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AI-DRIVEN DETECTION OF LUNG CARCINOMA: LEVERAGING DEEP LEARNING IN CHEST CT ANALYSIS

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Abstract. Lung diseases encompass a range of conditions that impair lung function and disrupt the respiratory system. Among these, lung carcinoma remains one of the leading causes of mortality worldwide. Early detection significantly improves survival prospects, as diagnosing lung cancer at an initial stage is crucial for effective treatment. Over time, early identification has contributed to an increase in the average survival rate for lung cancer patients, rising from 14 percent to 49 percent. Computed tomography (CT) imaging plays a critical role in this diagnostic process, offering higher sensitivity and accuracy compared to traditional X-ray imaging. Several imaging methods that complement one another. A deep neural network for lung cancer detection. The ability to detect cancer using CT pictures has been created and tested. In order to classify the lung picture as whether it's benign or malignant, a densely linked convolutional neural network (DenseNet) and adaptive learning can help. The researchers utilized a dataset of 201 lung scans, with 90 percent of the pictures being positive. 10 percent of the data are utilized for testing and classification, while the rest are used for training. The proposed approach obtained an accuracy of 97.50% in tests, according to the results.

Keywords: Deep Learning, CNN, CT scans, Lung Cancer, AI

INTRODUCTION

Lung carcinoma is identified as the most significant causes of mortality worldwide due to cancer, representing one of the most aggressive tumors impacting global health. It holds the highest fatality rate among all cancers and is the primary cause of cancer-related deaths in both men and women. Each year, approximately 1.8 million new cases of lung cancer are reported (about 13% of all cancers), leading to around 1.6 million deaths globally, which constitutes 19.4% of all cancer fatalities. This disease is marked by the proliferation of abnormal cells within the lungs, forming tumors that significantly hinder health outcomes. Lung cancer mortality is notably influenced by smoking, responsible for around 85% of cases in men and 75% in women. Particularly in developing countries, lung cancer has an alarmingly high mortality rate, with low survival rates post-diagnosis and a steadily rising annual death toll [1]. Size and appearance of nodules were the most common indicators of cancer, and they can be classed as benign or malignant based on this information. Lung nodules smaller than 3 centimeters in diameter are considered benign, but those greater than 3 centimeters in diameter are referred to as malignant or lung masses [2][3]. The goal of this work was to develop and test a deep learning-based model for identifying lung cancer on chest radiographs.

EXISTING SYSTEMS

Mehdi Fatan Serj et al. utilized a Deep Convolutional Neural Network (DCNN) to capture high-level features from the initial convolution layers in the early stages of lung cancer classification. Their results from the Kaggle competition were evaluated against other high-ranking methods, demonstrating the model's effectiveness [7].

In related work, **Hwejin Jung** and collaborators implemented Three-Dimensional Deep Convolutional Neural Networks (3D DCNNs) with shortcut and dense connections to classify lung nodules. These specialized connections mitigated the gradient vanishing issue by allowing gradients to flow efficiently through the network, enabling the extraction of both general and specific lung nodule features. By expanding the DCNN from two to three dimensions, the model was able to capture 3D characteristics, where deep 3D CNNs demonstrated superior performance in identifying the spatial attributes of spherical nodules compared to shallower models. This approach leveraged the checkpoint ensemble method for enhanced results [8].

Additionally, **Woniak et al. [9]** proposed a novel lung carcinoma classification system, starting with the detection and extraction of lung nodules through the computation of local variance for each pixel in the original image, yielding a variance image with matching dimensions. Lung cancer classification using **Mao et al.** used unsupervised deep auto encoder [10]. To achieve an accurate diagnosis of lung nodules, the framework includes the following two types of characteristics:

i) MGRF-described appearance features that can characterize spatial inhomogeneities inside the lung nodule; and

ii) MGRF-described geometric features that define the shape of lung nodule geometry. [11]

Suren Makajua et al. looked at the advantages and disadvantages of the currently used cancer cell detection models and found some interesting results. After upgrading to the real model, the scientists were able to develop a lung cancer diagnostic model based on detection precision. In order to categorize a lung lesion as either malignant or benign, researchers applied an image segmentation and watershed approach using CT images [12].

