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Lungs Cancer Identification by Deep Learning 3D CNN Architecture

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***Abstract*—The importance of early lung cancer diagnosis in enhancing patients' life expectancies cannot be overstated. Rapid and correct diagnosis is difficult for radiologists due to the large amount of Computerized Tomography (CT) images. As a result, demand for Computer Aided Diagnosis (CAD) lung cancer is increasing. The distinction between cancerous and non-cancerous tissues lies at the heart of all lung cancer detection systems. Binary categorization (benign and malignant) has been conducted on computed tomography (CT) images from the LUNA 16 database conglomerate and database image resource effort. The data has been pre-processed to remove noise as well as for feature selection. 3D CNN architecture has been used to classification. The 10-fold cross-validation method was applied to verify the results. Experiments revealed that the proposed lightweight architecture achieved an optimum classification accuracy of 90.13% when compared to existing classification algorithms.**

***Index Terms*—3D-CNN, Lung Cancer, Deep Learning, Image classification, Feature Extraction, CAD System.**

I. INTRODUCTION

Lung cancer is one of the most usually detected dangerous cells, as well as one of the most deadly cancer tissues that cause death in men in 2019. Bronchial cancer tissues have actually proven to be a significant threat to one's daily life. Low-dose computed tomography (CT) is a useful tool for detecting lung cancer tissues early [1]. Using component searching algorithms to find first-class portrayals right from the instruction and related information is one option for recognition through these established features. The following three tasks are performed by computer-aided detection and diagnosis systems for lung cancer: lung delineation, nodule candidate detection, and false positive reduction. The detection of nodule candidates in outlined lungs is hampered by a significant false positive rate. Because of the high amount of false positive nodules, CAD is difficult to use in clinical settings. To go to the stage of precise nodule evaluation, it is critical to limit the number of false positive nodules as much as feasible. As a result, we concentrate on the objective of reducing false positives[1]. Convolutional neural networks (CNNs), as a fast, scalable, and also end-to-end learning neural network, have significantly changed the landscape of goal learning, such as in image categorization, medical diagnosis and semantic division. A bronchial CT scan produces a volume of fragments that can be controlled to reveal different volumetric images of physical features in the bronchi. 2D convolution ignores the 3D spatial size, implying that it is unable to fully utilize the 3D condition relevant information, and 3D CNN can certainly be in agreement with this. Our goal is to optimized the 3D convolutional neural network (CNN) effectively to perform a binary distinction (benign and malignant) on CT images from the Lung Image Database Consortium picture collection

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(LUNA 16 Dataset)[2]. Deep neural networks have recently outperformed 2D convolutional neural networks in classification problems. Normally, they examine a slice of the CT scan. Because CT scan data is 3D, it will contain a variety of slices. 2D CNN examines the CT scan data from various angles, allowing for greater accuracy [1], [2]. So, while 2D CNN is one way, 3D CNN takes advantage of the whole nature of the 3D data. We have higher accuracy and specifically low knowledge section tasks instead of 2D data, and, and we may think about it from a human stand point to acquire a better understanding. This allows them to make a more accurate diagnosis of whether or not it is a lung nodule, and the convolutional neural network works in the same way.

II. RELATED WORKS

Multiple research communities throughout the world have done outstanding work on diabetes lung cancer. The following are some of the subsets of this research:

From CT images, Amrit Sreekumar et al. developed a model that predicts the coordinates of malignant lung nodules and demarcates the related areas. The C3D network architecture-based 3D CNN model was employed by them and obtained a sensitivity of 86% by using LIDC-IDRI as the major dataset, as well as a few resources from the LUNA16 grand challenge [3].

Jason L. Causey et al. discovered by integrating Spatial Pyramid Pooling and 3D Convolution, that deep screener has constant high accuracy performance; it achieves an AUC of 0.892 when tested with the challenge datasets in the Data Science Bowl 2017 competition (DSB2017) [4].

