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Automated Lung Cancer Classification from 3D CT Scans Using Deep Convolutional Networks

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Abstract
The research gives an artificial intelligence-based system that was designed to enhance early prediction and classification of lung cancer using 3D chest CT-scanned images. 3The system employs the use of deep learning by integrating a lean pipeline, segmentation of the lungs, detection of nodule candidates, and the subsequent classification of malignancy. In the system, lung tissue is initially isolated by threshold-based segmentation to distinguish it from other anatomy. However, it was not efficient to simply input whole segmented volumes in 3D Convolutional Neural Networks (3D-CNNs) due to high levels of noise and search space. To reduce this, a U-Net was developed as a modified version, which was trained on the LUNA16 database, which contains labeled nodules to identify candidate regions of the nodules. Such regions of candidates may allow for including false positives at times, but in turn, they allow the model to focus on the most relevant features. The defined regions are subsequently classified with a light and effective 3D-CNN, which achieved 92.6 % test accuracy. Unlike traditional CAD systems, our AI-based approach requires minimal amounts of labeled data and multiple (and complex) stages, and continues delivering high accuracy and generality. It then creates a compelling reason why it could be a good applicant in the search for lung cancer in a medical image, with scalability, efficiency, and early detection of lung tumors.

Keywords: Artificial intelligence, lung cancer, CT imaging, deep learning, 3D

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convolutional neural networks, medical diagnostics.

Introduction

Lung cancer is a highly prevalent and deadly cancer across the globe, with over 225,000 new occurrences and approximately 150,000 new deaths reported. In the United States alone, some deaths are reported yearly, totaling an estimated amount of 12 billion each year in terms of expenditure in healthcare [1]. Even though there have been some advancements in the treatment of lung cancer, the five-year survival rate remains low, at only 17%. Truth to be told, this is mainly a result of the late-stage diagnosis. These are worse statistics in the developing world [2].

Poor access to early detection and the latest technology equipment in diagnostics exists. Stages I and II lung cancer, in particular the hematogenous one, have no signs and symptoms and cannot be easily detected using traditional clinical methods [3]. However, early diagnosis at such levels benefits the treatment and survival rate the most. The diagnostic techniques that are employed now are founded on the imaging system, such as Computed Tomography (CT) testing, and invasive methods such as biopsies [4]. They are time-consuming, expensive, and open to expert interpretation, which may lead to delays or errors in the diagnosis. Deep learning, as well as Artificial Intelligence (AI), has become a revolutionary technique in the field of medical imaging [5]. The use of powerful algorithms enables the AI to assist radiologists in the process of detecting and labeling abnormalities in CT scans efficiently and accurately. In our study, we would be trying to develop an AI Computer-Aided Diagnosis (CAD) of lung cancer detection programme through the latest Deep Learning systems like the U-Net and the 3D Convolutional Neural Networks (3D-CNNs) [6]. It will be an automatic system that will be used to detect any possible cancerous nodules in the chest CT scan and sort them into categories, cancerous or non-cancerous.

The fundamental difficulty lies in finding small nodules, usually smaller than 10 mm in diameter, buried within high-resolution 3D volumes riddled with anatomical noise like airways, bones, and surrounding tissue. This is similar to searching for a needle in a haystack [7]. Therefore, our pipeline of AI includes three essential steps: preprocessing of images, detection of nodule candidates, and malignancy classification. To address the shortcomings of traditional approaches, we use a strong preprocessing method to segment lung tissue and suppress image noise. We train a modified U-Net model on labeled CT data to identify possible nodules, which are subsequently examined by an in-house-built 3D-CNN to classify malignancy. The data-driven and end-to-end nature of this process allows the model to learn high-dimensional, discriminative features directly from raw CT scans. We assess our system on a large dataset of more than 1,390 low-dose chest CT scans from the Kaggle Data Science Bowl 2017 and the LUNA16 data set as shown in Fig.1. Our results show that AI can greatly improve the accuracy and efficiency of lung cancer detection, making early screening more accessible and dependable.