PROPOSED METHODOLOGY

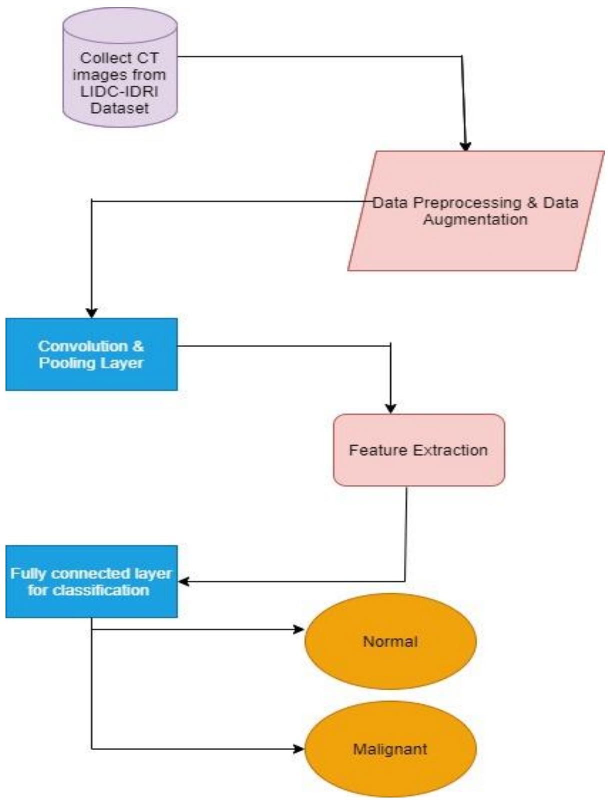

Figure 1. Process flow of classification model

When it comes to detecting lung cancer using CT images, CNN outperforms radiologists' manual detection, according to recent research. The detection of lung nodules has also been shown to be superior to that of experienced radiologists by CNN, according to several research. In order to better detect and classify lung cancer patients, CNN has taken two measures.

To categorize lung photos, artificial neural networks are first used to extract functionalities from the images, and then utilized to categorize them based on the extracted functionalities [4][5][6]. It is possible to use end-to-end learning in CNN or transfer learning by using previously trained models. A big dataset is necessary to overcome over-fitting difficulties and obtain improved accuracy. The end-to-end learning technique beats the transfer learning strategy [13] when working with a restricted dataset. To help differentiate between benign and malignant nodules on lung images, a classification model is given in above Figure 1.

PROPOSED MODEL OPERATIONS

Data Collection:
The LIDC-IDRI dataset was used to acquire the lung CT images, which may be seen here. Low-dose CT imaging images from 1010 individuals were acquired from eight medical enterprises and seven academic institutes as part of the LIDC-IDRI collection. Each of the 1018 occurrences in this collection comes with XML files describing the CT images.

Data Pre-processing & Augmentation:
During the preprocessing phase, CT DICOM images are converted to JPG format using the RadiAnt DICOM viewer. To optimize storage and processing efficiency, artificial intelligence techniques are applied to reduce image size by removing extraneous pixels that do not contribute to essential image information [14].

Convolution & pooling layer for feature Extraction
Classification in lung CT scan analysis is highly dependent on effective data extraction. Unlike manual feature extraction, a Convolutional Neural Network (CNN) learns features autonomously, allowing for more precise analysis. In identifying malignant nodules on lung CT scans, CNN models focus on lesions with diameters exceeding 3 mm. The CNN classification model processes images to categorize them as either normal or cancerous. During training, the CNN employs an automatic weight updating mechanism to optimize feature extraction.

In our proposed approach, the CNN model is divided into two distinct stages, each tailored to enhance classification accuracy.
(i) Convolutional layer
(ii) Pooling Layer

Classification
A performance metric for evaluating loss and accuracy is developed using the flattened feature map from the weighted layer obtained at the final pooling stage. Internal node values can be adjusted according to weights assigned within the performance metrics. After preprocessing, these layers are sequentially stacked, with the final output derived from the last layer, following standard procedures.

EXPERIMENTAL WORK

Creation of model
A performance score for loss and accuracy is generated using the flattened feature map from the weighted layer in the final pooling layer. The internal node values are automatically updated based on the weights from the performance metrics. At this stage, the layers are stacked sequentially, with the output from the final layer serving as the overall output.