Thiago Jose Barbosa Lima et al. suggested a 3D Convolutional Neural Network (CNN)-based algorithm to classify lung nodules as malignant or benign in three alternative architectures of 3D CNNs with varied input sizes and numbers of convolutional layers. Data augmentation and alterations in the network training cost studied by them and try to overcome the problem of data imbalance [5].

Using data from the United States Geological Survey (USGS), Zarli Cho, Khin Myo Kyi, and Kyi Thar Oo applied the concept of image feature extraction with AlexNet Convolutional Neural Networks (CNN) in Digital Elevation Map and Topological Map boundary classification and obtained an accuracy of more than 66 percent [6].

Haichao Cao et al. proposed a three-dimensional (3D) Convolutional Neural Network-based Multi-Branch Ensemble Learning architecture (MBEL-3D-CNN). Three fundamental concepts are combined in the method: 1) building a 3D-CNN to maximise the use of spatial information of lung nodules in 3D space; 2) embedding a multi-branch network architecture in the 3D-CNN that is well adapted to the heterogeneity of lung nodules; and 3) using ensemble learning to effectively improve the generalisation performance of the 3D-CNN model. The proposed technique was evaluated on the LUNA16 dataset, and the experimental findings show that the proposed design performs better [7].

Pouria Moradi and Mansour Jamzad presented a new technique based on 3D CNN architecture that may minimise the false positive rate by 91.23 percent by merging knowledge from many classifiers in a new fusion method. The model was trained using the LUNA 16 dataset [8].

D. Jayaraj et al. introduced a new automated model to identified lungs cancer by using LIDC dataset. In the proposed system used Median and Gaussian filter in preprocessing and segment the image by using watershed segmentation algorithm. The classification of image will be done by using RF classifier and obtain a maximum accuracy of 89.90% [9].

Chen Zhao et al. proposed a patch-based 3D U-Net and contextual CNN algorithm for autonomously segmenting and classifying pulmonary nodules. To improve model training, employment of generative adversarial network (GAN) and 3D Contextual CNN with inception block to check the nodule[10] .

Hao Tang et al presents a fully three-dimensional system for automatic pulmonary nodule detection. It comprises of a U-Net-like 3D Faster R-CNN and a 3D classifier for false positive reduction, both of which were trained with online hard negative mining. To incorporate both models for predictions, we introduce a consensus ensembling method. In the 2017 TianChi Healthcare AI Competition, the proposed technique may achieve a CPM of 0.815 [11].

Emine Cengi et.al. Introduced a model which can obtain a high accuracy and it can successfully categorized 1.2 million images with 1000 categories. This was performed by using Caltech-101 dataset and constructed by using CNN architecture [12] .

S. M Salaken et al. introduced deep automated classifier mechanisms for the low population dataset and the performance improvement is statistically significant with the accuracy of 80% [13] .

E.Cengil et al. introduced their image classification process by using CNN architecture by the help of Caffe library in Kaggle dataset using GPU technology and check the classification with an accuracy of 83% [14].
Emine Cengil et al. Introduced a method of 3D CNN architecture for training system and lungs cancer identification by using Tensor flow library. They used SPIE-AAPM-LungX database for classification and obtain an accuracy of 70% [15].

III. METHODOLOGY

In the proposed model employment of 3D CNN architecture for Optimal Solution and tweak its internal layers to make it light [14]. Figure1 depicts the general structure of the proposed system: The input, convolution, pooling fully connected, and output layers make up the structure of a Convolution Neural Network [8]. While the Convolution layer is useful for extracting features, the pooling layer is used to extend or reduce the size of the image. Subsampling layers replace the pool layer in various CNN networking models. The totally connected layer is connected to any or all of the neurons in the preceding layer and is used to categorise the extracted characteristics into a variety of categories based on the training dataset[2]. By merging all of the valuable features retrieved from the input data in the previous levels, the final layer of the convolution neural network will perform an ultra-specific classification. The 3D-CNN model is made up of two convolutional layers, two max pooling layers, and two fully connected layers. To avoid over fitting during training, a relatively compact design was chosen. The first convolution layer's input was convolved with two 3x3x16 kernels (3x3 in spatial dimension and 16 in spectral dimension), and the second convolution layer's input was convolved with four 3x3x16 kernels. The activation function for the convolution output was Rectified Linear Input (RELU). On the output of each convolutional layer, a 2x2x2 max pooling was implemented. After the first max pooling operation, dropout with a probability of 0.25 was conducted, and after the first fully-connected layer, dropout with a probability of 0.5 was performed.

