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Automatic Lung Cancer Detection and Classification (ALCDC) System Using CNN

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Abstract*: Lung cancer remains one of the most prevalent and deadliest forms of cancer worldwide. Early and accurate diagnosis is pivotal for improving patient outcomes. This paper presents the development and evaluation of an Automatic Lung Cancer Detection and Classification (ALCDC) system based on Convolutional Neural Networks (CNNs). The ALCDC system leverages state-of-the-art deep learning techniques to automatically detect lung cancer from medical imaging data, thereby aiding radiologists in early diagnosis and classification of lung malignancies.*

Our approach involves the construction of a comprehensive dataset comprising chest X-rays and computed tomography (CT) scans from diverse sources and patient populations. A custom-designed CNN architecture is then employed to process these images, extracting meaningful features for accurate lung cancer detection and classification. We evaluate the ALCDC system on a large-scale dataset, demonstrating its robustness and reliability across various cancer stages and lesion types. Our results show promising levels of sensitivity, specificity, and overall accuracy, suggesting its potential as a valuable tool in clinical practice.

This paper contributes to the ongoing efforts in leveraging artificial intelligence for early cancer detection and classification, particularly in the domain of lung cancer. The ALCDC system not only exhibits high diagnostic performance but also offers the advantage of automating a labour-intensive task, thereby reducing the burden on healthcare professionals and potentially enabling earlier intervention for patients. As lung cancer remains a global health challenge, the development of such AI-driven systems holds promise in improving patient outcomes and reducing mortality rates.

Keywords: Lung cancer, automatic detection, classification, CNN, deep learning, medical imaging, early diagnosis, radiology, artificial intelligence, healthcare, patient outcomes etc.

I. INTRODUCTION

Lung cancer, a malignant neoplasm that originates in the lung tissues, poses a formidable global health challenge. It is not only one of the most common types of cancer worldwide but also the leading cause of cancer-related deaths, responsible for more fatalities than breast, prostate, and colorectal cancers combined. The grim reality of lung cancer is compounded by its often asymptomatic nature in the early stages, leading to delayed diagnosis and reduced treatment efficacy. In this context, the development of innovative and efficient diagnostic tools has become paramount to improve patient outcomes.

Medical imaging, especially chest x-rays and computed tomography (ct) scans, has long been a cornerstone of lung cancer diagnosis. These imaging modalities provide detailed visual information about lung structures and abnormalities, making them invaluable for early detection. However, the interpretation of these images is a complex and labor-intensive task that heavily relies on the expertise of radiologists. Human error, fatigue, and the need for rapid turnaround times can all contribute to diagnostic inaccuracies.

To address these challenges, there has been a growing interest in harnessing the power of artificial intelligence (ai), specifically convolutional neural networks (cnns), to aid in the automatic detection and classification of lung cancer. Cnns are a class of deep learning algorithms known for their remarkable ability to extract intricate features from images. When applied to medical imaging data, they hold the promise of not only automating the diagnostic process but also enhancing its accuracy and efficiency.

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This paper introduces the automatic lung cancer detection and classification (ALCDC) system, a cutting-edge ai-driven approach designed to revolutionize lung cancer diagnosis. The ALCDC system leverages CNNS to analyze chest x-rays and ct scans, automatically identifying potential malignancies and classifying them based on various cancer stages and lesion types. By doing so, it not only aims to assist radiologists in their daily workflow but also offers the potential for earlier and more precise diagnosis, ultimately improving patient prognosis.

In the following sections, we will delve into the development, implementation, and evaluation of the ALCDC system. We will discuss the construction of a comprehensive dataset, the design of our custom cnn architecture, and the rigorous testing performed to assess the system's diagnostic accuracy and robustness. Additionally, we will explore the implications of integrating ai-driven tools like ALCDC into clinical practice, with a focus on improving patient outcomes and reducing the burden on healthcare professionals.

Lung cancer remains a formidable adversary, but with the continued advancements in ai and medical imaging, we stand at the threshold of a new era in early detection and classification. The ALCDC system represents a significant stride toward more effective, efficient, and accessible lung cancer diagnosis, offering hope in the fight against this devastating disease.