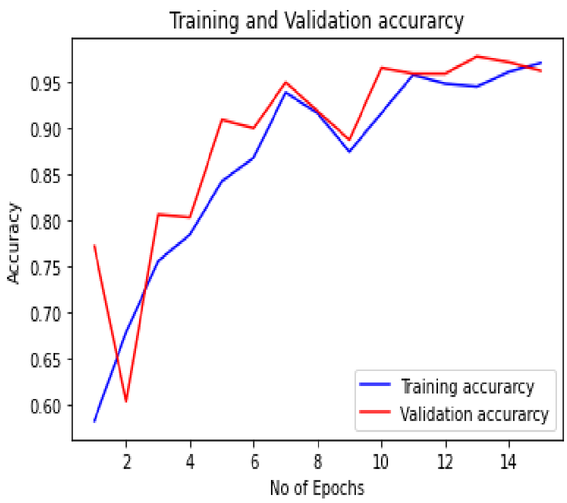

Figure 2. Training & Validation Accuracy

Result & Discussion

After the successful implementation of CNN model for detection of lung carcinoma following figure 2 & 3 shows the accuracy & loss graphs.

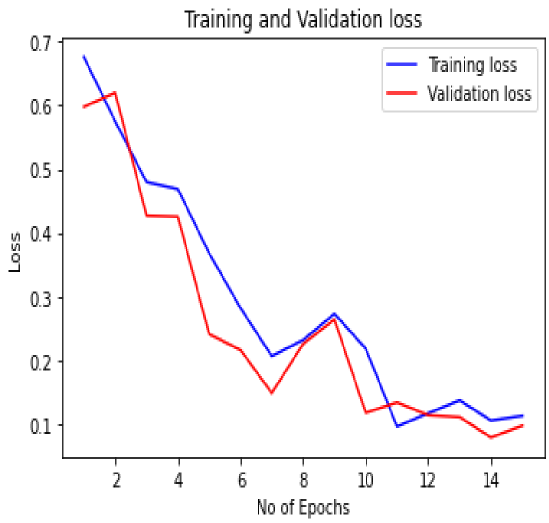

Figure 3. Training & Validation Loss

Validation loss: 0.0704193764925003
Validation accuracy: 0.9750145769119263

A single picture has been sent through our model for prediction after it was successfully implemented to determine if the image is normal or cancerous. Figure 4 shows the typical image obtained as a result of the following prediction output.

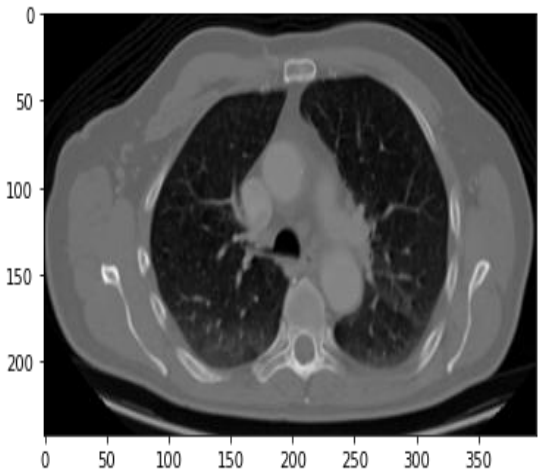

Figure 4. Output Image

CONCLUSION

Lung cancer is a complex issue, and deep learning technology has shown to be an excellent tool for dealing with it. In this paper, we have presented the CNN model, which we hope will help radiologists identify lung nodules more easily. As a powerful tool that physicians may employ in their work, deep learning has been shown to be as precise as a second diagnostic opinion.

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- Data Availability Statement- Data sets used here all are downloaded from GitHub
- Research Involving Human and /or Animals- No Human / Animals involved in this work
- Informed Consent- Yes

CONFLICT OF INTEREST

"The authors declare no conflicts of interest regarding the current research."

AUTHOR CONTRIBUTION

First author: proposed the research problem.
Second author: developed the proposed methodology
Third author: implemented proposed methodology and found results

All authors finally discussed the results and contributed in writing the paper.

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