

# Lung Cancer Detection using CNN

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**Abstract:** *The conversation about setting up a program for lung cancer screening was initiated with the publication of the results of the National Lung Screening Trial, which revealed lower mortality in high-risk participants undertaking CT screening. However, critical questions about the benefit-harm balance and the parameters of a screening programme, and its cost-effectiveness remain unresolved. A team of professionals in chest imaging, respiratory medicine, epidemiology, and thoracic surgery from all Swiss university hospitals prepared this joint statement following many sessions. The panel argues that premature and uncontrolled deployment of a lung cancer screening programme may cause severe harm that may stay unnoticed without thorough quality. This position paper examines how to initiate such a programme with the purpose of coordinating activities across specialisations and institutions involved while also establishing quality standards. It discusses current evidence that lung cancer screening can help people live longer lives, as well as what might happen in Switzerland if such a programme were established. There are also recommendations for CT technology for evaluating lung nodules, as well as criteria for lung cancer screening facilities. Important topics covered include patient management, registry development, and funding. Before considering population-wide screening, the panel recommends that lung cancer screening in Switzerland be limited to a nationwide observational study. This is because there are various critical issues that must be addressed first.*

**Keywords:** CNN, Machine Learning, pre-processing, Classification autonomous deep learning, detection.

## I. INTRODUCTION

Lung cancer is one of the most deadly and destructive forms of cancer, killing the majority of people who die from it. Only around 20% of them will survive for more than five years, according to a study published earlier this year. Because it was too late to diagnose them, the majority of them had little hope of surviving. There was a 70% likelihood that patients detected early would live for at least five years. [2,] Low-dose computed tomography (LDCT) screening can reduce a patient's risk of death by 20% in high-risk patients. In this study, it is emphasised how critical it is to begin therapy as soon as possible. To achieve an early diagnosis when CT scans suggest tumors, histological testing can be performed on tissue retrieved during the bronchoscopy procedure. When a pathologist examines a biopsy specimen, he or she is likely to make mistakes. The diagnosis has a lower than 80% likelihood of being right. The correct classification of squamous carcinoma, adenocarcinoma, small cell carcinoma, and undifferentiated carcinoma into key histological subtypes (squamous carcinoma, adenocarcinoma, small cell carcinoma, and undifferentiated carcinoma) is critical for treatment selection. The introduction of digital pathology, in which digital pathology scanners produce whole-slide images (WSI) with high resolution (up to 160 nm per pixel), allows computer vision to be used to detect cancer in WSIs. Convolutional neural networks (CNNs) have increased accuracy in a variety of computer vision applications in recent years, including medical imaging [4], and they are now the leading technology. We offer detecting cancer cells in WSIs of lung tissue in this work. To lessen the computational burden, the first step is to extract the WSI region containing tissue, which is known as a region of interest (ROI). Following that, picture patches are classified into tumour and normal classes using CNN. This assignment was offered as recent Automatic Cancer in Whole-slide Lung Histopathology (ACDC@LUNGHP) project, with preliminary findings described in [5.] We haven't found any additional papers that deal with CNN-based lung cancer. The following is a breakdown of the paper's structure. Section 2 provides a brief summary of relevant work, and discussion in Section 3. Part 4 contains the results, while section 5 has the conclusion.

## **II. PROBLEM STATEMENT**

The main cause of mortality from responsible for further than one out of all of cancer cases. After five years, the median survival rate of patients suffering from in this illness is less than 20%. As they were not diagnosed in time, the majority of patients have a dismal prognosis of recovery. Patients who were identified as high-risk early on had a five-year survival rate of around 70%. According to the findings of this study, treatment must begin as soon as possible.

## **III. LITERATURE SURVEY**

Matko Sari c, Mladen Russo, Maja Stella, Marjan Sikora "CNN-based Method for Lung Cancer Detection in Whole Slide Histopathology Images "[1] Early detection and treatment are very important for people to live. Histopathology is a regular procedure that is important for making an early diagnosis. Suit analysis is usually done by a pathologist, even though this method takes a long time and can be inaccurate. Automated detection of cancer zones would speed up the process and help the pathologist. There is a new way to find whole-slide photos of lung tumour samples that we show in this paper. It is done by using convolutional neural networks to classify images at the patch level (CNN). The performance of two different kinds of CNNs is looked at The a technique based on a CNN could help pathologists diagnose lung cancer.

Qing Wu and Wenbing Zhao "Small-Cell Lung Cancer Detection Using a Supervised Machine Learning Algorithm " [2] Cancer treatment costs and missed wages amount to huge amounts of money in annual expenditures. Lung cancer kills over 70,000 people every year. a substantial sum of money. In 2016, 225,000 new instances were discovered, but 4.3 million new instances were reported in China the year before. The vast majority of lung cancer-related deaths, according to available data, occur when the disease is discovered late in its course. It's critical to get a lung cancer diagnosis possible because early detection can save lives. The entropy deterioration method (EDM) is a new neural p2p method for detecting nselc cancer (SCLC) in tomography ( ct (CT) images that this publication. It's possible that this study early diagnosis of lung cancer. The researchers used high-resolution CT scans received to train and test. For this inquiry, the collection gave 12 CT scans. Six were healthy lungs, while the other six were for those with Stage 3 or SCLC, respectively. We used two photos and five scans from four groups to train our model.

