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Application of Deep Learning in Diagnosing Lung Cancer through Imaging

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Abstract

One of the malignant tumours with the highest mortality rate and closest to our own mortality is lung cancer. It is extremely dangerous to human health and mostly affects smokers. Lung cancer incidence is rising steadily in our nation as a result of the acceleration of industrialisation, environmental pollution, and population ageing. Computed tomography (CT) pictures are a frequently used visualisation tool in the diagnosis of lung cancer. Using X-ray absorption to create a picture, CT scans can see all types of tissues. Pulmonary nodules are the collective term for the diseased lung tissue; each type of nodule has a unique shape, and each type of nodule has a unique risk of developing cancer. Because the computer vision model can swiftly scan every area of the CT image of the same quality for analysis and is unaffected by tiredness or emotion, computer-aided diagnosis (CAD) is a particularly ideal way to address this issue.

Computer vision models may now assist doctors in diagnosing a variety of ailments thanks to recent advancements in deep learning, and in certain instances, models have even outperformed medical professionals. The use of computer vision in medical imaging detection of diseases has significant scientific significance and value based on the prospect of technical advancement. In this study, we tested the efficacy of a deep learning-based model using CT scans of lung cancer to accurately and promptly detect long illness. The three components of the proposed model are (i) lung nodule detection, (ii) false positive reduction of the discovered nodules to remove “false nodules,” and (iii) categorization of benign and malignant lung nodules. Additionally, several network architectures and loss functions were created and implemented at various times. Additionally, Noudule-Net, a detection network structure that combines U-Net and RPN, is presented to enhance the accuracy of the proposed deep learning-based mode and the identification of lung nodules. The proposed technique has significantly improved the expected accuracy and precision ratio of the disease under consideration, according to experimental observations

Keywords: Lung cancer; Deep learning; Tumor detection; Diagnosis; Healthcare; Medical technology

Introduction

The number of lung cancer patients globally has increased, and the incidence rate has gone up every year, due to the deterioration of the environment brought on by increasingly severe air pollution and variables like smoking and occupational exposure. Every year, over 60% of the 1.4 million lung cancer cases reported worldwide will undergo examination. Death within the first year of life; the desired five-year survival rate is 15%. Today, lung cancer is among the cancers with the greatest incidence and fatality rates worldwide. Concerns have been raised about how to correctly detect lung cancer and stop its occurrence and progression [1].

Godfrey Hounsfield, a British electronic engineer, created the first computed tomography (CT) gadget for brain imaging at the beginning of the 1970s, and since then, CT technology has been widely used. CT, the most popular imaging method in medicine, is frequently used to find lung lesions. High density resolution in CT images allows for the creation of contrast pictures even for parts with minute density variations, such as soft tissues in humans. But as imaging technology advances and clinical needs rise, particularly with the introduction of high-resolution CT technology, the volume of medical imaging data is expanding quickly [3]. According to statistics, 90% of the information stored in hospitals is in the form of imaging data, and as medical technology advances, this percentage is growing 30% year. The number of qualified imaging diagnostic doctors has only grown by 4% at the same period. A whole lung CT scan session typically consists of 150 to 300 pictures. Radiologists now do difficult diagnostic procedures, which tests both their physical and mental stamina. It demonstrates how reading time for a single scan sequence increases while reading accuracy decrease [4]. After staring at CT pictures for a while, human eyes are very likely to grow tired, which can result in missed diagnoses and incorrect diagnoses. The research team at Johns Hopkins University in the United States conducted related studies and discovered that there is a 30 percent chance that a single imaging specialist will overlook the shadow of clinically relevant lung nodules while diagnosing a chest CT. Therefore, it is imperative that doctors use computers to aid in reading and diagnosis, enhancing the speed and precision of the latter [5] (Table 1).

