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Lung Cancer Detection and Classification Using Deep Learning

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Abstract

Lung cancer is a disease that can be effectively treated if detected early. Various technologies, such as magnetic resonance imaging, isotopes, X-rays, and computed tomography scans, are employed for diagnosis. One of the most crucial strategies in combating cancer is early detection, which greatly enhances a patient's likelihood of survival; this is where artificial intelligence plays a significant role. The approach proposed in this study leverages historical medical data to assess a patient's likelihood of having lung cancer. It employs a convolutional neural network (CNN) to analyze computed tomography scans and ascertain the cancer stage. Accurately diagnosing the disease and determining its stage at an early stage can be lifesaving for patients. Although multiple methods, including image processing, biomarker analysis, and machine learning, are available for lung cancer detection, achieving high accuracy and timely diagnosis remains a challenge for healthcare professionals. This study uses data from the Lung Image Database Consortium and the Image Database Resource Initiative (LIDC-IDRI) to extract computed tomography images. In traditional approaches, manual examination of computed tomography images is necessary to determine if a patient has lung cancer. Overall, the primary goal of using deep learning for lung cancer detection is to enhance the accuracy and efficiency of diagnosis, improve patient outcomes, and contribute to ongoing medical research in the field of oncology. The effectiveness of using convolutional neural networks algorithms in digital pathology image processing, as previously described, and intends to further discover the high level and discriminative properties shown by cancer cells using convolutional neural networks for exact categorization of lung cancer subtype.

Keywords: Lung cancer, CT scan, CNN, deep learning, image processing

INTRODUCTION

Considering the high death rate among affected individuals, lung cancer is a deadly illness. Patients can be saved by receiving an early diagnosis and correctly determining the stage of lung cancer. Various techniques, including image processing, biomarker analysis, and machine automation, can be employed to detect lung cancer. However, achieving early detection and accuracy remains a significant challenge for healthcare professionals. In this study, computed tomography (CT) scan images are obtained from the Lung Image Database Consortium and the Image Database Resource Initiative (LIDC-IDRI). Traditional methods rely on manually examining CT scans to assess whether a patient has lung cancer. Overall, the primary goal of using deep learning for lung cancer detection is to enhance the accuracy and efficiency of diagnosis, improve patient outcomes, and contribute to ongoing medical research in the

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field of oncology. The effectiveness of using convolutional neural networks (CNNs) algorithms in digital pathology image processing, as previously described, and intends to further discover the high level and discriminative properties shown by cancer cells using CNNs for exact categorization of lung cancer subtype. Lung cancer is defined as the uncontrolled growth of abnormal cells in the lung area. The aberrant cells develop into tumors as they expand and obstruct the lungs' regular operation. Lung cancer is frequently diagnosed late since there are no obvious symptoms or indicators of the disease in its early stages, which results in costly and inefficient therapy. For cancer patients to receive the greatest care and have the best chance of recovery, early diagnosis is essential. Many lives could be saved if lung cancer could be detected early using CT scans, but radiologists would have an unimaginable load analyzing the bulk of scans. Cancer is a dangerous illness that claims countless lives each year. So far, researchers have invested billions of dollars in cancer research. As of yet, no finished product has been created for this use. It demonstrates the necessity for further effort to identify the source and formulate early forecasts. This gives scientists a fresh chance to create a system or carry out studies that will greatly aid in the early diagnosis of cancer [1–3].

This study uses the LIDC-IDRI to obtain CT scan images. Traditional methods involve manually providing CT images to determine if an individual has lung cancer. Overall, the primary goal of using deep learning for lung cancer detection is to enhance the accuracy and efficiency of diagnosis, improve patient outcomes, and contribute to ongoing medical research in the field of oncology. The effectiveness of using CNNs algorithms in digital pathology image processing, as previously described, and intends to further discover the high level and discriminative properties shown by cancer cells using CNNs for exact categorization of lung cancer subtype. Accurate feature extraction is crucial for identifying cancerous cells in the early stages, which can help save patients from this deadly disease. Our model based on deep learning offers a wide array of advantages and applications, ranging from early detection and accurate diagnosis to personalized treatment planning and medical research support [4, 5].

LITERATURE SURVEY

Lung cancer is recognized as one of the most serious health issues in developing countries. Historically, various image processing methods have been employed for its detection. Recently, neural networks and deep learning techniques have gained traction in the field of medical imaging [1]. Approaches, such as CNNs, deep belief networks, and stacked denoising autoencoders have been applied to relevant datasets, achieving accuracies of 79%, 81%, and 79%, respectively [2].