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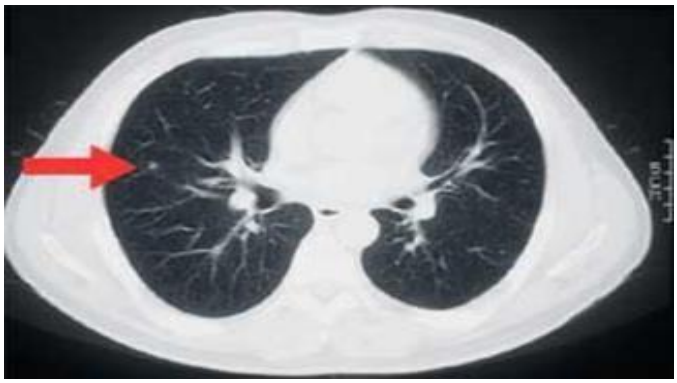

Fig. 1. CT scan image of lung cancer [8].

RELATED WORK

Machine learning is a part of the machine learning paradigm, deep neural networks are used to represent technologies that profoundly change the behavior of the technology itself are recently become common in most pattern recognition and machine use of learning applications, one of which is below the basic structures there are the Convolutional Neural Networks (CNNs) [9]. An author deployed a model that was employed to categorize images. The former state-of-the-art on ImageNet improved the previous state-of-the-art performance, and it became a star in the computer vision domain [10]. The contemporary trends have brought incredible progress in deep learning medical imaging applications. In describing the method to extract the shared and the latent features of the brain based on neuroimaging, [11] proposed another method to diagnose AD/MCI using Deep Boltzmann Machine (DBM) to monitor AD/MCI. The deep learning as presented by [12] would be described as making use of the several layers of the artificial neural network (ANN) feature extraction to enhance the deformable brain MRI registration. Xuet. The success of deep neural networks (DNNs) with supervised learning was evidenced by a case study conducted [13] by using features found in medical images. Another [14] developed a CAD system that utilizes the deep attributes of an auto encoder in the classification of lung nodules as either malignant or benign using the LIDC database.

To remove the need to collect medical images, to train a pathology detection system in chest x-ray CNNs, [15] trained on non-medical image datasets. Their hybrid model was called Decaf and PiCodes, which demonstrates reported efficacy in AUCs at 0.93, specifically in Right Pleural Effusion, and 0.89 in Enlarged Heart, and 0.79 in the process of identifying abnormal chest conditions on an image dataset of 93. In another experiment [16]. Another author [17] compared a conventional CAD system with three deep learning strategies that is: CNN, DBNs, and SDAE. They had eight stacked convolutional and pooling layers in their CNN model. In the traditional models, 35 features of texture and shape were applied using SVM classification. The evaluation was done on 1018 LIDC/IDRI cases through testing. Author [18] subsequently created a false-positive reduced detection system, utilizing a CNN-DNN hybrid of four convolutional and four pooling layers with filters of size 3x5 and depth 32. The LIDC-IDRI dataset of 85 Convolutional. The current research by Deep Belief Networks has been surpassed by neural networks on benchmark computer vision

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datasets. During the past years, the CNNs have gained much attention in the machine learning community owing to their powerful representation capacity, which involves learning beneficial features in the input data.

METHODOLOGY

3.1. Dataset

As the primary data, we use the Kaggle Data Bowl (DSB) 2017 patient lung CT scans data set [13]. Its labeled data is set up of 1397 patients, which we divide into the training set that consists of 978 and the test set that comprises 419. The data for every patient is CT scan data and a label (0 when there is no cancer and 1 when there is a cancer). Notice that the Kaggle data does not have labeled nodules. Every CT scan data of each patient is a variable image count (usually 100- 400 images, each is an axial slice) of 512 x 512 pixels. Slices are given in DICOM format. An average of 70 per cent 0s are there in the labels provided in the Kaggle dataset. The present research on benchmark computer vision datasets has demonstrated better results than Deep Belief Networks when using neural networks. In the past years, much attention in machine learning has been given to the CNNs due to their powerful representation capacities when learning worthy features in the input data.

