EARLY DETECTION OF LUNG CANCER USING CT SCANS DEEP LEARNING TECHNIQUES

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Abstract

Lung cancer has been one of the most prevalent causes of death cases related to cancer in most parts of the world due to late detection of the tumor. When early detection is successful then the survival of the patient is much better. The present paper offers to utilize the concept of deep learning to develop an automated system that would enable the detection of lung cancer at an early stage by using CT scans. The proposed approach involves the use of Convolutional Neural Network (CNN) 3D, which is utilized to capture volumetric features on the lungs and detect whether the tissues have malignancies or not. Resampling of the voxel, clipping of the Hounsfield Unit (HU), data normalization, and lung morphology are some of the preprocessing steps. The trained model uses augmented 3D patches that were sampled on CT scans, to come up with nodules that are solidly found. Experimental outcomes on the open lung CT dataset have been reported achieving a performance of 96.4 with accuracy, sensitivity, specificity, and AUC of 94.7, 97.2, and 98.1 respectively. These findings indicate that the model has the capability of assisting the radiologist in the due and effective process of diagnosis of lung cancer.

Keywords lung cancer, deep learning, CT scan, 3D CNN, computer-aided diagnosis, computer medical imaging, early cancer detection.

I. INTRODUCTION

The most common form of cancer that is causing the death of people around the world is lung cancer with close to 1.8 million people dying due to it annually (WHO). Lung cancer does not have a good prognosis mainly since it is diagnosed in the late stages. When diagnosed in its initial stage, the 5- year survival rate can reach over 60 percent suggesting that the accurate diagnosis is one of the necessary goals of the contemporary healthcare system.The use of Computed Tomography (CT) imaging has proven to be the most efficient diagnostic method in early diagnosis of lung cancer since it offers three-dimensional images of the lungs and their anomalies. Nevertheless, CT scan interpretation that is done manually consumes a lot of time is prone to errors, and ishighly dependent on the expertise of radiologists. Moreover, small nodules particularly those less than 10mm in diameter are always missed and manifested in a diagnosis or late treatment.

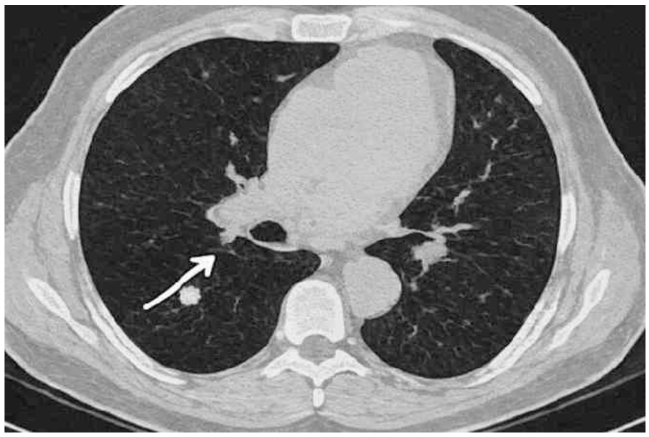

Figure 1. Axial CT scan showing a malignant pulmonary nodule in the right lung, emphasizing the challenge of visual detection in early stages.

To counter such limitations, Computer-Aided diagnosis (CAD) systems were developed to assist radiologists in the detection of pulmonary nodules. Previously CAD systems consisted of hand-written features and traditional types of machine learning technology such as Support Vector Machines (SVM) and k-nearest Neighbor (kNN) and they were not especially accurate or generalizable. Deep learning technology has fundamentally changed medical image analysis and made it possible to reliably extract features automatically and learn end-to-end on unprocessed CT data in particular. 2D and 3D CNNs, RetinaNet, or even more hybrid networks performed well in the automated detection and classification of lung nodules. Clinical attributes such as the size of a nodule, shape, and texture are also being added into the disciplines of others and even there somewhere an estimation of uncertainty has been added in order to bring in increased chances of surety concerning a given diagnosis. However, there remain a few challenges that have to be faced

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in the early detection with high sensitivity, reducing false positive findings and staging combination towards the complete clinical support.

