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(RESEARCH ARTICLE)

Automatic detection of lung nodules in computed tomography images using U-Net

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Abstract

Lung cancer is one of the leading causes of cancer-related deaths methods for lung nodules in computed tomography (CT) images rely on manual interpretation by radiologist, which can be time-consuming and prone to human error. This paper presents BreathSafe.AI a deep learning system for the automatic detection and segmentation of lung nodules in CT images using an enhanced U-Net architecture combined with dense network techniques. Our model is trained on the LUNA16 dataset, utilizing advanced image preprocessing and segmentation methods to optimize nodule detection. This system achieves a diagnostic accuracy of over 90%, significantly improving detection speed and consistency compared to existing methods. The results highlight the system's potential to enhance lung cancer screening by reducing diagnosis time and variability, making it valuable tool for clinical use. Our approach demonstrates superior performance compared to state-of -art techniques, offering a scalable and efficient solution for early detection of lung cancer.

Keywords: Lung cancer detection; Computed tomography; U-Net; Deep learning; Medical image segmentation

1. Introduction

Lung cancer is the leading cause of cancer-related deaths worldwide, accounting for approximately 18.4% of all cancer deaths, surpassing other common types such as breast, colorectal, and prostate cancer [1]. Early detection is crucial for improving survival rates, as it allows for timely treatment before the disease advances to irreversible stages. Computed tomography (CT) imaging is the most used method for detection lung nodules, which are early indicators of lung cancer. The manual interpretation of these images by radiologists is not only time-consuming, but also susceptible to human error. This process often leads to variability in diagnosis due to fatigue and subjectivity, which can compromise the accuracy of early detection. Furthermore, the growing global incidence of lung diseases, including lung cancer and complications from COVID-19, exacerbates the challenges faced by healthcare systems. These diseases are frequently diagnosed in later stages, complicating treatment and reducing survival chances.

The global rise in lung diseases, including lung cancer and complications resulting from COVID-19, represents a significant challenge to healthcare systems. These conditions are often diagnosed late, which aggravates their management and reduces patient's chances of survival. Traditional diagnostic methods, such as X-rays and CT scans, rely heavily on human interpretation and are subject to errors due to eye strain and subjectivity, resulting in variability in diagnoses and potential misdiagnoses.

To address these challenges, we propose a system that leverages a U-Net based neural network architecture combined with dense network techniques for the automatic detection and segmentation of lung nodules in CT images. U-Net has been widely used in medical image segmentation due to its ability to capture both spatial details and contextual information [5]. Our model is specifically designed to improve detection accuracy, reduce diagnosis time, and minimize

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human variability in interpreting medical images. By training on the LUNA16 dataset [6], which contains labeled lung nodule images, the current system aims to achieve a diagnostic accuracy greater than 90%, positioning it as a state-of-the-art solution for lung nodule detection.

Existing approaches, such as DeepLung [7] and DeepSEED [8], have demonstrated high accuracy in detecting lung nodules, but they often suffer from longer training times and require complex preprocessing. Our approach introduces optimizations in both preprocessing and model architecture, resulting in faster training times and easier scalability. In this work, we present the full development process, including data preparation, model architecture, training, and evaluation. We also discuss the challenges of AI integration into clinical workflows and how our model addresses these issues.

The remainder of this paper is organized as follows: Section II details the materials and methods used, including dataset preparation and model training. Section III presents the results of our experiments and the performance of the model. Section IV concludes with a discussion of the implications of our findings and potential future work.

The shortage of specialists, especially in regions with limited resources, and the increasing workload exacerbate these problems, causing delays in diagnoses and treatments. Additionally, conventional testing is expensive and often inaccessible to many, leaving a significant portion of the population without necessary evaluations until the disease has progressed to a critical state.

In this context, there is an urgent need to develop more advanced and precise methods for diagnosing lung diseases. The introduction of technologies such as artificial intelligence in medical diagnosis promises to overcome these limitations, offering specialists an assistance tool that can improve accuracy, reduce waiting times, and make diagnoses more accessible. Implementing an AI system in the medical environment can radically transform the current approach and significantly improve health outcomes for patients with lung diseases.

