International Journal for Innovative Engineering and Management Research

A Peer Revieved Open Access International Journal

www.ijiemr.org

IJIEMR Transactions, online available on 27th Nov 2022. Link :http://www.ijiemr.org/downloads.php?vol=Volume-11&issue=Issue 11

DOI: 10.48047/IJIEMR/V11/ISSUE 11/21

Title **SURVIVAL RATE OF PATIENTS USING 3D CNN AND LSTM ON LUNG NODULES**

Volume 11, ISSUE 11, Pages: 134-138

Paper Authors

K. Revanth, Dr. G. Venkata Rami Reddy

International Journal for Innovative Engineering and Management Research
A Peer Revieved Open Access International Journal
www.ijiemr.org

SURVIVAL RATE OF PATIENTS USING 3D CNN AND LSTM ON LUNG NODULES

K. Revanth[1], Dr. G. Venkata Rami Reddy[2]

[*1]Student, M. Tech (computer Science), School of Information Technology, JNTU Hyderabad, Hyderabad, India

[*2]Professor of IT, School of Information Technology, JNTU Hyderabad, Hyderabad, India

Abstract: One of the major causes of cancer-related death, lung cancer is notoriously difficult to detect until it has already spread to other parts of the body. A severe problem, lung cancer is almost always deadly if caught at a later stage. While chest X-rays and CT scans are often used for the first diagnosis of malignant nodules, the presence of benign nodules might lead to incorrect treatment decisions. It's hard to tell the difference between a benign nodule and a cancerous one in the early stages. Here, we provide a novel, multi-pronged deep learning-based strategy to nodule cancer detection. Recent advances in deep learning models have inspired our usage of CNN and LSTM architectures for identifying and classifying lung nodules. We measure the efficiency of the proposed classifier by its accuracy. The LSTM based classifier beats the CNN model at differentiating between malignant and benign nodules because it discards irrelevant data while remembering the essential characteristics for making this distinction. By detecting the disease at an earlier stage when it is more likely to be treatable, screening for people at high risk has the potential to significantly increase lung cancer survival rates. Results from experiments show that the proposed LSTM algorithm achieves a 95% success rate.

Keywords *– lung nodule classification; Convolutional neural network (CNN); Deep Neural Network; Long Short-Term Memory network(LSTM); Medical image analysis; Support Vector Machine (SVM);*

1. INTRODUCTION

The second most frequent cancer worldwide is lung cancer. There are primarily two kinds of lung nodules. Malignant (cancerous) and Benign(non-cancerous) . Early detection of pulmonary cancer encourages patients to get treatment right away, which boosts recovery chances. Accurately identifying cancerous nodules in chest CT scans is necessary for lung cancer early diagnosis. To find the nodules, medical professionals seek for intricate patterns and features. It takes some time to differentiate between benign and malignant nodules after worrisome nodules are identified from CT imaging.

The proper detection of malignant nodules by doctors would be aided by the automatic identification and classification of nodules. The primary difficulty in nodule categorization is separating nodules from a variety of variants. In order to handle all types of nodules in CT images efficiently, an automated method is in fact necessary. Making precise decisions requires the application of deep learning algorithms, which are now being applied to the diagnosis and classification of malignant nodules in medical pictures. The most deadly cancer in the world is regarded as lung cancer. Many nations are creating methods for the early detection of lung cancer. A CT screening program's objective is to identify lung cancer early and enable curative treatment**.** By detecting the disease at an earlier stage when it is more likely to be treatable, screening for people at high risk has the potential to significantly increase lung cancer survival rates. In high-risk populations, early identification using low-dose CT screening can reduce lung cancer mortality by 15 to 20%.