Research indicates that lung cancer is more likely to be successfully treated when detected at an early stage, especially when the tumor is small and localized. A large-scale trial involving 5000 participants demonstrated that using CT for lung cancer screening reduces the annual mortality rate by 20% compared to traditional chest radiography.

Integrating image processing techniques can significantly enhance manual analysis and diagnostic systems. Neural networks play a crucial role in distinguishing cancer cells from healthy tissue, providing valuable support for developing AI-assisted cancer detection technologies [3].

Radiologists can identify dangerous nodules at earlier stages through CT and other scanning methods. A recent approach aimed to minimize false positives during initial detection by using a 3D region-based CNN alongside a U-Net-like encoder-decoder for analyzing lung CT images [4]. This method incorporated various factors, such as family history, age, smoking habits, clinical biomarkers, and the size and location of detected nodules to improve classification accuracy [5].

The goal of a specific challenge was to identify potential nodule locations and assess the likelihood of nodules being present in designated areas. Other research has explored the use of chemotherapy techniques to understand the behavior of non-small and large lung cancer cells. Another study introduced a method for identifying cancer cells using neural network ensembles [6].

A prominent competition aimed at enhancing lung cancer detection provided participants with a platform to develop algorithms for accurately diagnosing the disease. One method utilized a support vector machine that analyzed 33 features from segmented lung images to classify them as cancerous or non-cancerous, outperforming existing systems. Additionally, a classification approach for lung tumors distinguished between benign and malignant cases using a specific neural network architecture and transfer learning techniques, achieving an impressive accuracy of 98% with a low false positive rate [7]. After training the model and optimizing the loss function through stochastic gradient descent, the final model was able to accurately locate malignant nodules, predict their likelihood of malignancy, and estimate their severity [8].

SYSTEM DESIGN

A Deep Ensemble 2D CNN Architecture was created to improve the effectiveness of a computer-aided detection (CAD) system for lung nodule identification. This architecture consists of three distinct 2D CNNs, each designed with varying layers and pooling techniques. Each CNN within the Deep Ensemble framework features a different number of kernel-based feature maps, utilizing Max Pooling, Average Pooling, and Batch Normalization. The convolutional layers are responsible for extracting features, with each kernel convolving over the input data to capture essential characteristics that will later be utilized in the learning process [9].

BLOCK DIAGRAM

The block diagram given below describes how our approach is going to be towards the detection of lung cancer nodules and further about the classification, that is, if malign or benign. The approach here is going to be by using LIDC-IDRI dataset where we are going to get annotated images with xml files. Then further weights and biases are assigned with thresholds for forward and backward propagation. Again the dataset is divided into training and testing datasets where both are processed and are used to derive the insights from which model can be more learnable. Further, the data are passed through CNN layers which consist of convolutional and pooling layers with activation functions more likely be ReLu activation functions. The softmax layer is the last layer of network just before the output layer and it has an equal number of nodes same as the output layer. At last learning from the insights and patterns model further classifies whether the nodule is malignant or benign (Figure 1) [10].

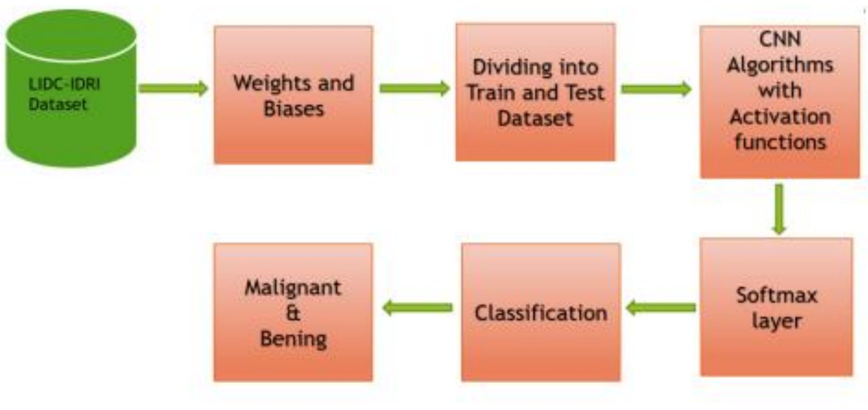

Figure 1. Workflow for Lung Nodule Detection and Classification..

Block Diagram Description

LIDC-IDRI Dataset

The LIDC-IDRI image collection includes diagnostic thoracic CT scans used for lung cancer screening, complete with annotated lesions. This resource is accessible online and serves as an international platform for developing, training, and evaluating CAD techniques for the detection and diagnosis of lung cancer [11].

