Frontiers in Engineering and Informatics
ISSN: 3049-3412 (Online)
Volume No: 01 – Issue No: 02 – 10 June 2025

A Visual-Modified Circular Dilated Convolutional Neural Network with Draco Lizard Optimizer Framework for Automated Lung Disease Detection Using CT Images

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Abstract

Lung Disease is one of the prominent causes of death, hence the need for its early diagnosis and accurate detection via CT images. Conventional approaches to diagnosis may have limitations in identifying intricate patterns in lung disorders; hence, the possibility of diagnosis may suffer, leading to delayed medical attention. To mitigate these limitations, the research proposes the Visual-Modified Circular Dilated Convolutional Neural Network with Draco Lizard Optimizer (V-CDCNNet-DLO) for efficient classification of lung disorders. CT images from the LIDC-IDRI dataset are first preprocessed using the Adaptive Self-Guided Loop Filter (AS-GLF) to enhance image quality. The research utilizes the V-CDCNNet for feature extraction and classification, with the help of the weights provided by the Draco Lizard Optimizer (DLO) to improve its performance. The research has demonstrated excellent performance with a high level of accuracy of 99.27%, precision of 99.20%, recall value of 99.15%, and error level of 0.73%. This model establishes a reliable framework for early lung disease detection.

Keywords: *Lung Disease Classification, CT Images, Visual-Modified Circular Dilated Convolutional Neural Network, Draco Lizard Optimizer, Adaptive Self-Guided Loop Filter.*

1. INTRODUCTION

The technology in the medical field has come a long way, especially in the field of biomedical imaging and artificial Intelligence, and has allowed early detection of disease Singh, A.P.et al , (2024). Due to the existence of small sacs, nodules, and complex tissue structures, lung diseases, especially the interstitial lung disease (ILD), are dangerous health complications because they need to be analyzed thoroughly in order to make accurate diagnoses Wankhade, S. et al , (2023). Computed Tomography (CT) images are widely used to visualize abnormalities in the lungs; meanwhile, the use of deep learning approaches, and especially the Convolutional Neural Networks (CNNs), has demonstrated potential in automated disease detection Karaddi, S.H. et al , (2023). Research has investigated multimodal characteristics, hybrid approaches, and transfer learning to detect ILD, which underscores the possibility of using a combination of radiological, pathological, and clinical data. The purpose of these approaches is

DoI: https://doi.org/10.63949/crinfo.v1i2.004

to improve the accuracy of the diagnosis and minimize the errors of manual interpretation in the detection of lung diseases Rajasekar, V. et al , (2023).

Effective lung disease diagnosis, with special focus on ILD, is still one of the most problematic issues because of the multifaceted composition of the lung tissue and the slight differences in the CT images Azam, S. et al , (2023). Manual diagnosis is costly in time and can be prone to errors, whereas traditional machine learning methods fail to point out complex trends in heterogeneous medical images. Despite the fact that CNNs and hybrid models have enhanced classification performance, current approaches are normally limited to the effectiveness of multimodal data, or they need a great deal of computing power Hussain Ali, Y. et al , (2023). In addition, irregularities in the quality of images, their size, and noise level additionally make the correct recognition more difficult. Thus, it is necessary to develop effective, computerized methods that will accurately classify ILD based on the CT scans so as to use them in early diagnosis and effective clinical decision-making Podder, P et al , (2023).

The early and precise diagnosis of lung diseases, specifically ILD, is essential to enhancing patient outcomes and treatment plans. The growing access to high-resolution CT scans, along with the changes in the field of deep learning, presents a prospect to automate and improve the diagnostic process. The current methods, though promising, have limitations in processing complex lung structures, multimodal features, and subtle tissue abnormalities. Driven by these problems, this research developed a model using deep learning to detect Lung Disease based on CT images with a high level of accuracy.