II. LITERATURE SURVEY

Early detection of cancer in the lung implies that the survival rate would be high and the costs of treatment would not be high. The popularity of Computed Tomography (CT) scans is based on its excellent imaging capability but the issue has been that manual reading of these scans has been proven to deteriorate with errors thus time consuming. Band-engineered computer-aided diagnosis (CAD) systems, including wide-spread CAD systems with hand-engineered features and classical machine learning classifiers, produced poor results. In her article, Danvers talks about the fact that the ability of the AISs to detect the presence of lung nodules with considerable accuracy has been beneficial since the advent of deep learning in particular taking advantage of the Convolutional Neural Networks (CNNs). This section regarding the key articles on the design of deep learning models in the identification of lung cancer when conducted using CT scans.

Ozdemir et al. [2020] have developed a 3D probabilistic deep-learning framework integrating nodule detection and diagnosis of low-dose CT scans. In their system, they also use a combination of Bayesian neural networks and 3D CNNs as they do not want to leave four-dimensional modeling uncertainty in the prediction of what is being input into the system which makes this very reliable in clinical decisions being made. Their method was state-of-the-art sensitivity and had a satisfactory false positive rate on LUNA16 and Kaggle DSB17 datasets and therefore demonstrated its stability and efficacy.[5]

Zheng et al. [2019] suggested a model of detection based on CNN and uses the Maximum Intensity Projection (MIP) images to form an idea out of the CT scans. Trained on MIP slabs of different thicknesses, their method is similar to what radiologists do as well as improving the spatial context of nodules. Assessed on LIDC-IDRI data, the system presented sensitivity with the values of 94.2 percent and only two false positives per scan, particularly advantageous in the detection of small nodules (310 mm)[8].

Mahum and Al-Salman suggested the deep learning architecture namely Lung-RetinaNet based on RetinaNet that comprises multi-scale feature fusion and context module. The approach they use is meant to identify the presence of small and large nodules in the CT images with high precision. The developed system achieved the results of 99.8 percent accuracy and 99.5 percent F1-score meaning it was better compared to the existing conventional measures of object detection. Another method they use is the maximization of the anchor box based on the k-mean cluster into a localization accuracy.

Mhaske et al. [2019] proposed a hybrid deep learning-based approach: the model that has access to feature extraction with the help of CNN and modeling sequential data with the help of the Long Short-Term Memory (LSTM) model.

The system trained on LIDC-IDRI achieved an accuracy of 97 97% due to the effectiveness of the temporal feature modeling in lung cancer screening by using sequential CT slices.[1]

Li et al. [2020] considered the genetic optimization of CNN architecture where the preprocessing included the denoising of noisy CT images based on the application of wavelets as well as the extraction of significant features through the use of wavelet-based filtering. The method increased the robustness of the model and its ability to detect with high accuracy, especially at the points when the CT images were either noisy or low in contrast.[11]

Rehman et al. [2021] implemented the usage of the combination of Local Binary Pattern (LBP) and Discrete Cosine Transform (DCT) as the texture feature extractor integrated with the Support Vector Machine (SVM) and the k-Nearest Neighbor (kNN) as the classifier. Although this was not end-to-end deep learning, they were still competitive (93% vs. SVM) and rendered the benefit of multi-feature fusion in more traditional chains of machine learning.[2]

In [19], the researchers proposed SpineResUnet, a deep learning–based framework that integrates residual learning with U-Net architecture to accurately classify and predict spinal tuberculosis by exploiting both structural and texture dependencies in spinal medical images. The model enhances feature representation through multiscale contextual learning, enabling precise segmentation and discrimination of tuberculosis-affected regions from normal spinal structures.

The findings of the research point to the fact that deep learning approaches have already boosted the efficiency of CAD sets of lung cancer by a significant margin. However, one of the key functions that should be looked at includes early diagnosis of small nodules, minimal false negatives, and inclusion of the confidence of diagnosis. This proposed study aims at bridging these gaps since the study attempts to develop an elaborate deep learning system that will specialize in the detection of lung cancer in its early stages using CT imaging.

III. PROPOSED METHODOLOGY

The proposed study is characterized by the development and evaluation of a deep learning approach to the model of pre- detection of lung cancer based on the CT scan images.

