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Lung Cancer knobs Classification Model Using Fusion Approach

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A B S T R A C T
Introduction: Cancer disorders are caused when certain body cells enlarge uncontrollably and spread throughout the body. The second most prevalent malignancy that causes cancer-related fatalities is lung cancer. Early detection makes it simpler to lower the mortality rate from lung malignant lesions. Radiologists can identify lung malignant lesion tumours utilising medical imaging methods such as chest X-rays, magnetic resonance imaging (MRI), and computed tomography (CT) scan images. In this article, we suggest a fusion technique based on a 3D Convolutional Neural Network (CNN) that can increase the precision in identifying lung cancer knobs. Based on the 1018 patients' CT scans from LIDC, a dataset comprising 2000 CT image nodule samples was created to train and assess the CNN model. To evaluate the output Accuracy, sensitivity, and specificity these parameters are used. A 95.8% accuracy, 95.3% sensitivity and 96.4% specificity for testing of nodule classification is attained after applying 3D CNN fusion. The benefit of knowledge obtained from the classifiers is that it helps to increase accuracy while also decreasing the rate of false positives

INTRODUCTION

Lung cancer is a malignant lung tumour identified by excessive growth of cell in tissues of the lung. According to global-2020 statistics report [1] the global cancer burden risen to 19.3 million new cases and 10 million deaths in 2020. It shows that lung cancer is one of the biggest killers and is responsible for 1.8 million deaths, 18.4% of the total. According to American Cancer society, if the lung cancer is detected early then the survival rate is 47%. Therefore, automated system to detect lung cancer lesion is highly essential. It can be used as a decision support system for doctors and radiologists. In past decades, researchers have done extensive research on this subject. It is observed that instead of using X-ray images, CT images can give more accurate results which reduced the death rate by 20% [3] Therefore, development of automatic identification of lung cancer knobs from CT images is still an urgent need.

Generally, lung cancer detection system has two phases: first is lesion detection and second is false positive rate reduction. The main goal of such systems is to ensure high sensitivity and to eliminate false positives detected at previous stage.

The training of a classifier that distinguishes between nodules and non-nodules is based on discriminative features. However, discrimination of lesion is very difficult because of size and type of lesion such as solitary lesions, cavity lesions and pleural lesions [4]. Sometimes nodules and non-nodules looks very similar. So, it is very important to define the features properly so that discrimination can be done well.

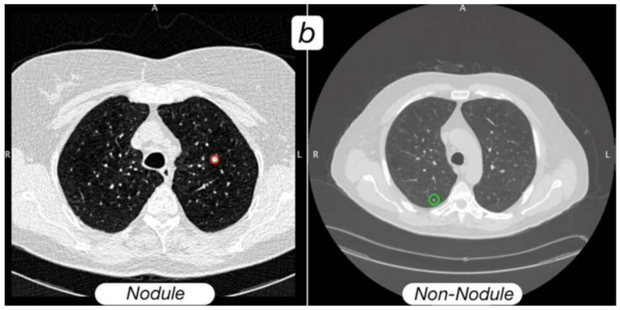

Figure 1 Sample of nodule and Non nodule CT scan Image

Figure. 1 displays samples of nodules as well as non-nodules. The relevant work is provided in the paragraph after this.

C. Liu and colleagues [5] described a cascade variant of CNN for the identification of lung cancer knobs and that also minimised false positives without impacting true positives. In S. Permal et al [6] the cancer suspicious zone in CT scan pictures is identified using Enhanced Artificial Bee Colony optimization (EABC) approaches. Saeed Alhmari et al. [7] employ the radomics technique to extract and analyse quantitative image-based information from a region-of-interest. They employed Naive Bayes, Decision Trees, Random Forests, and Support Vector Machine methods for categorization.

Two CNN networks, CNN21 with an input size of 47 X 47 X 5, and CNN47 with an input size of 47 X 47 X 5, make up the NoduleX framework suggested by Jason L. Causey et al [8]. The model reports a 91.3% accuracy rate. This paradigm might not, however, be directly relevant. The difficulty of a modest medical image database and small nodule size has been addressed by Agile CNN, a hybrid CNN combining LeNet and AlexNet [9].

Multi-resolution CNN is utilised in Wangria Zuo et al [10] to overcome the problems brought on by radiological heterogeneity, varied sizes, and forms of nodules in the classification. The task of distinguishing benign from malignant lung nodules in CT images was examined by R. Dey et al. [13] with the aim of directly learning a mapping from 3D images to class labels. To accomplish this goal, four two-pathway Convolutional Neural Networks (CNNs) are introduced: a 3D DenseNet, a distinctive multi-output network, a fundamental 3D CNN, and an enhanced 3D DenseNet featuring multi-outputs. The 2D CNN approach is suggested to gather pertinent information in between the slices. There are various CNN technique categories for nodule investigation. The nodule can be found using CNN algorithms without the need for feature extraction and segmentation by humans. The network needs additional data to be trained because there are millions of parameters that can be learned.

