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A NOVEL OPTIMIZED LEARNING FRAMEWORK WITH SWIN TANSFORMER FOR THE BETTER CLASSIFICATION OF LUNG CANCERS

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ABSTRACT

The development of the intelligent expert system is required mandatorily today for the clinical analysis and to make the accurate diagnosis for disease treatment.Among the various disease diagnosis process, lung cancer needs more brighter light of research because it affects both men and women and also leads to higher mortality rate. Computer tomography (CT) scan images can provide more helpful diagnosis information regrading the lung cancers. Many machine learning and deep learning algorithms are formulated using CT input scan images for the improvisation in diagnosis and treatment process .But , designing an accurate and intelligent system still remains in darker side of the research side. This paper proposes the novel classificationmodel which works on the principle of fused features and optimized learning network. The proposed framework incorporate the principle of Swin Transformers as a first tier segmentation , which improve the classification maps and eventually reduce the risk of overfitting problems. Furthermore, the proposed work has replaced the traditional neural network with Swin transformers to obtain the best classification of cancers in Lung CT scan images. The proposed algorithm has been implemented using Tensorflow 1.8 and Keras API with Python 3.8 programming. The extensive experimentations are carried out using the LIDC -IR image datasets and various performance metrics such as accuracy, sensitivity, specificity, precision and f1-score are calculated and analyzed. Simulation results show the proposed framework shows 99.89% accuracy, 99.8% sensitivity ,99.76% specificity, 99.8% precision and even 99.88% F1-score respectively. Furthermore , performance of the proposed framework has been compared with the other existing models in which the proposed model has outperformed the other existing model in terms of various performance metrics.

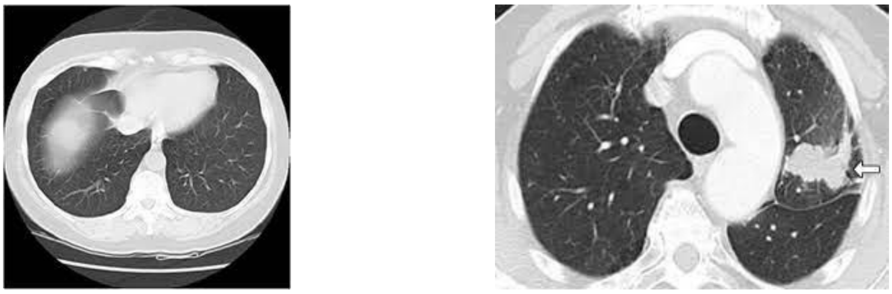
Keywords :
Computer Tomography(CT) Scan Images, Fused features, Swin Transformers.

1. INTRODUCTION :

Recently, alterations in environment, uneven climate changes, unbiased life styles are considered as important root causes for the rapid increase of diseases . Lung cancer is one of most dreadful diseases in the world**.[1-4].**Recent surveys by World Health Organization(WHO) says nearly 7.6 million worldwide deaths**[5,6]**are due to the impact of lung cancers on human life. Moreover , it has been predicted to reach nearly 17 Million worldwide deaths by 2030**[7].**Hence the risk of lung cancer is enormous in all major parts of world and it has been cultivating the more deaths per year.

To reduce the impact of lung cancer, early diagnosis system is badly required which is used to discover the cancer at early stage[8]. The different diagnosis methodologies such as Magnetic Resonance Imaging (MRI), X-rays, Isotopes and Computer Tomography(CT) scans are used as an effective tool for recognition of lung cancers. **[9,10**]. CT images are used by physicians and radiologists to identify and recognize the presence of cancers , directly visualize the morphologic extents of cancers

, describe the patterns and severity of diseases.**[11].**Figure 1 shows the CT Normal Images and CT Cancer Images.



(a) (b)

Figure 1 a) Normal CT Lung Image b) Abnormal CT Lung Image(Cancer Image)

Early classificationand classification of the lung cancers plays an critical aspect in designing the intelligent and accurate diagnosis system . With an advent of machine and deep learning algorithms, design of early diagnosis systems has reached its new heights. The machine learning algorithms such as artificial neural networks(ANN), Support Vector Machines (SVM), Naïve Bayes Classifiers(NB), Ensemble classifiers (EC) are primarily used for an early diagnosis of the lung cancers**[12-16].**Also Deep learning is considered to be most promising field which can enhance the performance of various medical imaging and diagnosis systems.**[17,18].**

However, handling the' heavier' images with different imaging protocols remains to be real challenge to train the learning modes for greater performance . To compensate for the above drawback of learning models , this paper proposes the novel intelligent diagnosis **framework DFF-RON(Deep Fused Features Based Reliable Optimized Networks), which utilizes the Swin Transformers for better segmentation and feature extraction, that are used to train.** To the best of our knowledge, this is first work which has integrated the fused features and optimized learning networks to design an efficient and high performance CT based Lung Cancer Diagnosis System.