Novelty and Contributions

- The paper presents a Visual-Modified Circular Dilated Convolutional Neural Network (V-CDCNNet) that is specifically created to detect lung diseases with the help of CT images, which is an effective combination of visual attention features and circular dilated convolutions to obtain more features.
- It also uses a Visual-Modified Attention Network to enhance the dependency modeling of both intra and inter-modal features, thus leading to more disease-relevant information being extracted from the CT scans.
- AS-GLF is used in preprocessing to improve the image quality and reduce noise, as well as maintain the appearance of edges, which enhances the finding of lung nodules.
- Draco Lizard Optimizer (DLO) is used to optimize the V-CDCNNet weights and emulates the gliding, camouflage, and adaptive manoeuvrability of Draco lizards to obtain accurate and effective convergence.
- The great number of experiments conducted on the LIDC-IDRI dataset allows us to conclude that the suggested framework is more robust, reliable, and capable of generalization than the current state-of-the-art methods, which proves its superiority.

DoI: https://doi.org/10.63949/crinfo.v1i2.004

In Section 2, the pertinent literature is thoroughly evaluated. The methods employed in this study are explained in detail in Section 3. The result and its ramifications are covered in Section 4. Section 5 contains personal observations and suggestions for further study.

2. LITERATURE SURVEY

In 2023, AR et al. AR, B. et al , (2023) indicated that lung cancer is second in prevalence and the leading cause of cancer-related deaths. Timely treatment is facilitated by detecting at an early stage using low doses of CT. To categorize lung cancer using CT images based on the spatial features that remain unchanged with the resolution, a hybrid deep learning model, Lung Cancer Detection Capsule Neural Network (LCD-CapsNet), was created that incorporated Convolutional Neural Networks (CNN) and Capsule Neural Networks (CapsNet). The approach enhanced the performance of classification compared to traditional Capsule Neural Networks, and it has high accuracy, recall, and precision. There were such limitations as large computational resources and complex model training.

In 2023, Bushara et al. Bushara, A.R. et al , (2023) indicated that lung cancer has one of the lowest five-year survival rates; therefore, early detection is essential. Initial identification was done with the use of CT scans, and nodule detection was the problem of the deep learning Convolutional Neural Networks (CNNs). Visual Geometry Group - Capsule Neural Network (VGG-CapsNet), a hybrid model comprising VGG and Capsule Neural Networks (CapsNet), was created, which was able to extract fine-grained spatial correlations. The algorithm enhanced better classification compared to traditional capsule networks. There were high computational requirements, complicated training procedures, etc.

In 2024, Gautam et al. noted that lung cancer is a killing disease, with early diagnosis bringing a high survival rate. Image analysis of CT scans was performed with a combination of deep learning models, which consisted of ResNet-152, DenseNet-169, and EfficientNet-B7 using deep transfer learning. A new weight optimization strategy built on ROC-AUC and F1-score improved model performance by reducing false negatives and improving sensitivity. The technique was better than the traditional ensemble methods. Limitations were that it is more complex to compute and requires high-quality imaging to be able to classify it properly.

In 2025, Gupta et al. reported that lung cancer is one of the deadliest diseases, and it is important to detect it early in the disease progression, which is not always easy. An automatic lung nodule detection and classification framework was designed, a U-Net-based Computed Tomography (UDCT), to be used with CT images. The method combined a modified U-Net (U-shaped Network) of multi-scale feature extraction with Differentiable Architecture Search (DARTS) of optimized network design and Multilevel

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Otsu Thresholding of image preprocessing and segmentation. The model enhanced the efficiency of detecting and the reliability of classification. There were drawbacks, such as a high complexity of computation and the access to high-quality CT images.

2.1 Problem Statement

Lung diseases are a significant concern for the global health community and require early and correct identification for efficient management and a lower mortality rate. Conventional techniques often tend to fail in decoding the intricate patterns from the CT images, and hence lead to incorrect identification and delayed treatment. Machine learning and conventional CNN techniques might not utilize the spatial and contextual features effectively, and hence tend to lead to inefficient identification. Moreover, the existing techniques tend to lack proper convergence and efficient performance because of inefficient weight optimization techniques. There appears to be a demand for an efficient deep learning model for the identification of lung disease.

