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Autonomous Decision Systems For Healthcare Diagnostics: Balancing Accuracy And Computational Efficiency

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Abstract

An Autonomous Decision System (ADS) has gained increased application in the medical field as a means of improving early detection of diseases, but most deep learning architectures are computationally expensive and have low efficiency when used in a real-world medical context. The dataset employed is that from Kaggle, which provides Computed Tomography (CT) scans of lung cancer with several classes of images, such as normal, benign, and malignant states. In light of the stated problem, the research introduces an efficient Siberian Tiger Optimization–based Intelligent Lightweight Convolutional Neural Network (ST-IntLCNN) model for detecting cancer in lung using CT images through feature extraction and classification. This model combines Contrast Limited Adaptive Histogram Equalization (CLAHE) is used for image handling stage and Histogram of Oriented Gradients (HOG) is used for dimensionality reduction. The features extracted from the images are classified using Intelligent Lightweight Convolutional Neural Networks (Int LCNNs).The design of the IntLCNN model with a lightweight architecture helps minimize memory consumption without compromising its ability to learn features effectively. Experimental results confirm that the developed ST-IntLCNN model provides excellent classification results with 98% accuracy and 97.98% precision, recall, and F1 score. The implementation is done using Python with the help of TensorFlow, Keras, OpenCV, and Scikit-learn for data preprocessing and model creation. The proposed ST-IntLCNN is capable of striking an ideal balance between performance and speed when classifying lung cancer from CT scans, thereby enabling its application in self-sufficient healthcare systems without the shortcomings of existing deep learning models.

Keywords: Artificial Intelligence (AI), Healthcare, Lung Cancer, Autonomous Decision Systems (ADS), Computed Tomography (CT), Deep Learning (DL).

1. Introduction

Cancer in lung endures a significant worldwide health issue and is one of the major reasons for cancer deaths around the world. Because this disease is often diagnosed at advanced stages, patient prognosis and survival rates are significantly affected. Therefore, prior and exact prediction plays a key role in improving treatment outcomes and reducing mortality. In this context, Deep Learning (DL) and Artificial Intelligence (AI) technologies offer promising solutions by enhancing diagnostic accuracy, supporting clinical decision-making, and facilitating timely disease identification [1]. Medical imaging techniques, including Positron Emission Tomography (PET), X-rays, Computed Tomography (CT) scans, and Magnetic Resonance Imaging (MRI), act as a key factor in detecting the cancer in lung, while DL and AI techniques enhance diagnostic accuracy by enabling automated and efficient analysis of medical images [2]. Lung nodules refer to irregular growths in the lungs that could signify benign ailments or cancer. Predicting the lung cancer initial phase is important in enhancing patient survival rates, and the integration of advanced medical imaging techniques with AI plays a crucial role in enabling accurate, timely, and reliable diagnosis [3, 4]. Lung cancer prognosis using Machine Learning (ML) algorithms is evolving due to the incorporation of imaging, genetics, and clinical information to enhance early diagnosis and treatment. However, these need to be validated across different settings to guarantee consistency [5]. Lung cancer is among the common cancers leading to deaths from cancer, mainly due to delayed diagnosis, which leads to low survival rates. Histopathology is important for proper classification of the tumor, while digital pathology and AI assist in diagnosis and decision-making [6].

Research Aim: This research focuses on proposing an efficient Autonomous Decision System (ADS) to predict the cancer in lung using CT Images which maintains the computational costs and accuracy. This research presents a Siberian Tiger-Intelligent Lightweight Convolutional Neural Network (ST-IntLCNN) along with CLAHE for pre-processing, Histogram of Oriented Gradients (HOG) features, and a Siberian Tiger Optimization (STO) technique.

Research Organization: The structure of the manuscript includes the following sections. The first section highlights the background of lung cancer, motivations, and problem definition. The second section deals with the literature review, along with their methodology. The third section describes the methodology for the proposed approach, which can include dataset details, data preprocessing, feature extraction, and design of the model. The fourth section describes experiment outcomes and evaluation. The last part is the conclusion of the research, including future scope and limitations of the research.