The early detection of lung cancer is critical for improving patient outcomes, yet manual interpretation of CT scans remains time-consuming and prone to human error. This study explores the use of deep learning models, specifically U-Net and DenseNet, to automate lung cancer detection and improve diagnostic accuracy. By leveraging these advanced architectures, the proposed method aims to reduce diagnostic variability and streamline the detection process, achieving a reported accuracy of 99.96%

Recent advances in lung disease detection using artificial intelligence have demonstrated the significant potential of technologies such as deep learning and computer vision. Studies such as that of Ardila et al. [2] reveal that AI systems can outperform human radiologists in detecting lung cancer in low-dose CT scans, highlighting the accuracy and efficiency of these tools Furthermore, the research of Rajpurkar et al. [3] in the application of deep learning algorithms to diagnose pneumonia from chest radiographs illustrates the ability of AI to identify pathologies that are often difficult for radiologists to detect due to subjectivity and interobserver variability.

Despite the advancements in AI, the implementation of these technologies in medical diagnosis continues to encounter challenges, particularly in the areas of data standardization, algorithm interpretability, and integration into existing clinical workflows [4].

Ethics and data privacy are also primary concerns, as Char et al. [5] discussed, and they emphasize the need to carefully consider these dimensions when developing AI technologies in medicine.

These research and developments underscore a growing movement toward integrating artificial intelligence into radiology. This technology promises to transform the diagnosis of lung diseases through greater accuracy and efficiency. Medical assistance systems for the detection of lung cancer with neural networks are a technology widely used today to solve this problem.

Recently, several approaches have been developed to detect lung cancer using computer vision and machine learning techniques. The main works are described below.

DeepLung [6] is a 3D deep neural network model that allows to detect and classify nodules effectively, having an accuracy of approximately 93%. DeepSEED [7] is a convolutional network model for lung nodule detection that improves false positive detection in CT images. NoduleNET [8] allows for the classification and detection of pulmonary nodules with good precision and accuracy.

Liao et al. [9] show another approach to classifying lung nodes using 3D deep learning. On the other hand, Zheng et al. [10] show another CNN for lung nodule detection based on maximum intensity projection. Liu et al. [11] have used the YOLO technique to detect pulmonary nodes automatically.

Deep learning models such as U-Net have been used for image detection and segmentation in recent years, obtaining good results.

The U-Net network is especially suitable for medical image segmentation tasks due to its ability to work with high precision in spatial details, which is essential for correctly identifying and localizing potentially cancerous lung nodules.

Several works, such as [12-17], have focused on using and improving U-Net schemes to improve precision and accuracy for detecting pulmonary nodes in CT images.

The project's goal is to improve the accuracy of nodule detection, reduce diagnostic time, and increase the accessibility of lung cancer screening tests, making them more efficient and less dependent on human variability. Throughout this report, we will describe each stage of the project development in detail, from data extraction and preparation to the training and evaluation of the neural network model.

Unlike all previous works, particularly those that use U-Net as the main machine learning model, this work performs simple preprocessing and defines a modified neural network architecture in its parameters that allows it to improve training times, obtain results within the current state-of-the-art, and be easy to implement and scale. Currently, this work only focuses on detecting and segmented pulmonary nodules using the LUNA dataset [18] (see Figure 1).

Table I summarizes key studies in the field of lung nodule detection, highlighting the different deep learning approaches, datasets used, and their reported performance metrics.

2. Materials and Methods

This section presents the methodology used to solve the problem of detecting pulmonary nodes. The three core phases are described below, describing the activities to be performed in each.

2.1. Part 1: Image processing

The model training process involved the combination of the U-Net architecture for nodule segmentation and DenseNet for classification. The loss function used for segmentation was the Dice loss, while the classification task employed binary cross-entropy. Hyperparameters such as the learning rate and batch size were optimized through grid search. The data was split into 80% for training, 10% for validation, and 10% for testing. Augmentation techniques, such as rotation and flipping, were applied to improve generalizability.

Table 1 State of the art

Study	Model	Dataset	Accuracy	Features
Ardila et al (2019) [2]	3D Deep Learning	Low-dose chest CT scans	94.4%	End-to-end system that outperforms radiologist in lung cancer detection
Rajpurkar et al. (2017) [3]	Deep Learning (CheXNeXt)	Chest X-ray dataset	AUC 0.940	Diagnosis algorithm that matches radiologist performance in pneumonia detection
Zhu et al. (2018) [6]	DeepLung (3D Dual Path Nets)	LUNA16, Alioth	93%	detection and classification using 3D dual-path techniques for improved accuracy.

