Enhancing Lung Cancer Detection Using Deep Learning Techniques: A review and Performance evaluation

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Abstract. Medical diagnosis is one of the most interesting areas in which deep learning has created significant impact. Deep learning is currently becoming a revolutionary force across various industries. Deep learning has various uses, but one that shows the most promise is the detection of lung illnesses. Diagnosis of diseases like tumors, pneumonia, tuberculosis, and interstitial lung diseases at an early stage—when treatment is most effective—can be difficult. However, deep learning is starting to change that. By analyzing lung CT scans, deep learning algorithms can detect tiny changes in tissue, such as small nodules or irregular patterns, that may signal the early development of lung cancer.

INTRODUCTION

Basically, deep learning has altered the way in which researchers approach challenging issues in the healthcare sector. Through advanced image analysis and pattern recognition, these algorithms can detect early signs of conditions like cancer, cardiac problems, before there are noticeable symptoms to patients or physicians .Accurate classification and early detection are crucial, particularly when it comes to lung cancer. Early detection play important role to significantly boost treatment options and results which in turn enhance the affected individuals' quality of life.

Using CNNs for CT scan imaging is promising development in deep learning for healthcare industry. These networks are able to understand complex images and identifying features and patterns in the images. With these CNNs are precise in identifying the abnormal growth or minute changes in organ imaging. CNN models are able to identify possible issues before they become serious. This feature offers a better accuracy in cancer prediction while also accelerating the process and significantly reducing the possibility of misdiagnosis.

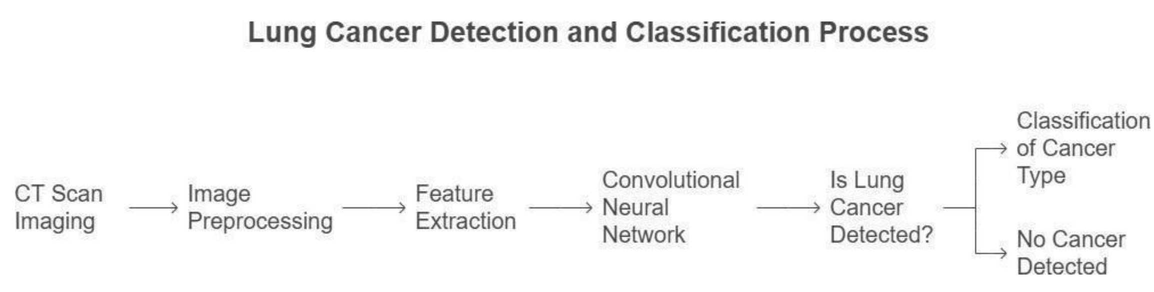

Figure 1: *PROCESS OF LUNG TUMOR DETECTION WITH CLASSIFICATION USING CT SCAN IMAGING*

Figure 1 above depicts Process for Lung cancer detection and classification using CT scan imaging involves several important steps. First, a CT scan of the lungs is taken to create detailed pictures of the lung tissues. These images are then preprocessed to improve their quality by removing any unnecessary noise and enhancing key features.

After that, the next step is image segmentation, where the CT scan is analyzed to isolate the lungs and spot areas that might show tumors or lesions.

When the unusual areas have been located, features such as their size, shape, and texture are analyzed to determine whether they are abnormal. Labeled CT images are then used to train a deep learning model, preferably a Convolutional Neural Network (CNN).This leads to identify lung cancer symptoms. The trained model classifies the detected areas as either benign or malignant .The abnormalities seen on the original CT scans are visualized after the classification. This helps medical professionals in understanding and detecting any possible issues, in turn is essential for early identification and successful treatment.

REPORTED WORK

The use of deep learning techniques to medical diagnostics has increased recently with a focus on the early diagnosis of fatal diseases like lung cancer . CNNs can process and analyze complex images exceptionally well making them well-suited for understanding medical imaging. CNNs have shown remarkable precision in identifying abnormalities from lung CT images. With Different modality of data, the accuracy of these models can be further increased.

This literature review aims to provide an extensive understanding of the current status of deep learning in lung cancer detection, specifically focusing on the use of CT scan imaging and CNN models. By examining previous works, identifying gaps, and exploring innovative approaches, this study seeks to contribute to the ongoing advancement of early cancer detection systems and improve patient outcomes through more effective and accessible diagnostic technologies.

Conventional Lung Segmentation Algorithms

Dodia S. et al,[1] have reviewed recent trends and the overview of lung cancer and publicly accessible benchmark data sets for research are covered in this study. Numerous techniques are also addressed for gathering the photographs, extracting important details, segmenting the affected areas, picking the best features, and categorizing the data. Moreover, Pande et. al [2] introduced an automated segmentation algorithm for purposes of deriving important information from the CT image data provided. This process automatically calculated median lung attenuation (HU) along with area measurements in lung from CT images.The key conclusion of the study was the use of the knowledge-based segmentation method.