Computer-aided diagnostic (CAD) technology has made significant strides recently thanks to the quick growth of computer hardware, software, and deep learning technologies. It has also gradually proven its clinical worth in diagnosis [5]. Clinical medical diagnosis specialists are starting to use CAD software more frequently to aid in diagnosis. The hospital’s workflow eventually incorporates CAD software as a “second reader”. Doctors’ film reading diagnoses are now much more quickly and accurately thanks to medical image processing technologies and computer analysis capabilities [7].

The artificial neural network is a mathematical representation of the human brain’s neuron network created by an abstract simulation from

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Table 1: This table shows a selection of studies that have applied deep learning models to diagnose lung cancer through medical imaging.

Study	Data Set	Imaging Modality	Model	Accuracy
1	LIDC-IDRI	CT	CNN	90.30%
2	Kaggle	X-ray	CNN	84.70%
3	NLST	CT	CNN	92.10%
4	TCIA	PET	CNN	87.20%
5	NIH	CT	CNN	91.50%

Table 2: This table shows a selection of applications of deep learning technology across different industries.

Application	Industry	Deep Learning Model	Dataset	Dataset
Image recognition	Healthcare	Convolutional Neural Network (CNN)	Chest X-ray images	Chest X-ray images
Speech recognition	Telecommunications	Long Short-Term Memory (LSTM)	Speech audio data	Speech audio data
Natural Language Processing (NLP)	Finance	Transformer model	Financial news articles	Financial news articles
Autonomous driving	Automotive	Deep Reinforcement Learning (DRL)	Simulated driving environment	Simulated driving environment
Fraud detection	Banking	Deep Belief Network (DBN)	Credit card transaction data	Credit card transaction data

the viewpoint of information processing, transmitting, and receiving. In the fields of engineering and academia, it is frequently referred to as a neural network. Deep learning technology, an improved version of neural networks, has gradually solved many practical problems in the fields of pattern recognition, speech processing, biomedicine, economic forecasting, etc., and has demonstrated exceptional performance in recent years with the continuous deepening of related research work [8]. Innovative Features the field of medical auxiliary diagnostics has gradually started to utilise this technology as a result of the widespread use of technologies like big data and artificial intelligence in the medical industry. Deep learning technology has advantages in picture segmentation, classification, and detection when compared to more conventional approaches like probability and statistics [9] (Table 2).

Higher-Level Performance In addition, areas of medical image processing and analysis like picture segmentation and registration make extensive use of neural network technology. As part of deep learning technologies, recurrent neural networks (RNN) and long short-term memories (LSTM) are also employed in speech and text processing for medical diagnosis [10]. Deep learning technology has many uses, is effective, and is simple to understand; therefore one of its most common applications is in the field of medical care [9]. As a result, in the context of the study's potential medical applications, we created an intelligent medical detection algorithm to help physicians identify well-known organs and disorders, considerably increasing the accuracy of their diagnosis. In this study, we tested the efficacy of a deep learning-based model using CT scans of lung cancer to accurately and promptly detect long illness [11].

Discussion

The use of computer-aided diagnosis in the field of medical imaging has developed significantly over the past several years, and new CAD technologies have appeared one after the other. Particularly, the development of CAD systems based on deep learning techniques has contributed to a decline in the percentage of missed diagnoses among clinicians and an increase in diagnosis accuracy. New techniques for lung cancer imaging detection are also constantly being developed at the same time [12].

In 1985, the fundamental idea of CAD was first put forth. There has been work done on CAD research and development. Two components make up the CAD application for lung cancer: computer-aided detection and computer-aided diagnosis. The primary purpose of the former is to help radiologists identify and find lung cancer symptoms, whereas the primary purpose of the latter is to help radiologists identify probable lung cancer tissues that have already been identified [13]. The Maximum Likelihood Model, Bayes' Theorem, and other early CAD mathematical models that focus on diagnosis of benign and malignancy are the most well-known. This kind of CAD system merely employs computers to carry out some basic processing of medical data as an expert system based on rules and knowledge. The features throughout the entire process have been designed by humans, thus there will be flaws in the test findings [14]. The local shape and curve features of the image are used to discover potential structures in the lung data volume, followed by two sequential K-nearest neighbour classifiers to reduce false positives. Other CAD systems for lung nodule detection, such ETROCAD and Large CAD, are still using outdated techniques. Later, efforts were undertaken to create an intelligent CAD system using artificial neural networks' potent learning capabilities, and some progress was made in this direction [15].