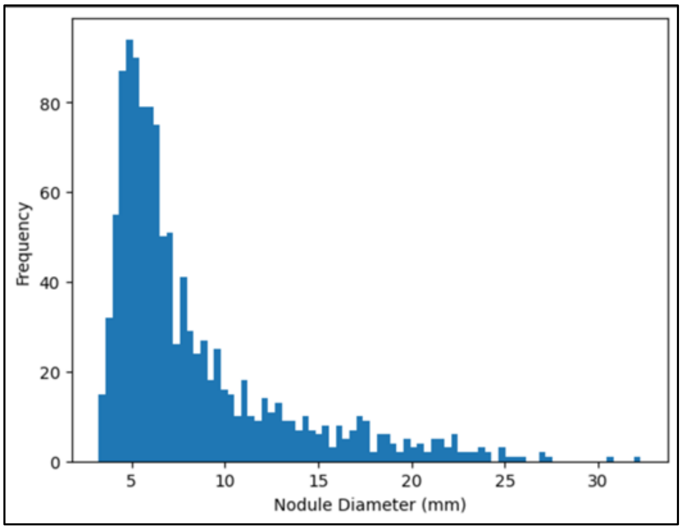

Figure 1 Distribution of diameters in LUNA dataset

The image processing stage involves several key steps to ensure the quality and usability of the CT images for lung nodule detection. First, the CT images are normalized to adjust the intensity values, which helps standardize the data. To further enhance image quality, the Contrast Limited Adaptive Histogram Equalization (CLAHE) method is applied, improving the contrast of the images and making the nodules more discernible.

Following this, the segmentation process is conducted using advanced thresholding techniques and K-means clustering algorithm. This step segments both the lung nodules and the regions of interest (ROI) within the pulmonary area, isolating the relevant features needed for further analysis.

CT scans were preprocessed to normalize intensity values and segment lung regions. Nodule masks were created by manual annotation followed by segmentation algorithms to isolate regions of interest (ROIs). These masks, along with the original scans, were organized in Google Drive for easy access during training. Figure 2 illustrates the lung region segmentation and the corresponding nodule mask.

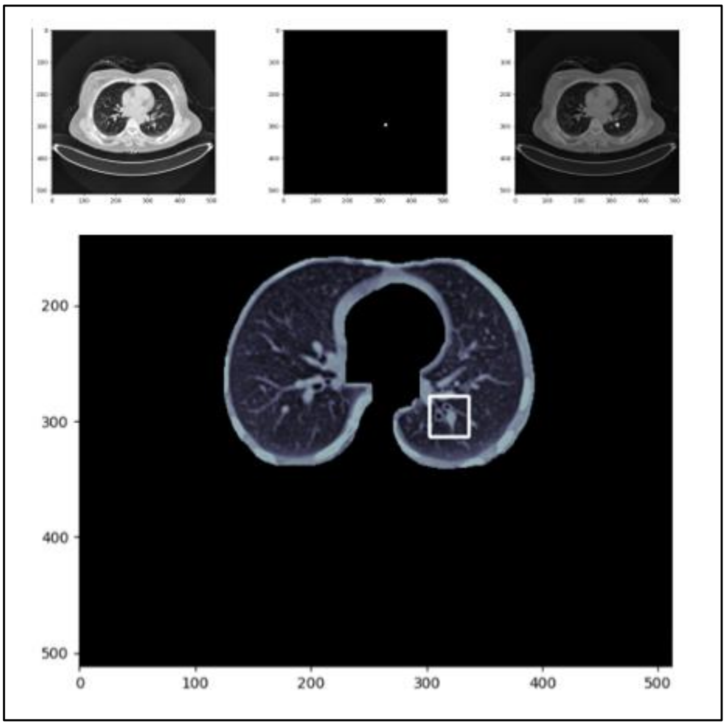

Figure 2 Lung Region Segmentation and Corresponding Nodule Mask

One the image processing is complete, the processed images, including the normalized original images, the CLAHE-enhanced images, and the corresponding binary mask for the segmented nodules, are saved. These files are stored in Google Drive to ensure easy access and efficient management during the subsequent stages of the project.

