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Fusion of CNN and 2DCNN features in Lung nodule Malignancy Classification

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ABSTRACT: Pulmonary cancer is one of the diseases in the people of the whole world. Doctors use different methods for recognition and diagnosis of pulmonary cancer, such as CT, MRI, isotope, and X-ray. Such manual methods failed to correctly classify the lung nodule malignancy. That causes lung-infected patients rate of survival get reduced due to late detection of cancerous lung nodule malignancy. To solve this classification problem and early detection of lung nodule malignancy, the feature fusion of CNN and 2DCNN deep learning algorithms are proposed to obtain the different feature vectors. Which are fused using concatenation fusion. Softmax use fused features to classify the malignant nodule. To locate the cancerous pulmonary nodules from the provided real input pulmonary CT images. The YOLO8 algorithm is proposed at last to find the location of lung nodules in the classified lung malignant image. The implemented system is tested on a real data set collected from Latur Super Specialty Hospital. From the implemented experiment result, the overall accuracy of the system is improved than the existing system. The CNN and 2DCNN features fusion attain 98.56% accuracy.

1. INTRODUCTION

Pulmonary cancer is one of the diseases in the people of the whole world. As per World Health Organization (WHO) [1] estimation the highest number of deaths were happen in the world due to pulmonary cancer. Smoking is the top cause of pulmonary cancer. Radon Gas, Air pollution and Industrial Chemical gases are another cause of pulmonary cancer.

Doctors use different methods for recognition and analysis of lung cancer, such as CT, MRI, isotope, and X-ray. Such manual methods failed to correctly classify the lung nodule malignancy. That causes lung-infected patients rate of survival to get reduced due to late detection of cancerous lung nodule malignancy. Also doctors use automated methods based on single deep lrarning model such as CNN, 2DCNN. But suct unimodal takes much time to give decision. Also, accuracy of such methods is not much imrved

If lung cancer nodules are noticed in initial stage, then the rate of survival can be increased. Today doctors refer the increased number of lungs computed tomography (CT) images for the initial analysis of pulmonary cancer to increase the patient survival rate. Automatic method is required for initial phase and accurate detection of lung nodule malignancy for diagnosis of patient. Today doctors are using single deep learning-based learner algorithms for training. Such algorithms include CNN, ResNet 50, VGG16, 2DCNN. But it gives unsatisfied performance due to limited hypothesis space.

The above discussed problem can be solved. An automated DL system is proposed for initial level and automatic classification of pulmonary nodule malignancy. In this pulmonary nodule classification system two architectures are proposed for module training. The first architecture contain CNN is used for training the existing lung nodule CT images data set. The second architecture contain 2DCNN is used for training the existing lung nodule CT images data set. The outcome of both architecture that is feature vectors are integrated using concatenation feature fusion algorithm. The fused outcome is provided as input for SoftMax layer for final classification of lung malignancy.

The next part of this paper is as follows: Section 2 represents the related work. Section 3 describes data set prepared. Method used is described in Section 4. Experimental outcomes and discussion are provided in Section 5. Lastly follows the conclusion.

2. RELATED WORK

Bowen Liu [2] has used an asymmetric residual network (3D ARCNN) that extracts the 3D features as well as spatial information of lung nodules to improve classification performance. Aria Pezeshk [3] has used 3-D fully convolutional network for fast screening and generation of candidate suspicious regions in the first stage. Then in the second stage he has used 3DCNN for training and classification of nodules. The developed system achieves 91% sensitivity. Hassaan Malik [4] has used Deep CNN models such as ResNet-101, ResNet-50, VGG-19, simple CNN, VGG-16, Inception-v3, DenseNet-201, and DenseNet-169. The extracted features obtained from Deep CNN models were then he has categorized using ML approaches, It includes AdaBoost, Q-SVM, softmax function, and RF, to identify ten distinct chest diseases.