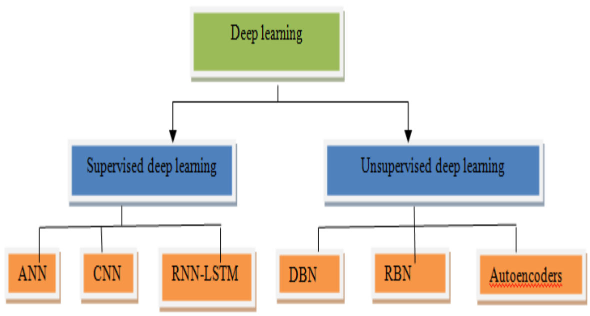

Fig 1 Types of Deep Learning

2. LITERATURE SURVEY

2.1 Evolution of image segmentation using deep convolutional neural network: a survey

Segmenting images is a task that pops up everywhere, from autonomous car navigation to medical diagnosis.

Segmenting images is a crucial first step in the field of computer vision. This task is more challenging than many others that use vision because it requires low-level spatial information. Images may be segmented in two broad categories: semantic segmentation and instance segmentation. The fusion of these two essential steps is panoptic segmentation. As a result of recent developments in deep convolutional neural networks, the segmentation field has seen tremendous transformation in recent years (CNN). Our focus in this article is on the evolution of CNN-based semantic segmentation with instance segmentation. We also compare the architecture of certain state-of-the-art models and go into depth about their training to help you have a firm handle on hyper-parameter tweaking. In addition, we have compared the efficiency of these models on different types of data. We conclude with a survey of state-of-the-art models for panoptic segmentation.

2.2 A Multi-Scale Convolutional Neural Network Approach to Classifying Lung Nodules

Here, we discuss the topic of thoracic Computed Tomography (CT) screening for diagnostic lung nodule classification. In contrast to recent work that mostly relied on nodule segmentation for regional analysis, we undertake the more challenging job of directly modeling raw nodule patches without any prior description of nodule morphology. We introduce a hierarchical learning framework called Multi-scale Convolutional Neural Networks (MCNN) to capture nodule heterogeneity by extracting discriminative features from layers of varying sizes. In specifically, our method employs multi-scale nodule patches to gain a set of class-specific attributes simultaneously by concatenating response neuron activations recorded at the last layer from each input scale, allowing for a sufficient quantification of nodule properties. The proposed method is evaluated using CT images annotated for lung nodule screening from the Lung Image Database Consortium and Image Database Resource Initiative (LIDC-IDRI). The experimental results demonstrate the efficacy of our method in identifying malignant and benign nodules without the necessity for nodule segmentation.

2.3 Identification and classification of pulmonary nodules automatically using 3D deep convolutional networks (Deep lung)

Using a CT scan, we present Deep Lung, an automated method for identifying lung cancer. Deep Lung consists of a nodule identification system and a nodule classification system. As lung CT data is spatially dimensional, two distinct 3D networks are designed to detect and label nodules. Using an encoder-decoder structure similar to that of a U-net, a 3D Faster R-CNN is created for nodule detection, allowing for quick learning of nodule characteristics. We introduce a gradient boosting machine (GBM) for nodule classification that makes use of 3D dual path network (DPN) characteristics. We demonstrate that the nodule classification sub network outperforms state-of-the-art approaches and the average performance of four human doctors using a dataset made available by LIDC-IDRI. The DeepLung system employs a neural network for nodule detection first, then a second neural network for nodule categorization for final diagnosis. The comprehensive experimental results on the LIDC-IDRI dataset demonstrate that Deep Lung's nodule-level and patient-level diagnoses are on par with those of experienced doctors.

2.4 Scientists have created the convolutional LSTM network, a machine learning technique, to forecast precipitation.

Precipitation now casting is used to predict how much rain will fall in a certain location in the near future. Although accurate weather forecasting is crucial, machine learning approaches have been scarce in the existing literature. Here, we present a formalization of precipitation now casting as a spatial-temporal sequence forecasting problem, where the input and the prediction objective are both spatial-temporal sequences. We propose the convolutional LSTM (ConvLSTM), an extension of the fully connected LSTM (FC-LSTM) that incorporates convolutional structures into both the input-to-state and state-to-state transitions, and we use it to build a fully trainable model for the precipitation now casting problem. Experiments show that our ConvLSTM network, with its superior ability to capture spatiotemporal correlations, routinely outperforms FC-LSTM and the state-of-the-art operational ROVER algorithm for precipitation now casting.