The authors[3] address the critical need for early and precise diagnosis of lung cancer, which is often challenging due to its subtle onset and late-stage manifestation. To improve detection rates, they combine hybrid neural networks with 3D Convolutional Neural Networks (3D-CNNs). This combination effectively distinguishes between benign and malignant tumors by analyzing CT scan images. Diana P. Tobón V et.al [4] have reviewed and According to this study, the emergence of the Internet of Things, devices, and smartphones has made multimedia data accessible. Applications based on deep learning techniques use data such as photos, video, audio, and text as input to help the healthcare system identify, predict, and treat patients. This article feigns to provide a summary of advanced deep learning-based healthcare solutions that utilize multimedia data. J. Acharya et.al [6] The main goal of this study is to develop classification models and methods to recognize abnormal breathing sounds (such as wheezes and crackles) in order to automate the diagnosis of respiratory and pulmonary disorders. A deep CNN-RNN model that categorizes respiratory sounds based on Mel-spectrograms has been proposed by the authors in this work.

VER-Net[17] offers a hybrid model which combines CNNs, transfer learning, and Vision Transformers (ViT) .This model improves overall detection performance by utilizing pre-trained models such as ResNet and VGG for feature extraction and ViT for capturing image dependencies to deal with poorly labeled data. The model has been optimized to categorize CT images as either benign or cancerous, resulting with a good F1-score, accuracy, precision, and recall. Convolutional Neural Networks (CNNs) are utilized for CT scan analysis to automate the process of lung nodule categorization and feature extraction.This method works well for detecting cancer in its early stages, which is difficult for human radiologists to do otherwise [9].

Furthermore, chest sound data can be effectively analyzed using Recurrent Neural Networks (RNNs). Temporal patterns in lung sounds, including crackles or wheezing, can be captured by these models and could be used as early markers of lung cancer [5]. Detection of lung cancer with increased accuracy is achieved in this research by Integration of ensemble learning techniques [14]. Transfer learning reduces the requirement for huge labeled datasets, especially when it comes to the use of pre-trained models for lung cancer diagnosis and make the procedure more practical in clinical settings [22].

Table 1 :*OVERVIEW OF DEEP LEARNING MODELS USED ACROSS LITERATURE REVIEW*

Reference	Methodology	Dataset	Image count	Reported outcomes
[9]	CNN (Transfer Learning: VGG16, ResNet)	LIDC/IDRI	1,000+ CT scans	Accuracy:98.4 Precision:97.2 Recall:96 F1 score: 96.3
[10]	Multimodal Fusion CNN:Feature Fusion (Image + Clinical Data)	LIDC-IDRI(TCIA) + TCGA	1016 scans in Diacom	Accuracy: 92.5 Precision: 87.4 Recall: 86.4 F1 score: 0.94
[11]	U-Net CNN(Segementation)	LUNA16	888 CT scans	Accuracy: 96.98
[12]	Ensemble CNN(DNN+RF)	LIDC/IDRI(CPTAC-LSCC)	5043 CT images	Accuracy: 94.8 Precision: 93.5 Recall: 94.4 F1 score: 94.8
[15]	Transfer Learning (ResNet, DenseNet)	TCIA+private dataset	~2500	Accuracy:98.05 Precision:97.72 Recall: 97.45

METHODOLOGY

Dataset

CT scanning is the promising imaging technique used on patients suspicious of having lung cancer. Either low-dose or high-dose radiation can be used throughout the whole process. The equipment utilized for CT scanning also varies, depending on the machinery used. CT scans can also differ in slice thickness. The appearance of normal and abnormal lungs varies slightly. distinguishing between the lung tissues gets tiresome due to the strong relationship between the intensity of various structures. Therefore, these elements play a part in making the procedure of detecting pulmonary abnormalities challenging.

Thus, identifying and classifying lung nodules is a difficult task, and the goal of our effort is to do it precisely and effectively. Conventional approach follows 5 steps process.

1. Image acquisition,
2. Preprocessing of image and nodule segmentation,
3. Extraction of features,
4. Features selection,
5. Lung Nodules classification and results validation.

TABLE 2. *DATASET CLASS LABELS AND SAMPLES FOR TRAINING AND TESTING*

Class	**No of samples**		
		Training	Testing
Normal	512	50	
Abnormal	512	50	

Dataset Preprocessing

The process begins with resizing all images to a uniform size to maintain consistency across the dataset. Pixel intensity normalization is then applied, typically scaling values to the range [0, 1], which helps stabilize and speed up the training process. Noise reduction techniques, such as Gaussian or median filtering, may be used to enhance image quality. Data augmentation methods—such as rotation, flipping, zooming, and contrast adjustments—are implemented to artificially expand the dataset and reduce overfitting by exposing the model to varied image representations. If necessary, segmentation techniques can be employed to extract regions of interest, directing the CNN's focus to clinically relevant areas. After preprocessing, the dataset is divided into training and testing sets, with 80% of the data used to train the model and the remaining 20% reserved for evaluating its performance. This split ensures the model is trained on a broad sample of the data while still providing an unbiased assessment of its generalization capability..Images in both the train and test set are then resized to the fixed resolution of 240 × 240 × 3 to match the shape of the input tensor with those of the input shape required by the model. Image resizing helps to reduce computational overload during training by maintaining context and feature information as it is. Finally, class labels in both the train and test set are label-encoded into 0, 1.