2. Related works

Adaptive Attention-Augmented Convolutional Neural Network-Vision Transformer (AACNN-ViT) is introduced on account of classifying lung cancer using CT scans. The model utilizes the combination of Convolutional Neural Network (CNN) local features, ViT global context, adaptive fusion, and focal loss to address the issue of imbalance with 96.97% accuracy. External clinical validation needed for generalization purposes is limited in this research [7]. The research was held to enhance early detection of cancer in lung through prediction with Internet of Medical Things (IoMT) technology. The results of this method demonstrates 95.1% accuracy and superior classification accuracy. The major limitation is the dependency on cloud computing and advanced technology [8]. The research aimed at introducing an ML algorithm that can be used in predicting Length of Stay (LOS) for cancer patients admitted to the Intensive Care Units (ICUs) from the Electronic Health Records (EHRs) data. The Random Forest (RF) algorithm was found to have the highest accuracy rate, but it depends on one historical dataset [9]. The research was to enhance the diagnosis process for lung cancers with the help of a computational approach based on AI. An approach comprising SqueezeNet [10] for feature extraction and Logistic Regression (LR) for classification resulted in 92.9% accuracy in differentiating benign, malignant, and normal cases, but it depends on a smaller sample size. Research [11] developed a DL transfer-based stacked model known as the Vision-based Ensemble Representation Network (VER-Net) for the detection of lung cancer from CT scan images. The model uses three models, viz., Efficient Convolutional Neural Network baseline version B0(EfficientNetB0), Visual Geometry Group 19-layer Network (VGG-19), and Residual Network with 101 layers (ResNet101), and achieves 91% accuracy and 91.3% F1-score in classifying four types of cancers; it needs validation with larger datasets. Research presented an approach that uses Support Vector Machine (SVM) and DL to identify lung cancer from CT scans. It is based on analysis of the 888 Lung Image Database Consortiums and Image Database Resource Initiative (LIDC/IDRI) CT scans with an accuracy of 94%, which is better than other techniques; its reliance on annotated data sets can impact real-world generalization and scalability [12]. Research introduced a hybrid meta-heuristic model, termed Sand Cat Swarm Optimization-Whale Optimization Algorithm (SCSO-WOA), to segment the image using a multilevel thresholding technique. SCSOWOA has shown excellent results, obtaining a value of Feature Similarity Index Measure

(FSIM) 0.9542 and Structural Similarity Index Measure (SSIM) 0.9340 when tested using the Lung and Colon 25000 (LC25000) dataset [13]. Research presented the design of the Lung Attention Network (Lung-AttNet), which is an efficient CNN model augmented, by a Lightweight Global Attention Module (LGAM) to classify cases of cancer in lung through CT scan images. This model has been able to obtain accuracies of 91.5% for training models and 92% for federated learning [14]. Research [15] suggested the combination of RF, CNN, and Long Short-Term Memory (LSTM) models for the classification of lung cancers based on CT scans available at The Cancer Imaging Archive (TCIA). This model obtained an accuracy of 97% with an AUC greater than 0.95; it had imbalanced data and excluded rare cancer types. The research was introduced to enhance capability to predict and categorize cancers in lung based on CT image scans. This was done using a customized CNN model alongside XAI and Grad-CAM, which had an accuracy rate of 93.06%, limiting the validation on larger datasets [16].

3. Methodology

The suggested methodology shown in Figure 1 focuses on the development of ADS for the detection of lung cancer from CT scan images. The workflow entails data collection, preprocessing through the CLAHE technique, and feature extraction through the HOG method. The obtained features are then classified using the IntLCNN, which focuses on efficient learning and lower computational complexity. The hyperparameters of suggested approach is upgraded with STO algorithm.