Anum Masoodan [5] has used enhanced multi-dimensional region-based fully convolutional network (mRFCN) based automated decision support system for lung nodule detection and classification. Imran Ahmed [6] has used an automated deep learning-based system for classifying and detecting lung nodules. Also, he has used a detection architecture, including, YOLOv3 for detection purposes. Rashmi Mothkur [7] has used binary classification networks such as vanilla 2D SqueezeNet, 2D CNN, and 2D MobileNet to recognize lung cancer in patient CT images. Out of all these three models SqueezeNet model having good accuracy and low processing time.

Baihua Zhang [8] has used eight deep CNNs as primary learners and ten fusion methods for ensemble learners. Lastly, he has compared the ten fusion strategies and their predictions. Xingjian Yan [9] has compared slice-level 2D-CNN, nodule-level 2D-CNN and nodule-level 3D-CNN. The classification accuracy of 3D-CNN is greater i.e. 87.4% and which is better than 2D-CNN. Patrice Monkam [10] has proposed a system to differentiate between the micro-nodules and non-nodules in CT images by an ensemble learning of multiple-view 3-DCNN. Five 3D-CNN models are built and implemented on one size of the nodule candidates. An extreme learning machine (ELM) network is used to combine the five 3D-CNN outputs and producing the final classification results. Spoorthi Hiremath [11] has used novel CNN for tumor classification as well as for small cell lung cancer image partitioning and finding the exact location of the tumor attached to the border of blood veins. He has also used the deep CNN based YOLO framework to identify the exact location of the lung tumor.

Haichao Cao[12] has developed a two-stage CNN (TSCNN) for pulmonary nodule detection. In the first stage U-Net segmentation network is to create an initial recognition of lung nodules. In the second stage, the 3D-CNN classification networks is used for false positive reduction. Rabbia Mahum[13]has used a innovative and effective lung nodule detector based on a RetinaNET, namely Lung-RetinaNET. A multi-scale feature fusion-based module is used to amassed various network layers, simultaneously increasing the semantic information from the narrow prediction layer. He has achieved the 99.8 % accuracy. For segmentation M. Dhasny Lydia[14] has used improved k-means clustering algorithm. The segmented region is sent into an optimized convolution neural network (OCNN) to identify the object as cancerous or benign. The adaptive sunflower optimization (ASFO) algorithm is applied to select the hyperparameters efficiently to expand the effectiveness of the CNN classifier. Ward Hendrix [16] has used AI based method in which 2DYOLOV5 is used for detect region of interest from Lung CT, then he has applied multi view ResNet50 for final lung nodule malignancy classification. [17] has built a 3D CNN based lung nodule detection system, it contains two subsystems. first one is lung nodule segmentation system which uses 3D Res U-Net. The second one is lung nodule diagnosis system. The improved plain 3D ResNet50 is applied, in which kernel size of some convolutional layers was reduced. Qianqian Zhang [18] has eliminated the nodule segmentation and feature extraction in CAD system. For that purpose there is end-to-end classification is done using raw 3D nodule CT patches using CNNs. Explicitly, the state-of-art CNN models, e.g., VGG16, VGG19, ResNet50, DenseNet121, MobileNet, Xception, NASNetMobile, and NASNetLarge, are modified to 3DCNN models and it is tested on a public CT lung dataset. Syed Asiya [19] applied Custom VGG16 algorithm to analyze CT images of pulmonary and accurately classify malignancy of nodules. The Custom VGG16 model was tested using the LIDC-IDRI database to evaluate its usefulness. The experimental results show the notable performance of the Custom-VGG16 network, It achieves 95% accuracy.

