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RESEARCH ARTICLE

LUNCERDEN: LUNG CANCER CLASSIFICATION USING DEEP LEARNING BASED DENSE NEURAL NETWORK

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Abstract – Lung cancer is one of the most prevalent illnesses in the world and a leading contributor to rising death rates. Early detection of cancer enables treatment. Early-stage lung cancer classification is difficult because of varied clinical presentations, leading to increased processing time and resource demands for clinicians. Deep learning techniques have been used extensively in a number of medical professions in recent years to improve early diagnosis and treatment stages. In cases of various malignant tumors, such as lung cancer, when time is of the essence for promptly recognizing the patient's condition. A novel deep learning-based LUNCERDEN model has been presented for lung cancer classification in order to address these issues. Lung cancer can be detected from CT scans using this process. Initially the input image CT is gathered from the available datasets. Adaptive median filters are used as a pre-processing technique to lower noise and enhance input image quality. For feature extraction, the pre-processed image is fed into Inception ResNet. Finally, a dense neural network is employed to categorize the many forms of lung cancer, including lung nodules, small-cell lung cancer, and normal lung cancer. The proposed classification accuracy is 98.17%, which is extremely accurate. The proposed LUNCRDEN model improves overall accuracy by 4.17%, 7.32%, and 0.97% in comparison to support vector machines, GoogleNet, and convolutional neural networks, respectively.

Keywords *– CT scan image, adaptive median filter, Inception ResNet and dense neural network.*

1. INTRODUCTION

Human tumors can occur everywhere in the body due to aberrant cell mutations (DNA), includes the skin, breast, lungs, and brain. Due to external causes that typically affect the respiratory system, among the different types of cancer [1]. Lung cancer has a major impact on individuals all over the world because of its high fatality rates. In order to classify problematic objects early on, CAD methods were developed by researchers and can be used with computed tomography (CT) images [2]. CT scan images are used to diagnose lung cancer for detecting pulmonary nodules. Small pulmonary nodules are easily identified, and three-dimensional computed tomography (CT) images can eventually identify early abnormalities in nodule size and quantity [3]. According to the World Health Organization (WHO), lung cancer is a common illness that spreads globally and is brought on by tissues growing out of control. The mortality rate from lung cancer has significantly increased [4].

CNN is a popular deep learning technique for classifying and recognizing images. Usually, it considers an input image, separates the images, and applies weights and biases to the images [5]. CAD-based lung cancer detection systems typically consist of four steps such as processing images, classification, feature selection, and ROI extraction. The most important of these processes are feature selection and classification, which enhance the CAD system's sensitivity and accuracy is used to obtain trustworthy characteristics [6]. A radiologist's evaluation of a tumor is an important and time-consuming process. Size of the tumor can be determined more precisely with a CT scan. The latest breakthrough in lung cancer early detection is computer-aided diagnosis (CAD) [7]. A range of data augmentation strategies have been used to improve the accuracy and decrease overfitting [8]. Computer-assisted lung tumor identification and diagnosis can be accomplished with accuracy and efficiency because to DL technology [9]. A wide range of imaging modalities, such as molecular imaging, sputum smear microscopy images (SSMI), PET, CT, MRI, and chest X-rays, have been used to identify and assess lung illnesses. The two most used anatomic imaging modalities for recognizing and managing different lung conditions are CT scans and X-rays [10]. The key contributions are as follows:

- The primary objective of this study is to create a novel deep learning-based LUNCRDEN is to classify lung cancer such as normal, small lung cancer cells, and lung nodules.

- Adaptive median filter is a pre-processing technique used by the proposed LUNCERDEN model
- Then proposed image is fed into Inception ResNet for feature extraction.
- Finally, the three types of LC—normal, small lung carcinoma, and lung nodules—are categorized using a dense neural network.
- Using particular criteria recall, f1 score, specificity, accuracy, and precision, the proposed LUNCERDENs effectiveness was assessed.