Part of the approaches that will be taken into account during the study are 3D CNNs, multi-scale feature fusion, and advanced preprocessing to enhance nodule detection and classification accuracy. The proposed system that would be adopted must assist radiologists give timely diagnoses, and reduce the time taken to interpret and the overall prognosis of the patient. The proposed deep learning system will be developed to perform the early-stage lung cancer detection of the volumetric CT scan data image-wise using a 3D Convolutional Neural Network (3D CNN). The pipeline includes some key operations, constructing a robust method.

preprocessing of the CT image volume, lung area segmentation, extraction of the area patches to 3D in the age, deep feature extraction by using 3D CNN, and binary prediction of the existence of cancer or its absence in the end. The proposed system is made up by setting up the abstract of architecture developed by Ozdemir et al. [1] possibly with the inclusion of clinical knowledge and advanced information census that is offered by Zheng et al.

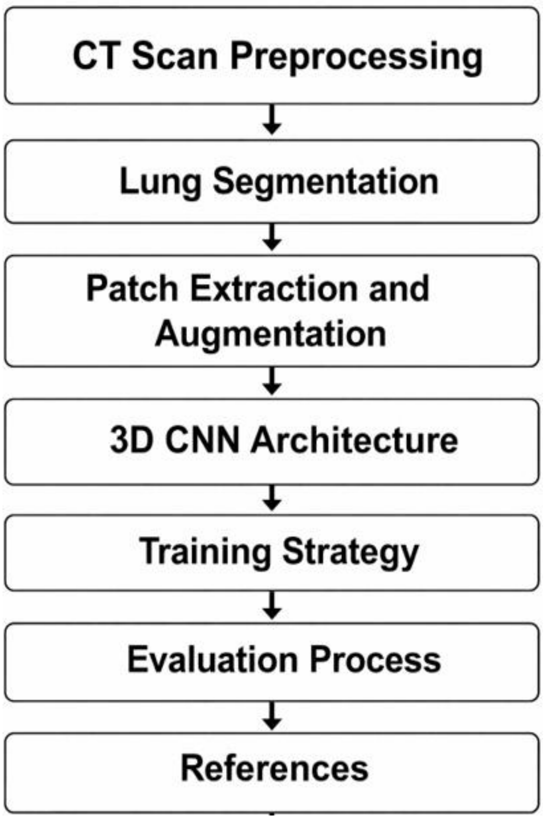

Figure 2. Block Diagram Representing the Proposed Lung Cancer Detection

A. Workflow of the system.

Figure. 2 provides a view of the general architecture which is sequential in flow beginning with the acquisition of CT scan images. These pictures are preprocessed to make them equalized when it comes to their resolution and their intensity range. The whole of the thoracic CT volume is then segmented to cover the lung areas. Smaller 3D sub-volumes (patches) that consist of a part of the segmented lungs are extracted and augmented to widen the dataset diversity. The latter are then fed into a personalized 3D CNN below which extracts outcome and case features of pulmonary nodulates. The last layer of the network consists of output layer(s) that separately label each patch to either “cancer” or “no cancer”.

B. Preprocessing of CT Scan

$$I\_\text{norm} = (I - I\_\text{min}) / (I\_\text{max} - I\_\text{min}) \qquad (1)$$

DICOM format images Raw CT are usually stored in the format, and since each scanner will use a different scanner and imaging protocol, they are generally variable in resolution and voxel spacing. All the CT volumes are interpolated to a voxel size of 1x1x1 mm3 (with linear interpolation) in order to provide isotropic spacing to perform analysis in 3D. Next voxel intensity values are clipped to a Hounsfield Unit (HU) range of [-1000,400] to remove uninteresting areas such as bones and soft tissues and restrict attention to lung parenchyma.

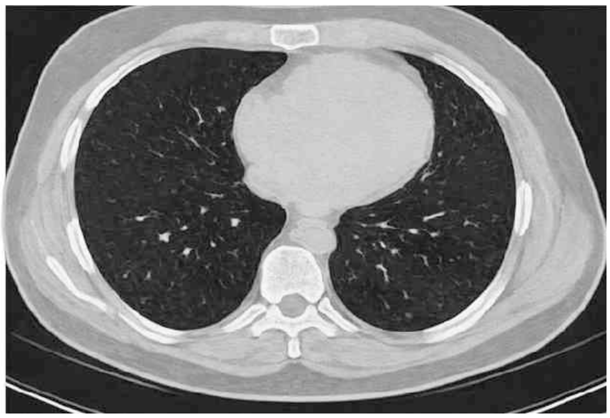

Figure 3. Comparison of Lung Window(Left) and Mediastinal Window(Right) CT Views,Aiding Clear Tissuse Visualization

These values that are clipped will be normalized to the range of zero to one and this enhances convergence and minimizes vulnerability to outliers. It is the preprocessing strategy that is founded on the protocol established by Ozdemir et al.