Comparatively speaking, the 3D CNN model outperforms the 2D CNN model. To detect and classify lung cancer, we therefore present a new architecture in this study that is built on the merging of three 3D CNN. Our goal is to decrease the rate of false positive detection and increase the model's diagnosis accuracy rate compared to more established techniques.

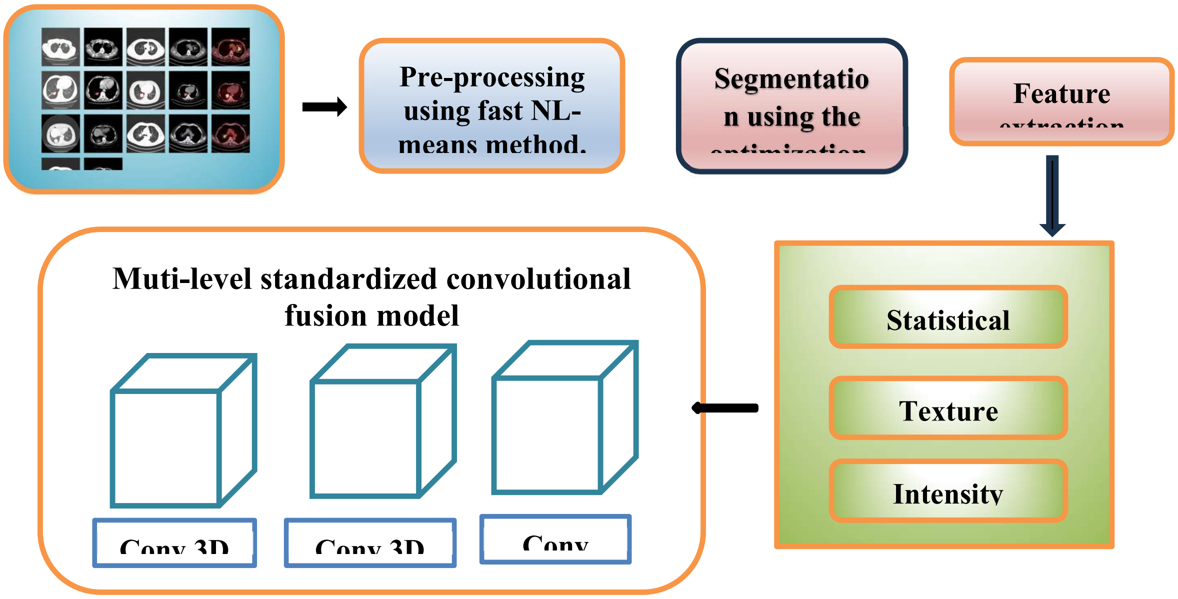

Figure 2. The proposed lung cancer categorization block diagram's workflow

The remaining section of the paper is structured as methodology which addresses fusion based classifier, experimental findings, and finally a conclusion.

METHODOLOGY

The proposed lung cancer categorization block diagram's workflow is shown in Figure 2. The main processes are Pre-processing using fast NL means method, segmentation using optimization, feature extraction, Multilevel standardized convolution fusion model, sample classification with performance evaluation.

This section encompasses the data used for training and testing the model, along with the outlined architecture for the detection and classification of lung cancer nodules.

1. Data

The Lung Image Database Consortium image and Image Database Resource Initiative (LIDC-IDRI) [18] collection includes CT scan images with detected lesions that have been highlighted. This serves as a global resource accessible online, facilitating the development, teaching, and evaluation of computer-assisted diagnostic (CAD) methods aimed at the early detection and diagnosis of lung cancer. It is utilized to evaluate the efficacy and performance of the proposed system. Data from 1010 patients (2,71,113 CT Scan pictures) are included in the LIDC-IDRI collection for digital imaging and communications in medicine (DICOM). dcm format [12]. The database is primarily divided into four classifications: unknown, benign, malignant, and metastatic. However, as a Metastatic category explains the spread of cancer and categorization of an unknown category is worthless, we only took into consideration the benign Figure. 3 (a) and malignant Figure. 3 (b) labelled data.