3. USED DATASET

The system is trained using two datasets. The first dataset is the IQ-OTHNCCD data set which is collected from the kaggal site. This dataset contains total 1097 lung CT images are present. Out of which 120 CT images are benign cases, 561 are censors (malignant) cases, and 416 lung CT images are usual cases. For testing the implemented system, the six subject(patient) real pulmonary CT images dataset is gathered from LATUR SUPER SPECIALITY Clinic. The pulmonary nodule malignancy

classification system containing both the architectures that is VGG16 and ResNET50 are trained using IQ-OTHNCCD Dataset and collected real Dataset. System testing purpose 197 pulmonary images that is 20 % images are choose from real Dataset as well as from IQ-OTHNCCD Dataset. This test dataset is not used for system training initially.

4. USED METHOD

The proposed system contains two pretrained deep learning architectures are used. Before pretrain the architectures, the preprocessing is the first module. Which is used for removing the different type of noise. Noise gets introduced in the CT images at the time of preparing the dataset. The first architecture is the CNN based deep learning pretrained architecture and the second architecture is the 2DCNN based deep learning pretrained architecture as shown in figure 1. Initially both the architectures are trained using existing data set. The collected real data set CT images are preferred at the time of testing the system. The feature fusion algorithm is used to integrate the generated features of CNN and 2DCNN deep learning algorithms as shown in figure 1. The feature fusion outcome is then provided as input for SoftMax function for classification of lung nodule malignancy. Lastly YOLO8 algorithm is used to locate the location of lung nodule in the classified lung malignant image. The detailed algorithms explanation is mentioned in the following subsection

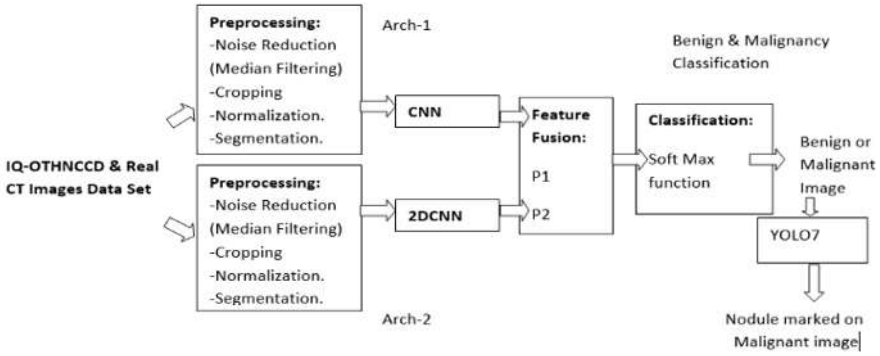


Figure 1. Lung Nodule Malignancy Classification and YOLO8 based Nodule marking architecture

4.1 Preprocessing

Preprocessing is the initial stage in classifying pulmonary nodule malignancy. The IQ-OTHNCCD dataset serves as the input for both architectures. This step enhances the quality of pulmonary CT images by reducing noise and preparing the data for subsequent processes, such as training the architectures and classifying pulmonary nodule malignancy. During image acquisition, noise can be introduced, which is mitigated using a median filtering technique to improve image quality. Additionally, the dataset images are standardized by converting them into a uniform format and resizing them to 224×224 pixels. The pixel values are then normalized to a standard range, typically between 0 and 1. Finally, data augmentation is applied to increase dataset diversity, ensuring consistency in image data.

4.2 Training

The system uses two pretrained architectures based on existing dataset. Training is done using a supervised DL framework. The first architecture uses CNN[11] algorithm for training. The pre-processed lung CT images from IQ-OTHNCCD dataset are provided as input for training the first architecture as shown in figure 2. Following are the CNN algorithm steps.

1. Input Layer: pre-processed CT images are provided as input with size 224X224X1
2. Convolutional Layers: These layers are used to extract the features. Larger kernel size is used in first convolution layer. Kernel size is reduced in later layers.
3. ReLU activation, BatchNormalization, MaxPooling and dropout are the remining layers.
4. Output layer is the softmax activation with the number of classes.