The structure of the paper is organised as follows, section-2 briefly explains the literature survey, the proposed LUNCERDEN was explained in section-3, The performance results and their comparison analysis were provided in section-4 and section-5 encloses with conclusion and future work.

2. LITERATURE SURVEY

In recent days several frameworks were introduced by the researchers primarily to classify the lung cancer in patient using CT scan images. Some of those frameworks are studied briefly in this section.

In 2022 Shafi, I., et al., [11] proposed a support vector machine (SVM)-based cancer detection model with deep learning capabilities. The suggested computer-aided diagnosis (CAD) model for lung cancer lesions evaluates the physiological and pathological alterations within the soft tissues of the cross-section. The model is trained to diagnose lung cancer by comparing specific CT scan profile values taken from both cancer patients and healthy control subjects at the time of their diagnosis. With a 94% accuracy rate, the proposed SVM-based model with deep learning support can identify pulmonary nodules, a sign of early-stage lung cancer.

In 2020 Riquelme, D. and Akhloufi, M.A., [12] proposed computer-aided diagnostic (CAD) systems based on deep learning approaches to improve performance. Computed tomography is used to improve the lung cancer screening efficacy of CAD systems. The proposed CAD systems diagnose lung cancer by utilizing deep learning techniques and architectures. These systems are divided into two types: false positive reduction systems, which classify a group of suspected nodules as benign or malignant tumors, and nodule detection systems, which identify probable nodules in the initial CT scan.

In 2024, Fei, X., et al., [13] suggested a lung medical image recognition system based on DL.

This model enhances the network feature extraction capabilities by combining a specially created feature fusion layer with a pretrained GoogleNet Inception V3 network. The LUNA16

pulmonary nodule dataset experimentation showed that the optimized network model obtained a sensitivity of 87.18% and an accuracy of 88.78%.

In 2020, Elnakib, A., [14] proposed a computer-aided detection (CADe) technique to use low dose computed tomography (LDCT) images to identify lung nodules early. This technique proposes to preprocesses the raw data to improve the contrast of the low dosage images.

Among the deep learning networks are Alex, VGG16, and VGG19 architectures are examined in order to extract compact deep learning characteristics. The proposed model achieves the highest detection accuracy of 96.25% by utilizing the VGG19 architecture and SVM classifier.

In 2023, Mohamed, T.I., [15] proposed a CNN algorithm and hybrid metaheuristic for classifying lung cancer in CT scans. Lung cancer classification accuracy is improved by using the CNN model. The solution vector of CNN approach was optimized by the EOSA technique. Various 2D samples are grouped based on their anomalies and is used to train the model. According to the results, EOSA-CNN obtained a sensitivity values for benign, malignant, and normal patients are 0.9038, 0.13333, and 0.9071, respectively.

In 2022, Pandian, R., et al., [16] proposed CNN and Google Net for LC detection and classification. This paper suggests an approach to identify abnormal lung tissue growth using ANN. A VGG-16 architecture is used as the basis for both a classifier network and a region proposal network. There is a 98% accuracy in the algorithm, detection and classification.

In 2020, Hatuwal, B.K. and Thapa, H.C., [17] proposed a computer-aided diagnostic (CAD) to detect lung nodules. A neural network model uses a technique for recurrent neural networks (RNNs) and the Grey Wolf optimization algorithm. Comparing the proposed method to other state-of-the-art techniques, it yielded extraordinarily high levels of accuracy, sensitivity, specificity, and precision.

In 2020, Cao, H., et al., [18] proposed a two-phase CNN designed to identify lung cancer. Based on U-Net segmentation network, early detection of lung cancer is established using CNN architecture in the first stage. Three-dimensional CNN classification networks are constructed in the following stage using the dual pooling structure that was suggested for the CNN architecture in the first stage. In addition to experimental data, the proposed TSCNN architecture may accomplish competitive detection operation.