3. PROPOSED METHODOLOGY

This section proposes a form of Visual-Modified Circular Dilated Convolutional Neural Networks with Draco Lizard Optimizer (V-CDCNNet-DLO) in Lung Disease Detection with the use of CT images. First, the CT data are obtained in the Lung Image Database Consortium and Image Database Resource Initiative (LIDC-IDRI) dataset that contains various scans of the lungs with annotated disease areas. The images obtained are then preprocessed with an Adaptive Self-Guided Loop Filter (AS-GLF) to improve image quality, remove noise, and maintain significant structural information. Lastly, the processed images are input into the V-CDCNNet model with its weights trained on the Draco Lizard Optimizer (DLO) to deliver precise and reliable lung disease classification. The proposed architecture is described in Figure 1.

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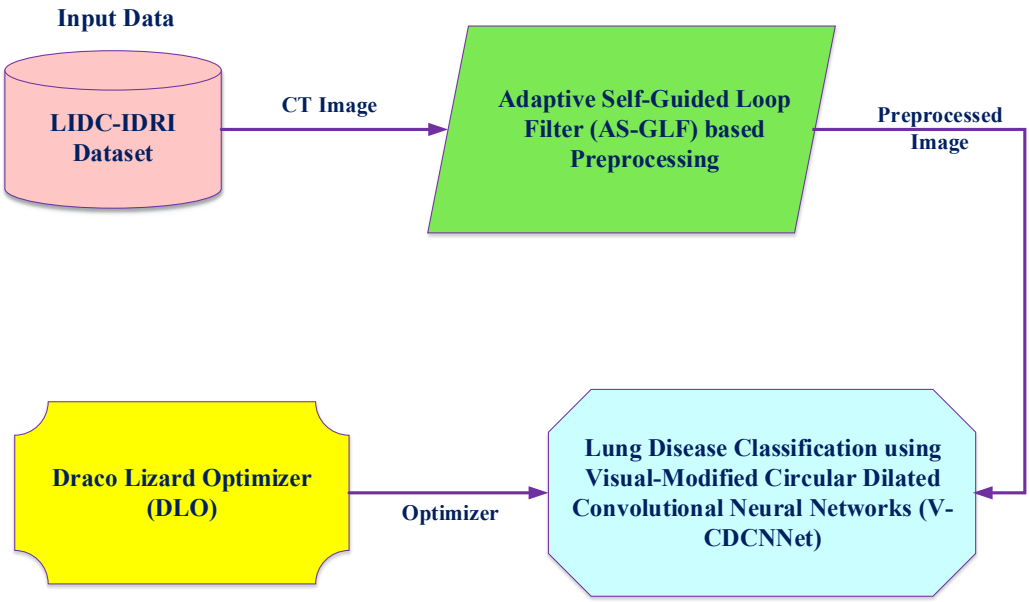

Figure 1. Proposed Architecture

3.1 Data Collection

The Lung Image Database Consortium and Image Database Resource Initiative (LIDC-IDRI) dataset is used in lung cancer analysis because it offers a wide range of images from CT scans that have been conducted at various clinical institutions. The images in the dataset have various patterns of lung cancer with different sizes, shapes, and textures. Following that, a continuous processing procedure, this involves eliminating noise, normalizing intensity, resizing images, and segmenting the lungs, takes place.

3.2 Adaptive Self-Guided Loop Filter (As-Glf) Based Preprocessing

The Adaptive Self-Guided Loop Filter (AS-GLF) Yin, W. et al , (2021)-based preprocessing is used to improve the quality of the input image by removing the noise and, at the same time, preserving the details. The input image is divided into blocks, and then the blocks are classified on the basis of the texture complexity. The blocks containing highly textured areas and edge areas are treated less aggressively compared to the smooth areas.