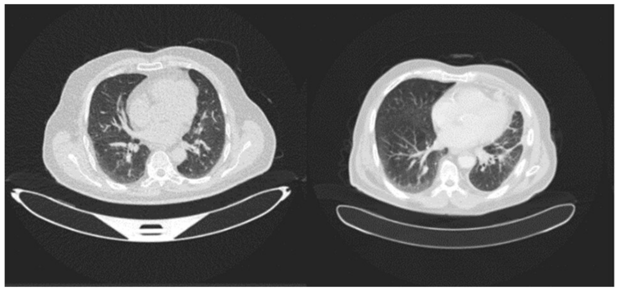

Figure (a) Benign CT Scan Image (b) Malignant CT Scan Image

2. Preprocessing using Fast NL-Means

The noise in the image is eliminated using the Non-Local-Means technique. Non-local means filtering employs a mean of all picture pixels, weighted by the degree of similarity between the target pixel and these pixels. The NLM filter makes use of redundant data from the target image, such as recurring patterns or textures, to differentiate between the underlying signals and noise. You can prevent the well-known negative impacts of commonly used neighbourhood filters by using this filter. The mathematical equation of this method is

$$g(i,j) = v(i,j) + h(i,j), (i,j \in K) \quad (1)$$

where v(i,j) is the real value, h(i,j) is the additive noise, and g(i,j) is the observed pixel value at the point of (i, j). We suppose that the noise in this scenario is white, Gaussian, and has a mean and variance of zero. The weighted sum of each pixel in the image is used to calculate the restored value using the non-local means approach.

$$w(i,j) = \sum_{d,e} r(i,j\colon k,l) * g(k,l) \quad (2)$$

where w(i,j) is the algorithm's estimated value and r(i,j:k,l) denotes the weight given to the pixel at position (k,l) . The weight's size reflects how comparable (k, l) and the reference pixel (i,j) are.

3. Segmentation

Image segmentation is one of the crucial and necessary procedure in pre-processing and analysing images. Segmentation can solve issues with a variety of dimensions in a reasonable amount of time and with good outcomes. This study's segmentation makes use of the vulture search technique, and this optimisation helps with the extraction of information relevant to the cancer region. The segmentation finally isolates the malignant and non-cancerous areas of the lung for further processing.

4. Feature Extraction

Following segmentation, the objective of the feature extraction method is to portray the image in its simplest and distinctive representation, either as a set of individual values or as a matrix vector. Feature extraction is used to decide which images can be used for categorization while calculating feature reduction. The original information must be reduced to a more manageable, diplomatic set of features. After obtaining the features as inputs, the classification algorithms classify the characteristics into the group that most closely reflects what they stand for. By estimating positive qualities, feature extraction seeks to minimize the volume of data. We employed statistical, textural, and intensity features extracted from various bands of CT images, all of which are elaborated upon in the following sections.

4.1. Statistical features

The statistical elements that aim to minimise loss dimension reduction are the most essential aspects of CT scans. Entropy, standard deviation, variance, and mean are all included in the extensive analysis of this statistical factor.

i) Mean: The mean of the CT image provides a quantitative representation of its overall brightness level, capturing the average intensity of the image Let μ is used to represent the mean of the input CT image. The mathematical representation of the image mean can be expressed using the following equation:

$$\mu_i = \frac{1}{N}\sum_{c=1}^{N} x_i^c \quad (3)$$

Here, N denotes the total number of instances in the image, x_i^cstands for the image at the ith image at the cth time instance.

ii) Variance: It helps in assessing the degree of fluctuation or texture in the image. Depending on the output class, the variance monitors the slight variations in the CT image. The following equation provides a quantitative expression for the variance of the CT image:

$$\sigma_i = \frac{\sum_{c=1}^{N}\left(x_i^c - \mu_i\right)^2}{c-1} \quad (4)$$

iii) Standard deviation: The standard deviation, assesses the minute fluctuations in the CT picture in line with reality. The standard deviation can be expressed quantitatively using the following equation:

$$S = \sqrt{\frac{\sum_{c=1}^{N}\left(x_i^c - \mu_i\right)^2}{c-1}} \quad (5)$$

iv) Entropy: Entropy is the average degree of surprise and uncertainty caused by the enormous number of probable results. It's used to capture the texture and complexity of the image. The entropy of the CT picture is written as,

$$H \quad = 2 \times \left[1 - \frac{1}{1+e^{\left(-X(d_i)\right)}}\right] \quad (6)$$

where X(d_i) denotes the weighting function of the relevant image.

4.2. Texture features:

Areas of interest in photos are categorized and divided using the texture feature. Texture is characterized by the arrangement of intensity levels across a specific neighbourhood in space. Local Binary pattern (LBP) approach is used to get texture features of the image.