In 2020, Hatuwal, B.K. and Thapa, H.C., [19] proposed a Convolutional Neural Network for histopathology image-based lung cancer detection. Images were categorized using convolutional neural network (CNN) into three groups such as benign, squamous cell cancer, and adenocarcinoma. Lung cancer diagnosis is usually difficult and prone to mistakes. Convolutional neural networks are useful for rapidly identifying and categorizing different forms of lung cancer. During training and validation, the model attained an accuracy of 96.11% and 97.20%, respectively.

In 2019, Lakshmana Prabu, S.K., [20] Proposed an Optimal Deep Neural Network (ODNN) in addition to Linear Discriminate Analysis (LDA) for lung CT scan analysis. LDR reduces the number of retrieved pictures needed to categorize lung cancer in ODNN CT scans. Following the ODNN's application to CT scans maximize the results in the classification of lung cancer, the Modified Gravitational

Search Algorithm (MGSA) is used. The proposed classifier has 94.56% accuracy, 96.2% sensitivity, and 94.2% specificity, according to the comparison results.

Based on the literature survey, numerous approaches show a potential focus on input images for accurately classifying lung cancer. This research shows a strong focus on classifying lung cancer in patients from the images of CT scans. Primary goal of the proposed LUNCERDEN is to employ deep learning (DL) to increase the accuracy of classifying lung cancer in patients.

3. PORPOSED METHODOLOGY

In this section, lung disease classification is processed and classify the disease. The image is first extracted from the dataset and fed into an adaptive median filter is used to pre-process the gathered images, eliminating noise artifacts and adjusting image size to ensure consistency for analysis. The pre-processed image is fed into Inception ResNet to extract features such as edges, textures, and color. Following that, dense neural network is used to categorize various forms of lung cancer. In Figure 1, the proposed LUNCERDEN is shown below:

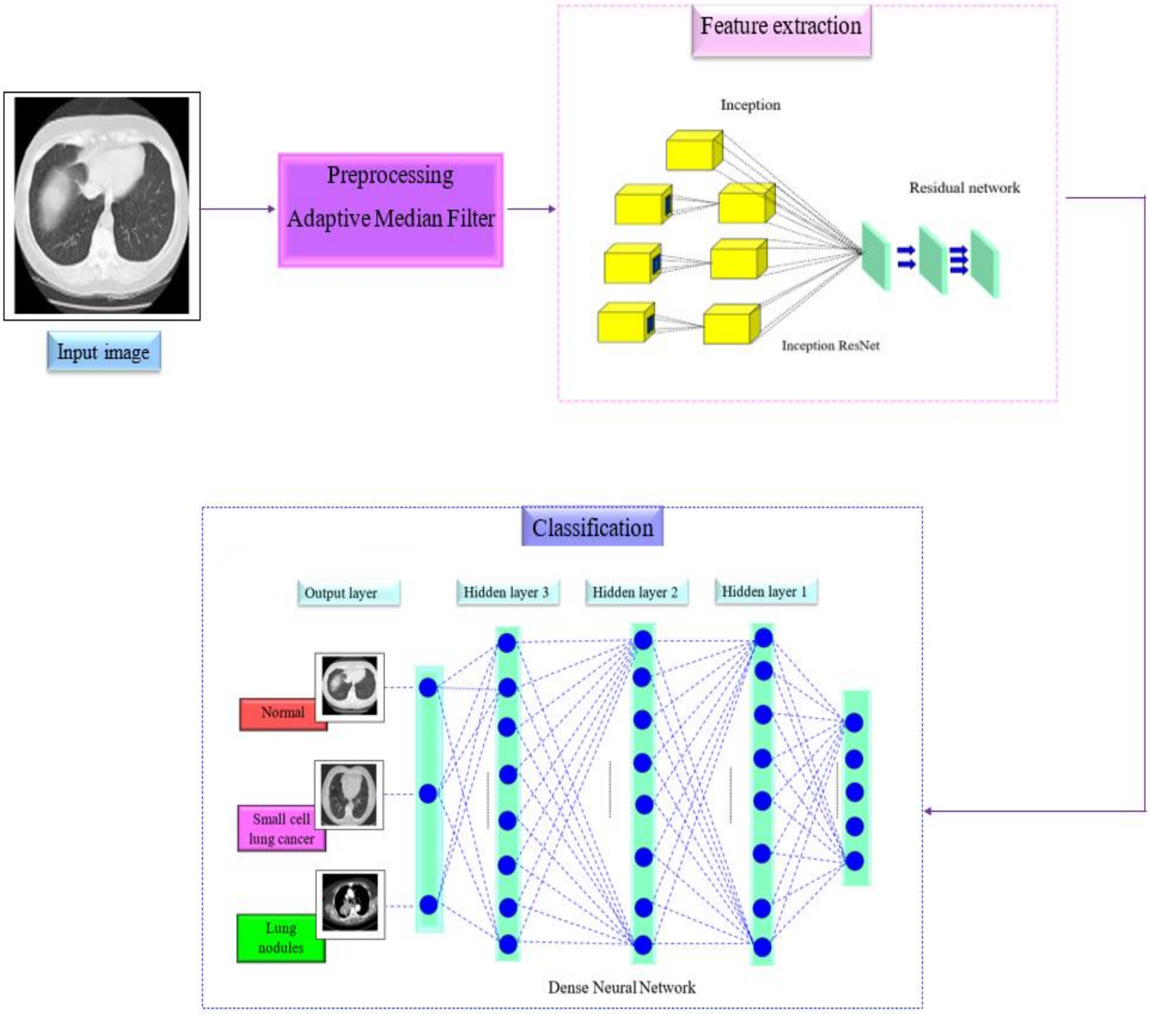


Figure 1. Block diagram for proposed LUNCERDEN methodology

Data description

The primary dataset includes patient lung computed tomography from the 2017 Kaggle Data Science Bowl. The collection of information contains 2101 patient-labeled data points, which are further divided into three sets: a training set of 1261, a test collection of 420, and a validation collection of 420. The data includes the results of each patient's CT scan as well as their label. The CT scan data for each patient is composed of a variable number of pictures (often 100–400) with 512 × 512 pixels apiece, each of which represents an axial slice.

Adaptive Median Filter

Adaptive Median Filter (AMF) has used as preprocessor to lower the noise in the input CT image. AMF is an effective method for image preparation that lowers noise, particularly impulse noise, while preserving edges and fine details. To eliminate noise and highlight subtle changes in medical imaging, preprocessing is required. It is employed to lessen undesired distortions and enhance the qualities of input images. Images from pap smears are less noisy when a median adaptive filter is used. By adjusting the kernel's width across the broken image, an adaptive median filter can modify the expected result. Before determining whether the cost of a modern pixel is an impulse, the adaptive filter calculates the median cost of the kernel. This filter handles both undistorted pixels and impulse damaged image pixels. The median cost is either used in place of or in addition to the cost of a corrupted pixel. The adaptive behaviour of a filter is the image within the transparent filter. Even in the presence of considerable additional spatially dense impulse noise, the adaptive clear filter can also smooth out a small number of non-impulse noises. AMFs ensure that screen details are preserved even when noise levels are reduced. The mathematical expression of adaptive median filter is as follows:

$$A_1 = Z_{med} - Z_{min} \tag{1}$$

$$A_2 = Z_{med} - Z_{max} \tag{2}$$

Where Z_{min} is the minimum current pixel value window . Z_{max} is the maximum pixel value in the current window. Z_{med} is the current window's median pixel value.