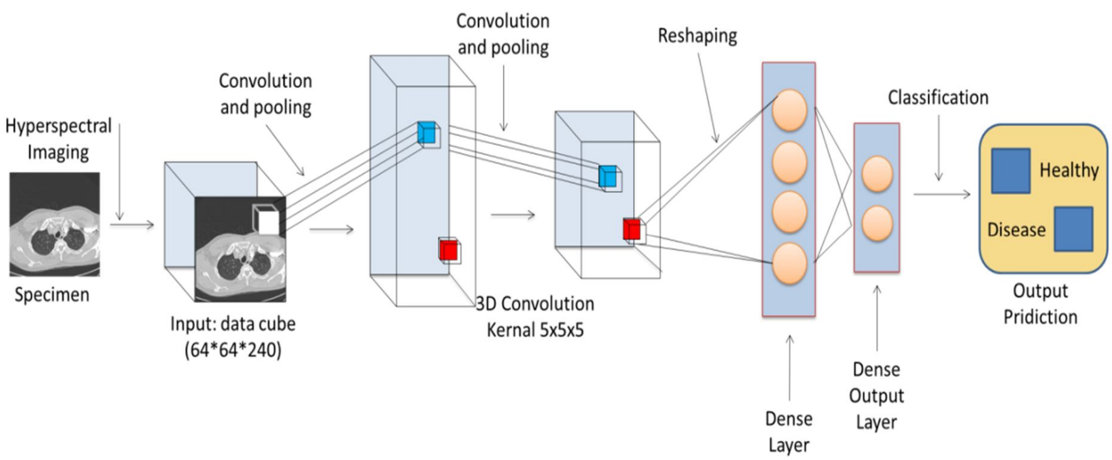

Figure 1: Architecture of the 3D CNN

A. Data Collection

Total 888 clinical thoracic CT images of size 512 GB are included in the LUNA 16 dataset. CT scans having slice thickness higher than 3mm or slice spacing that was irregular were removed. Four thoracic radiologists worked together to annotate the images. Each radiologist labelled the lesions they found as non-nodule, nodule 3 mm, or nodule > 3 mm. All nodules more than 3mm that are accepted by at least three out of four radiologists serve as the reference standard. The entire dataset is broken down into ten subgroups, each of which should be used for 10-fold cross-validation. All the images are in DICOM (Digital Imaging and Communication in Medicine) format which is standard internationally accepted format to view, store, retrieve and share medical images. The image in dataset is differing w.r.t its tumours location, size, slice depth and outline. The normal and malignant pictures are shown in Figure 2.

B. Training Data

The training and testing data have been separated from the complete dataset. In this model, 75% of dataset are uses for training and 25% of data are use as testing dataset.

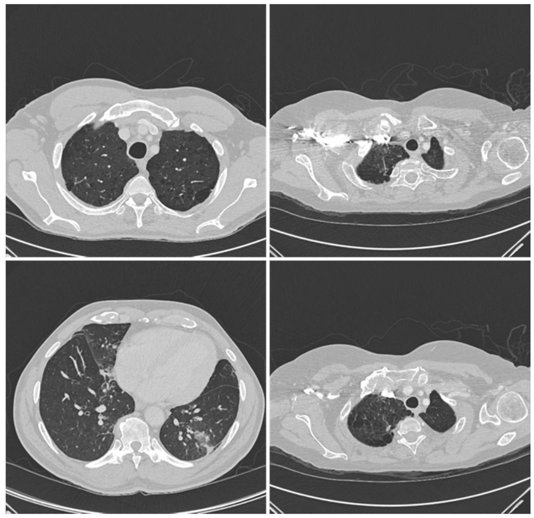

Figure 2: Input Benign images from the database

TABLE I. DESCRIPTION OF LUNA-16 DATASET

	Cancer Dataset Records	
	Record Size	Total Records
Data of Cancer Patients	512 GB	888

C. Proposed System Architecture

The suggested system design is depicted in Figure 3.The LUNA-16 dataset are used for the system, where records of Lung Cancer patients' symptoms are present. In the suggested model, the layers of a 3D CNN architecture are altering to illuminate its intermediate layers. The goal of this research is to get the optimised result while training the model.