For each pixel at point (j,k) AS-GLF calculates the pixel intensity through a weighted sum of the pixel intensity and average neighboring pixel intensity in a cross-shaped window consisting of five pixels. This can be written using the expression shown in equation (1).

$$J_{out}(j,k) = b(j,k) \times J_{in}(j,k) + c(j,k) \times mean_{win}(j,k) \quad (1).$$

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where, $J_{in}(j,k)$ is the input pixel intensity, $J_{out}(j,k)$ is the filtered output intensity, and $mean_{win}(j,k)$ is the average intensity of the pixels in the local filtering window around (j,k). The filtering strength is controlled by coefficients $b(j,k)$ and $c(j,k)$, which fulfill the requirement $b(j,k)+c(j,k)=1$. The initial adaptive weights are computed by local statistical measures given by equation (2).

$$b_{init}(j,k)=\frac{\mathrm{var}_{win}(j,k)+\varepsilon\times\gamma(j,k)}{\mathrm{var}_{win}(j,k)+\varepsilon/\tau(j,k)}, c_{init}(j,k)=1-b_{init}(j,k) \quad (2).$$

where, $\mathrm{var}_{win}(j,k)$ is a measure of variance of pixel intensities within the filtering window, which reflects local texture complexity. The parameter ε is a block-dependent control factor that regulates overall filtering strength. The factor $\tau(j,k)$ accounts for the relative importance of the current pixel by relating local variance to block average variance; the larger $\tau(j,k)$ is, the stronger edge preservation can be at a location deemed important. Factor $\gamma(j,k)$ captures the measure of edge confidence based on the deviation of local and block-level mean intensities, ensuring fewer effects of smoothing on edge pixels. As for further stability and coherence, final weights $b_{init}(j,k)$ and $c_{init}(j,k)$ are obtained by averaging the initial weights of all pixels within the filtering window allowing shared statistical information across overlapping regions. After AS-GLF-based preprocessing, enhanced images show reduced noise, well-preserved edges, and enhanced contrast, which directly contributes to further robust feature extraction and subsequent classification accuracy.

3.3 Lung Disease Classification Using Visual-Modified Circular Dilated Convolutional Neural Networks (V-Cdcnnet)

The classification of the lung disease from the preprocessed CT scans is conducted through the use of the Visual-Modified Circular Dilated Convolutional Neural Networks (V-CDCNNet) Song, X. et al , (2025), Cheng, L. et al , (2023). The method incorporates the visual-modified attention mechanism along with the use of circular dilated convolutions. The visual-modified attention is responsible for the emphasis on the disease-related areas, while the circular dilations are capable of addressing the boundary distortions in the scans.

The visualization-modified attention mechanism has modeled intra-area and inter-area dependencies. Self-attention (SA), which has modeled intra-area dependencies, is expressed by equation (3).

$$SA(r_x,l_x,x_x)=soft\max\left(\frac{r_x l_x^U}{\sqrt{e}}\right)x_x \quad (3).$$

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where, r_x is referred to as the visual query matrix, which encodes the current lung features, l_x^U as the visual key matrix, which encodes reference features, x_x is referred to as the visual value matrix, which contains feature information to be aggregated, and e is referred to as the scaling factor, which is applied to stabilize the attention computation process.

Cross-modal attention (CA) refines the visual features and has the form of equation (4).

$$CA(r_x, l_d, x_d) = soft\max\left(\frac{r_x l_d^U}{\sqrt{e}}\right)x_d \tag{4}.$$

where, r_x stands for the visual query, and l_d and x_d are referred to as the contextual key and value matrices, respectively, with e as the scaling factor. The factor helps to increase interactions among features as well as to focus visualization features on finding patterns related to diseases. Multi-head attention helps to learn better representations through co-attention to a range of feature subspaces and can be calculated as described in equation (5).

$$MHA(r, l, x) = concat(\alpha_1 x_1, \alpha_2 x_2, \ldots, \alpha_i x_i)W_P \tag{5}.$$

where, i is the number of attention heads, α_i denotes the attention weight of the i^{th} head, x_i is the corresponding value vector, and W_P is the learnable output projection matrix.