Inception ResNet

The Inception has seven input settings. Inception modules come particularly handy when creating extremely broad and deep models. The convolutions are executed concurrently by each Inception module using varying kernel sizes. The outcomes of these parallel operations are then concatenated. The connected 1x3 max pooling operation is known as MaxPool1D and a 1-dimension convolution layer (Conv1D). After eliminating the additional channel, this 1 × 1 Conv1D method lowers the dimensionality of the input features and is significantly less expensive to utilize. Since it only permits one input channel, this 1 × 1 Conv1D is known as a bottleneck. Three categories of layers forms the majority of a ResNet framework. The initial layers are the first layers; residual block stacks are the second layer; and the final layers are the third layer. Additionally, there are three different kinds of residual blocks such as down-sampling residual blocks, standard residual blocks, and starting residual blocks. The first residual block uses bottleneck components and is located at the start of the first stack. In the first convolutional layer, the down sampling block layers are resampled by the initial residual layers using only a stride of [1,1]. Each stack contains many instances of the typical residual block, which retains the activation sizes. With the exception of the first stack, the down-sampling residual block appears once at the start.

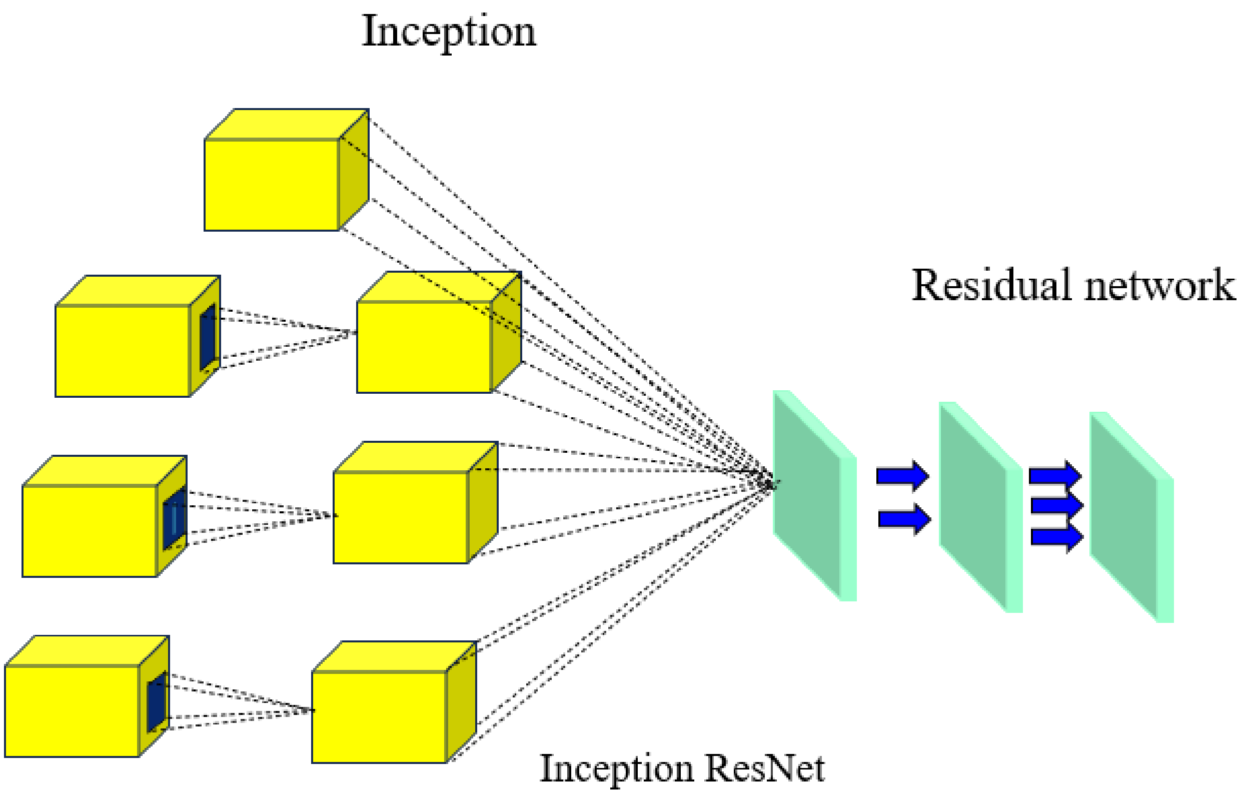


Figure 2. Diagram of Inception ResNet

The Residual Network converts multiple layers into a residual block. The residual block consists of layers called Reflection Pad, Convolutional (kernel 3x3, output channel 256), Instance Norm, ReLU, and Reflection Pad. The Residual Block Network solves the degradation problem of deep learning networks, promotes faster network convergence, and increases the training speed of these networks**.** Input features X are transformed using several convolution operations are given in the equation ().