3. SYSTEM ANALYSIS

3.1 EXISTING SYSTEM:

Lymph fluid, which bathes the lung tissues, acts as a conduit for the dissemination of cancer cells into the bloodstream. The lymph travels via lymph arteries before draining to the lungs and chest lymph nodes. One of the greatest challenges facing mankind today is the examination and treatment of lung illness. The survival rate of a tumor is significantly increased if detected and treated early. Chemical treatment, targeted therapy, and radiation are only few of the methods utilized in the lab and on patients to eradicate or halt the multiplication of cancer cells. Cancer detection and diagnosis processes take more time, cost more money, and

International Journal for Innovative Engineering and Management Research
A Peer Revieved Open Access International Journal
www.ijiemr.org

cause patients greater discomfort. Thus, appropriate machine learning algorithms were employed to analyze these medical pictures, which consist of CT scan images, to get around all these challenges.

3.1.1 DISADVANTAGES

- The current system makes it harder, more expensive, and more painful for people to be diagnosed with cancer and undergo treatment.
- Over-fitting, poor interpretability, and a dearth of annotated data are just a few of the numerous obstacles that still need to be overcome.

3.2 PROPOSED SYSTEM:

The combination of clinical criteria and a deep learning model for nodule identification and classification helps reduce misdiagnoses and leads to early detection of lung cancer.

- With an average accuracy of 95%, the suggest model is superior than LSTM classifiers. Since the LSTM based classifier ignores superfluous information while remembering the crucial details for detecting cancer nodules, it outperforms the CNN model at distinguishing between malignant and benign nodules.

3.2.1 BENEFITS OF THE SUGGESTION:

- Image characteristics for optimal accuracy;
- LSTM model construction and improvement;
- improved accuracy.

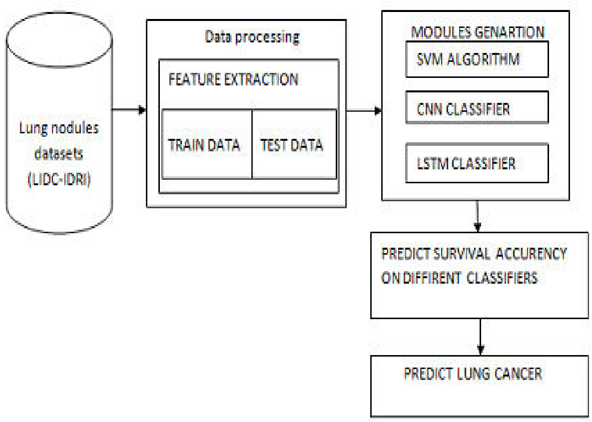

Fig 2 System architecture

4. METHODALOGY

4.1 Module Description:

1. Data Collection

The original data set creators performed this step. the make-up of the data set. learn how certain characteristics are related to one another. Combined scatter diagram combining essential characteristics and whole dataset. 80% of the data is used for training the algorithms and 20% is used to evaluate how well they perform. The training and test datasets also include about the same number of instances from each class as the whole dataset does, ensuring a good representation of the data. The research makes use of a variety of training and testing datasets, each with its own unique ratios.

2. Preparing the Data

There may be inconsistencies in the data because to missing values. Preprocessing the data may increase the algorithm's productivity and lead to better outcomes. Both the outliers and the variables need to be transformed. We use the map function to solve these problems.

3. Selection of a Model

The goal of deep learning is to automatically recognize patterns, make predictions based on those patterns and then provide relevant outputs based on that knowledge. Algorithms using DL look for and learn from patterns in data. It is possible to train a DL model to get better results the more times you use it. If you want to evaluate a model, you need to first separate the data into training and test sets. To train our models effectively, we first partitioned the data, setting aside 80% for the training set and 20% for the test set. In the next step, we needed to apply a variety of performance criteria to our model's forecasts

i. **Run SVM Algorithm:** now processed train data will be input towards SVM algorithm towards trained prediction model & this model will be applied on 20% test data towards compute SVM prediction survival accuracy.

ii. **Run CNN Algorithm:** now processed train data will be input towards CNN algorithm towards trained prediction model & this model will be applied on 20% test data towards compute CNN prediction survival accuracy.

iii. **Run LSTM Algorithm:** now processed train data will be input towards LSTM algorithm towards trained prediction model & this model will be applied on 20% test data towards compute LSTM prediction survival accuracy.