It uses the Circular Dilated Convolutional Neural Networks to model the long-range spatial dependencies in lung CT images without losing boundary information. Symmetric dilated convolution can be defined as equation (6).

$$c_u = \sum_{l=0}^{L-1} w_l^{(q)} \bullet b_{u+\left(l-\frac{L-1}{2}\right)e_q} \tag{6}.$$

where, c_u is the input feature at spatial position t, c_u is the output feature, $w_l^{(q)}$ is the convolutional weight at the l^{th} kernel position in layer l, L is the kernel size and e_q is the dilation factor that expands the receptive field with network depth. To reduce boundary effects, circular dilated convolution is formulated as equation (7).

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$$c_u = \sum_{l=0}^{L-1} w_l^{(q)} \bullet b_{u+\left(l-\frac{L-1}{2}\right)e_q \bmod M} \tag{7}.$$

Here, M denotes the spatial length of the feature map, and the modulo operation enforces circular padding. This type of circular mixing achieves uniform information flow at all spatial positions to achieve more robustness and obtain high classification accuracy regarding lung disease. Finally, weight parameters in V-CDCNNet are optimized by using Draco Lizard Optimizer that enhances the speed of convergence, avoids entrapment in local minima, and attains increased robustness in classification performance.

3.4 Draco Lizard Optimizer (Dlo)

The weights of V-CDCNNet are then tuned using the Draco Lizard Optimizer (DLO) Wang, X et al , (2025). This metaheuristic method is inspired by the gliding capabilities, camouflage ability, and adaptive maneuvering techniques of the Draco lizard. In this technique, the individual Draco lizard corresponds to the potential solutions in the weight space with D dimensions of V-CDCNNet. In this case, it explores the weight space of V-CDCNNet using gliding techniques, Lévy flight techniques, or Gaussian mutation techniques. This, in turn, optimizes the weight values by reducing the loss in the classification task, thus optimizing the overall performance of V-CDCNNet in classifying lung disease.

The initialization of the weight values for the candidate solutions is written in equation (8).

$$Y_j^{(k)} = Lb_c^{(k)} + s \bullet \left(Ub_c^{(k)} - Lb_c^{(k)}\right) \tag{8}.$$

Here, $Y_j^{(k)}$ represents the k^{th} weight of the j^{th} candidate Draco lizard, while $Lb_c^{(k)}$ and $Ub_c^{(k)}$ represent the lower and upper bound values of the search space related to the weight, and s is a uniformly distributed random number between [0,1]. The fitness of each candidate's weight vector is evaluated by using equation (9).

$$fitness = \min(V - CDCNNet(w)) \tag{9}.$$

In this case, w is the weight vector for V-CDCNNet, and the aim is to minimize the classification loss for the network, with better-performing weights selected for the next iterations. The candidate locations are updated using the DLO's exploitation strategy, which is given by equation (10).

$$y_j(u+1) = \begin{cases} h_{best} + levy(E) \bullet (h_{best} - y_p(u)), & if\ rand < q \\ h_{best} + h \bullet \left(1 - \frac{u}{U_{max}}\right) \bullet (y_{best,j} - y_p(u)), & otherwise \end{cases} \tag{10}.$$

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Here, h_{best} refers to the best solution obtained out of all candidate solutions, $y_p(u)$ refers to the randomly chosen Draco lizard solution at the current iteration u, q is the probability variable controlling the transition between the $levy(E)$ and Gaussian mutation search strategies, h is a Gaussian random variable, u is the current iteration number, $U_{\max}$ is the maximum number of iterations, and E is the dimensionality of the solution space. While the Lévy flight term favors the exploration process to avoid local minima, the Gaussian mutation term locally optimizes the solution. This optimization helps ensure that the V-CDCNNet converges to the most appropriate set of weights, which enhances the accuracy of classifications in discovering pulmonary disease utilizing the images obtained from computed tomography.