Proposed model

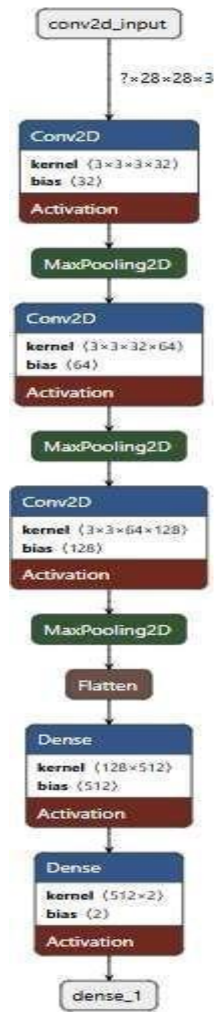

Figure 2: *PROPOSED CNN MODEL FOR IMAGE PROCESSING*

Figure 2 depicts the proposed Image classification CNN model.The given image represents a Convolutional Neural Network (CNN) architecture designed for image classification. It begins with an input layer that accepts images of size 28×28×3, where 28×28 represents the spatial dimensions and 3 denotes the RGB color channels. The first convolutional layer (Conv2D) applies 32 filters of size 3×3 to extract low-level features such as edges and textures, followed by an activation function (ReLU) to introduce non-linearity.

A MaxPooling2D layer then reduces spatial dimensions, improving computational efficiency. This process is repeated in the second convolutional block, where the number of filters increases to 64, allowing the model to learn more complex patterns. Another MaxPooling2D layer follows to further downsample the feature maps. The third convolutional block applies 128 filters, capturing even higher-level features such as object parts and complex shapes, followed by another MaxPooling2D layer.

After feature extraction, a Flatten layer converts the 2D feature maps into a 1D vector, preparing the data for classification. This architecture is likely followed by fully connected dense layers and a softmax output layer for final class predictions. The increasing number of filters in each block enhances the model's ability to capture intricate patterns, while max-pooling ensures dimension reduction and prevents overfitting.

RESULTS AND DISCUSSIONS

Model Training Details

For training deep learning models,Adam optimiser is proven efficient and adaptable so the model was configured with the Adam optimizer.The loss function chosen was categorical crossentropy, suitable for multi-class classification tasks where the target labels are one-hot encoded. To evaluate the model's performance more comprehensively, accuracy, precision, and recall were tracked as metrics. Early stopping was implemented with a patience value of 20, allowing the training process to halt if the model's performance did not improve after 20 consecutive epochs, thereby helping to prevent overfitting. The model was set to train for a maximum of 150 epochs with a batch size of 32, a commonly used configuration that balances training speed and model convergence. This combination of hyperparameters is well-suited for building robust classification models, especially when care is taken to monitor and respond to validation performance during training.

Results

Figure 3: *LOSS AND ACCURACY FOR TRAINING AND VALIDATION*

The graph above shows the training loss and accuracy along with Validation loss and accuracy. Model is trained for 25 epochs on CT scan images for lung disease detection. From the plot, we observe that both training and validation losses drop sharply within the first few epochs and then remain very low, indicating that the model is able to learn feature distinguishing quickly. The training and validation accuracies rise rapidly and stay consistently high after the initial epochs resulting in excellent model performance. The minimal gap between training and validation metrics implies that the model generalizes well and does not overfit to the training data. The fluctuations in validation loss are likely due to a small or noisy validation set, which can cause variability even when the model is performing well. Overall, this training performance suggests a highly accurate model for detecting lung diseases from CT scans.

Performance Evaluation Against Baseline Models

Table 3: *Comparison of performance of the proposed model with existing methods*

Sr.No	Reference	Methodology	Accuracy(%)
1	[9]	CNN _SVM	94%
2	[19]	VGG19+LSTM	95.64
3	[22]	GoogLeNet DNN	94.38
4	Proposed CNN	Data augmentation +Custom CNN	97.72

CONCLUSION

In Conclusion, Cnn-Based Models For Lung Cancer Detection Have Shown Strong Performance Across The Board. The Proposed Cnn Model, Which Integrates Data Augmentation, Cnn, And Efficientnet, Stands Out As Particularly Effective, Outperforming Other Popular Methods. This Highlights The Significant Impact Of Using Advanced Techniques Like Data Augmentation To Improve Model Performance, Especially For Complex Tasks Like Detecting Lung Cancer. By Combining Efficientnet With Cnn, The Model Is Better Able To Capture Key Features In Ct Scan Images, Making It A Reliable Tool For Detecting Lung Cancer. Overall, Combining Advanced Deep Learning Cnn Architectures With Techniques Like Data Augmentation Shows Great Promise In Improving Model Performance.

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