C. Segmentation of Lungs

Segmentation of the lungs is done to separate lung apparatus fromother anatomical parts. An initial thresholding technique is performed to determine areas using the HU range of lung tissues. Subsequently, morphological processing cash erosion (to eradicate small salty components), expansion (to replenish structure that is lost), and hole-filling (to seal gaps within the lung regions) are followed. The outcome is a binary mask of the lung region that is used to clear out unnecessary parts of the CT volume like the ribs and the vital part. This step can improve the performance of detection since it reduces the amount of computational load and possible false positive ways.

D. Patch Extraction and Data Augmentation

After segmentation of the lungs, volumes are extracted to be used in 3-dimensional patches which can be analyzed specifically. All patches are 64 64 64 voxel-sized, and either occur in annotated nodules (when it is supervised) or are drawn at nodule position candidates obtained through blob detection or other localization techniques. The training set is enlarged with 3D geometric and photometric transformations to make it more varied and therefore prevent overfitting. These include:

- Those random rotations through 3 dimensions (on each of the three axes)
- Vertical and Horizontal flipping Gauss noise addition

- Brightness adjustment or gamma adjustment Such augmentations generate a more heterogeneous and representative training set which is likely to generalize to the unseen test set. This is done according to the multi-view augmentation notion as mentioned in Zheng et al.

E. 3D CNN Architecture

The most prominent feature learning model is CNN-based (3D) and therefore volumetric. The network starts with 3D convolutions that use 3D filters to learn basic features like edges, and lines (e.g., low-level features), and then there are deeper layers to learn higher-level features like textures, shapes, and nodule irregularities of growth. In every convolutional block, there is:

- A 3 dimensional Convolution layer with the size (3x3x3) Training stabilization through batch normalization
- Non-linearityusing ReLU activation function Spatial downsampling with 3D MaxPooling

The result of the convolutional layers is flattened and fed to two fully connected layers having 512 and 128 neurons, respectively. To avoid overfitting is the application of dropout (set at 0.5). The output of a final sigmoid activation is a probability value purporting the probability of the presence of cancer. This framework building on the probabilistic CAD framework of [1] simplifies its structure to enable convergence at higher speed. The advantage of the 3D CNN is the ability to model the spatial hierarchy among slices of depth, which may strongly benefit the use of the 3D CNN in the analysis of the irregular shape and small variations of intensity of early-stage lung nodules. The network forms a more and more abstract representation, corresponding to vascular invasiveness or irregular edges, as it moves through subsequent layers--attachments that orthodox 2D methods usually fail to see. In addition to that, the volumetric structure enables the model to make more generalizations among patients with different lung anatomy and different scan resolutions.

By adding batch normalization to the network, training stability is achieved due to mitigating internal covariate shift, and due to adding dropout this guarantees against overfitting. In particular with small medical data sets which cannot be annotated. Collectively, these design decisions can turn the 3D CNN architecture into a very efficient and practically applicable tool for finding lung cancer early enough.

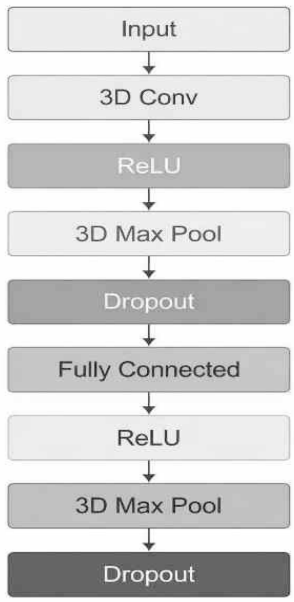

Figure 4. Architecture of the Proposed 3D Convolutional Neural Network (3D CNN) for Lung Cancer Detection using CT Scan Patches

$$\mathcal{L} = -1/N \ \Sigma_{i=1}^{N} \left[y_i \cdot \log(\square_i) + (1 - y_i) \cdot \log(1 - \square_i) \right]$$