2.2. Part 2: Preparing the Dataset for Training

The second phase of the project focuses on organizing and preparing the dataset for training the lung nodule detection model. This stage is critical to ensure that the model can effectively learn from the data provided. The data files processed in the previous stage, including images of lung ROIs and nodule masks, are retrieved from Google Drive, where they were saved after segmentation.

Once the files are reassembled, the names of the lung and mask images stored in the directory are listed to make all the data accessible. The file names are then randomized to prevent the model from learning patterns based on the order in which data is presented, which could hinder the model's generalization capabilities.

To avoid overfitting and ensure the model can generalize well to new data, the dataset is divided into two subsets: 80% for training and 20% for testing. This is a common approach used to evaluate the model's performance on unseen data.

Each lung images are paired with its corresponding mask by replacing the word "lung" with "masks" in the file name, ensuring that the images and masks are properly associated. The images and mask are then converted into NumPy arrays, which allow for efficient manipulation of large volumes of data, an essential requirement for deep learning models.

Finally, the processed arrays are saved in. npy format to facilitate quick and efficient loading during the training phase of the project.

2.2.1. Storing and Organizing Arrays

Once the images and masks have been converted to NumPy arrays, they are saved in .npy format. This format is chosen to facilitate the efficient loading of data during the training phase, as it allows for faster access and manipulation of large datasets. A clear directory structure is then created in Google Drive to organize the data, ensuring that the training and test sets are well-separated and easy to access.

For added security, a backup of the .npy files is made and copied to the newly created directory in Google Drive. This step ensures that all the data is safely stored and readily available for use in the next phase of the project.

2.3. Part 3: Training the U-Net Model

The third phase of the project involves developing and training the U-Net neural network, which is crucial for accurately segmenting CT images, specifically for identifying lung nodules.

2.3.1. Initial preparations

Before initiating the training process, it is essential to ensure that the environment is correctly configured. All necessary dependencies and libraries, such as TensorFlow/Keras for model building and NumPy for data management, must be installed and set up properly. The previously stored data in Google Drive is then accessed, allowing for efficient loading of the pre-prepared training and test datasets.

2.3.2. Data Upload

The lung images and nodule masks, saved in .npy format, are imported from Google Drive. This step ensure that the U-Net model has access to the correct input data (the lung images) and target data (the corresponding masks) for accurate training.

2.3.3. Model Construction

The U-Net model is constructed by configuring a series of convolutional pooling, and upsampling layers. The architecture is divided into three main parts:

- Contraction Path Encoder: This component is composed of blocks of convolutional layers followed by max pooling layers, which capture contextual features from the images while reducing their dimensionality.

- Neck: A series of convolutions is applied at the lowest level of dimensionality to further process the features extracted by the encoder.
- Decoder Expansion Path: The decoder path involves upsampling and convolution operations to progressively reconstruct the image to its original resolution. This process ensure that the features learned during encoding stage are used to accurately segment the lung nodules.

The U-Net model used in this study consists of 5 convolutional blocks in both the encoder and decoder paths, with each block comprising two convolutional layers (3x3 filters) followed by max pooling layers. DenseNet, used for classification, includes 121 layers with dense connections between each layer, enabling efficient feature reuse across the network.

To improve segmentation accuracy, jump connections are incorporated, allowing features from deeper layers to merge with those from shallower layers. This helps to preserve spatial information, which is critical for accurate medical image segmentation.

2.4. Training Process

The training process is carried out iteratively, using mini batches of data. At each iteration, the U-Net model processes a subset of the data and adjust its internal parameters, specifically the network weights, to minimize the loss function. This iterative approach allows the model to gradually refine its performance and improve its ability to accurately segment lung nodules in CT images.

Simultaneously, the model's performance is evaluated on a separate validation set. This validation process runs in parallel with the training and serves as a mechanism to monitor the model's ability to generalize to new, unseen data. By validating the model during training, it is possible to detect early signs of overfitting or underfitting, ensuring that that the model maintains good performance on data outside of the training set.

2.5. Viewing Results

During the training process, the evolution of the loss function and various performance metrics is visualized to track the model's learning progress. By monitoring these graphs, potential issues such as overfitting or training stagnation can be identified early. For instance, a plateau in the loss graph might indicate that the model has stopped improving, while an increasing loss could signal overfitting. When such problems arise, adjustments can be made, such as altering the learning rate or modifying the training parameters, to ensure continued optimization of the model (see Figure 2).