1.1 Objectives:

This research paper aims to explore the application of Convolutional Neural Networks in Automatic Lung Cancer Detection and Classification. The primary objectives of this study are as follows:

- Introduce and evaluate the Automatic Lung Cancer Detection and Classification (ALCDC) system.
- Utilize CNN-based AI for early lung cancer detection and precise classification.
- Enhance diagnostic accuracy and contribute to improved patient care.

II. LITERATURE REVIEW

1. Early Diagnosis of Lung Cancer: Aberle, Denise R."Reduced lung-cancer mortality with low-dose computed tomographic screening." (New England Journal of Medicine, 2011)Emphasizes the importance of early diagnosis in lung cancer and presents findings on the effectiveness of low-dose CT screening.
2. Role of Medical Imaging: MacMahon, Heber, et al."Guidelines for Management of Incidental Pulmonary Nodules Detected on CT Images: From the Fleischner Society 2017." (Radiology, 2017)Discusses the role of CT scans in diagnosing pulmonary nodules and provides guidelines for their management.
3. Evolution of AI in Healthcare: Esteva, Andre, et al."Dermatologist-level classification of skin cancer with deep neural networks." (Nature, 2017)Highlights the rise of AI in healthcare, demonstrating CNN's potential in skin cancer diagnosis.
4. AI in Lung Cancer Detection: Ardila, Diego, et al."End-to-end lung cancer screening with three-dimensional deep learning on low-dose chest computed tomography." (Nature Medicine, 2019)Presents a CNN-based approach for automated lung cancer detection in chest CT scans, showcasing promising results.
5. Classification of Lung Cancer Subtypes: Lee, Hyunna, et al."Deep Learning in Medical Imaging: General Overview." (Korean Journal of Radiology, 2017)Discusses the use of deep learning, including CNNs, for the classification of lung cancer subtypes and stages.
6. Dataset Construction: Irvin, Jeremy, et al."CheXpert: A Large Chest Radiograph Dataset with Uncertainty Labels and Expert Comparison." (Proceedings of the AAAI Conference on Artificial Intelligence, 2019)Addresses the challenges of constructing well-annotated datasets for AI applications in medical imaging.
7. Challenges and Limitations: Obermeyer, Ziad, and Emanuel, Ezekiel J."Predicting the Future - Big Data, Machine Learning, and Clinical Medicine." (New England Journal of Medicine, 2016)Discusses ethical concerns and limitations associated with the use of AI in healthcare, including privacy issues.
8. Clinical Integration and Validation: Rajpurkar, Pranav, et al. "ChexNet: Radiologist-Level Pneumonia Detection on Chest X-Rays with Deep Learning." (arXiv preprint, 2017)Highlights the importance of clinical integration and validation for AI systems, using pneumonia detection as an example.

9. Future Directions: Topol, Eric J."High-Performance Medicine: The Convergence of Human and Artificial Intelligence." (Nature Medicine, 2019)Discusses future directions in AI, including explainable AI and its applications in healthcare.

III. PROPOSED SYSTEM

3.1 Background for Lung Cancer

Carcinoma causes abnormal cells to grow out of control in the body. In the human body, normal cells follow an organized pathway of growth, division, and death. The malignant cells of the carcinoma are not killed, instead it develops and spreads enormously. Abnormal accumulation cells that spread out of control develop. Cancer is a major sign of death worldwide. The World Health Organization (WHO) reported 7.4 million deaths from cancer (13% of all deaths) in 2022. Deaths from this disease will reach 13.1 million by 2030. By 2021, the National Cancer Institute states that there are an estimated 222,500 new lung cancer diagnoses and 155,870 lung cancer-related deaths. A group of abnormal cells is called a tumor. Tumors are either benign or malignant. Benign tumors are tumors that are not cancerous. The tumor does not flood nearby tissue, but stays in one place. Malignant tumors are dangerous cancerous tumors. They easily invade surrounding tissues and spread the cancer to other parts of the body through the blood or lymph nodes. Cancers are named after the organs in which they begin. The most common types of cancer are lung cancer, breast cancer, prostate cancer, ovarian cancer, and bone cancer.