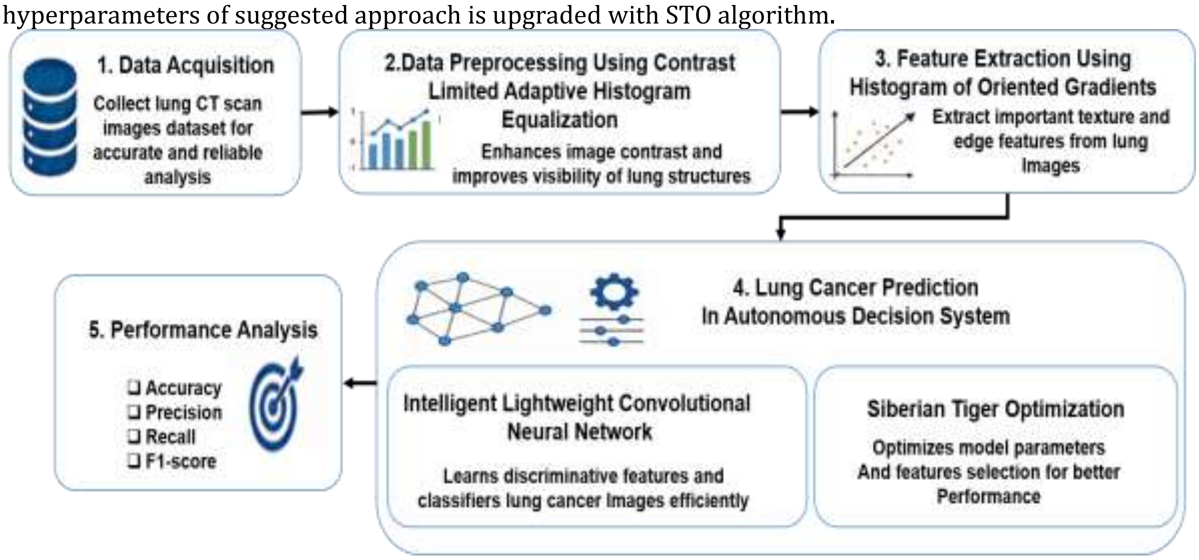


Figure 1: Methodology Flow of Introduced Model

3.1 Image Acquisition

The CT scan image set for lung cancer diagnosis from Kaggle (https://www.kaggle.com/datasets/mdnafeesimtiaz/ct-scan-images-of-lung-cancer) is employed for building the proposed ST-IntLCNN approach for detecting the cancer in lung. Dataset comprises 1,535 CT scans from various classes that include normal, benign, and malignant instances, with a collection of several thousand images according to the Kaggle data source. These images provide a variety of lung conditions in healthcare, which would be useful for developing the proposed model. The division of these images into training and testing datasets includes 80% and 20%, respectively.

3.2 Contrast Limited Adaptive Histogram Equalization (CLAHE) for Image Preprocessing

For improving image quality obtained through a CT scan, the CLAHE method is employed as a pre-processing step. This increases the contrast of local regions within a medical image without enhancing the noise level. The CLAHE method proves effective in making small intensity differences more visible in lung tissues, which cannot be seen easily in their original CT scan images in healthcare. These small intensity differences help in identifying tumors and extracting features for lung cancer detection in ADS.

$$\beta = \frac{KT}{V}\left\{1 + \frac{\alpha}{100}(BD_{max} - 1)\right\} \quad (1)$$

In Equation (1), β denotes the quality factor of the image, Kand T represent the number of pixels in each region,V indicates the number of grayscale levels,αrefers to the factor of the clip, B denotes the intensity level of brightness,D refers to the measurement factor of distortion,max refers to the maximum allowable limit, D_{max} indicates the value of maximum distortion.

3.3 Histogram of Oriented Gradients (HOG) for Image dimensionality

Feature extraction using HOG enables the acquisition of significant attributes from CT scans. Features such as edge detection and variations in the textural pattern of the image play a vital role in detecting cancerous areas in the lung tissues. HOG utilizes analysis of directional intensity variations in the image to produce useful features, making computation less complex but at the same time ensuring preservation of information. The acquired features serves as effective inputs for lung cancer detection in the ADS.

$$\nabla l(k,e) = \begin{bmatrix} l(k,e+1) - l(k,e-1) \\ l(k+1,e) - l(k-1,e) \end{bmatrix} \quad (2)$$

In Equation (2),∇ denotes the gradient,l is the Intensity of pixel,k is the horizontal position of pixel, and e denotes pixel's vertical position in the image grid,$l(k,e)$indicates the intensity of the pixel at the position, $\nabla l(k,e)$denotes the vector of the gradient at the position,$e+1$ and $e-1$ refers to the upcoming and prior vertical pixel, and $k+1$ and $k-1$ represents the upcoming and prior horizontal pixel.