Weights and Biases

Weights are numerical values assigned to each input or feature, indicating the significance of that feature in predicting the final output. Bias is used to adjust the activation function to the left or right, similar to how the y-intercept works in a linear equation.

Splitting of Dataset in Training and Testing Dataset

The next crucial step is to divide the data into training and testing or training and validation sets. This approach allows us to provide the machine with training data and then use validation data to assess the model's accuracy. The process involves reading data from a CSV file and categorizing it into cancerous and non-cancerous groups for proper labeling. It's important to create separate folders for cancer and non-cancer files so that the machine can learn to recognize them during training. The training data are what the artificial neural network and CNN will analyze to gain insights and improve their learning. Splitting the data is a vital step, as it ensures that a portion is available for training purposes [8]

CNN Layers with Activation Function

The pooling layer, much like the convolutional layer discussed earlier, reduces the spatial dimensions of the features convolved within a CNN. The activation function layer plays a crucial role in enabling the network to learn non-linear relationships between inputs and outputs. It introduces non-linearity into the network, allowing it to capture complex patterns and relationships in the data. This function is typically applied to the output of each neuron, taking the weighted sum of the inputs and generating an output that is then forwarded to the subsequent layer. One of the most commonly used activation functions in CNNs is the Rectified Linear Unit (ReLU). Additionally, the Batch Normalization (BN) layer is often utilized in CNNs to standardize the input for each neuron, ensuring a zero mean and unit variance. This normalization process stabilizes the learning process and helps prevent internal covariate shifts, which can occur when the input distribution to a layer changes during training [9].

Softmax Layer

Softmax assigns probability values between 0 and 1 to each class in a multi-class classification problem, with the sum of these probabilities equaling 1.0. This constraint facilitates faster convergence during training compared to other methods. Softmax is typically applied in a neural network layer right before the output layer.

Classification Layer

The classification layer is the last in a CNN. It generates the output class scores for a given input image. There are two primary types of classification layers found in CNNs: fully connected layers and global average pooling layers.

SYSTEM IMPLEMENTATION

Classifying lung cancer in CT scans is a critical task for the early detection of the disease. Accurate identification of malignant lung nodules could save many lives. As a result, several deep learning models have recently been developed to differentiate between malignant and benign nodules. However, the considerable variability in nodule size and their heterogeneous appearance makes this classification particularly challenging. Various types of CNN have been employed to detect cancerous lung nodules in CT scans, but the size of these nodules can vary significantly, ranging from 3 to 30 mm. This wide range of sizes adds to the difficulty of accurately classifying them [5].

ALGORITHM FOR ACCURACY, PRECISION, AND RECALL

The purpose of this ensemble CNN, which consists of various CNN blocks, is to accurately extract the features essential for distinguishing a true nodule from other candidate nodules. Ultimately, we calculated the accuracy, precision, and recall using the formulas provided below.

$$\text{Accuracy} = \frac{TPV + TNV}{TPV + FPV + TNV + FNV}$$

$$\text{Precision} = \frac{\text{TPV}}{\text{TPV} + \text{FPV}}$$

$$\text{Recall} = \frac{\text{TPV}}{\text{TPV} + \text{FNV}}$$

In these formulas, TPV represents the true positive value, TVN denotes the true negative value, FPV indicates the false positive value, and FNV refers to the false negative value.

The confusion matrix clearly shows variations in the true positives (TP), true negatives (TN), false positives (FP), and false negatives (FN), indicating that the combination of all three CNNs was a wise decision to enhance accuracy and decrease false positives (Figure 2).

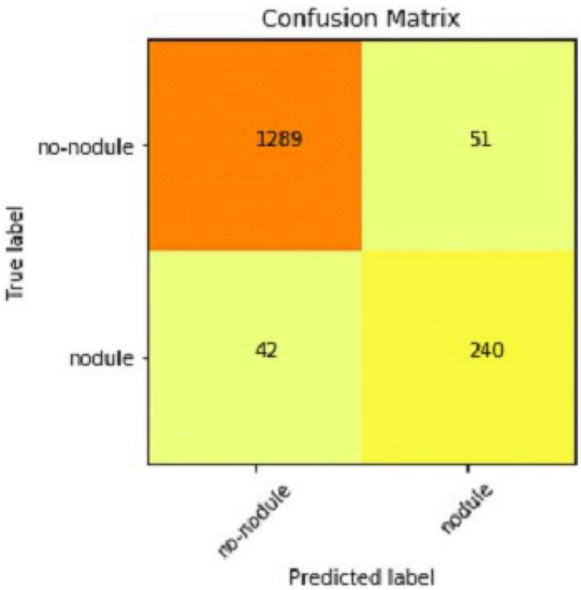

Figure 2. The confusion matrix shows the classification performance with 1325 true negatives, 226 true positives, 15 false positives, and 56 false negatives.