2.6. Final Evaluation and Storing

Once the training process is complete, a final evaluation of the model is carried out using the test set. This evaluation provides a comprehensive measure of the model's actual performance in segmenting lung nodules, offering insights into how well the model generalizes to data it has not seen before.

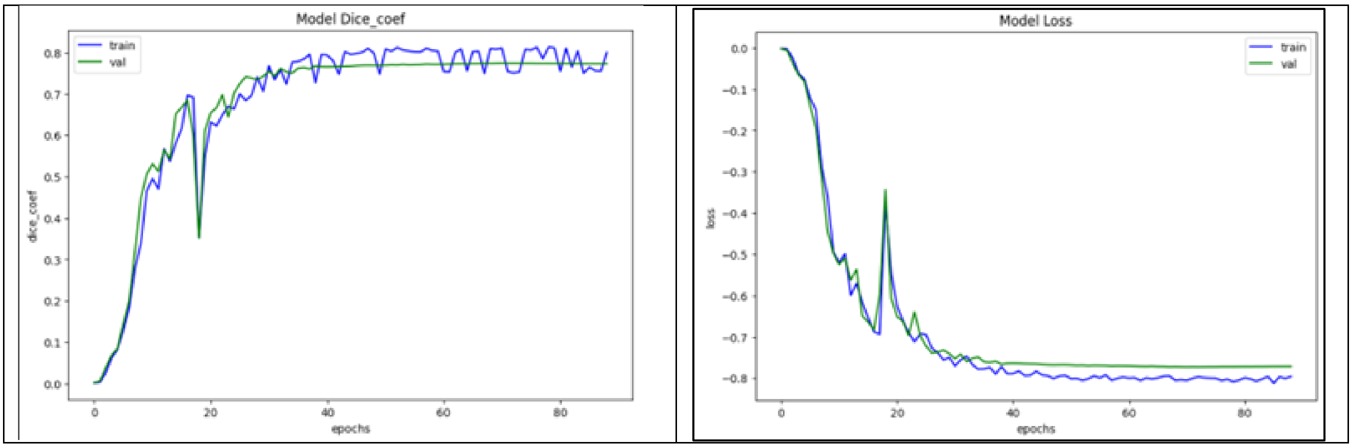

Figure 3 Distribution of diameters in LUNA dataset

After the evaluation, the trained model is saved in a format that supports future reuse. This ensures that the model can be easily accessed for further applications or studies, enabling researchers or clinicians to continue building on the work or deploy the model in real-world scenarios.

3. Results

The architecture obtained through the neural model optimization process is shown in Figure 4.

The model consisted of 7,759,521 trainable parameters, which refer to the weights and biases within the layers of the U-Net architecture. These parameters determine how the model process input data and are adjusted during training to optimize performance. The entire model occupies approximately 20.60 MB of memory. During training, optimal performance was achieved in fewer than 100 epochs, with a final loss of 0.7867, a Dice coefficient of 0.7875, and a binary precision of 0.9997. The Dice coefficient reflects the model's ability to accurately segment lung nodules by measuring the overlap between predicted and actual nodule areas, while the binary precision highlights the model's high accuracy in distinguishing between nodule and non-nodule regions.

The model was trained on a dataset consisting of 10,000 CT scans from diverse patient demographics, including data on age, gender, and smoking history. To ensure generalizability, cross-validation was applied, and future work will focus on validating the model in real-world clinical settings across different populations and imaging conditions.