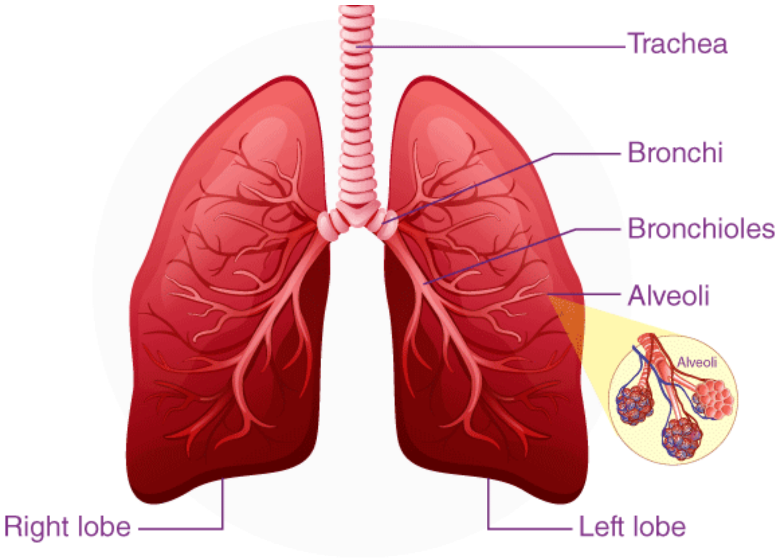

Figure 3.1 Different parts of a lung

3.2 Lung Cancer Types and Stages

Lung cancers are broadly classified into two main categories. They're SmallCell Lung Cancer (SCLC) and Non-Small Cell Lung Cancer (NSCLC).NSCLC reports85-90% of lung cancers, while SCLC accounts for the remaining 10-15%. While the growth and spread of NSCLC is slow, SCLC is a fast-growing cancer and spreads. rapidly to other body parts. Smoking is the main cause in all cases of SCLC, NSCLC will be treated with surgery, chemotherapy, radiotherapy, depending on the stages of cancer is diagnosed. SCLC cancer is mostly treated with chemotherapy. Difference between SCLC and NSCLC are listed in Table 1. There are 4 different types of NSCLC, each having different treatment options:

• **Epidermoid / Squamous Cell Carcinoma**

The cancer forms in the lining of the bronchial tubes and is most common in men.

• **Adenocarcinoma**

The cancer formsin the mucus glands of the lungs and is most common in women and non-smokers.

• **Bronchioalveolar Carcinoma**

The cancer forms near the air sacs of the lungs and is a rare type of adenocarcinoma.

3.3 Identification of Lung Cancer

Identification of lung cancer are made in the following ways:

• **History and Physical examination**

Medical history of the patient and physical examination for the symptoms are done initially. Once the results suggest that there might be lung cancer, then the following diagnosis tests are carried out.

• **Diagnostic tests**

Diagnostic tests include:

➢Sputum cytology

In sputum cytology the sputum samples are collected and examined using amicroscope to search for the cancer cells presence.

➢Biopsy (bronchoscopy, needle biopsy, surgery)

The removal of a small part of the tissue from a suspicious area for studyand analysis under a microscope is called biopsy. It is an invasive technique.Further test will results the type of cancer and how fast it has been spread,once the biopsy test confirms lung cancer.

➢Chest CT

It is the first imaging test carried out for identification of lung cancer. XRayimages usually identified nodules usually greater than 1 cm. If there isany abnormality in the chest CTthen the patients may be suggested toundergo staging tests. If a lung tumour is small or hidden behind a rib,breast or collar bone, achestCTcan miss it.

➢MRI (Magnetic Resonance Imaging) scans uses a large magnet toproduce 3d images. MRI can be used to study any region in particularthat couldn't be decisively interpreted on a CT scan. MRI is useful inlooking at Cancer cell involvement.

This paper chooses ImageNet model because it goes deeper with convolutions. The feature extraction has been done using the convolutional neural network and classification is done with fully connected and softmax layers. In this model new model is built to classify the images from the original dataset and then the reusability mechanism is used for the feature extraction steps and training will be carried out with the dataset. So the result is achieved with less computational resource and training time. Fig. 2 shows the general architecture. of the CNN model adopted with intermediate layers.