4.3. Intensity features

One of the most popular features is intensity-based, and in this study, an intensity characteristic like Histogram of oriented gradient (HOG) is considered. The fundamental concept underlying HOG is that the appearance and shape of localized items within an image can be effectively represented by the distribution of gradient intensities or edge directions. A histogram of the gradient axis for each pixel in each cell can be created to take advantage of the image's ability to be divided into small, interconnected groups, or cells. The aggregate of these histograms then serves as the descriptor's representation.

5. Convolutional Neural network

Convolutional Neural Networks (CNNs or ConvNets) are useful for classifying and recognising images, and linear coats of stack are helpful in this process. Convolutional neural networks are composed of a series of distinct convolutional layers, each independently trained to autonomously extract relevant information from the input data, eliminating the need for manual feature engineering or pre-processing. Convolutional, pooling, fully linked, and SoftMax layers make up the fundamental components of a CNN. The convolutional layer in CNN is the fundamental method used for feature discovery. To create the feature maps, a mathematical process called a "dot product" must be applied to the entire content of each input data sample. Another important CNN process is pooling. It is usually applied after the convolution process. Pooling helps reduce the dimensionality of the output, preserving more significant key information as a result.

6. Proposed multi-level standardized convolutional fusion model

Multi-level standardised convolutional fusion is used to extract the low-frequency and high-frequency features from the input images and to enhance network training. The suggested Multi-level Standardised Convolutional Fusion Model, which learns spectral and spatial features, consists of three convolutional layers and max-pooling layers based on 3D kernels. Every convolutional layer has unit stride kernel sizes and padded straps. We designed and trained three different size 3D CNN so that fusion of these three networks can cover error of classifiers. Fig. 5 depicts the proposed system's general architecture.

Fig. 6 depicts the 3D CNN's architecture. We introduce a specialized 3D Convolutional Neural Network (CNN) architecture tailored for the classification of lung cancer nodules. Each model begins with an input layer shaped to accommodate the 3D input data. Each 3D CNN model consists of two sets of convolutional layers followed by activation functions.

Within the architecture of the 3D CNN model1, the initial set comprises two Conv3D layers, each featuring 8 filters and a kernel size of (3, 3, 3). The subsequent set includes two Conv3D layers with 16 filters and a (3, 3, 3) kernel size. These layers extract spatial features from the input data. Following each convolutional layer, the Rectified Linear Unit (ReLU) activation function is applied, introducing non-linearity to the model. After each pair of convolutional layers, a 3D Max Pooling layer with a (3, 3, 3) pool size and 'same' padding is utilized to reduce spatial dimensions and capture essential features. To prevent overfitting, dropout regularization is implemented with a rate of 0.25 after each pair of pooling layers. Dropout randomly deactivates neurons during training. The output from the last set of pooling and dropout layers is flattened into a 1D vector, preparing the data for fully connected layers. Two fully connected Dense layers are incorporated: the first Dense layer, comprising 512 neurons, utilizes the Sigmoid activation function, and a dropout rate of 0.5 is applied for additional overfitting reduction. The final Dense layer, with two output classes for classification, employs the SoftMax activation function to generate class probabilities.

In the configuration of 3D CNN model2, the initial set comprises two Conv3D layers featuring 32 filters, while the subsequent set includes two Conv3D layers with 64 filters and a (3, 3, 3) kernel size.

For 3D CNN model3, the first set involves two Conv3D layers with 128 filters, and the second set encompasses two Conv3D layers with 256 filters, utilizing a (3, 3, 3) kernel size.

7. Training

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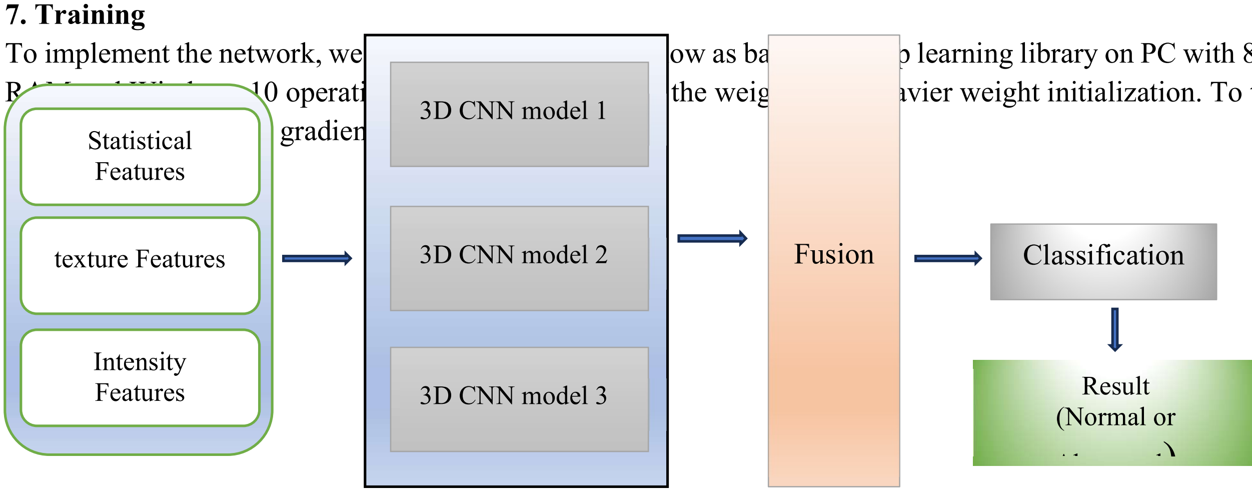