As the Kaggle dataset was not large enough to distinguish the validation set, we used the patient lung CT scan dataset with annotated nodules of the Lung Nodule Analysis 2016 (LUNA16) Challenge [19] to train a U-Net to detect lung nodules. The LUNA16 dataset consists of 888 labeled patients that we, in turn, divided into a training subgroup (710) and a validation subgroup (178). In case of each patient, the information will contain CT scan information and nodule label (nodular center coordinates list and diameter). In every one of the patients, the data supplied in the CT scan consists of an assortment of images (typically 100-400, or so images, each one an axial slice) that are 512x512 pixels in size. One of the steps of the classification pipeline was the LUNA16-trained U-Net that detects nodules. The challenge is to predict efficiently the label of a patient (cancer, no cancer) based on a Kaggle lung CT scan of the patient. We will evaluate our CAD system's accuracy/sensitivity/ specificity, and AUC of ROC on the Kaggle test set.

3.2. Basic Architecture of 3D CNN Model

The common pipeline of typical CAD systems on lung cancer is composed of preprocessing of the image, finding the possible locations of the cancerous nodules, reducing false positives involved in nodules candidates, predicting malignancy in each of the nodules candidates, and predicting malignancy in the entire CT scan [20]. Such a series of pipelines is computationally costly, with each stage demanding well-labeled data when being trained. As an example, limiting the error of false positives involves the utilization of a selection of false and true nodule candidate labeled databases, and the nodule malignancy prediction phase involves the use of a database that is labeled on the presence of nodules and tagged with the case of its malignancy.

Nodule candidate True/False labels and of nodules, cancer malignancy, are sparse in the case of lung cancer, and possibly unavailable in other types of cancer, such that any CAD system trained on such data would not be able to generalize to other cancers. To obtain higher levels of computational

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effectiveness and eventual applicability to other cancer forms, the suggested CAD system boasts both a reduced pipelines and requires only as a source of information the following data both when training: a collection of CT images with genuine nodules marked, and a collection of CT images that carry an overall label of malignancy. The most advanced CAD tools that do just that, malignancy prediction based on CT scans, reach to AUC of 0.83 [21]. But as stated above, input to these systems is different sorts of labeled data that are not incorporated into this framework. It is the primary objective of the proposed system to achieve performance that is near this.

Starting with the 3D CT scans preprocessing via segmentation, normalization, down sampling, and zero-centeredness, the proposed CAD system continues with its subsequent stage of processing the 3D CT scan data via statistical analysis, data transformation, and stack operations. The simplest approach was no special preprocessing of 3D CT, transferring it to 3D CNN only, but things turned out pathetic. Thus, another preprocessing method that limited 3D CNNs to receive only the regions of interest was carried out. To detect regions of interest, U-Net was applied to capture areas of interest, which were the nodule candidates [22]. Thereafter, the regions of interest's definition through nodule candidates that the U-Net would offer would be offered to the 3D CNNs to ultimately determine whether CT scans are or are not positive for lung cancer. The general structure is depicted in Fig. 2; all the specifics of the layers and their names will be depicted in the following sections. Only the best activated patches were chosen to prevent overlapping or repetitive patches: i.e., only the activated regions with the highest L2 norm of the output probability maps were chosen. There were non-overlapping constraints to make sure that diversity in the selected inputs has been provided, and that there is a reduced chance of bias in the predictions. These candidate patches were used to train a 3D CNN, where a weighted loss function was used to address class imbalance. The general structure is shown in Fig. 2.