4. Results

In this section, the experimental analysis of the proposed V-CDCNNet-DLO lung disease classification model based on CT images is given. The model is written in Python 3.9 using TensorFlow, Keras, and is backed by NumPy, Pandas, and Scikit-learn to process data and evaluate its performance. Tests are run on an Intel Core i7 (2.8 GHz), 16 GB RAM, 4 GB graphics card, and a Windows 64-bit-based system. A summary of the most important parameters of the simulations is provided in Table 1.

Table 1. Simulation Parameters

Parameters	Description
Operating System	Windows 64-bit
Dataset	LIDC-IDRI
Data Type	CT Images
Proposed Model	V-CDCNNet
Optimizer	Draco Lizard Optimizer (DLO)
Number of Epochs	100

4.1 Dataset Description

The LIDC-IDRI https://www.kaggle.com/datasets/zhangweiled/lidcidri dataset consists of CT scans with lesion annotations marked by thoracic radiologists, along with images in a DICOM format. The dataset includes images classified as Normal and Abnormal categories. For training purposes, the Normal group includes 1,362 images, and the abnormal group includes 2,597 images, summing to 3,959 images for training purposes. For testing, there are 455 Normal and 866 abnormal images, adding up to 1,321 test

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Frontiers in Engineering and Informatics
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images altogether. An 80:20 split will then be used for training a new approach, with 80% for training purposes and 20% for generalization testing purposes.

4.2 Performance Analysis

To determine the performance of the proposed V-CDCNNet-DLO model in classifying lung disease, the model is implemented on the LIDC-IDRI CT image dataset and compared to the current models, such as LCD-CapsNet AR, B. et al , (2023), VGG-CapsNet Bushara, A.R. et al , (2023), DenseNet-169 Gautam, N. et al , (2024), and U-Net Gupta, A. et al , (2025). Some of the metrics that are used to measure the performance include accuracy, precision, recall, F1-score, and error rate. These metrics allow us to evaluate the whole model appropriately in terms of identifying and classifying various patterns of lung disease and show the model to be superior to the conventional ones regarding reliability and classification efficiency.

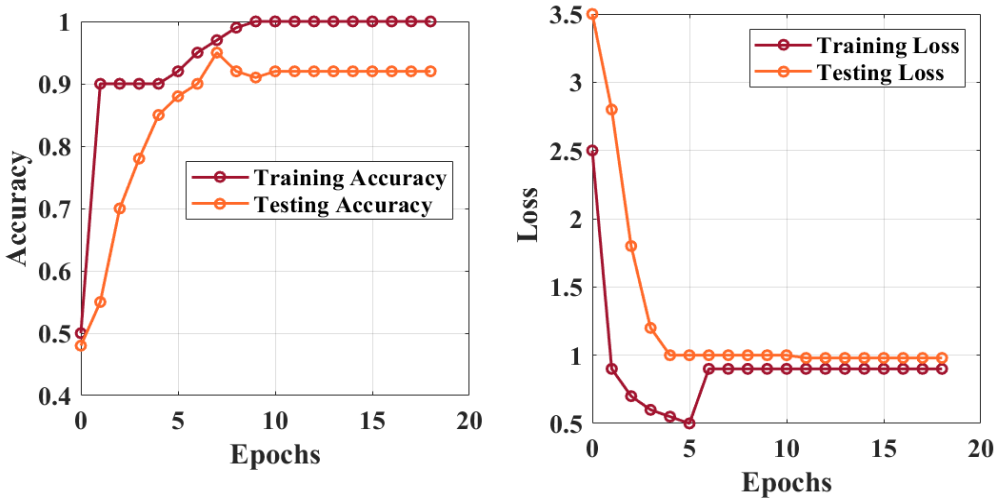

Figure 2. Training and Testing Performance of V-CDCNNet-DLO

Figure 2 (the first graph) demonstrates how the proposed V-CDCNNet-DLO trains and tests its accuracy during 20 epochs. The training accuracy is gradually growing to more than 99% and the testing accuracy is gradually stabilizing to around 99%, which is a sign of successful learning and small overfitting. The second graph presents the loss curves associated, where both training and testing loss are initially reduced and kept constant at low values, indicating that the model converges quickly, and there is no change in the model.