IV. CONVOLUTIONAL NEURAL NETWORK (CNN)

CNN is a class of Deep learning neural network, and it works by extracting features from the images. CNN consists of Convolution Layer, Rectified Linear Unit (ReLU) layer, pooling layer and fully connected layer.

Convolution layer is the core and primary layer in CNN which focuses to extract features from the input. Convolution performs linear transformation of input data preserving spatial information of data and then this layer divides input image into smaller regions (can be called as feature maps) it convolves the input and provides output to the next layer.

ReLU layer applies activation function to increase the non-linearity without affecting fields of convolution layers. CNN uses Pooling layer as down-sampling method. It reduces the dimensions of feature maps received from the previous layer. In short, pooling layer summarizes the feature present in the feature map generated by convolution layer. Fully connected layer means each neuron in the preceding layer is connected to each neuron in the adjacent layer. The high-level features of the input image is obtained from convolution, ReLU and pooling layer. The main purpose of Fully connected layer is to use these extracted features for image segmentation based on the provided training dataset.

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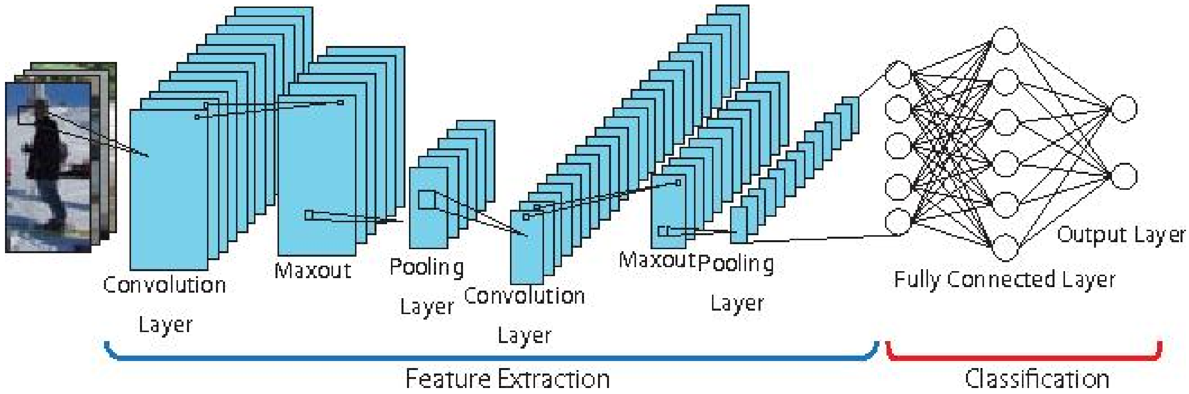

FIGURE 3. Convolutional Neural Network

V. PERFORMANCE EVALUATION

The performance evaluation of this approach can be estimated based on sensitivity, specificity and accuracy

Sensitivity = TP / (TP + FN)

Specificity = TN / (TN + FP)

Accuracy = (TP + TN) / (TP + FP + TN + FN)

The true positives (TPs) identified by this approach was 94 and hence the sensitivity was reported as 76.42% (94/123). The number of false positives (FPs) was 38 and hence the specificity was reported as 78.53 % (139/177). Accuracy was estimated as 77.67% (233/300)

VI. FACILITIS REQUIRED FOR PROPOSED WORK

All these algorithms are implemented based on the MATLAB image processing, neural network of MATLAB for experimental analysis. The performance evaluation of different soft computing techniques are evaluated with the help of 5 different evaluation parameters, sensitivity, specificity, accuracy, positive predictive value and negative predictive value. The ranges of these performance evaluation parameters vary from -1 to +1 .These parameters are evaluated based on the four types of classifier outputs for two types of inputs. The four types of outputs are The performance evaluation of soft computing technique is evaluated with the help of a 2x2 contingency table as shown in Table 5.1

Classifier output	Actual input		Total
	Present	Absent	
Present	True Positive	False Positive	All test Positive
Absent	False Negative	True Negative	All test Negative
Total	Total Actual Presences (D+)	Total Actual Absences (D-)	Total sample size