$$|\nabla l| = \sqrt{g_k^2} + g_k^2 \quad (3)$$

In Equation (3), $|\nabla l|$is the magnitude of the gradient, g_k^2denotes the height difference,k is the pixel's horizontal position, g_k denotes the difference in height in the horizontal direction, and $g_k^2 + g_e^2$ represents the values of the gradient in directions, respectively.

$$\theta = \tan^{-1}(\frac{g_k}{g_e}) \quad (4)$$

In Equation (4), θ refers to the direction of the gradient, $\tan^{-1}$ denotes the inverse Tangential function, g denotes the height difference,k is the pixel's horizontal position, g_k denotes the difference in height in the horizontal direction, and g_e refers to the difference in height in the vertical direction.

3.4 Lung Cancer Prediction using Siberian Tiger Optimization–based Intelligent Lightweight Convolutional Neural Network (ST-IntLCNN) model

The ST-IntLCNN technique was introduced to predict cancer in the lung through the CT images, which increases the efficiency and reduces complexity in autonomous healthcare applications. In IntLCNN, lightweight convolution operations combined with an attention mechanism were applied to extract discriminative features of lung tissues in CT scans. The IntLCNN improves the representation of squamous cell carcinoma, normal, large cell carcinoma, adenocarcinoma, and benign patterns in CT images. STO was used to optimize the parameters of the IntLCNN model to increase efficiency.

Intelligent Lightweight Convolutional Neural Network (IntLCNN): The IntLCNN shown in Figure 2 is developed to predict the cancer in lung via images of the CT scan. It aim to decrease computational complexity, along with being efficient at learning features of medical imaging data. In IntLCNN, lightweight convolutions are performed to learn important patterns in the structure of lung tissues from CT scans. The IntLCNN ensures better convergence during training as well as generalization for diverse cases of lungs.

$$Z = X_{ox} * (X_{ex} \otimes y) \quad (5)$$

In Equation (5), Z represents the representation output of the fused feature, X indicates the feature matrix of convolution, o represents the index of the output channel, x refers to the tensor of the input feature, X_{ox} denotes the transformation tensor of the output, $*$ refers to the operator of the optimal solution, e refers to the feature map of excitation,X_{ex}denotes the tensor of excitation feature, $\otimes$ indicates the operation of element-wise interaction, andy represents the feature map of the input.

$$w = y \odot \sigma\left(X_2 \mathrm{ReLU}\left(X_1 \mathrm{gap}(y)\right)\right) \quad (6)$$

In Equation (6), w indicates the output of the weighted feature, y represents the feature map of the input,$\odot$ operation of element-wise multiplication, σ refers to the activation function of sigmoid,X indicates the feature matrix of convolution, X_1 and X_2 represent the transformation of first and second convolution, ReLU denotes the function of Rectified Linear Unit, gap refers to the operation of global average pooling, and gap(y) represents the operation of global average pooling over the feature map of the input.