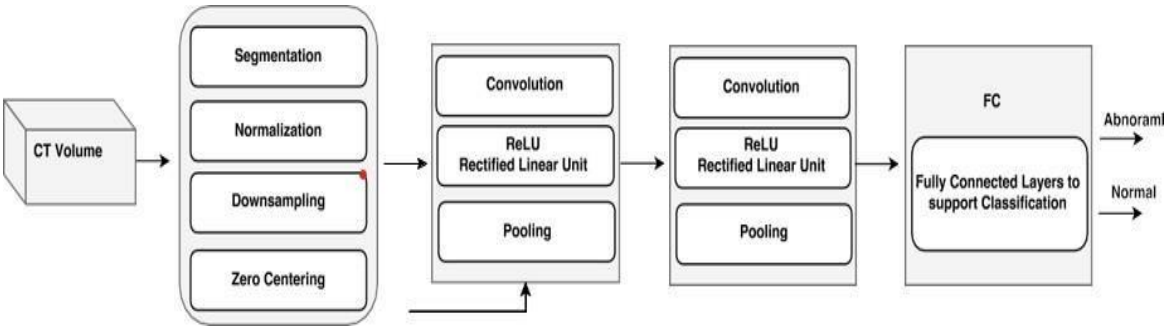

Fig 2. The architecture of a 3D convolutional neural network is present in 3D form [23].

There are a few True/False tags in nodule candidates and malignancy tags in nodules in any case in lung cancer, and may have none such tags in certain other known cancers, and therefore CAD systems implemented using this data would not translate to other cancers. To acquire a stronger computational performance and generalizability to other cancers, the projected CAD system will obtain shorter pipeline to acquire the computational performance, and the training data would only be the following sets: a set of CT scans (true nodules as labeled), and a set of CT scans (overall malignancy as labeled). The value of the AUC of state-

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of-the-art computational-aided-design malignancy prediction systems based on CT scans is up to 0.83 [24]. It is through these systems, however, as stated in the paragraph above, are fed by several labeled datasets are fed that do not feature in this framework. The motive behind the proposed system is to achieve a performance that is nearly the same. Segmentation, normalization, and down-sampling of the 3DCT scans with the subsequent zero-centering have been proposed as the starting point of the proposed CAD system. The first one was simply feeding the preprocessed 3D CT scans to 3D CNNs, and they did terribly. Therefore, another preprocessing was carried out where only regions of interest were fed into the 3D CNNs. U-Net was used to train a nodule candidate detector to distinguish areas of interest. Subsequently, candidates of nodules, which had been detected by the U-Net, and regions around them were transformed into 3D CNNs to eventually pronounce the CT scans positive or negative depending on the presence or absence of lung cancer.

PROPOSED MODEL

The proposed model will utilize a 3D Convolutional Neural Network (3D-CNN) to complement pulmonary nodule classifications in CT scan volumes. Specifically, architecture is organized in such a way that it can learn spatial and volumetric attributes of a LIDC-IDRI dataset that includes more than 1000 low-dose X-ray CT scans of the chest with a slice count of 248,580, as shown in Fig. 3.