$$X_{out} = Concat\ (Conv1D_{1X1}(X), Conv1D_{3X3}(X), Conv1D_{5X5}(X), MaxPool_{3X3}(X)) \tag{3}$$

Dense Neural Network (DNN)

The classification of CT images for the identification of normal cases is accomplished using the proposed deep learning-based Dense neural network. DenseNet is made by connecting several dense blocks. A collection of layers that are connected to all of their previous levels is called a dense block. A Dense Neural Network model that has already been trained is used. It consists of four dense blocks (DB) and three transition blocks (TB), respectively. This enhances information transfer and allows for effective feature reuse. The feature map is used into DenseNet to address the gradient loss issue. In the architecture diagram of the dense neural network. As a result, it is effective to acquire the prospective characteristics from CT images. Unlike methods that summarize the connections in the feature map,the dense block module feature extraction through concatenation as:

$$X_{nl} = E([x_0, x_1, \ldots . x_{n-1}]) \quad (4)$$

Here, X_n signifies the output of layer l and E (•) describes a nonlinear transformation. At j^{th} layer, there are K × (i − 1) +k_0 convolution maps. K explains complicated feature maps for every layer. DenseNet advances a N layer architecture with (N(N+1))/2 connections.

The batch normalization (BN) layer is a well-known regularization method that is used to speed up training. By taking the mean out of each mini-batch and scaling to unit variance, BN is used to standardize the input feature. Dense layer for output classification with nodes that correspond to the three target classes that have been linked to SoftMax activation function.

$$P_j(\, x \,\in\, C_j) = \sigma(y_j^3) \quad (5)$$

where P_j of the input (x) is in the jth class and is sent to the output of the third hidden dense layer above (y^3).

4. RESULT AND DISCUSSIONS

In this section, the proposed LUNCERDEN model was evaluated by using the gathered datasets and several factors like precision, f1 score, specificity, recall and recall. The LUNCERDEN's performance overall accuracy rate-which is specifically defined and assessed-are included in the benchmark. Additionally, the proposed network's assessment uses the traditional DL methodology.

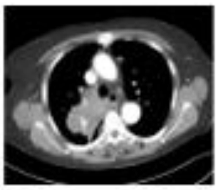
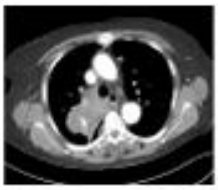
Patients	Input image	Preprocessing	Feature extraction	Classification
1.				Normal
2.				Small cell lung cancer
3.				Lung nodules

Figure 3. Classification results of proposed LUNCERDEN

Figure.3 shows the outcomes of the proposed LUNCERDEN using a CT image sample for lung cancer classification. Pre-processing methods such as adaptive mean filter are used to remove undesired distortions from the medical images from the Kaggle dataset. After preprocessing, the images are run through an inception ResNet. Lung cancer is categorized using a dense neural network. To extract appropriate categorization for lung cancer, the output images are used as input.

4.1 Performance analysis

The evaluation metrics of f1 score, accuracy, specificity, and recall is utilized to evaluate the efficacy of the proposed LUNCERDEN model.

$$\text{Specificity} = \frac{T_{neg}}{T_{neg} + F_{pos}} \tag{7}$$

$$\text{Precision} = \frac{T_{pos}}{T_{pos}+F_{pos}} \tag{8}$$

$$\text{Recall} = \frac{T_{pos}}{T_{pos}+ F_{neg}} \tag{9}$$

$$\text{Accuracy} = \frac{T_{pos}+T_{neg}}{Total\ no.\ of\ samples} \tag{10}$$

$$\text{F1 score} = 2(\frac{Precision+Recall}{Precision+Recall}) \tag{11}$$

Where T_{pos} and T_{neg} represents the actual positives as well as negatives of one of the images F_{Pos} denotes the false positives and F_{neg} denotes the false negatives.

