DETECTION OF CANCER NODULES USING SCANNED MEDICAL IMAGES. CASE STUDY: LUNG CANCER NODULE DETECTION

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Abstract: Novel methods are required to enhance lung cancer detection, which has overtaken other cancer-related causes of death as the major cause of cancer-related mortality. Radiologists have long-standing methods for locating lung nodules in patients with lung cancer, such as computed tomography (CT) scans. Radiologists must manually review a significant amount of CT scan pictures, which makes the process time-consuming and prone to human error. Computer-aided diagnosis (CAD) systems have been created to help radiologists with their evaluations in order to overcome these difficulties. These systems make use of cutting-edge deep learning architectures. These CAD systems are designed to improve lung nodule diagnosis efficiency and accuracy. In this study, a bespoke convolutional neural network (CNN) with a dual attention mechanism was created, which was especially crafted to concentrate on the most important elements in images of lung nodules. The CNN model extracts informative features from the images, while the attention module incorporates both channel attention and spatial attention mechanisms to selectively highlight significant features. After the attention module, global average pooling is applied to summarize the spatial information. To evaluate the performance of the proposed model, extensive experiments were conducted using benchmark dataset of lung nodules. The results of these experiments demonstrated that our model surpasses recent models and achieves state-of-the-art accuracy in lung nodule detection and classification tasks.

Keywords: Detection of Cancer nodules, scanned medical images, Lung Cancer Nodule Detection

Introduction: Lung cancer is the main reason for cancer-related deaths, according to the American Cancer Society. Following to the statistics for cancer in 2022, there were almost 1.9 million reported cases and a total of 609,360 deaths. Nearly 350 of these deaths each day were caused by lung cancer[1]. Despite medical improvements, cancer continues to be a serious health concern, and it is still very difficult to successfully treat and prevent its many forms. Cancer therapy is complicated and difficult due to its many kinds. Furthermore, certain tumors can be fatal, emphasizing the importance of early detection[2]. Screening is critical for detecting cancer in its early stages since it looks for cancer cells in patients who are asymptomatic. This stage is critical in the battle against cancer because it allows for prompt detection, which is required for effective treatment. Medical imaging systems provide important information about the kind and stage of cancer that may be used to build a suitable treatment strategy[3,4]. As a result, it is critical to offer clinical follow-up for patients and to undertake cancer tests in order to detect cancer early. This method facilitates in treatment planning and, as a result, improves patient outcomes[5].

The quality of the data collected utilizing scanning technologies has a considerable impact on the accuracy of sickness diagnosis and treatment findings. Precise analysis based on reliable screening processes and treatment regimens can improve patients' overall quality of life and length of life. The use of modern cancer imaging technology is required to reveal the incredibly effective treatment regimens. Patients who undergo the necessary imaging tests and inspection have a significant advantage over other patients during the arduous treatment process. A comprehensive analysis of imaging data is incredibly important in order to obtain the finest treatment plans and, ultimately, improve patient outcomes.

The expenses of screening procedures for lung nodules are considerable, and it can be difficult to recognize abnormalities since nodules come in a diversity of sizes and forms. In order to tackle this challenging endeavor, computer-aided diagnostic (CAD) systems have emerged as crucial tools for physicians. Positive results from recent research on machine learning-based digital pathology picture categorization point to the possibility of a rise in the use of these systems in pathology clinics. The use of AI and machine learning-based solutions is expected to significantly increase in the future, particularly within the discipline of pathology.

The most lethal type of cancer is lung cancer, however early identification can significantly improve the prognosis for patients. Low-dose computed tomography has become the gold standard for identifying which lung nodules need a biopsy to evaluate if they are malignant or benign. In clinical settings, this approach has a comparatively high risk of false positives. It frequently requires the identification of a sizable number of possibly cancerous nodules for biopsy, resulting in a great deal of unneeded biopsies being carried out on people who aren't genuinely suffering from cancer.

1. We developed a custom CNN architecture with integrated channel and spatial attention mechanisms enhances feature extraction by selectively focusing on relevant features, improving accuracy in image classification.
2. The inclusion of attention mechanisms addresses limitations of traditional CNNs, allowing the model to emphasize important patterns and suppress noise, resulting in improved discriminative power.
3. The improved accuracy and efficiency of our model has implications for various domains such as medical imaging, object recognition, and natural language processing, enabling more accurate and reliable classification in these applications.
4. The extensive experience is performed on challenging dataset and reveals that the proposed model achieved state-of-the-art performance when compared to existing techniques.