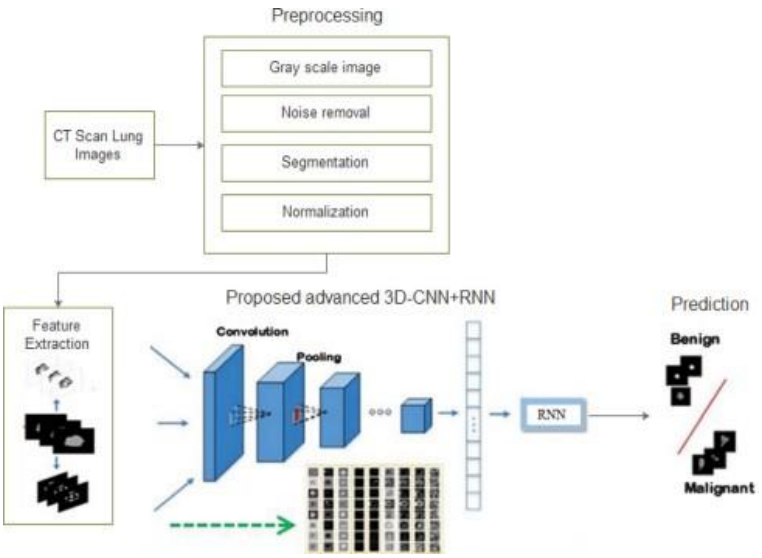

Fig 3. Proposed model.

4.1. Data Preprocessing

4.1.1. Nodule Segmentation

- **Segmentation:** U-Net is used to extract possible nodule areas.

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- **Normalization of Intensity**: The CT scans are normalized in Hounsfield Units (HU).
- **Volume Construction:** The 2D slices are also construct into 3D volumes.
- **Patch Extraction:** Patches with nodules (3 mm- 30 mm) are extracted as an input to the model.

4.2. Model Architecture

The four dimensions of the CT scans of the lung will be used due to the proposed 3D Convolutional Neural Network (3D-CNN) architecture that allows capturing spatial and volumetric information. The architecture of a model consists of the three-dimensional convolutional layers, which process a 3D volume rather than a 2D image and thus can apply to the image slices stacked along the depth dimension of a CT scan. These layers assist in acquiring the required spatial-temporal properties that are central to the proper classification of pulmonary nodules.

A seven 5 x 5 x 5 filter is used in the first convolutional layer. These 3D filters move across the volume in search of low-level structures, e.g., boundaries, textures, and shapes that denote the first-order structure of the lung tissues. It is a layer that establishes depth-wise contextual information in the data input.

The second convolutional layer has seventeen filters, which are dimensioned 5 x 5 x 3. This layer also takes the feature maps of the previous layer to another level, where a more abstract and complex form of the features extracted by the initial layer is learned. These pictures play a major role in enabling the difference between benign and malignant features.

The convolutional layers are followed by the pooling layers that serve the purpose of lowering the array dimensions of the feature maps. Not only does this reduce the computational complexity, but it also contributes towards making the learned features more robust by down-sampling them and keeping only the most pronounced activations.

The results of the pooling layers are then routed to some fully connected layers, where the high-dimensional 3D feature maps will be flattened into 1D vectors. The input of such vectors to a layer of 256 neurons allows the model to synthesize the spatial features to arrive at a definitive decision regarding classification.

A dropout layer with a rate of 0.2 is used to minimize the threat of overfitting in training. It randomly kills a subset of the neurons with each training step, which makes the model learn more generalized features and does not depend on a particular pathway of neurons.

The softmax activation function in the output layer is set to a binary classification task, which enables the model to be able to say that a given nodule is either

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benign or malignant, conditioned on the learnt features.

To train the network, a cross-entropy loss is evaluated as the difference between predicted and actual class labels. It is a typical loss phrase toward classification issues and aids in sensible punishments for inaccurate forecasts.

Adam optimizer is used to optimize the model because it adaptively computes the learning rate and achieves convergence effectively. The learning rate of 0.0001 was chosen to make the learning stable and yet gradual, and not to be over the minima in the process of backpropagation.

4.3. Training the Model

Its training part was performed in the proposed 3D Convolutional Neural Network (3D-CNN) based on the LIDC-IDRI dataset, comprising over 1,000 low-dose chest CT scans totaling 248,580 individual slices, as shown in Fig. 4.