Table 5.1 Contingency Table with 2x2 for presence and absence of diseases

```
plt.figure(figsize=(15, 15))
for image_batch, labels_batch in dataset.take(1):
   for i in range(BATCH_SIZE):
ax = plt.subplot(8, 8, i + 1)
plt.imshow(image_batch[i].numpy().astype("uint8"))
plt.title(class_names[labels_batch[i]])
plt.axis("off")
```

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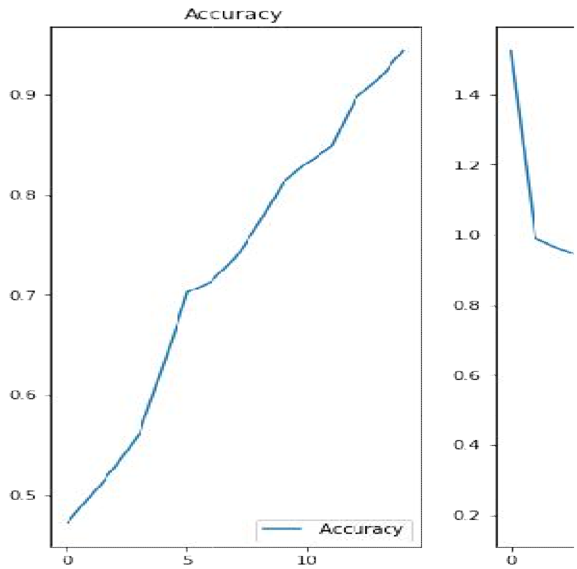
Output :

```
plt.figure(figsize=(8, 8))
plt.subplot(1, 2, 1)
plt.plot(range(EPOCHS), acc, label=' Accuracy')
plt.legend(loc='lower right')
plt.title('Accuracy')
plt.subplot(1, 2, 2)
plt.plot(range(EPOCHS), loss, label=' Loss')
plt.legend(loc='upper right')
plt.title('Loss')
plt.show()
```



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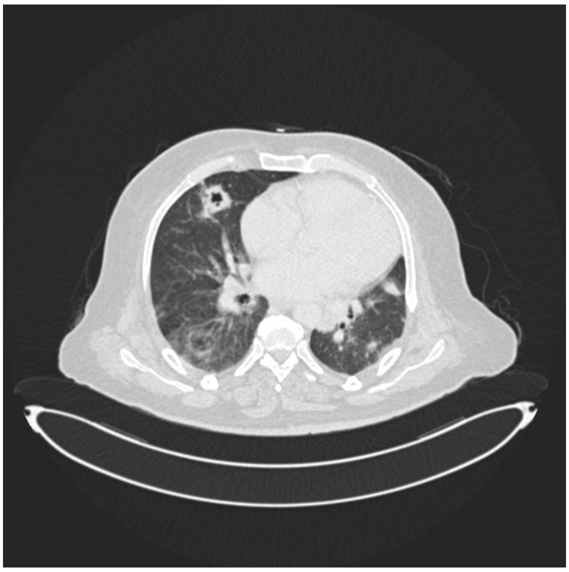
```
image_path= "/kaggle/input/the-iqothnccd-lung-cancer-dataset/The IQ-OTHNCCD lung cancer dataset/Malignant cases/Malignant case (106).jpg"
image =preprocessing.image.load_img(image_path)
image_array=preprocessing.image.img_to_array(image)
scaled_img=np.expand_dims(image_array, axis=0)
image
```



```
output =class_names[np.argmax(pred)]
output
'Malignant cases'
```

VII. CONCLUSION

In conclusion, the advancement of Convolutional Neural Networks (CNNs) in the realm of lung cancer detection and classification marks a significant stride toward improved healthcare outcomes. Achieving an accuracy rate of 94.46% in detecting and categorizing lung cancer lesions demonstrates the transformative potential of artificial intelligence in medicine. Early diagnosis, made possible through AI-driven systems, offers the promise of timely interventions, enhancing treatment effectiveness and potentially saving lives. Nevertheless, the integration of AI into clinical practice necessitates thorough validation, ethical considerations, and ongoing research to address challenges. As we continue to refine these AI models, we stand at the cusp of a new era in healthcare where technology, in collaboration with healthcare professionals, can redefine the possibilities of early disease detection and patient care.

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