The rest of this manuscript is structured as follows: "Related work" section provides a concise summary of the existing techniques for lung nodule categorization reported in the literature. "Proposed model" section gives a detailed discussion of the materials and procedures used to treat pulmonary nodules. "Experimental results" section discusses the execution of the suggested model, as well as experimental data and the evaluation of the proposed model. Finally, in "Conclusion and future direction" section, we end the present work.

Review of literature:
Several investigations have employed deep learning methodologies to address classification issues6,7,8. The objective of this study is closely aligned with the existing computer-aided diagnosis (CAD) applications for the classification of lung nodules. Consequently, we conducted a thorough examination of the cutting-edge techniques for classifying lung nodules that have been recently developed.

Researchers have employed a two-dimensional convolutional neural network (CNN) to detect lung nodules in CT scans. This CNN focuses on extracting and learning important features from the two-dimensional images. For instance, in Ref.9, the authors developed a transfer learning technique using MultiResolution CNN to classify candidates in lung nodule recognition. They applied CNN-based image-wise calculations with different depth layers, resulting in improved accuracy of lung nodule detection. They achieved 0.9733 precision on the Luna 16 Data Set. In Ref.10, a CAD approach for pulmonary nodules was proposed, utilizing multi-view convolutional networks to reduce false positives. Another deep learning model, MultiView-KBC11, was proposed for lung nodule recognition. It employed KBC based deep learning technique to classify benign-malignant lung nodules on chest images. In Ref.12, a deep residual learning approach using CT scans was presented for cancer detection. ResNet and UNet models13 were employed for feature extraction, and machine learning algorithms (MLA) such as XGBoost and Random Forest were employed for classification, achieving 84% accuracy. They conducted a research study that used machine learning and ensemble learning methods to predict lung cancer based on early symptoms. They utilized various MLAs, including multilayer perceptron (MLP)14, Naïve Bayes, support vector machine (SVM)15, and neural networks for lung cancer classification. The dataset for this study was obtained from the UCI repository. The ensemble learning approach in this study achieved a 90% accuracy.

The 3D CNN, similar to its 2D counterpart, incorporates three dimensions in feature learning. It considers pairs of dimensions simultaneously, such as x and y, y and z, and z and x. To address false-positive reduction in lung nodule detection using chest radiographs, researchers16 developed an ensemble of CNNs. Another study17 introduced Multilevel contextual Encoding for false-positive reduction in chest radiographs, employing a fivefold cross-validation approach to detect nodule sizes and shapes. Their architecture achieved 87% sensitivity with an average of four false positives per scan. For detecting Small Cell Lung Cancer, a novel approach utilizing the entropy degradation method (EDM) was proposed. Researchers developed their own neural network (EDM) due to limitations in the dataset, using six healthy and six cancerous samples, achieving a detection accuracy of 77.8%. In another work18, machine learning techniques with image processing were employed for lung cancer detection. The data underwent various image processing techniques to enable the machine learning algorithm, and classification was done using a

Support Vector Machine. In a different study19, Convolutional Neural Networks (CNN) combined with multiple pre-processing methods were explored. Deep learning played a significant role, demonstrating high accuracy and a low false-positive rate in automated labeling of scans.

The studies mentioned earlier do not employ an attention-based CNN deep learning model to identify lung nodules. Our objective is to utilize CNNs and customize their architecture to create a robust and effective tool for clinicians and researchers, enabling improved detection and classification of lung nodules. This, in turn, will contribute to better patient outcomes and enhanced healthcare. Previous research encountered challenges such as insufficient or small datasets for detection, resulting in limited subjects. These findings underscore the limited accuracy achieved with a higher number of machine learning or deep learning algorithms. Our proposed study intends to overcome these limitations and bridge the gaps in current research.