SUMMARY

The step-by-step working of the model is explained as:

1. Access the dataset from LIDC-IDRI.
2. Data pre-processing (data balancing, plotting, segmentation, feature extraction).
3. Splitting the dataset into training and testing data.
4. Applying Deep 2D Neural Network to the training and testing dataset.
5. Final prediction of lung cancer.

RESULTS AND DISCUSSIONS

Image segmentation is another key concept in computer vision. It involves partitioning an image into distinct regions based on pixel characteristics to identify objects or boundaries, making it easier to analyze and simplify the image. This technique plays a significant role across various fields, from filmmaking to medicine. For example, the technology used in green screens relies on image segmentation to isolate the foreground and overlay it onto a different background for scenes that are impractical or unsafe to film in real life. Additionally, image segmentation is employed to track objects across a series of images and to classify terrains, such as identifying petroleum reserves in satellite imagery. In the medical field, segmentation has several applications, including detecting injured muscles, measuring bones and tissues, and identifying suspicious structures to assist radiologists in CAD (Figure 3).

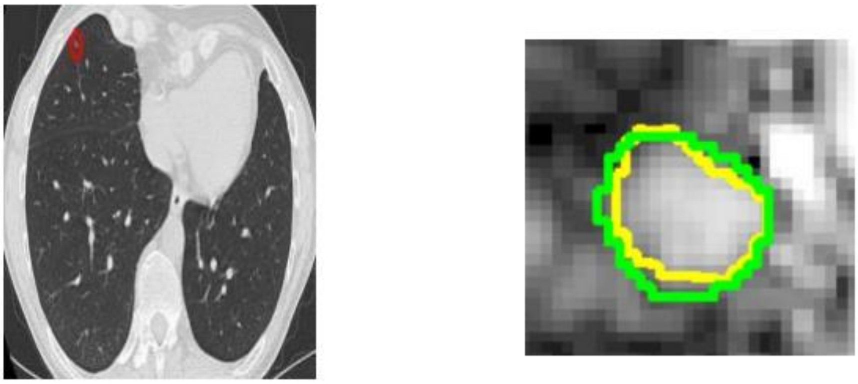

Figure 3. Result.

Figure 3 illustrate how segmentation functions. One way to understand segmentation is through clustering, where pixels with similar characteristics – such as color, intensity, or texture—are grouped together and treated as a single unit (Figure 4).

```
In [*]: pip install tensorflow

In [*]: import warnings
        warnings.filterwarnings('ignore')

        import numpy as np
        np.random.seed(123) # for reproducibility

        from keras.models import Sequential
        from keras.layers import Flatten, MaxPool2D, Conv2D, Dense, Reshape, Dropout
        from keras.utils import np_utils



        # Load pre-shuffled MNIST data into train and test sets
        (X_train, y_train), (X_test, y_test) = mnist.load_data()
        X_train = X_train.reshape(X_train.shape[0], 28, 28, 1)
        X_test = X_test.reshape(X_test.shape[0], 28, 28, 1)
        X_train = X_train.astype('float32')
        X_test = X_test.astype('float32')
        X_train /= 255
        X_test /= 255
        Y_train = np_utils.to_categorical(y_train, 10)
        Y_test = np_utils.to_categorical(y_test, 10)

In [ ]:
```

Figure 4. Code snapshot.

The images above demonstrate the method for dividing data based on testing and training needs. A model is an entity that combines layers and can be trained on data. The most basic type of model is the sequential model, which consists of a linear arrangement of layers. For more complex architectures, you can use the Keras functional API, allowing you to create flexible layer graphs, or opt for subclassing to develop models from the ground up.

CONCLUSIONS

A lung cancer detection model based on deep learning offers a wide array of advantages and applications, ranging from early detection and accurate diagnosis to personalized treatment planning and medical research support. This model has the potential to revolutionize lung cancer care by improving outcomes and enhancing the efficiency of healthcare delivery. Cancer research is an ongoing effort that will continue indefinitely, as a definitive solution has yet to be achieved. Currently, there are no established standards for the detection and prediction of cancer.

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