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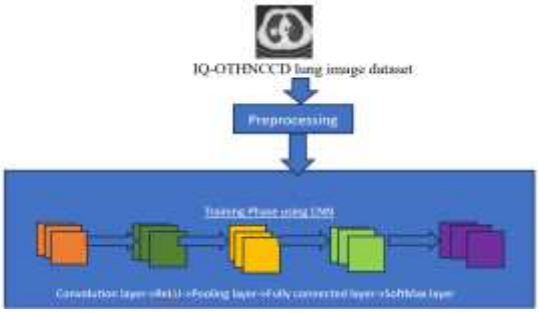


Figure 2. Training CNN architecture using IQ-OTHNCCD lung images dataset

The second architecture uses 2DCNN algorithm for IQ-OTHNCCD lung images dataset training. Pre-processed lung CT images from IQ-OTHNCCD dataset are provided as input for training the second architecture as shown in figure 3. Following are the 2DCNN algorithm steps.

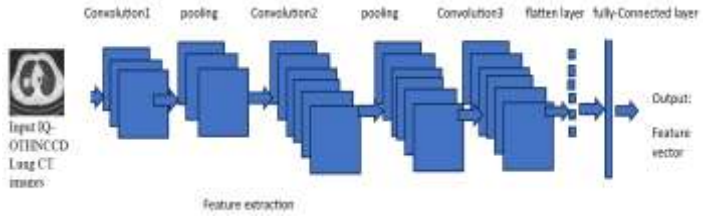


Figure 3. 2DCNN for training of IQ-OTHNCCD lung CT images

Following are the 2DCNN [15] algorithm steps:

(1) Input provided is IQ-OTHNCCD lung CT images dataset for 2DCNN training.
(2) Preprocessing i.e Data augmentation (rotation, flipping, noise addition) is done to increase dataset variability.
(3) Conv2D layers- it helps to extracts the feature.
(4) Batch Normalization- this step improves training stability.
(5) MaxPooling2D layers- this layer reduces spatial dimensions.
(6) Dropout layers- this layer prevents overfitting.
(7) Fully connected (Dense) layers- it is used for classification of malignancy.

4.3 Feature Fusion

Currently, doctors rely on single deep learning-based algorithms for training, but these often yield suboptimal results due to the limited hypothesis space. To address this issue, two training algorithms—CNN and 2DCNN—are utilized for model training. Feature fusion plays a crucial role in enhancing the accuracy of nodule recognition. There are several feature fusion techniques such as weighted fusion, average fusion, concatenation etc. In this system concatenation fusion is used. Initially, CNN and 2DCNN models are trained using existing real-world datasets. When classifying pulmonary malignancy in the test dataset, the pulmonary images are first processed through the pre-trained CNN and 2DCNN architectures. The feature vectors generated by these models are then combined using concatenation feature-level fusion techniques to create a unified feature representation. The developed system employs concatenation-based feature fusion, which merges the feature vectors produced by CNN and 2DCNN models. This approach enhances pulmonary nodule detection by leveraging the strengths of both architectures.

Considering two groups of feature vectors, such as set f and set g, obtained from the output layers of the two CNN constructions. Set "X" is the feature vector generated from the CNN source. "Y" is the feature vector generated from the 2DCNN . The following formula is used to concatenate these two types of feature vectors.

Concatenated Features=Concatenate(f,g)

$$F_{concat} = f_1 , f_2 \ldots . f_n , g_1 g_2 \ldots , g_n$$

The function "Concatenate" denotes the process of integrating the features X and Y. The feature concatenation fusion model is trained. Then the output of the fusion model is provided as input to a classification model.