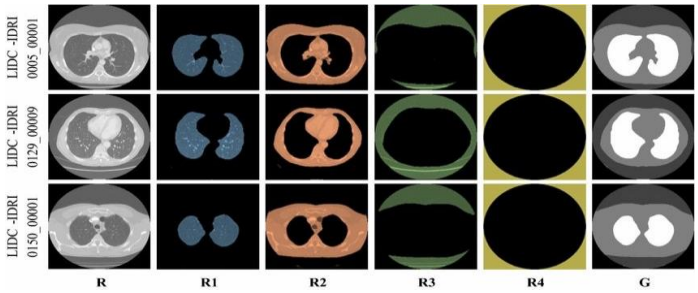

Fig. 4. LIDC/IDRI dataset [25].

Before training, the dataset was divided into training (50%), validation (20 %), and testing sets (30%). The pipeline of preprocessing included the segmentation of lung nodules with the U-Net-based architecture, intensity normalization with the Hounsfield Units (HU), and stacking blocks of 2D sections into 3D. Each volume in 3D was cropped to patches of regions of interest. The 3D-CNN model utilised two convolution layers. The initial layer contained seven filters with the size 5 5 5, and the second layer had seventeen 5 5 3 filters, and there was a pooling layer which reduced the number of feature maps. These were followed by the fully connected layers having 256 neurons each. Overfitting was lowered by applying dropout regularization with a rate of 0.2. Training of the network was parameterized under the Adam optimizer with a learning rate parameter of 0.0001, and the objective function parameter was the cross-entropy loss. Further control overfitting is reached using L2 regularization, also known as weight decay. They also ran training experiments to measure the effects of various minibatch sizes (1, 10, 50, and 100), and found that small batch sizes improved model performance, perhaps because they cause a more thorough exploration of the loss landscape by the increase in gradient noise.

RESULTS AND DISCUSSION

The trained 3D-CNN showed great results in the process of lung nodules

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classification, indicating that it is either benign or malignant. On the 30 per cent test set, it gave an accuracy of 92.6% as shown in Fig. 5.

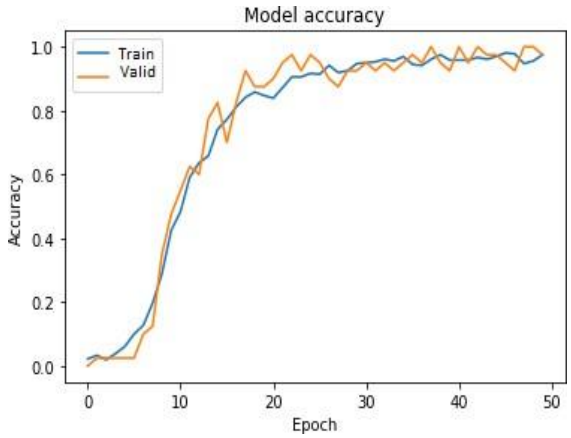

Fig. 5. Accuracy of Proposed Model.

The CNN preprocessing model adopted made a considerable contribution to the enhanced classification since it managed to isolate targets exceptionally well and filter irrelevant background noise in the input data. The depth and architecture of networks, such as the choice of the filter sizes and layers, also affected the performance considerably, since deeper networks were found to be substantially better than shallow ones.

CONCLUSION

This research was the first to suggest and test a deep learning framework in the detection of lung cancer based on a 3D Convolutional Neural Network (3D-CNN), fed with the volumetric CT-scan results. A preprocessing pipeline was used to segment nodules with the help of U-Net, and the 3D-CNN classified them. The model had good performance, as the testing accuracy was 92.6%, and the values of precision and recall were favorable, showing that the model can discriminate between benign and malignant nodules. This study shows a convincing path in the direction of creating AI-based applications of clinical diagnosis, more specifically, lung cancer detection. To pursue in the future, the segmentation of the process can be improved with the help of such highly sophisticated algorithms as watershed, and some more sophisticated hyper parameter tuning methodologies should be applied, as well as such evaluation indicators as F1-score and AUC. The outlined system can also be expanded further to other 3D medical image cancers, allowing for more applicability with minimal need for large labeled data.

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