4. Result Predictions

The designed system's performance is guaranteed after being tested with a test set.

- Detect lung cancer from Test Data: using this module we will upload test data & then LSTM will predict weather test data is normal or contains lung cancer .
- Visualization of the data: using this module we will plot survival rate accuracy graph about all algorithms.

International Journal for Innovative Engineering and Management Research
A Peer Revieved Open Access International Journal
www.ijiemr.org

4.2 Algorithms:

SVM: Support Vector Machine (SVM) is a supervised machine learning approach that can be applied to classification or regression problems. However, categorization issues are where it is most frequently applied. In the SVM algorithm, each data point is represented as a point in n-dimensional space, with each feature's value being the value of a certain coordinate. Then, we accomplish classification by identifying the hyper-plane that effectively distinguishes the two classes.

CNN: Convolutional neural networks (CNNs) are feed-forward neural networks that typically evaluate visual pictures by processing data in a grid-like architecture. Another name for it is a ConvNet. For object detection and classification in images, a CNN is used.

- CNN have the following layers: i) Convolutional ii) ReLU Layer iii) Pooling iv) Fully Connected Layer

LSTM: An artificial recurrent neural network (RNN) architecture called long short-term memory (LSTM) is utilized in deep learning. LSTMs have feedback connections as opposed to typical feed-forward neural networks. It can analyze whole data sequences as well as individual data points (like photos) (such as speech or video).

- The LSTM memory cell is made of three gates. They are forget gate, update gate (input gate), and output gate.