2. CONTRIBUTION OF THE RESEARCH WORK :

1. A **Novel deep learning based model is proposed**for early detection of lung cancer using CT Scan Images. The proposed model architecture has been trained with LIDC-IDDAI datasets and performance metrics has been calculated and compared with the other existing models.
2. The proposed architecture introduces **Swin Transformers for the better segmentation and feature extraction** . Also the proposed algorithm can increase the high diagnosis rate also.
3. The **Swin Transformers are proposed**for training the features obtained from the saliency maps. The feed forward layers are designed based on the principle of Extreme Learning Machines(ELM).

3. PROPOSED METHODOLOGY :

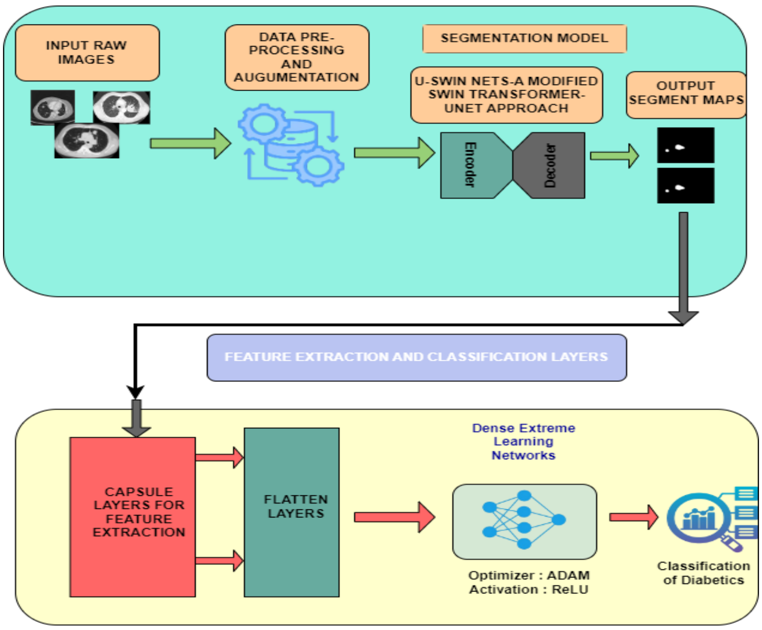


Figure 2 Proposed Framework for Segmentation ,Feature Extraction and Classification Layer.

Figure 2 shows complete architecture for the proposed framework. The working mechanism of the proposed deep learning based diagnosis and classificationsystem is sub-divided into three important phases. Image preprocessing and Augmentation process, Visual extractions, Accurate feature extraction using the customizedSwin Transformers and finally trained by the novel ant-lion optimized feed forward networks.

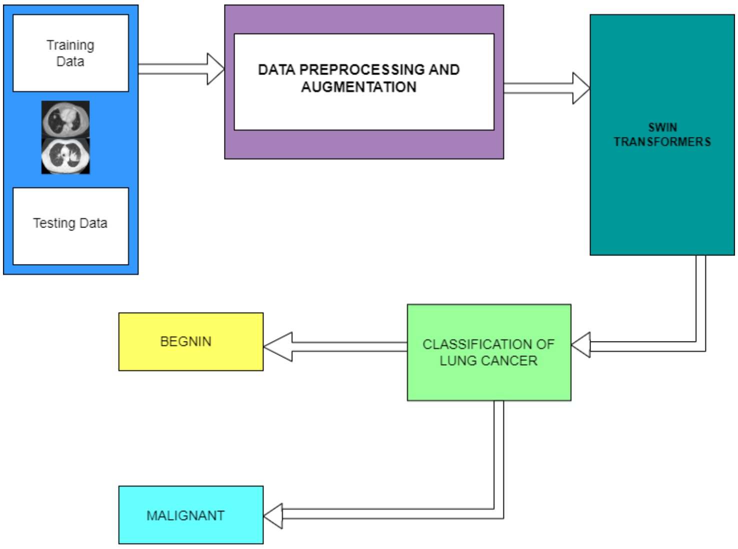


Figure 3 Overall Working Flow Diagram for the Proposed Architectures

3.1.Data Preprocessing and Augumentation:

The medical preprocessing technique is used to remove noise pixels ,low -quality pixels which affects the detection of lung cancers. Pixel Intensive testing process has been utilized to remove the inconsistent pixel and the noise pixels from the Input CT scan images. Also , Image histogram methods are adopted for enhancing the image quality because it works better on different images. Figure3 shows the preprocessed CT scan images after applying pixel classificationand image histogram methods.

3.2 Data Augumentation:

After preprocessing the input images, image augmentation process is used in the proposed architecture. Neural Networks leads to the overfitting problems where a limited quantity of labelled data is available. The most proficient and efficient method to tackle this problem is data augmentation. During the data augmentation phase, each image undergoes a series of transformation , producing the huge amount of newly corrected training image samples. A affline transformation is employed for an efficient data augmentation. The affline transformation techniques such as translation, scaling and rotations are used.Mostly the training image samples obtained from the augmentation process have a correlation , this step is recommended to overcome the overfitting problems. Figure4 shows the different lung images obtained after applying the affline transformations.

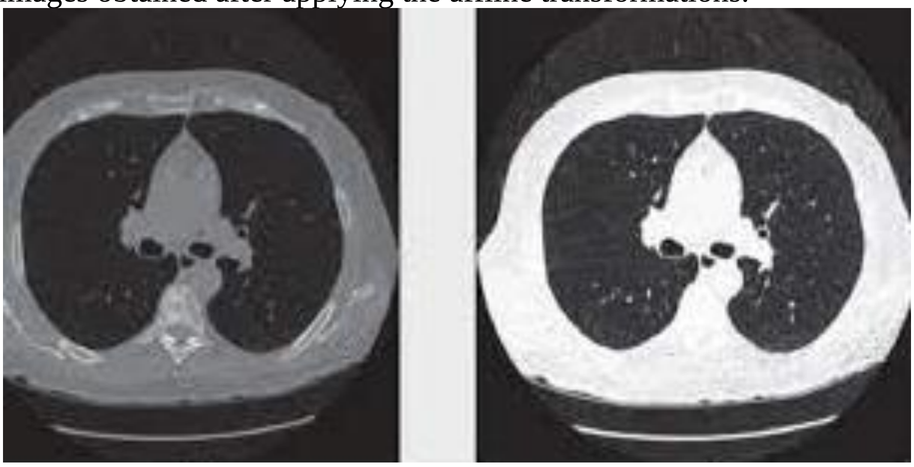


Figure 3 Sample Preprocessed CT Lung Images

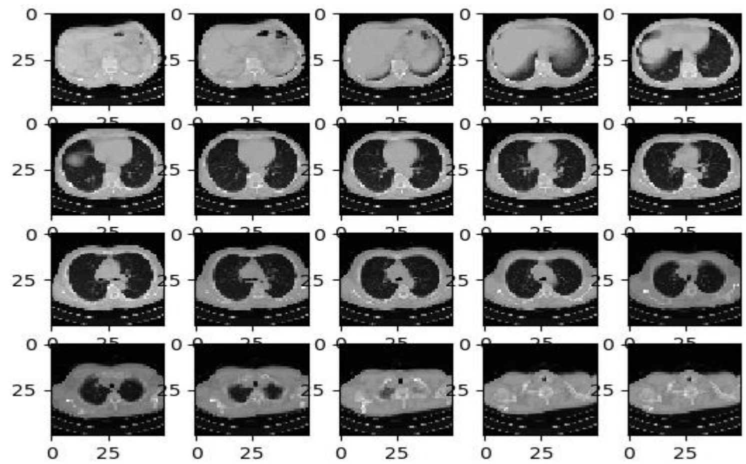


Figure 4 Sample CT Lung Images after Augmentation Process

3.3 Swin Transformer Model

The schematic representation of the Swin Transformer module is presented in Figure 4 .Each Swin transformer block consists of layer –normalization(LN),regular window multi-headed self attention (W-MHSA) module and multi-layer perceptron(MLP). These modules are used alternatively to form the complete swin transformer blocks. The mathematical expression for the Swin transformer block can be expressed as