Figure 5 System Architecture Fusion of three 3D CNN

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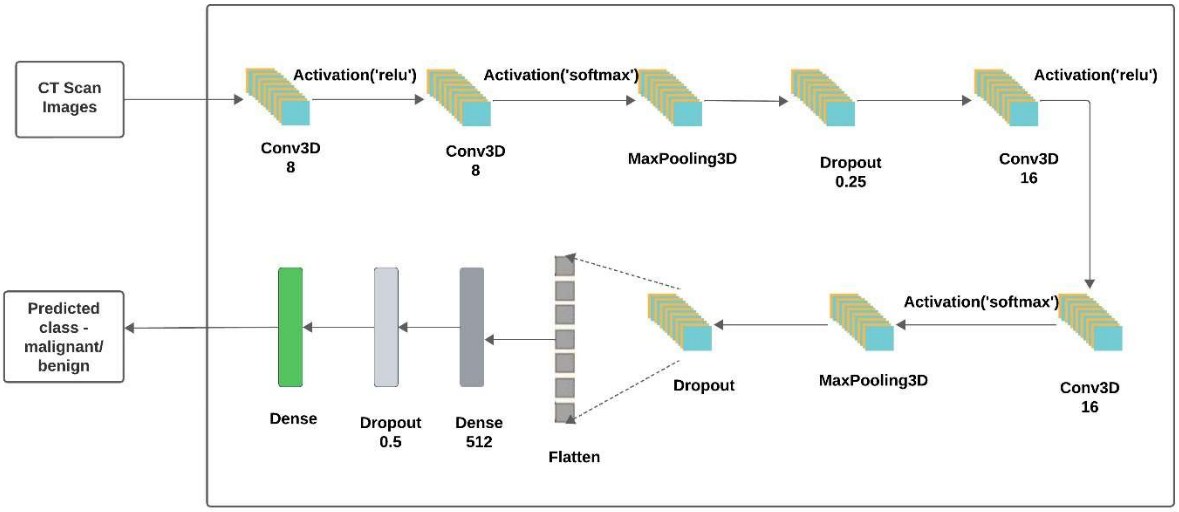

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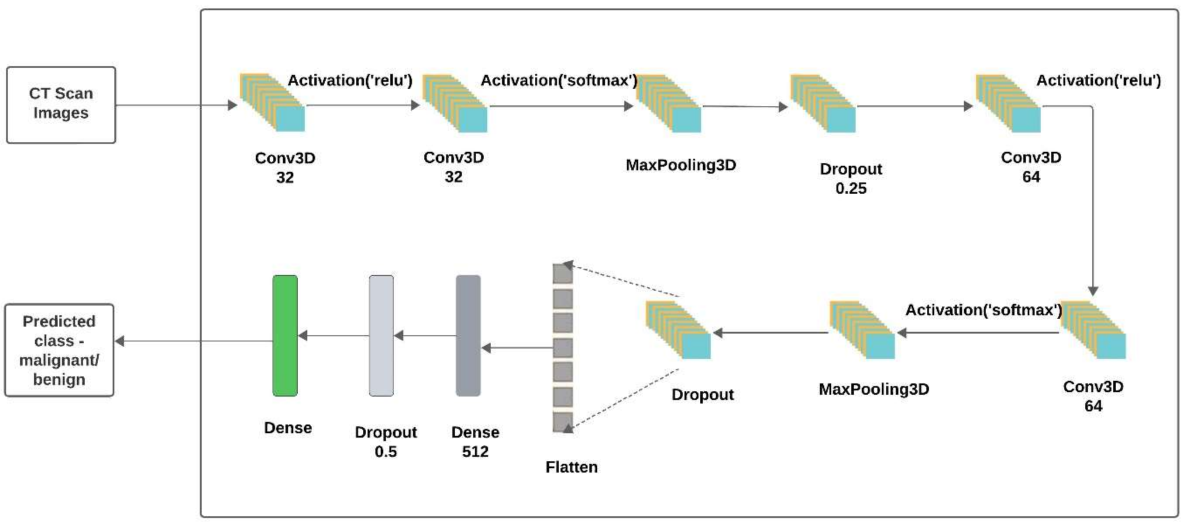