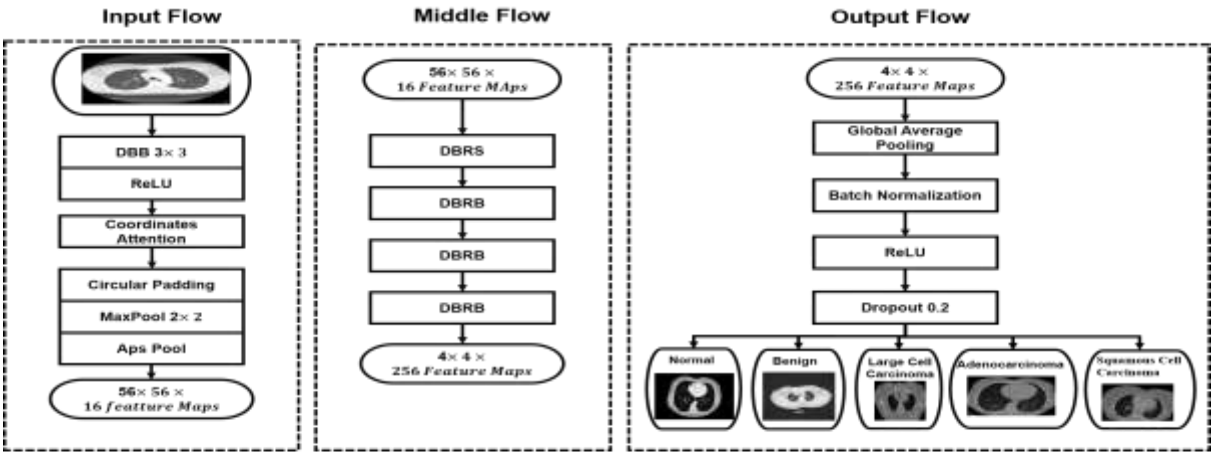


Figure 2: Architecture of IntLCNN

Hyperparameter tuning with Siberian Tiger Optimization (STO): The STO algorithm is used for optimal parameter tuning for lung cancer prediction through the CT scan image dataset. This algorithm is used to optimize parameters include the architecture of network and rate of learning, to enhance the learning process. The STO algorithm boosts the convergence ability and ensures model stability even when different types of CT scan images are used. This algorithm minimizes the noise fitting of the model and enhances generalization in health care applications.

$$\theta^* = \mathrm{ARG} \min_{\theta} \mathrm{K_H}(\mathrm{H_0}, \mathrm{F_H}, \mathrm{V}) \quad (7)$$

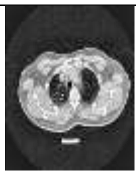
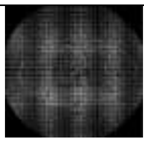
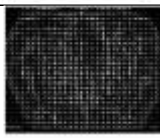
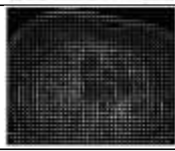
In Equation (7), θ refers to the vector of model parameter, θ^* indicates the set of optimal parameter, ARG refers to the function of argument, min represents the selection operator of minimum value, $\min_{\theta}$ minimization of values according the model parameter, K denotes the value of cost function, H refers to the hidden feature, $\mathrm{K_H}$ indicates the loss function, $\mathrm{H_0}$ represents the initial distribution of feature, F indicates the output of feature extraction, $\mathrm{F_H}$ refers to the space of extracted feature, V denotes the dataset of validation.

Hyperparameter of the Proposed model: For effective lung cancer prediction based on CT images, an optimal configuration for the proposed ST-IntLCNN model is provided by choosing optimized hyperparameters. In the process of training, standard inputs having dimensions 224 x 224 and 32 batch sizes with 100 epoch numbers can be employed. For multi-class classification purposes, an Adam optimizer along with ReLU activation function and Softmax output layer can be used. Optimization of important parameters, including learning rate, dropout, and convolutional blocks, can be performed by STO.

4. Result and discussion

The suggested ST-IntLCNN model is trained using a robust computational environment via NVIDIA RTX 4090 GPU, 64GB Random Access Memory (RAM), and Intel Core i9 processor, to facilitate efficient execution of the DL method. The application programming environment comprises Python 3.11, TensorFlow, Keras, Scikit-Learn, and OpenCV during deployment of the method and CT scan. Experiments were conducted using Anaconda and Jupyter Notebook. This system utilizes Graphics Processing Unit (GPU) acceleration, the Adam optimization algorithm, and STO-based hyperparameter optimization to obtain robust training, fast processing, and accurate lung cancer prediction. Table 1 shows sample CT scans from the lungs of patients with squamous cell carcinoma, normal, large cell carcinoma, adenocarcinoma, and benign conditions. It showcases the original image, CLAHE preprocessing outcomes, and features extracted via the HOG method.

Table 1: Classification of lung Computed Tomography scans

Methods	Normal	Benign	Adenocarcinoma	Large Cell Carcinoma	Squamous Cell Carcinoma
Original					
Image Pre-processing: CLAHE					
Feature Extraction: HOG					

Explorative Data Analysis: Figure 3 displays the classification results achieved by the proposed model on five distinct groups of lung cells, including squamous cell carcinoma, benign, large cell carcinoma, normal, and adenocarcinoma. As can be seen from the confusion matrix, the predicted values have a tendency to cluster around the diagonal, meaning a high accuracy of classification was achieved. The low count of off-diagonal elements implies low errors between the classes.