$$y2 = W - MHDA\big(LN(y1)\big) + (y1 - y2) \quad (1)$$

$$y1 = MLP(y1) + (y1) \quad (2)$$

$$y1 = W - MHDA\big(LN(y2)\big) + (y1 + y2) \quad (3)$$

$$y2 = MLP(y2) + (y2) \quad (4)$$

The modified swin transformer(MST) model used as the backbone for the proposed structure. The MST consists of a batch normalization (BN) layer, SW-MHSA, a shift window based hybrid multi-head convolutional attention (SW-HCMA) module, a residual connection, BN layer and a MLP with residual connection. The SW-HCMA is introduced in the proposed block, which can significantly distinguish the feature maps of the thermal foot images. The SW-HCMA is constructed by combining the channel attention and spatial attention which helps to achieve the adaptive attention that focus on an accurate segmentation of the images. The channel attention aims to focus on the image's category information by keeping the channel dimension unchanged and compressing the spatial dimension into a scalar. Furthermore, the spatial attention assists the network in paying more attention to the location information of targets inside an image by keeping the spatial dimension unchanged and compressing the multiple-channel dimension into one single channel. The proposed block incorporates the HCMA with the shift window operations can reduce the adverse effects in the modelling ability that aids for achieving the better accuracy. To perform the best fit on the thermal images, SW-MHSA and SW-HCMA are used laternatively in the proposed swin transformer block. Figure shows the HCMA incorporated in the proposed block.The mathematical expression of the proposed SWT can be expressed as follows :

$$y2 = W - MHSA\big(LN(y1)\big) + (y1 - y2) \quad (4)$$

$$y1 = MLP(y1) + (y1) \quad (5)$$

$$y3 = W - HCMA\big(LN(y2)\big) + (y1 + y2) \quad (6)$$

$$y2 = MLP(y2) + (y2) \quad (7)$$

4. DATASETS DESCRIPTIONS :

The experimentations are carried out using lung CT images which are obtained from the cancer imaging archives (https://wiki.cancerimagingarchive.net/display/Public/LIDC-IDRI). The database consists of 1018 lung CT images which are obtained from national cancer institute that correlated with proteomic and genomic clinical data . In this paper, all training images are classified into malignant and benign nodules. A malignancy nodule will have scored lower than 3 are called as a benign nodule and a malignancy nodule will have scored higher than 3 are called as a malignant nodule. The pulmonary nodules with a score of 3 in malignancy are removed to avoid the ambiguousness of nodule samples.Separate software NBIA retriever is used for the conversion of tcia format data to DICOM image data which can be used for further processing.

4.1 Experimentation Details:

The whole experimentation is carried out in the Intel I7CPU with 2GB NVIDIA Geoforce K+10 GPU, 16GB RAM ,3.0 GHZ with 2TB HDD. The proposed architecture is implemented using Tensorflow 1.8 with Keras API. All the programs are implemented in the anaconda environment with python 3.8 programming .

4.2 Performance Metrics and Evaluation:

The proposed architecture implements the six CNN layers for the better classificationof cancer cells in lung images. Table 1 depicts the partitioned datasets used for training and testing the network. Table 1 Total number of Datasets (after Augmentation) Used for Training and Testing the Proposed Network

Sl.no	Total Number of Images	Training Data(%)	Testing Data(%)
01	78090	70	30

Six Convolutional layers are used in the proposed architecture whose hyperparameters of the are optimized by antlion optimization. The details about the tuned hyperparameter is discussed in section3.6.s the next step, the proposed architecture is tested with the images in which the convolutional layers extracts the image features and feeds to the optimized feed forward training networks that classifies the appropriate categories. To evaluate the performance of proposed architecture, metrics such as accuracy, sensitivity, specificity, recall and f1-score are calculated. Table 2 shows the mathematical expressions for calculating the metrics used for evaluating the proposed architecture.