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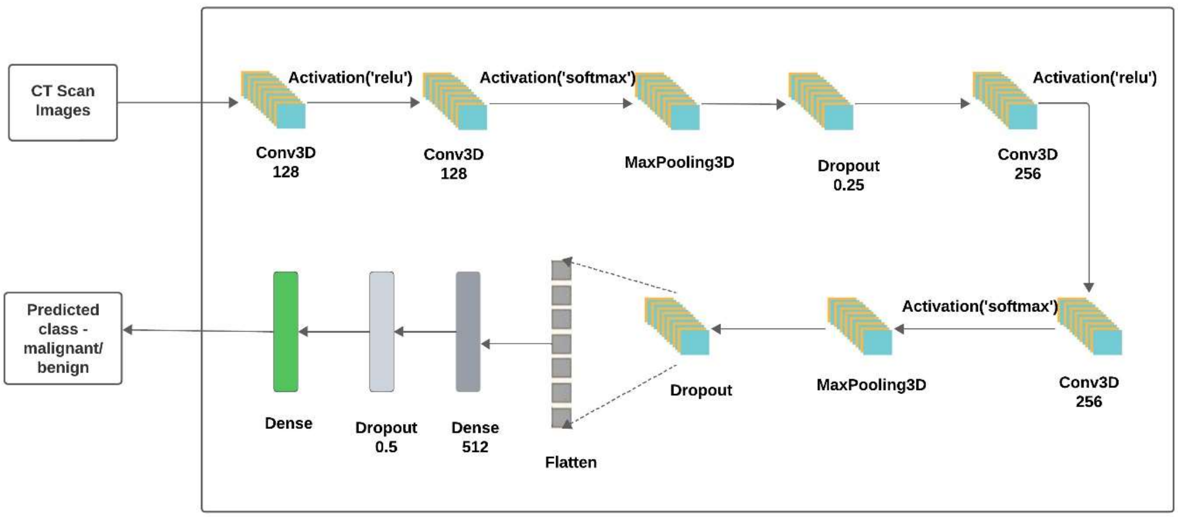


Figure. 6 3D CNN Architectures

s used with learning rate 0.001. Data preparation steps are already explained in previous section. Since our classification model is binary, the loss function used is the weighted binary cross entropy.

RESULTS AND DISCUSSION

The implementation of multi-level standardized convolutional fusion model for lung cancer classification and an analysis of the developed model's performance in comparison to current approach is discussed below.

Here, we contrast the outcomes of our suggested approach with those of 1D CNN fusion and 2D CNN fusion. The dataset is separated for analysis into training and testing purposes in a proportion of 70% and 30%, respectively. Sensitivity, and Specificity are utilised to evaluate the system, together with ACC (accuracy, the proportion of accurate predictions) [11] [14][17]. The definition of Sensitivity, Specificity, and Accuracy is follows:

$$Specificity = \frac{TN}{TN + FP}$$

$$Sensitivity = \frac{TP}{TP + FN}$$

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN}$$

Where TP (True Positive) signifies the count of accurately classified samples. Conversely, FP (False Positive) denotes the count of samples erroneously identified as belonging to a particular class, while FN (False Negative) represents the count of samples wrongly classified as not belonging to a specific class, despite belonging to it.

Both benign and malignant class types make up our class type. TP and FP represent instances where malignant samples are accurately classified and benign samples are incorrectly categorized as malignant, respectively. On the other hand, TN and FN denote cases where benign samples are correctly classified and malignant samples are inaccurately labelled as benign.

A. Results

Figure 7 shows the results obtained using the proposed method during the segmentation process for additional processing to separate the lung's cancerous and non-cancerous regions. The segmented images `reduce the complexity by eliminating larger number of regions.

We examined our proposed fusion algorithm with both the original 1D CNN fusion and 2D CNN fusion. The Accuracy, Sensitivity, and Specificity graphs of all three methods are shown in figure 8 And 9.