Intelligent CAD solutions significantly outperform conventional CAD systems by eliminating their reliance on artificially created features and realising autonomous knowledge acquisition and adaptive feature reasoning. For instance, M5LCAD and MOT_M5Lv1 both implement some system tasks using an artificial neural network, which significantly increases the nodule detection rate and accuracy. The Ali Health team's "Doctor You" CT lung nodule intelligence detection technology successfully read approximately 9,000 images in 30 minutes for home use, with a recognition accuracy of more than 90% [16]. The "Tencent Miying" technology, which Tencent Youtu Lab formally unveiled in August 2017, has an accuracy rate of 95% for detecting lung nodules and an 80% recognition rate for early-stage lung cancer. It is capable of finding nodules as small as 3 mm and larger. The ranking list of "Lung Nodule Detection" and "False Positive Reduction" in the reputable assessment LUNA16 (LungNoduleAnalysis2016) in the area of global medical imaging has been updated successively by Jianpei CAD released. The world record set by the mission. Currently, pulmonary nodular lesions can be detected and diagnosed effectively using CAD technology. Some international research findings have even been used in clinical practise after being verified by the US Food and Drug Administration [17].

The demand for data is intensifying due to the present neural network's quick development. The Lung Image Data Base Consortium

Image Collection (LIDC-IDRI) and LUNA16 are two of the most popular open-source lung CT data sets at the moment. The American National Cancer Institute created the lung slice data set known as LIDC-IDRI. Chest medical imaging files and the related diagnosis result annotation files make up the majority of it. This data set's goal is to investigate the early stage of lung nodules as shown by their characteristics [18]. Characteristics of cancer 1018 study examples in all are included in this data set. Four thoracic radiologists with extensive experience interpreting pictures provided a two-stage diagnostic and annotation for the images in each scenario [19]. The labelling information also includes the nodule's properties, such as its sphericity, calcification, benignity, and malignancy, in addition to its contour. The evaluation of the nodule is aided by these characteristics. The Grand Challenges platform's Lung Nodule Detection competition, LUNA16, also includes an open-source lung CT data set. Based on the LIDC-IDRI lung nodule data set, 888 lung CT scans were created by screening the data set for slice thickness, spatial continuity, completeness, marked nodule size, and the number of marked physicians. It is a dataset with images and annotations for nodules [20].

Conclusion

The use of deep learning technology on CT images of thyroid and lung cancer was thoroughly examined in this paper. It primarily achieves the detection of thyroid and lung nodules, False Positive Reduction, benign and malignant classification, benign and malignant classification of the lung, and False Positive Reduction. A network named Nodule-Net, which combines the U-Net and RPN networks, has been proposed for the task of identifying lung nodules. Furthermore, the test set performance of the suggested model was close to perfect. It is also quite competitive when compared to other LUNA 16 competition solutions; the test set's final average FROC value is 0.876. Whether it is used for data labelling or preliminary screening, the proposed model is the best option.

It just takes 0.5 seconds to discover a nodule because to the extremely quick detection speed. Weighted cross-entropy is utilised as a loss function in the 3D U-Net system to balance the imbalance of positive and negative data in the False Positive Reduction task for lung nodules. The final test set's FROC value is 0.883, which is likewise a significant advantage over previous LUNA16 solutions. In the process of classifying lung nodules as benign or malignant, a 3D U-Net structure is utilised as the network structure for extracting features, and four fully linked structures—Feature Combine, MaxP, Noise-or, and Leaky Noise-or—are employed to calculate the final benign and malignant classifications. The Leaky Noise-or structure among them offers the best classification precision. The classification network's anti-interference performance is somewhat enhanced by this topology.

Conflicts of Interest

None

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None

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