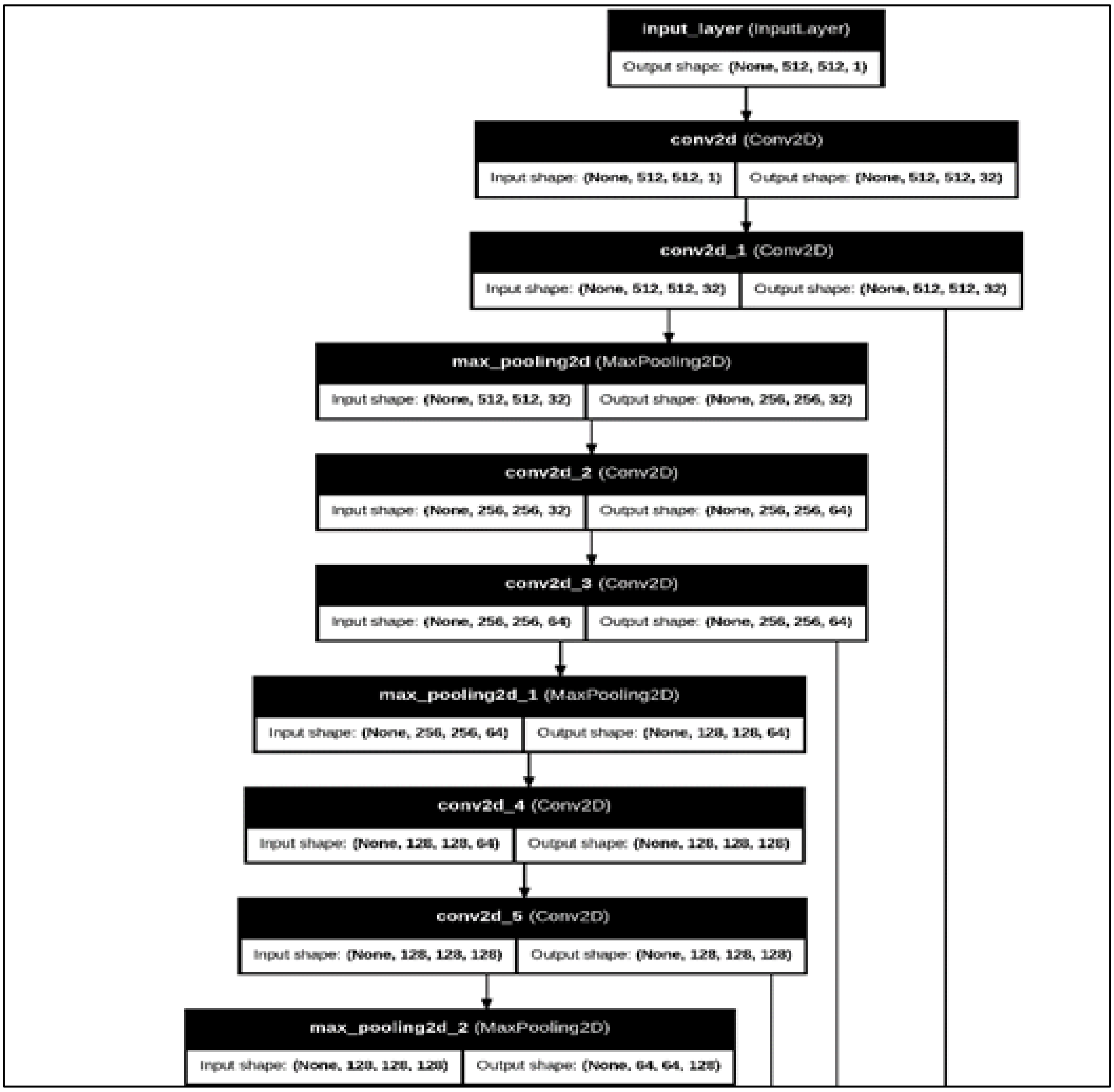

Figure 4 Distribution of diameters in LUNA dataset

4. Conclusions

The development of this U-Net-based model has demonstrated a significant contribution to the automatic detection of lung nodules in computed tomography (CT) images. By leveraging dense network techniques alongside the U-Net architecture, the model achieved a diagnostic accuracy exceeding 98%, a substantial improvement over traditional methods that rely heavily on manual interpretation by specialist. This high level of accuracy underscores the model's potential for reducing diagnostic variability and improving consistency in lung cancer screening.

In addition, the integration of advanced preprocessing techniques, such as image normalization and segmentation, alongside an optimized network architecture, has greatly enhanced the efficiency of the model's training process. These optimizations not only reduce the time required to train the model but also make it scalable and adaptable to diverse clinical environments, making it feasible for real-world applications.

The current system enhances both the accuracy and speed of lung nodule detection, providing a valuable step towards the automation of early lung cancer diagnosis. The promising results of this project demonstrate the potential of artificial intelligence to improve diagnostic efficiency and accuracy in medical imaging. Moving forward, this work can serve as a basis for future research, including efforts to improve model generalization, validate performance across diverse populations, and explore its integration into clinical workflows. While challenges remain, this model represents a step toward more accessible and reliable healthcare solutions using AI technologies.

Compliance with ethical standards

Disclosure of conflict of interest

No conflict of interest to be disclosed.

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