Table 2 Mathematical Expressions for the Performance Metrics' Calculation

SL.NO	Performance Metrics	Mathematical Expression
01	Accuracy	$\frac{TP+TN}{TP+TN+FP+FN}$
02	Sensitivity or recall	$\frac{\mathrm{TP}}{\mathrm{TP+FN}}$ x100
03	Specificity	$\frac{TN}{TN+FP}$
04	Precision	$\frac{TN}{TP+FP}$
05	F1-Score	$2.\frac{Precison * Recall}{Precision + Recall}$

TP is True Positive Values, TN is True Negative Values, FP is False Positive and FN is False negative values

5. RESULTS AND FINDINGS :

The excellence of the proposed architecture and performance of other existing models are presented in this Section. The performance of the proposed architecture is validated in four folds. In the first fold, confusion matrix is used to verify the performance of the proposed architecture. Additionally Receiver operating characteristics(ROC) is used for verifying the performance of the proposed architecture. In the next fold, the performance of the proposed architecture is compared with the other existing models such as Convolutional Neural Networks, Long Short Term Memory, combined CNN and LSTM and Vision Transformer by measuring the different performance metrics as mentioned in table IV. Furthermore , the computational complexity is calculated for different optimization algorithm used for tuning the hyperparameters in the proposed architecture . Finally , the performance of the proposed architecture is compared with the state-of art architecture proposed by different authors. The proposed algorithm is tested with the random **1000 Lung CT (50% Begnin and 50% Malignant)** scan images in order to overcome the imbalance problems.

Table 3 Different Deep learning Architectures' Performance such as Accuracy, Sensitivit , Specificity, Precision, Recall in predicting the Malignant Cancers in LUNG CT Images .

	Accuracy(%)	Sensitivity(%)	Specificity(%)	Precision(%)	F1-Score(%)
CNN	80.7%	79.7%	80.5%	79.8%	79.7%
LSTM	82.8%	80.8%	79.8%	80.48%	80.9%
CNN-LSTM	87.05%	85.75%	85.98%	84.97%	85.7%
Vision Ransformer	87.7%	86.58%	87.67%	86.66%	87.88%
Proposed Architecture	99.89%	99.88%	99.88%	99. 92%	99.92%

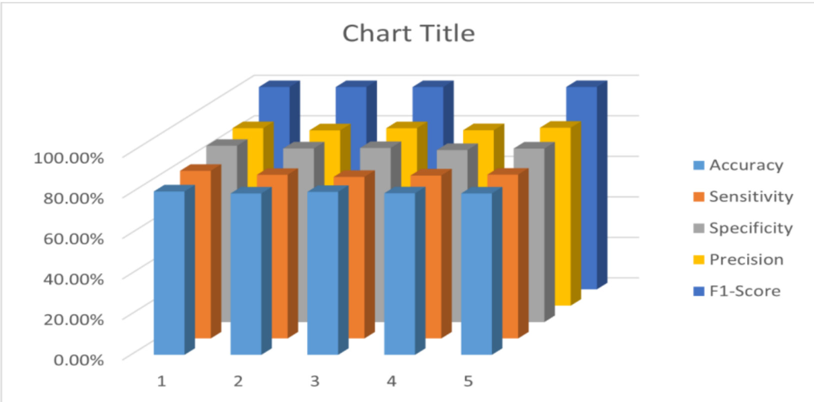


Figure 4 Comparative Analysis of Average Performance Metrics of different deep learning framework in predicting the lung cancer in CT Images

The confusion matrix and ROC curve of the proposed framework in detecting the categories of CT scan Lung Images . Table 3 presents the comparative analysis between the performances of proposed and existing algorithms. It is found that proposed algorithm has shown the accuracy of 99.8% with 99.85% sensitivity, 99.86% specificity and high f1score of 99.88% in detecting the begnin CT images . Figure 4 shows the comparative analysis of average performance between the proposed and existing algorithm. From the figure 4, it is also clear that proposed algorithm has outperformed the other existing algorithms.

6. CONCLUSION :

This main objective of the research is to detect and classify the malignant and begnin cancer cells using CT Scan Lung Images. To detect the location of cancer cells, this work uses the Swin transformers for an effective segmentation and feature extraction that are used to train the network for the better classificationwith the high accuracy and less computational complexity. The proposed algorithm was developed using Tensorflow 1.8 with Keras API and compared with other existing state-of -art architectures. The results shows that the proposed architecture has outperformed the other state-of art architectures and obtained maximum results such as 99.89% accuracy,99.8% sensitivity and specificity, 99.86% precision and 99.89% F1-score. In future, more vigorous testing is required using the larger real time clinical datasets. Additionally, proposed algorithm needs it improvisation in terms of grading the images based on the malignant characteristics of lung cancers ,which will play significant role for the diagnosis and accurate treatment of lung cancer in clinical applications.

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