Wadood Abdul "An Automatic Lung Cancer Detection and Classification (ALCDC) System Using Convolutional Neural Network" [3] Early identification of lung cancer in humans is critical due to the consequences for the individual. The detection of lung cancer tumors at an early stage is likewise a difficult task. The early detection of tumors has the potential to save a substantial number of human lives. Although an automatic lung cancer detection and classification (ALCDC) system based on computed tomography (CT) scan images is successful, developing a robust lung cancer detection and classification system is a difficult task. The current designs of lung cancer detection and classification systems are based on hand-engineered methodologies, with limited accuracy and other performance criteria. An AL CDC CT scan picture using DL is introduced as a result of the extraordinary achievement in numerous recognition-related tasks. An ALCDC system is constructed for this aim, employing the convolutional neural network (CNN) model, to detect and categorize whether tumours identified in the lungs are malignant or benign. The proposed ALCDC system's robustness and effectiveness are validated using Lung Image Database Consortium (LIDC) and the Image Database Resource Initiative (IDRI). The planned ALCDC system has a 97 percent accuracy. 2comparison indicates ALCDC system outperforms the existing state-of-the-art systems form. The proposed ALCDC will aid in medical diagnosis research and healthcare delivery systems.

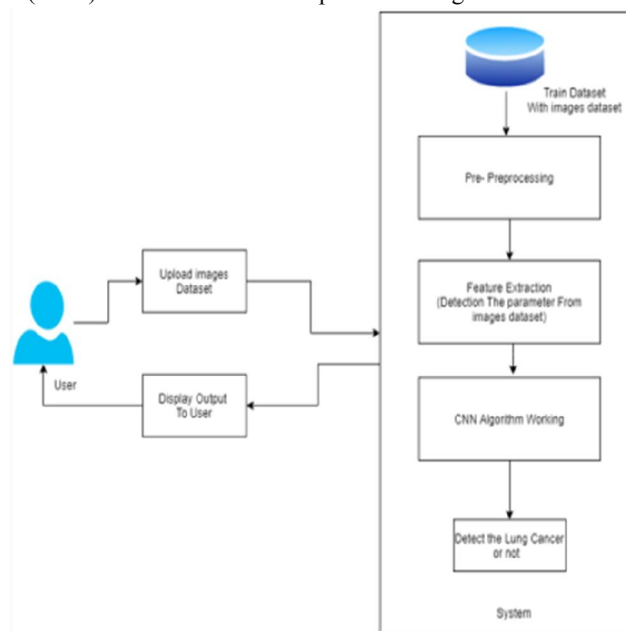
Sanjukta Rani Jena,Dr. Thomas George "Texture Analysis Based Feature Extraction and Classification of Lung Cancer" [4] the deadliest disease, and its cure must be the principal focus of all scientific research. Early cancer detection can aid in the total cure of the literature, there are several methods for detecting lung cancer. Several researchers have given data for cancer prediction. These papers mostly examine contemporary lung cancer detection methods available in the literature. To improve the effectiveness of cancer detection, a variety of approaches have been developed. As explained in this study, a range of applications such as support vector machines, neural networks, and image processing are employed for cancer diagnosis.

Tiantian Fang "A Novel Computer-Aided Lung Cancer Detection Method Based on Transfer Learning from GoogLeNet and Median Intensity Projections" [5] This study proposes a rapid, accurate, and stable lung cancer detection method based on revolutionary deep learning techniques. A transfer learning strategy was used to create a structure similar to GoogLeNet. In contrast to prior investigations, multi-view features of three-dimensional computed tomography (CT) scans were included using Median Intensity Projection (MIP). The LIDC-IDRI public dataset of lung nodule pictures was used to test the system,

and 100-fold data augmentation was used to ensure training efficiency. After 300 epochs, the trained system yielded 81% specificity, which was higher than other available systems. A t-based confidence interval for the population mean of the validation accuracies was also used to ensure would yield consistent findings across several trials. Following that, a controlled variable experiment was conducted net effects of the system's two fundamental elements - fine-tuned GoogLeNet and MIPs - on detection accuracy. fine-tuned GoogLeNet and Alexnet on MIPs and common 2D CT scans, respectively, resulted in four treatment groups. MIPs enhanced the network's accuracy by 12.3%, and GoogleLeNet surpassed Alexnet by 2. Access to the GPU-based system was provided via a web server, allowing for long-distance maintenance and eventual transition into a practical tool.

#### IV. PROPOSED SYSTEM

Figure 1 shows how the proposed system is broken down into three parts. In the first step, the method is said to get the CT images from the LIDC database. In the second step, expert markings are used to separate nodules into groups. Convolutional Neural Network (CNN) is the model that completes the diagnosis after all the tests have been looked at.



