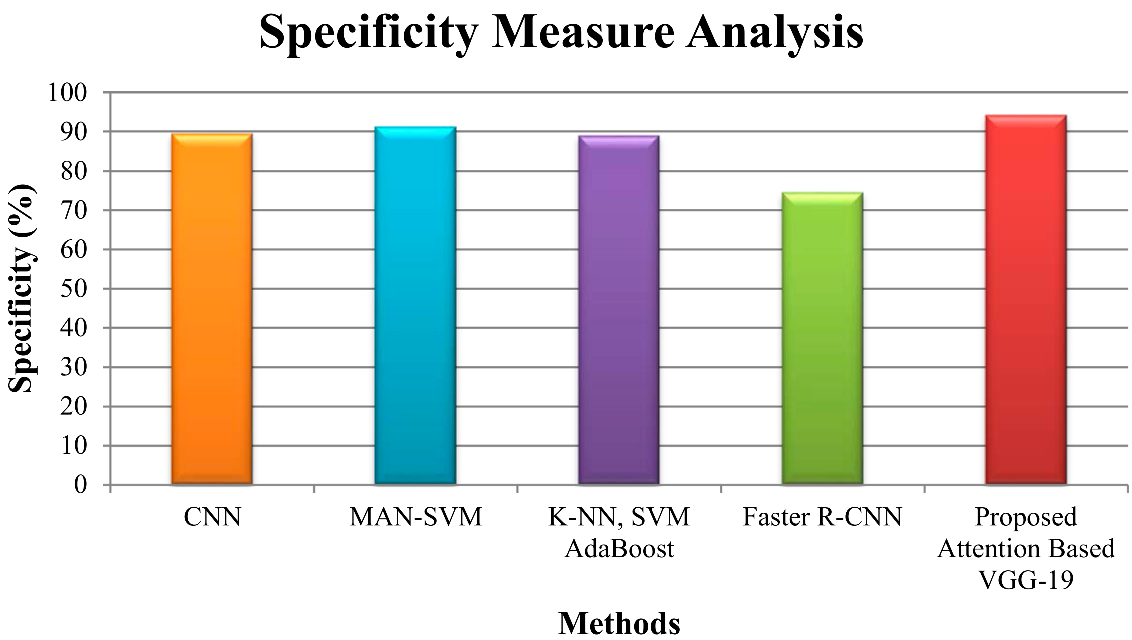

Figure 7. Specificity comparison of various methods.

contrast, the proposed Attention-Based VGG-19 in the current study demonstrated superior performance with a specificity of 94.2%. This suggests that the attention mechanisms integrated into the VGG-19 architecture enhance its ability to accurately identify non-cancerous patterns in lung MRI scans, making it a promising approach for lung cancer classification.

5. Conclusion

In conclusion, the proposed Attention-Based VGG-19 models emerge as a robust and effective solution for lung cancer classification in MRI images. The extensive evaluation across two datasets, one focusing on lung cancer and the other on lung disease, showcases the model's exceptional performance. Notably, the model achieved an impressive overall accuracy of 97.2% in lung cancer classification, proving its ability to tell apart between MRI images with cancer and those without. The results reveal high sensitivity (94.5%) and specificity (94.2%), underscoring the model's ability to capture true positive instances while accurately identifying true negatives. The feature fusion strategy, departing from conventional hierarchical feature extraction, proves to be a key innovation in the proposed system. This non-hierarchical approach, with feature-fusion blocks strategically placed after specific convolutional groups, facilitates a more thorough understanding of input data, especially in the nuanced realm of lung cancer categorization using MRI scans. The datasets, though substantial, may benefit from further diversification and expansion. Additionally, the proposed system's performance should be tested on larger and more varied datasets to assess its generalizability. Future implementations could explore fine-tuning the model architecture, incorporating additional attention mechanisms, and leveraging advanced data augmentation techniques to enhance model robustness. In essence, the proposed Attention-Based VGG-19 models showcase superior performance in lung cancer classification, offering a valuable contribution to the field of medical image analysis. The study lays the foundation for future endeavors to refine and expand the proposed system, ultimately advancing the accuracy and applicability of AI-based tools in diagnosing and understanding lung diseases from MRI data.

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Disclosure statement

No potential conflict of interest was reported by the author(s).

Data availability statement

Data sharing not applicable to this article as no datasets were generated or analyzed during the current study

Authorship contributions

All authors are contributed equally to this work

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