4.4 Classification

The concatenated feature fusion generates the output as integrated feature vector. This output is given as input to the subsequent classification layer. This layer receives the concatenated features of CNN, and 2DCNN from fusion model. Then this layer stores them in the dense layer as the outcome of classification. The dense layer outcome is then used by SoftMax activation function or layer. This SoftMax activation function classifies pulmonary nodule malignancy. The formula of the SoftMax function in the classification layer as follows:

$$\sigma(z)_i = \frac{e^{z_i}}{\sum_{j=1}^{K} e^{z_j}} \quad (1)$$

In above formula, the SoftMax function is represented using σ. The input vector z is gained as the output from fusion model. The standard exponential function e^{z_i} is for input vector. In the multiclass classifier, K be the number of classes (malignant, Benign). The standard exponential function e^{z_j} is for output vector.

In the SoftMax function for every output there is a calculation of the exponents and then normalization of every value by the sum of those exponents to ensure that the total output vector adds up to one, the SoftMax function converts logs values into probabilities. The SoftMax function assurances that the outcomes of our probability values added together will always equal one. The predicted class of lung image and its related probability be the final output achieved from the developed system.

Categorical cross-entropy was employed as the loss function for the three-class classification task. The loss is defined as:

Mean Squared Error (MSE) Calculates the average of the squared differences between the predicted values (ŷ) and actual values (y).

$$\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2$$

5. EXPERIMENTAL RESULT AND DISCUSSION

The feature Fusion of CNN and 2DCNN for pulmonary nodule malignancy classification system has been developed. The concatenation feature fusion model is used to improve the pulmonary nodule malignancy classification system performance. Figure 4 shows the developed system graphical user interface for real pulmonary CT images nodule malignancy classification and nodule localization using YOLO8. The trained CNN and 2DCNN models generate feature vectors of provided pre-processed lung CT image; While testing the trained system, Real lung CT images are selected as input by clicking the choose file button from the GUI. the choose file button is used to choose a real CT lung image. After selecting the CT image, the predict button is pressed, the system generates a pulmonary nodule malignancy classification result i.e. malignant or benign. If the result generated is malignant image, then YOLO8 algorithm mark the exact location of the nodule on malignant image.



Figure 4. Pulmonary Nodule malignancy classification and nodule Detection using feature fusion and YOLO8.

The performance of the implemented system is measured using confusion matrix. For pulmonary nodule malignancy

classification, confusion matrix shows the SoftMax model estimates align with the actual labels. A confusion matrix is useful tool to measure the performance of a lung nodule classification system, particularly when using fusion techniques that combine different features or models. A confusion matrix for lung nodule classification using a fusion of CNN and 2D-CNN provides a detailed breakdown of the model's performance by showing the number of correctly and incorrectly classified samples across different classes as shown in figure 5. Here is confusion matrix is applied in the context of pulmonary nodule classification for example, benign vs. malignant nodules. The developed system is compared with other implemented existing methods.

For measuring the developed system outcome performance, the parameters such as Precision, Accuracy, F1 Score, Recall, and Area under the curve (AUC) are employed. The mathematical equations are represented as follows.

1. Accuracy = TP+TN/TP+TN+FP+FN

2. Precision (Positive Predictive Value, PPV) = TP/TP+FP

3. Recall (Sensitivity, True Positive Rate, TPR) = TP/TP+FN

4.F1-Score = 2×(Precision×Recall)/(Precision+Recall)

The table 1 shows the performance comparison of the deep learning methods which were applied and fusion of CNN and 2DCNN applied for pulmonary nodule malignancy classification. The comparison is done based on the performance parameters such as accuracy, precision, recall and F1-score.

Table 1. comparison of the existing deep learning methods and fusion of CNN and 2DCNN.

DL Methods for malignancy classification	Accuracy	Recall	Precision
3D-ARCNN [2]	98 %	92.40	93.00
DenseNet121 [18]	87.77%	88.45	89.91
CustomVGG16 [19]	95%	93.5	94.01
VGG16 [20]	70.1%	75.6	76
CNN [21]	89.45%	91.44	92.3
3D CNN [22]	97%	95.00	92
Fusion of CNN and 2DCNN	98.56 %	91.40	95.91

The CNN and 2DCNN features fusion attain 98.56 % accuracy, Recall is 91.40%, specificity is 96.10, Precision 95.91%, & F1 score is 93.60. From the table 1 , the implemented feature fusion of CNN and 2DCNN based malignancy classification system performance is improved than the existing system.