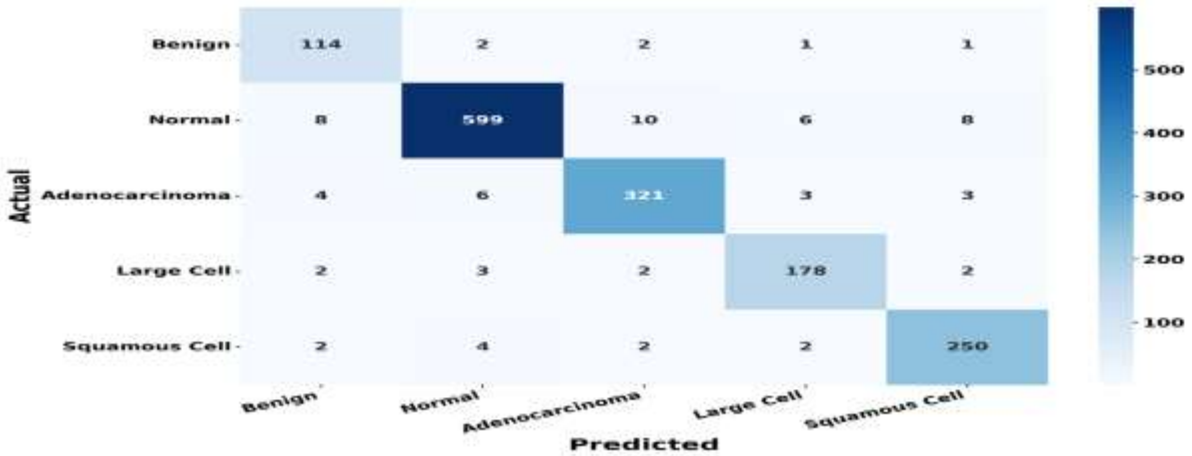


Figure 3: Confusion Matrix of Lung Cancer

Figure 4 displays the performance of introduced approach shows a continuous accuracy level increases and a continuous decrease in loss during the training phase. Figure 4(a) represents the accuracy curve designed to validation and training phases. It can be observed that there is an increase in accuracy levels, indicating successful learning by the method. Figure 4(b) denotes the loss curve designed to both the validation and training phases. It is seen that there is a continuous decrease in losses, which shows that the model is converging successfully.