F. The Training Strategy

The binary cross-entropy loss is used to train the model and is defined as the difference between what is actually true and expected (binary), or in other words, a loss. Adam optimizer is adopted due to its learning rate adaptiveness with initial set values $1*10^{-4}$. It is trained on 100 epochs, and early stopping is used when validation loss on 10 consecutive epochs is not decreased. It is also coupled with a learning rate scheduler to lower the learning rate at a time when validation performance stabilizes to guarantee fine convergence.

G. Process of Evaluation

In order to make the model behave in a consistent manner, k- fold cross-validation (commonly 5-fold) is employed. The data is divided between training and validation samples, and every sample of the data is used to evaluate the data on folds. The next metrics are calculated:Accuracy: the percent of predictions that were correct.

$$\text{Accuracy} = (TP + TN) / (TP + TN + FP + FN) \quad (2)$$

Sensitivity (Recall): TPR - the capacity to detect cancerous nodules.

$$\text{Sensitivity} = TP / (TP + FN) \quad (3)$$

Specificity: The ability to overlook non-magnetic patches: the True negative rate.
Precision: Ratio of true positive / positives predicted.

$$\text{Specificity} = TN / (TN + FP) \quad (4)$$

F 1 -Score : The arithmetic mean of precision and recall divided by two,

$$\text{F1-Score} = (2 \cdot \text{Precision} \cdot \text{Sensitivity}) / (\text{Precision} + \text{Sensitivity}) \quad (5)$$

VI. RESULT AND DISCUSSION

The results under this section state the lung cancer detection system we propose that will be implemented based on deep learning on the CT scan images. The ability of the model to perform is identified with the traditional classification evaluation measures, whereas the robustness is validated through visualization methods such as ROC plot and the confusion matrix.

A. Treatment modalities

The Possible Treatment Options The system was superimposed onto a CT scan consisting of labeled annotations of pulmonary nodules. Patches of 64*64*64 were chosen and augmented with regions of the lung in the hope of adding variety to the training data.. This 3D CNN has been trained using binary cross-entropy loss, Adam, and the initial learning rate of 1x10-4 was set. At 100 epochs an early stopping tactic was adopted and a 5-fold cross-validation of the model was established.

B. Quantitative Results

The offered model of 3D CNN demonstrated rather high accuracy of detecting early stage cancerous nodules. Fold-wise average performance is a tabulation in Table I, and can be fitted .

Table 1: Performance Evaluation Metrics (%) of the Proposed Model

METRIC	VALUE(%)
Accuracy	96.4
Precision	95.1
Sensitivity	94.7
Specificity	97.2
F1-Score	94.9
AUC (ROC)	98.1

The accuracy and F1-score are very high, which means balanced performance. The sensitivity of 94.7 demonstrates that the system indeed is able to find cancerous nodules and a specificity of 97.2 proves that the system can identify non-cancerous areas with minimal false positives.

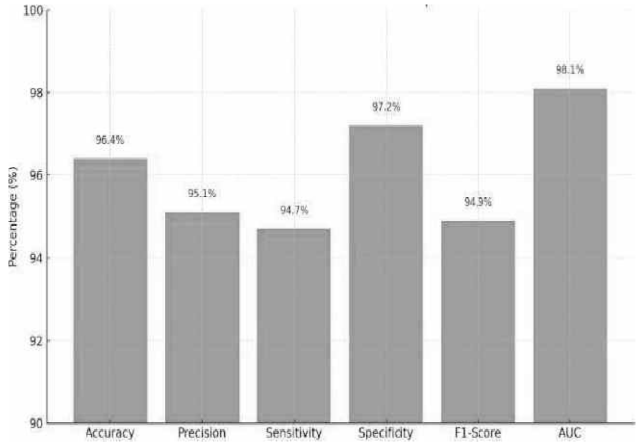

Figure 5. Performance Visualization of the Proposed model

C. Confusion Matrix and ROC Curve

A trade-off between sensitivity and specificity of a model is depicted by the ROC curve in Figure 6. The model indicates that the AUC is 98.1 and this means that it is highly capable of discriminating