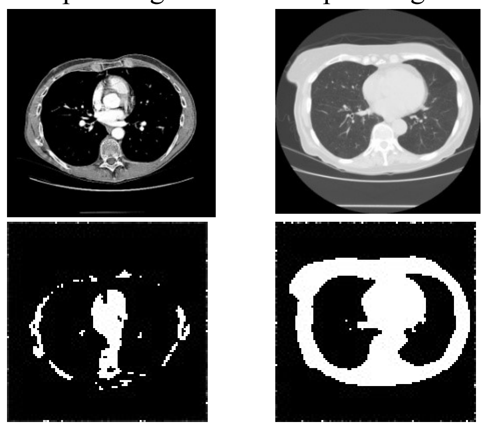


Figure 7: Experimental results of the segmentation process

The comparison is summarised in Table 1. On the LIDC-IDRI dataset, it displays the outcomes of our suggested methodology along with 1D and 2D CNN fusion method results.

Table 1. Network performance on the LIDC-IDRI dataset. Sensitivity; Specificity; ACC: accuracy, the percentage of correct predictions.

Network	Sensitivity %	Specificity %	ACC%
1D CNN Fusion	91.3	92.1	91.7
2D CNN Fusion	92.5	93.5	93.1
3D CNN Fusion	95.3	96.4	95.8

The classification accuracy of our suggested technique fusion is encouraging, reaching 96%. Figure 8 compares the test accuracy of the 3D CNN Fusion technique, the 2D CNN Fusion method, and the 1D CNN Fusion method. It indicated that 3D fusing classifiers improves the result. The comparison between the baseline methodology and our suggested 3D CNN Fusion method is given the Table2.

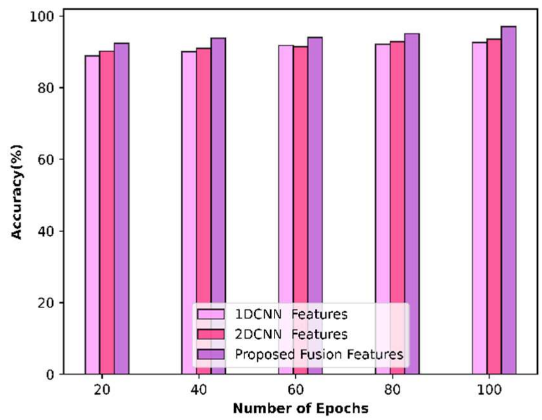


Figure 7 (a) Performance analysis adapted on Training Phase a) Accuracy.

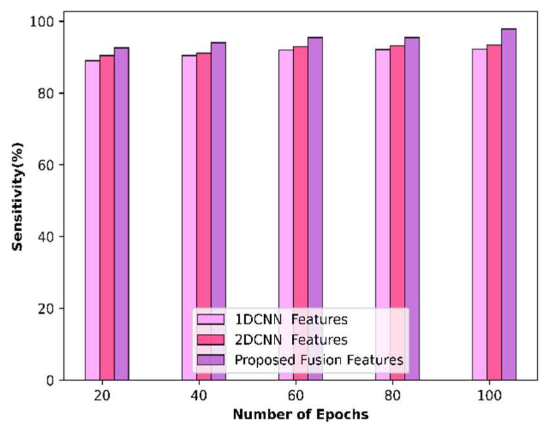


Figure 7 (b) Performance analysis adapted on Training Phase b) Sensitivity.

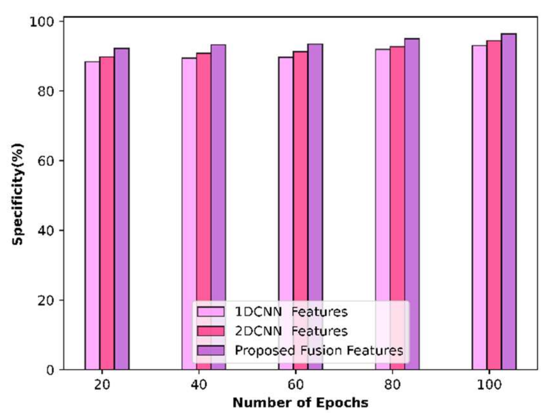
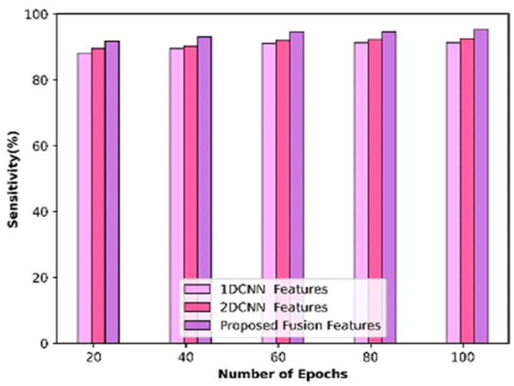


Figure 7 (c) Performance analysis adapted on Training Phase c) Specificity.