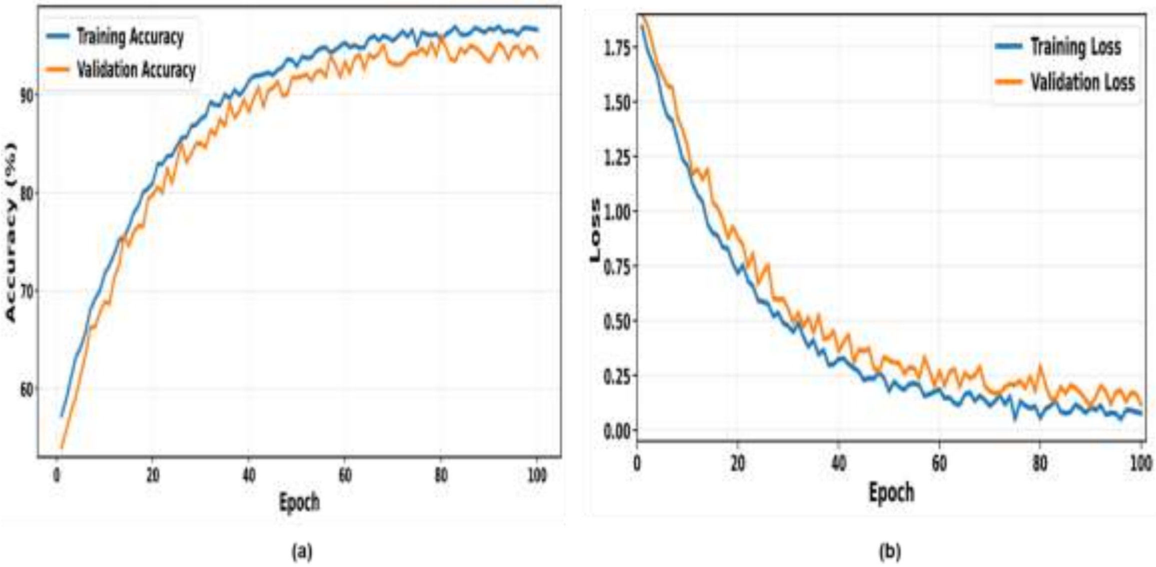


Figure 4: Visualization (a) Accuracy Patterns, and (b) Loss Patterns

Evaluation Metrics: Accuracy refers to the system performance of cancer classification in lung by count of correctly classified CT scan images out of all test data. **Precision** indicates the fraction of positive classification made by the method that prove to be true predictions, which lowers the error of misdiagnosis in lung cancer cases. **Recall** helps to determine the extent to which the classifier can detect all actual instances of lung cancer, avoiding any case where there could be a possibility of missing actual positives.**F1-score** is the most important metric for granting a systematic assessment concerning the behavior of model, which treats recall and precision while calculating an accurate result.

Performance Comparison: Comparison of the results indicates the effectiveness of the developed ST-IntLCNN approach regarding the prediction of cancer in the lung through CT scans, represented in Table 2 and Figure 5. While the traditional DL algorithms such as DenseNet201 [16], Residual Network with 101 layers (ResNet100) [16], VGG-19 [16], and AlexNet [16] exhibit satisfactory results, they are not efficient, as they have shortcomings either in terms of accuracy or overall balance among the assessment criteria. Moreover, the Custom CNN [16] also provides comparable results that are less than those achieved by the proposed solution. On the other hand, the proposed ST-IntLCNN model produces better results with an accuracy of 98% and precise scores of 97.98%.

Table 2: Analysis of the Baseline Models and Proposed Model

$\boldsymbol{Model}$	$\boldsymbol{Accuracy}$ (%)	$\boldsymbol{Precision}$ (%)	$\boldsymbol{Recall}$ (%)	$\boldsymbol{F1-score}$ (%)
$DenseNet201$ [16]	92.73	86.67	75.71	81.19
$ResNet100$ [16]	81.50	81.30	80.50	81.30
$VGG-19$ [16]	94.20	94.38	94.00	94.19
$AlexNet$ [16]	92.80	93.14	92.40	92.77
$Custom\ CNN$ [16]	93.06	95.53	93.09	93.84
$ST-IntLCNN$ [$Proposed$]	98.00	97.98	97.98	97.98