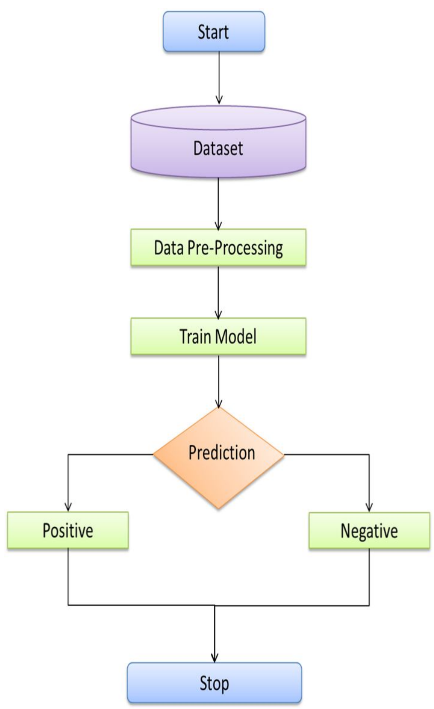

Figure 3: Proposed System Architecture

D. Applied Algorithm

The difference between a 3D CNN and a single layer CNN is that the input will be 3D data rather than a single layer. Filters will be 3D as well. So, rather than identifying 2D features like edges and corners, it will detect the same features in 3D, which is extremely important in this lung nodule situation because all of the data is 3D. The basic concept is that the medical image is entered. It passes through some convolutional layers before being assessed as healthy or diseased in the fully connected layer; in this situation, one module or no module occurs in the CT image. Other deep neural network medical picture assessments, in addition to this CNN, have been black boxes, leaving consumers with no idea how they are forecasting.
In the proposed architecture the layers of the 3D CNN are manipulate to make it lighter and take less time to train the entire dataset. This is done by tinkering with its hyper-parameter tuning. Finally, a new architecture is design with a learning rate of 0.3 and an epoch value of 80, which can train model earlier than the previous architecture and deliver a 90.13% optimised output.

IV. Result Analysis

The Proposed system is tested on a LUNA-16 dataset that had been pre-processed, and then trained. The entire dataset was first separated into training and testing datasets in 3:1 and then pre-processing is applied to remove unwanted noise from the input dataset. The model may be trained using photos from the LUNA-16 training dataset that have been extracted as features. Finally, a model is design that takes less time to train and produces output sooner than the previous model with an accuracy of 92% without and 90.13% with 10 fold cross validation. Table II compare the other proposed method against our proposed algorithm.

TABLE II. Test Score

	Learning Algorithm		
	3D CNN	CLA	Proposed Architecture
Obtain Accuracy	70%	90%	92%

A. Cross Validation Analysis

The 10-fold cross validation technique was utilised to see how our models performed on new data that had not been used during the training period. Table II shows the average cross validation score of the algorithms used. Using the 3D CNN architecture, we were able to reach the greatest result in 10-fold cross validation, which was 90.13 %.

TABLE III. Cross Validation Score

Obtain Accuracy	
Testing	10 fold cross validation
92%	90.13%

V. Conclusion and Future Scope

The forecast in the classification of benign and malignant lung blemishes in the LUNA 16 dataset was contrasted in this paper. The results of the experiments indicate that the improvised 3D-CNN archived optimised result as compare to previous architecture with greater efficiency of 90.13% with 10 fold cross validation. Because of the alterations in intermediary levels, the semantic network layers in this paper are quite small and light. The proposed method should improve the accuracy of the other data sources. In the future, the approach could be used to various medical imaging jobs using high-performance CADx equipment.

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