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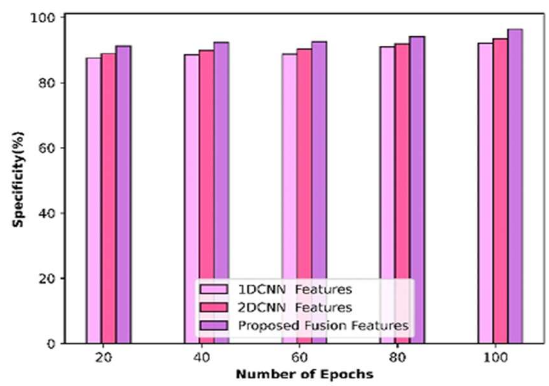

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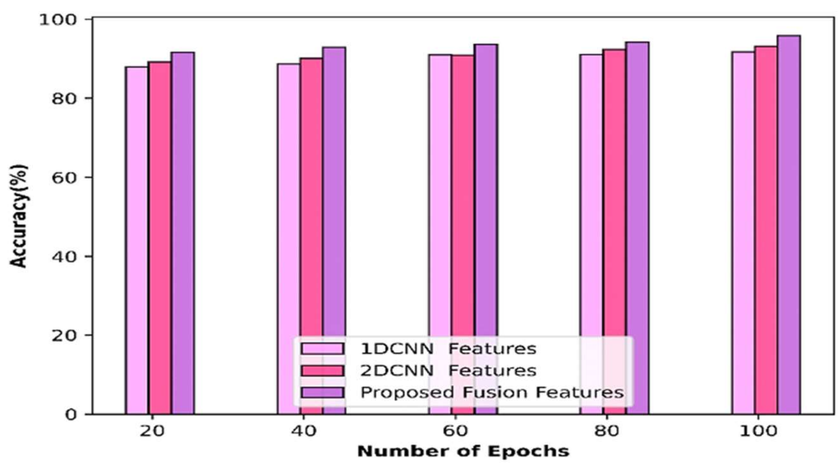

c)

Figure 8 Performance analysis adapted on Testing Phase a) Sensitivity b) Specificity c) Accuracy.

Table 2 Comparison of the results with existing papers

Author	Dataset	Approach	Accuracy (%)
(J Yang, *et al.* 2019)	LIDC_IDRI	Online Streaming Feature Selection with CD_SU_SF	70.95
(J Yang, *et al.* 2019)	LIDC_IDRI	Online Streaming Feature Selection with SVM_SF	88.28
(J Yang, *et al.* 2019)	LIDC_IDRI	Online Streaming Feature Selection with CD_SF	88.24

(Shah, A.A., *et al.* 2023)	LUNA 16	Ensemble 2D CNN	93.9
Proposed method	LIDC_IDRI	3D CNN Fusion	95.8

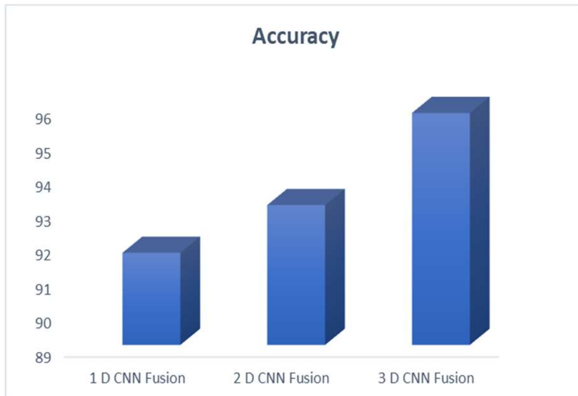

Figure 9 Test Accuracy Comparison of 1D CNN, 2D CNN and 3D CNN Fusion

CONCLUSION

The detection and evaluation of malignant nodules is one of the best methods to lower the death rate from lung cancer. The deep learning architecture may significantly affect how well lung nodules are classified. To detect and categorise pulmonary lesions in a CT picture into benign or malignant categories, we proposed the memory-enabled vulture search optimization in conjunction fusion of three 3D CNN approach in this study. Our findings demonstrate respectable classification performance in the detection of lung cancer. Accuracy depends on trainable parameters as well as on the dataset. The 3D CNNs fusion model performs the best on the test set. Our results demonstrate high performance, with values of 95.8% for accuracy. In future we would like to try for ReNet-50 and ResNet-152 framework to evaluate the system. Any research project has potential for improvement. No finished product has been created for the purpose of detecting cancer. For detecting and forecasting malignancies, no worldwide standard has been established. Therefore, there is always a good chance that prediction and detection accuracy can be raised. New avenues and approaches for early cancer detection will arise from increased efforts in identifying and predicting various types of cancer.

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