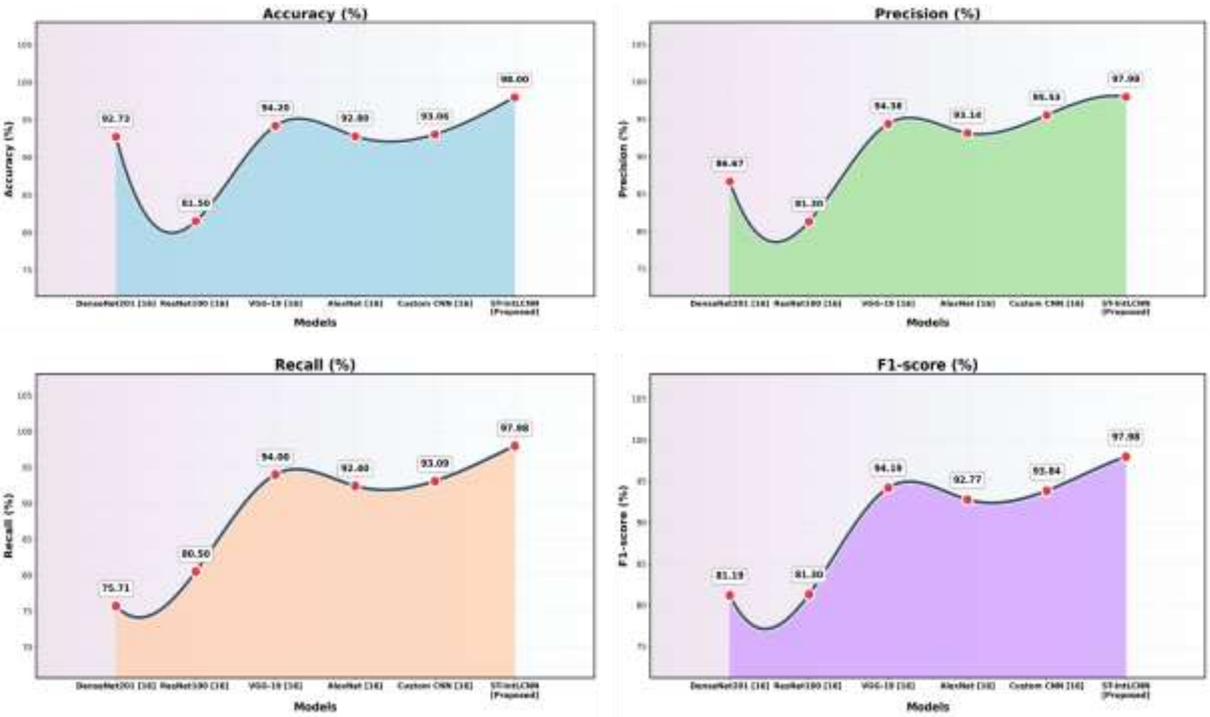


Figure 5: Comparative Performance Analysis of baseline methods with the Proposed Model

Baseline DL algorithms from previous research and the proposed ST-IntLCNN algorithm were retrained using the Kaggle CT scans of the lung cancer dataset shown in Table 3 with the same experimental conditions for a fair assessment. Both sets of algorithms were trained with the use of the same pre-processing algorithm, which includes image enhancement with CLAHE and feature extraction using HOG. The outcomes demonstrated that the ST-IntLCNN model is more effective in detecting lung cancer by achieving a classification accuracy of 98%.

Table 3: Retrained Baseline Model Comparison with the suggested Architecture

$\boldsymbol{Model}$	$\boldsymbol{Accuracy}$ (%)	$\boldsymbol{Precision}$ (%)	$\boldsymbol{Recall}$ (%)	$\boldsymbol{F1-score}$ (%)
$DenseNet201$ [16]	91.20	85.10	74.30	79.20
$ResNet100$ [16]	80.40	80.10	79.20	79.60
$VGG-19$ [16]	93.10	93.40	93.00	93.20
$AlexNet$ [16]	91.80	92.30	91.50	91.90
$Custom\ CNN$ [16]	92.20	94.10	92.40	93.20
$ST-IntLCNN$ [$Proposed$]	98.00	97.98	97.98	97.98

Discussion: There are several drawbacks in the models that have been used in this research for classifying CT scan images into lung cancer types. DenseNet201 [16] is quite computationally expensive and consumes much time while training, requiring more memory than other models. ResNet100 [16] is a very complex architecture and proves less effective at coping with variations in the features of the medical images. VGG-19 [16] is a model that consists of too many parameters, thus consuming much memory and being inappropriate for real world applications in healthcare. Moreover, AlexNet [16] is relatively shallow and therefore has limited capability to derive attributes via challenging CT scan sequences. Custom CNN [16] offers modest results because it is not optimally designed and cannot capture intricate features. The suggested model ST-IntLCNN addresses the limitations of previous models through lightweight convolutions and optimizations to increase efficiency and accuracy, while predicting the cancer in lung.

5. Conclusion

The research proposes ADS to determine cancer in the lungs from CT scan images. The new ST-IntLCNN approach combines CLAHE to improve the images, HOG for extracting features, and the STO Algorithm to optimize hyperparameters, providing better accuracy, while reducing the complexity of computation. Convolutional layers are made lightweight, and the attention mechanism is also used, contributing to both high accuracy and computation efficiency. The introduced approach performs surpasses DL approaches with 98% accuracy and excellent 97.98% precision, 97.98% recall, and 97.98% F1 score measures. The presented ST-IntLCNN method is tested using only one dataset of CT scans, hence limiting its ability to generalize with respect to different datasets from different institutions. The future direction of work will involve validation using multiple datasets from various modalities and real-world clinical applications.

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