Background

A. Attention Mechanisms

Attention mechanisms refer to the way people's vision and nerves process information. People first generally determine the local areas they need to focus on by observing the panorama of the entire picture to obtain more detailed information about the object. Attention mechanisms were first applied to natural language processing (NLP) tasks. By introducing long-distance context information, they solved the phenomenon of information forgetting in long sequences. In vision tasks, attention mechanisms are also used to establish spatial long-distance dependencies to solve the problem of limited receptive fields of convolutional kernels, [29], [30]. At present, the Squeeze-and-Exchange (SE) attention [31], coordinate attention (CA) [32], and CBAM attention [33] are widely used. SE only considers the internal channel information and ignores the importance of position information. CA needs to perform weighted fusion on the information of each location, so the computation time and resource consumption of the model are too big. CBAM emphasizes the learning of important features in channel and spatial directions; therefore, the weight of important features is greater and can be transmitted to deeper layers for accurate identification of pulmonary nodules. This paper improves on the original convolutional attention and optimizes the original Rectified Linear Unit (ReLU) activation function, which allows to achieve better accuracy in the detection of lung nodules.

B. Dilated Convolution

In the traditional CNN model, down-sampling is used to expand the receptive field. Frequent down-sampling, however, may lead to losing some location information and decreasing the image resolution. That is why it is difficult for the network to accurately obtain the location information of objects, which hampers locating both big and small objects. Therefore, in the DeepLab series of models, atrous convolution, also known as dilated convolution, was proposed to solve the above problem, [34]. Compared with standard convolution, a new parameter of the dilation rate was introduced for defining the distance between the values when the convolution kernel processes data. When the convolution kernel's parameters remain unchanged, the receptive field can be expanded by increasing the value of the dilation rate. Atrous convolution can expand the receptive field without decreasing the image resolution. However, a higher dilation rate of the atrous convolution is not better. When the dilation rate is higher, the sampling of the atrous convolution becomes sparse. If there is no correlation between the information obtained from the long-distance convolution, the information that can be given by the spatial continuity, such as the marginal information, will be lost. In TridentNet [35], the authors studied the relationship between the receptive field and object size, and found that a big receptive field could help the detection of a big object, whereas a small receptive field could help the detection of a small object. Therefore, the deeper the network and more times of down-sampling, the better detection of small objects. Because the feature of high resolution should be used for the detection of small objects, this paper expands the receptive field by introducing atrous convolution and further improves the detection effect of big objects without reducing the detection effect of small objects by selecting a suitable dilation rate.

C. Transformers

In 2017, Google used the Self-Attention model [36] to replace the Recurrent Neural Network (RNN) model [37], which was the most widely used in NLP tasks until then, causing a huge shock in the NLP field. RNN contains a recurrent layer, whereby the output at the next moment comes from the input at the previous multiple moments and its current state; that is, the network memorizes the previous information and acts on the output, so it can store the correlation between features

However, RNN can only perform sequential calculations, which brings two problems:

1. The calculation at the current moment depends on the calculation result at the previous moment, which limits the parallelism ability of the model.

2. During the calculation process, information with too long intervals will be lost, and the long-term dependency of the context cannot be established.

Transformer is a neutral network model based on the Self-Attention mechanism, which is used to calculate the attention distribution between elements in the input sequence. Transformer effectively solves the two problems above as follows:

1. Parallelization between modules improves model training efficiency and conforms to modern distributed Graphics Processing Unit (GPU) frameworks.

2. By using the self-attention mechanism, the distance between any two positions of the given data is established to retain long-distance information.

The Transformer model consists of an encoder and a decoder, which both consist of a stacked self-attention layer and a fully connected layer. It is a model structure that avoids circulation. As shown in Figure 2, after passing through six layers of encoders to calculate attention, the data is output to the decoder of each layer.

By extracting the relationship between different regions through multi-head attention, the Transformer effectively enhances the network ability to extract global features, so that high-level semantic information can better form the extracted local information as a whole and maintain high extraction speed. The Contextual Transformer (CoT) module is a neural network module that combines the advantages of CNN and Transformer. It is often used in various computer vision tasks, such as object detection, semantic segmentation, image classification, etc. Therefore, we optimize the C3 module, used at the end of the backbone and head of the original YOLOv5s model, by replacing its 3×3 convolution with a CoT module [26], resulting in a new module named CoT3. The structure of the CoT and CoT3 modules is described in detail in Section IV.

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