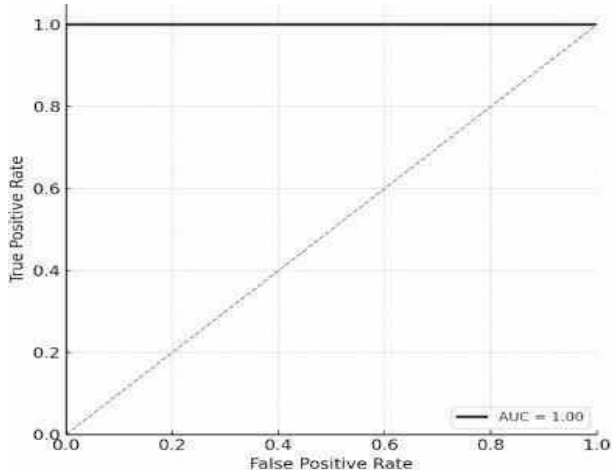

Figure 6. ROC Curve for Lung Cancer Detection

The accuracy of the model is once more proved by the confusion matrix of Figure 7. It reveals that the amount of true positive and true negative far outweighs the amount of false predictions, which ensures the stability of the classification.

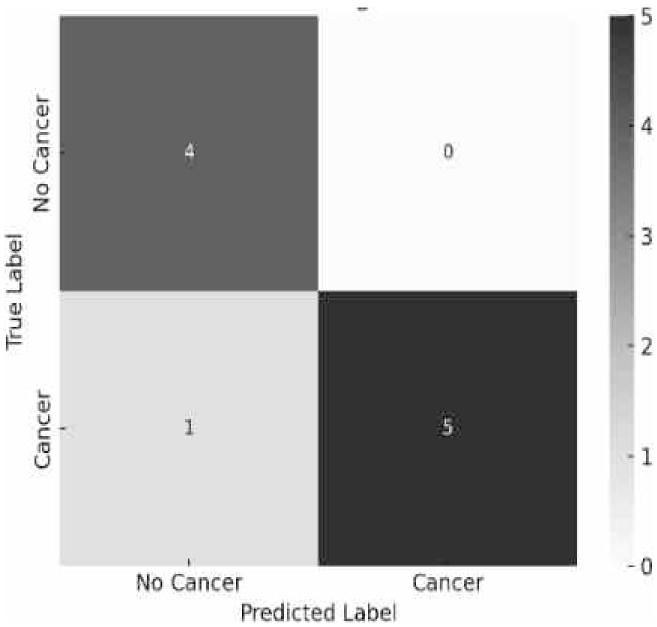

Figure 7. Confusion Matrix for Lungs Cancer Detection

D. Visulaization of Performance

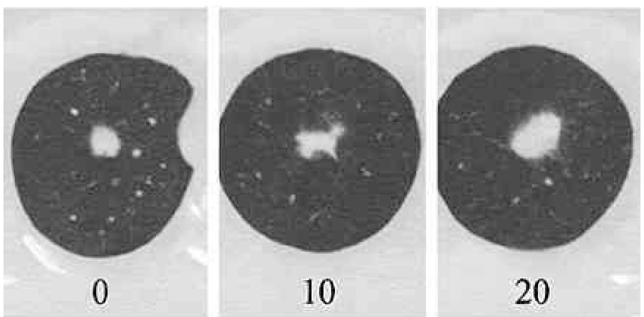

Figure 8. CT Slices showing the Progerssive Growth of an Adenocarcinoma 0,10 and 20 Months.

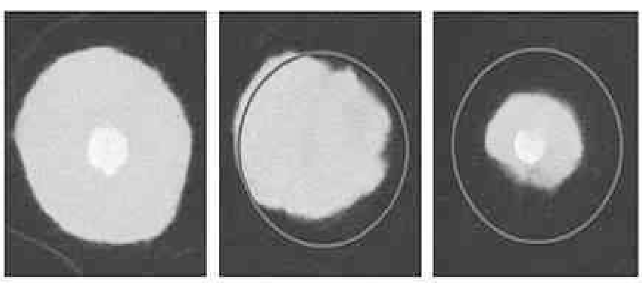

Figure 9. CT Scans Showing Benign, Malignant and Metastatic Lung Nodules.