Table 1. Proposed LUNCERDEN Performance assessment

Classes	Specificity	Precision	Recall	F1 score	Accuracy
Normal	94.12	95.24	96.25	95.19	98.41
Small cell lung cancer	95.27	96.12	96.48	96.48	98.23
Lung nodules	95.65	95.22	96.29	96.78	97.89

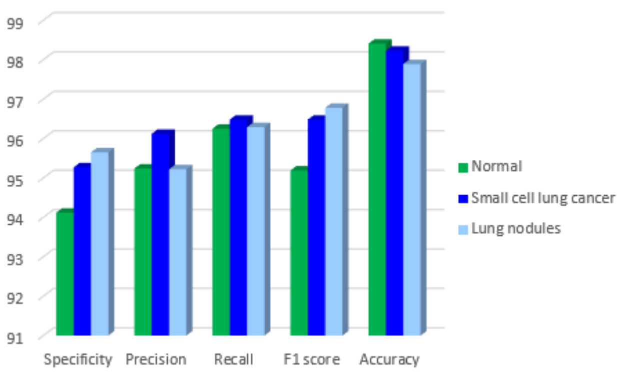


Figure 4. A graphical analysis of performances in classifying lung cancer

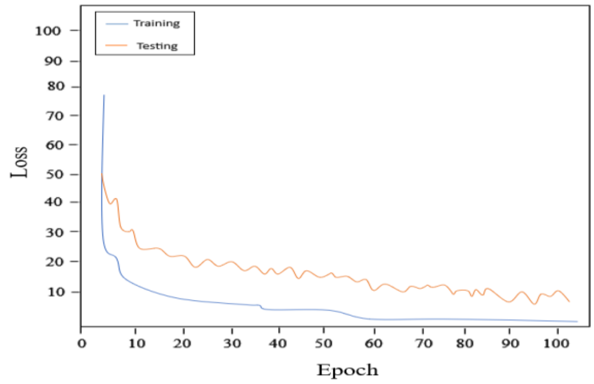


Figure 6. Training and testing loss of proposed LUNCERDEN.

The proposed LUNCERDEN's performance outcome for classifying lung cancer. Table 1 displays lung nodules, normal, and small cell lung cancer. Overall accuracy of the proposed LUNCERDEN is 98.17%. Overall recall, accuracy, specificity, and f1 score for the proposed LUNCERDEN were 94.68%, 96.67%, 96.00%, and 96.04%, respectively. Figure 3 shows a graphic representation of the proposed LUNCERDEN's performance evaluation.

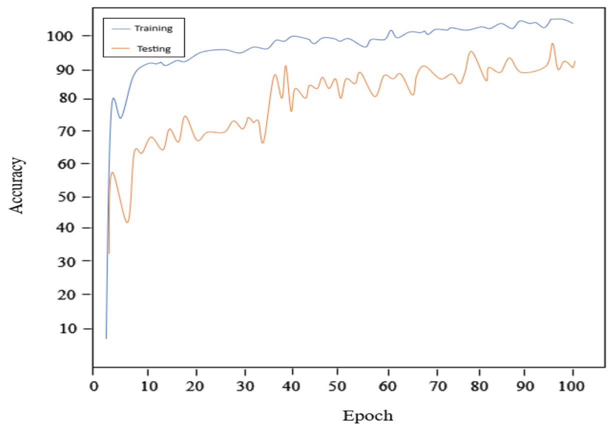


Figure 5. Training and testing accuracy of proposed LUNCERDEN.