**Figure 1: System Architecture**

#### V. ALGORITHM

##### CNN (Convolution Neural Network)

People use them to do things like see and find patterns. Among other things, CNNs can be used to identify images, and objects, and separate them, figure out how to do this. layers: CNNs has four types of layers: this one is called a "convolutional layer," and it looks like this:

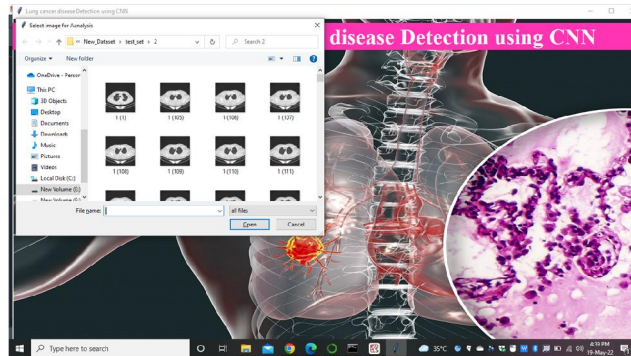
This is called a "convolution layer." All of the input neurons connect to this layer, which is called the "convolution layer." A small group of neurons in the ABC news input nodes connect to the part of the brain that is hidden from view. It is the feature map as small as possible. Pooling is the layer that is used for this. In the buried layer of a CNN, there will be activation and pooling next layer, it's important to make a one-dimensional grid. There are many convolutional layers, and when we smooth the output of each one, we get a single long feature vector. Network "Fully Connected Tiers" are the last connected. Flattened data from the previous Pooling or Convolutional Level is sent into the fully linked layer as the first data there, as shown in the figure.

**VI. OUTPUT**

**6.1 Frontend of the project. (GUI)**



We have to fetch dataset images using python libraries



We have to perform image procession on a given dataset.



and finally, we detected our desired output by applying the CNN algorithm to a given dataset.

**VII. CONCLUSIONS**

The fully automatic deep learning-based method for the identification of lung cancer in entire slide histopathology images is proposed in the proposed system. The AUC and patch classification accuracy of the VGG16 and ResNet50 CNN architectures were compared, with the first showing greater AUC and patch classification accuracy. The results suggest that convolutional neural networks have the ability to to diagnose lung cancer using complete slide images; additionally, in the proposed system, we use the CNN algorithm, which has the highest accuracy. We are also conserving our time.

**REFERENCES**

- [1]. Dinggang Shen, Guorong Wu, and Heung-II Suk. Deep learning in medical image analysis. Annual review of biomedical engineering, 19:221–248, 2017.



- [2]. Zhang Li, Zheyu Hu, Jiaolong Xu, Tao Tan, Hui Chen, Zhi Duan, Ping Liu, Jun Tang, Guoping Cai, Quchang Ouyang, et al. Computer-aided diagnosis of lung carcinoma using deep learning-a pilot study. arXiv preprint arXiv:1803.05471, 2018.
- [3]. Andre Esteva, Brett Kuprel, Roberto A Novoa, Justin Ko, Susan M Swetter, Helen M Blau, and Sebastian Thrun. Dermatologist-level classification of skin cancer with deep neural networks. *Nature*,542(7639):115, 2017.
- [4]. Stephen Baek, Yusen He, Bryan G Allen, John M Buatti, Brian J Smith, Kristin A Plichta, Steven N Seyedin, Maggie Gannon, Katherine R Cabel, Yusung Kim, et al. What does ai see? deep segmentation networks discover biomarkers for lung cancer survival. arXiv preprint arXiv:1903.11593, 2019.
- [5]. Wei Li, Peng Cao, Dazhe Zhao, and Junbo Wang. Pulmonary nodule classification with deep convolutional neural networks on computed tomography images. *Computational and mathematical methods in medicine*, 2016.
- [6]. Yuanpu Xie, Fuyong Xing, Xiangfei Kong, Hai Su, and Lin Yang. Beyond classification: structured regression for robust cell detection using convolutional neural network. In *International Conference on Medical Image Computing and ComputerAssisted Intervention*, pages 358–365. Springer, 2015.
- [7]. Kaiming He, Xiangyu Zhang, Shaoqing Ren, and Jian Sun. Deep residual learning for image recognition. In *Proceedings of the IEEE conference on computer vision and pattern recognition*, pages 770–778,2016.
- [8]. Kyunghyun Paeng, Sangheum Hwang, Sunggyun Park, and Minsoo Kim. A unified framework for tumor proliferation score prediction in breast histopathology. In *Deep Learning in Medical Image Analysis and Multimodal Learning for Clinical Decision Support*, pages 231– 239. Springer, 2017
- [9]. Automatic Cancer Detection and Classification in Whole-slide Lung Histopathology (ACDC@LUNGHP). <https://acdc-lunghp.grand-challenge.org/Challenge/>, 2019. [Online; accessed 1-April-2019].
- [10]. Christian Szegedy, Wei Liu, Yangqing Jia, Pierre Sermanet, Scott Reed, Dragomir Anguelov, Dumitru Erhan, Vincent Vanhoucke, and Andrew Rabinovich. Going deeper with convolutions. In *Proceedings of the IEEE conference on computer vision and pattern*