From the comparison it is clear that the proposed method, that is fusion of CNN and 2DCNN applied for pulmonary nodule malignancy classification is outperforms than the any other existing systems. Figure 6 represents the bar graph of DL methods and its accuracy of malignancy classification.

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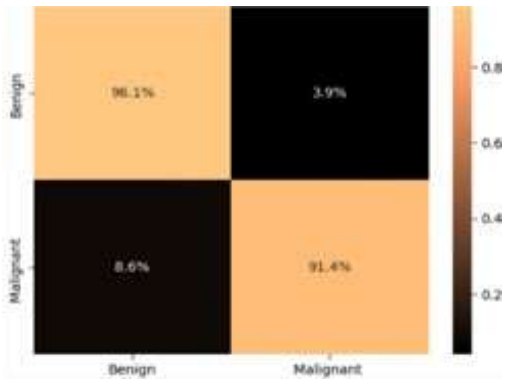


Figure 5. Confusion matrix of number of accurate and unfitting predictions for each class of IQ-OTHNCCD lung images dataset.

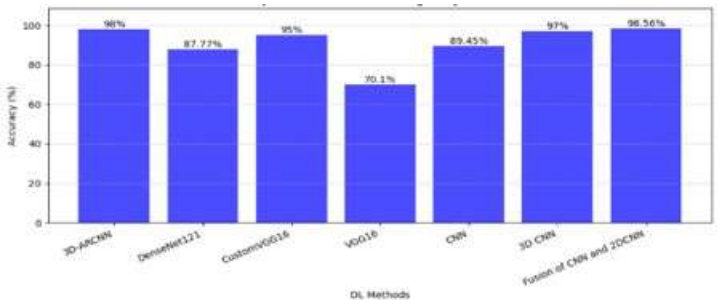


Figure 6. Bar graph of DL methods and its accuracy of malignancy classification.

6. CONCLUSION

Pulmonary nodule malignancy is the most common and hazardous disease and it is the measure cause of people death around the world. To increase the survival rate of pulmonary malignancy disease people, in this implemented system focus is on accurately and timely detection of pulmonary nodule. Instead of using manual method for lung malignancy classification doctors can use deep learning methods to avoid misdiagnosis. Also, the manual methods are not able to locate the small-size lung nodule. Our system help to solve this problem. For accurately and timely recognition of pulmonary nodule from CT images, in this system CNN and 2DCNN are the two pretrained architectures are used , both are trained using existing IQ-OTHNCCD lung CT dataset. The outcome of two architectures are different feature vectors fused using concatenation fusion. The fused features classification is done using softmax layer. The implemented system is tested using Real lung CT dataset. The classified pulmonary malignant image nodule is detected using YOLO8. The performance of the implemented pulmonary nodule malignancy classification system is 98.56 %, which is improved as compared to other existing system.

7. FUTUER SCOPE

There is scope to use advanced deep learning methods for classification of lung malignancy. By using such methods there is possibility of early detection lung malignancy. Also there is possibility to use good quality 3D lung CT images for improving performace and accuracy.

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AUTHOR CONTRIBUTIONS

Keshav S Bhagwat: Conceptualization, Investigation, Literature Survey, Methodology, Implementation, Analysis, Data Curation, Formal Analysis, Training , and Testing

Dr D. R. Thirupurasundari: Supervision, Review & Editing.

CONFLICT OF INTEREST

We as a authors state no conflict of interest for this paper

ETHICS STATEMENT

Ethical approval was not required for this study.

DATA AVAILABILITY STATEMENT

The data that support the findings of this study are openly available at https://www.kaggle.com/datasets/hamdallak/the-iqothnccd-lung-cancer-dataset.

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