Figure 5 presents the training and testing accuracy curve by displaying epochs on the x- and y-axes. The proposed LUNCERDEN attains an accuracy rating of 98.17% according to its training and testing accuracy curves. Loss curve plotted against epochs is shown in figure 6. This shows that the loss reduces with rising epochs. The proposed procedure yields an accurate result with a reasonably low loss of 1.83%. Tested and trained, LUNCERDEN exhibits good performance.

4.2. Comparative analysis

The efficiency of deep learning networks was assessed to confirm that the proposed LUNCERDEN produces high-frequency outputs. The proposed LUNCERDEN with Naive Bayes, logistic regression, and decision trees had compared and evaluated. The performance of proposed dense neural network was evaluated using metrics like specificity, accuracy, recall, precision, and f1 score metrics. With 98.17% accuracy rate, proposed LUNCERDEN performed better than the DL networks.

Table 2. Comparison between traditional Deep learning networks and proposed LUNCERDEN

Networks	Specificity	Precision	Recall	F1 score	Accuracy
Decision tree	83.7	86.2	85.3	85.7	89.5
Naive Bayes	89.2	87.5	84.6	87.1	91.2
Logistic regression	93.12	94.6	90.8	83.21	96.2
Dense Neural Network	95.19	96.67	95.8	93.05	98.17

Table 2. is used to compare various networks according to performance metrics by calculating the relevant classification accuracy percentage. Nevertheless, the proposed networks outperformed the conventional networks LUNCERDEN. The proposed dense neural network improves the total accuracy range by 8.67%, 6.96%, and 1.97% when compared to decision trees, naive bayes, and logistic regression. Figure 6 compares the performance of the proposed and existing techniques.

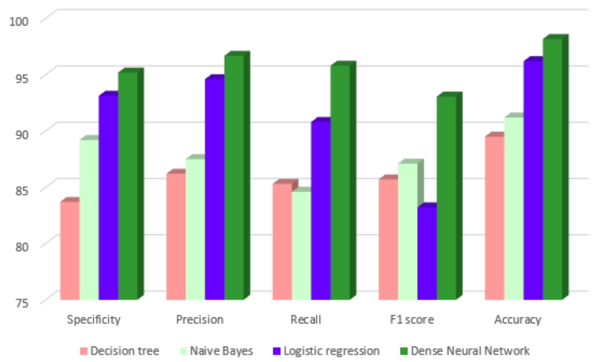


Figure 6. A graphical analysis of performances by proposed LUNCERDEN

Table 3. Comparing the accuracy of current models with the proposed LUNCERDEN

Authors	Methods	Accuracy
Shafi, I., et al., (2022) [11]	Support Vector Machine (SVM)	94%
Fei, X., et al., (2024) [13]	GoogleNet	87.18%
Hatuwal, B.K. and Thapa, H.C., (2020) [19]	Convolutional Neural Network	97.20%
Proposed	LUNCERDEN	98.17%

Table 3 examines accuracy by contrasting the proposed technique with the existing technique. Support vector machines [11], GoogleNet [13], and convolutional neural networks [19] are all outperformed by the LUNCERDEN in terms of overall accuracy range by 4.17%, 10.99%, and 0.97%, respectively. Therefore, the proposed LUNCERDEN are highly reliable for classifying lung cancer.

5. CONCLUSION

In this research, dense neural network has been proposed for classifying lung cancer through CT images. Initially input image are gathered from publicly available datasets. The input images are pre-processed using adaptive median filter for lower noise and enhance image quality. Images are applied to the inception ResNet for extracting the feature in the preprocessed image. By using dense neural network, the extracted image is classified into the normal, small cell lung cancer, and the lung nodules. The performance of the proposed LUNCERDEN is evaluated by using specific parameters like accuracy, F1 score measures, precision, recall, and specificity. Experimental findings reveals that the propose approach achieves a better accuracy range of 98.17% for classifying lung cancer in early stages. In future, accuracy of the proposed LUNCERDEN will be improved to classify the lung cancer.

CONFLICTS OF INTEREST

The authors declare no conflict of interest.

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