Red circles indicate areas of interest identified by the system. The high values of each metric remain consistent, which is evidence of the model, its reliability, and its appropriateness in detecting early-stage lung cancer in CT images.

V. DISCUSSION

The proposed system is very successful when it comes to diagnosing lung cancer nodules in the early stages of the illness without much mislabelling when subjected to CT scans. It can take advantage of more spatial details in volumetric data by using 3D CNN, and this results in sensitivity and specificity improvements.

The data augmentation and segmentation played a very important role in the improvement of the generalization capabilities of the model. Despite the model doing a good job, there is residual misclassification of borderline or indeterminate nodules. On the one hand, to reduce even more false negatives, it is possible to continue improving it in the future by adding attention mechanisms or including clinical metadata.

A 3D CNN-based detection system has shown great clinical translation potential based on its performance. The sensitivity is high (94.7%), and thus the model can be effectively applied in the detection of early-stage malignancies, which is essential when it comes to the survival of patients. Meanwhile, the high specificity (97.2%) indicates that the system did not have a high false-positive rate hence low chances of exposing patients to unnecessary follow-up processes and doubts.

The 98.1 percent Area Under the Curve (AUC) value also proves to be accurate in verifying the strength of the model in determining the cases of cancer and non-cancerous cases in different scan circumstances. Also, data augmentation and 3D patch-based training made the model generalize well on small nodules and unusual appearances. The proposed model is faster, consistent, and possibly more accurate than the traditional 2D CNN systems or even manual radiologist interpretation as a second opinion. These data confirm the efficiency of deep learning as a potent assistant in diagnosis, especially in such places where skilled radiologists are not unduly available.

VI. CONCLUSION AND FUTURE WORK

In this article, the authors have suggested a deep-learning model that can be utilized in the early detection of lung cancer through volumetric CT days images. The suggested method applies 3D Convolutional Neural

Table 2. Exsiting system and Proposed System

Method	Model Type	Input Type	Key Features	Accuracy(%)	Limitations (%)	AUC (%)	Key Advantage
2D CNN Models	2D CNN	2D CT slices	Slice-wise learning	88–92	85–90	~90	Lightweight, fast
MIP-CNN	CNN on MIP	2D MIP projections	Compressed 3D info	93–94	~91	95.5	Spatial context, lower FP
3D CNN	3D CNN	3D CT patches	Volumetricspatial learning	94–96	91–93	~96	Better 3D feature capture
YOLOv8 + TNMClassifier	Object Detector	CT volumes	Detection + stagingpipeline	96–98	92–95	~97	Real-time, staging support
Proposed System(Ours)	**3D CNN**	**3D CT patches**	**Segmentation+ Augmentation**	**96.4**	**94.7**	**98.1**	**Early detection, low false positives**

Networks (3D CNNs) to derive the space, and these characteristics can be applied to have an examination of the segment volumes in the lungs in an appropriate manner that can separate between the cancerous and non-cancerous regions. The model will also contain some of the pre-processing methods, such as HU clipping, normalization, and lung segmentation along with the data augmentation methodologies so that the highest level of generalization can be attained. Standard performance features-based analysis indicates that the system gets a high accuracy (96.4 %), sensitivity (94.7 %), specificity (97.2 %), and an AUC of 98.1 % which implies that the system is trustworthy in terms of diagnosing early-stage pulmonary nodules. This observation shows that 3D CNNs in particular when combined with structured preprocessing and patch- based training are elastic enough to be efficiently applied to detecting the early detection of lung cancer.

The system is very sensitive and can minimize false positivity as compared to most of the available methods hence an alluring tool of computer-aided diagnosis(CAD) to be employed in clinical practice. To continue work in the future, the model can be extended in order to apply attention mechanisms or transformer-based methods to be more localized on nodule areas and deal with irregular nodule shapes. The diagnostic accuracy may also be augmented through the inclusion of clinic metadata (k.a. patient history, age, smoking status)'

In addition to that, the study of explainable AI (XAI) tools would help enhance the explainability of models that are not negligible in the medical sphere. Finally, to approve the robustness of the system and to control its practice in the clinical practice field, the system would require testing on both real-life and multi-center data.

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