4. EXPERIMENTAL RESULTS

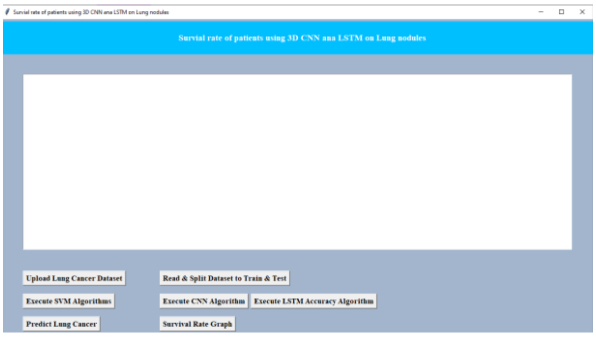

Fig 3 Home Page

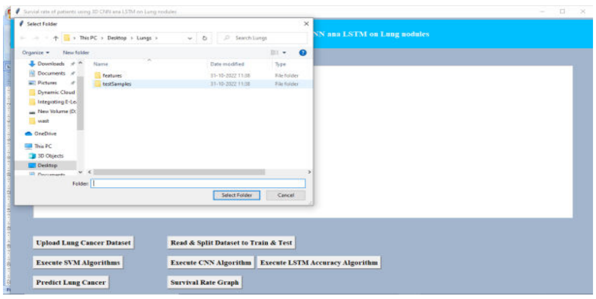

Fig 4 Feature Uploaded

Fig 5 Read & Split Dataset To Train And Test

Fig 6 Algorithms Implementation

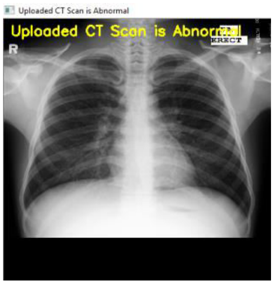

Fig 7a) CT Image Abnormal

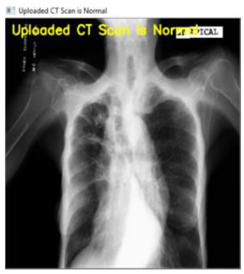

Fig 7b) CT Image Normal

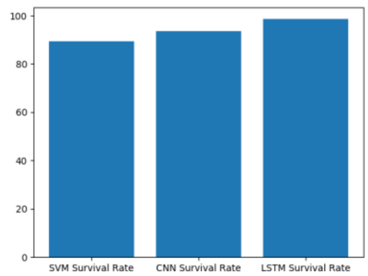

Fig 8 Survival Rate Accuracy Graph

Algorithm	SV M	CNN	LSTM
Survival rate accuracy (average)	75%	90%	95%

Table1 survival rate accuracy in different classifiers

6. CONCLUSION

In this study, we introduce the Long Short-Term Memory (LSTM) and assess its performance as a classification tool in terms of accuracy and precision. In order to gauge the efficacy of the proposed LSTM classification model, it is applied to the LIDC-IDRI dataset. Compared to CNN classifiers, the suggested model's 95% test accuracy is validated by the data we've gathered. However, a simple LSTM based classifier cannot account for the two-dimensional spatial properties that are crucial for determining whether nodules are benign or cancerous. The temporal-spatial features vital to differentiating the nodules are best preserved by the LSTM. The LSTM-based classifier can filter out irrelevant information while retaining key features that are relevant to the task at hand, such as the location of cancer nodules. Using temporal morphological data, the suggested a series of LSTM based classifier outperformed the CNN model in identifying benign from malignant nodules. The effectiveness of the proposed approach in classifying all kinds of nodules, however, falls short of expectations. The proposed model may be extended across several datasets to improve its generalization capabilities; this in turn, might help with the development of effective CAD systems for lung cancer. By detecting the disease at an earlier stage when it is more likely to be treatable, screening for people at high risk has the potential to significantly increase lung cancer survival rates. Results from experiments show that the proposed a series of LSTM algorithm achieves an average 95% success rate.

7. REFERENCES

[1] F. Sultana, A. Sufian, and P. Dutta, “Evolution of image segmentation using deep convolutional neural network: a survey,” Knowledge-Based Syst., vol. 201, p. 106062, 2020.

[2] L. Liu, J. Cheng, Q. Quan, F.-X. Wu, Y.-P. Wang, and J. Wang, “A survey on U-shaped networks in medical image segmentations,” Neurocomputing, vol. 409, pp. 244–258, 2020.

[3] H. Yu, L. T. Yang, Q. Zhang, D. Armstrong, and M. J. Deen, “Convolutional neural networks for medical image analysis: State-ofthe-art, comparisons, improvement and perspectives,” Neurocomputing, 2021.

[4] W. Shen, M. Zhou, F. Yang, C. Yang, and J. Tian, “Multi-scale convolutional neural networks for lung nodule classification,” in International Conference on Information Processing in Medical Imaging, 2015, pp. 588–599.

[5] A. Nibali, Z. He, and D. Wollersheim, “Pulmonary nodule classification with deep residual networks,” Int. J. Comput. Assist. Radiol. Surg., vol. 12, no. 10, pp. 1799–1808, 2017.

[6] X. Liu, F. Hou, H. Qin, and A. Hao, “Multi-view multi-scale CNNs for lung nodule type classification from CT images,” Pattern Recognit., vol. 77, pp. 262–275, 2018.

[7] S. Hussein, K. Cao, Q. Song, and U. Bagci, “Risk stratification of lung nodules using 3d cnn-based multi-task learning,” in International conference on information processing in medical imaging, 2017, pp. 249–260.

[8] W. Zhu, C. Liu, W. Fan, and X. Xie, “Deeplung: 3d deep convolutional nets for automated pulmonary nodule detection and classification,” arXiv Prepr. arXiv1709.05538, 2017.

[9] X. Shi, Z. Chen, H. Wang, D. Y. Yeung, W. K. Wong, and W. C. Woo, “Convolutional LSTM network: A machine learning approach for precipitation nowcasting,” Adv. Neural Inf. Process. Syst., vol. 2015, pp. 802–810, 2015.