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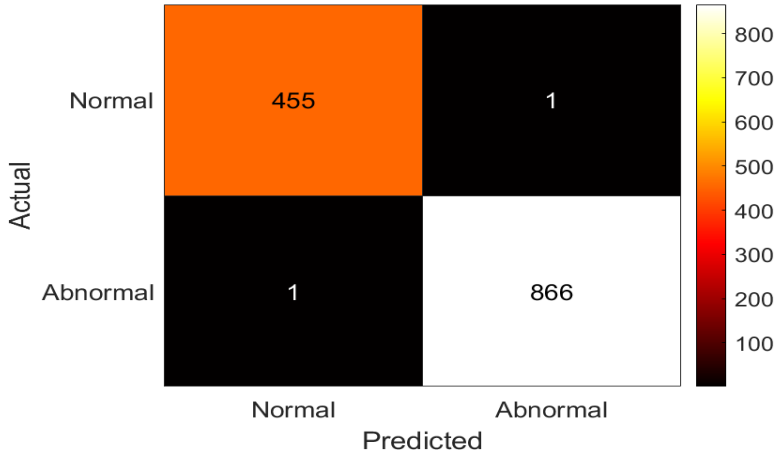

Figure 3. Confusion Matrix for Lung Disease Classification Using V-CDCNNet-DLO

Figure 3 shows the confusion matrix used to classify lung CT images as normal and abnormal. In 456 normal cases, 455 are categorized correctly, and one is categorized as abnormal. Likewise, 867 abnormal cases are rightly identified, with 866 being wrongly identified as normal. It shows that the proposed model is very precise and reliable in the distinction of normal and diseased lung tissues.

Table 2. Performance Comparison of Existing Models and Proposed V-CDCNNet-DLO for Lung Disease Classification

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)	Error Rate (%)
LCD-CapsNet AR, B. et al , (2023)	92.15	91.80	91.50	91.65	7.85
VGG-CapsNet Bushara, A.R. et al , (2023)	94.30	94.00	93.70	93.85	5.70
DenseNet-169 Gautam, N. et al , (2024)	95.80	95.50	95.20	95.35	4.20
U-Net Gupta, A. et al , (2025)	96.50	96.20	96.00	96.10	3.50
Proposed V-CDCNNet-DLO	99.27	99.20	99.15	99.18	0.73

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Table 2 provides a comparative study of the V-CDCNNet-DLO model on the available lung disease classification models, such as LCD-CapsNet, VGG-CapsNet, DenseNet-169, and U-Net. The findings show that the suggested model has a better performance in all assessment measures. In particular, V-CDCNNet-DLO achieves the highest accuracy of 99.27%, precision of 99.20%, recall of 99.15%, and F1-score of 99.18%, with the lowest error rate of 0.73%. These advances are evidence of the optimality of the visual-modified circular dilated convolutions with the DLO in correctly recognizing the lung diseases on the CT images.

5. CONCLUSION

The proposed Visual-Modified Circular Dilated Convolutional Neural Network with Draco Lizard Optimizer (V-CDCNNet-DLO) in this work shows excellent results in lung disease classification, based on the CT images of the LIDC-IDRI dataset. The model successfully combines the visual-modified attention mechanisms and the circular dilated convolutions that allow extracting and learning the features accurately and capturing both the local and global dependencies. Experimentally, V-CDCNNet-DLO achieves 99.27%, 99.20%, 99.15%, 99.18%, and has an error rate of 0.73%, compared to other methods. Its benefits are the ability to detect complicated lung structures, learn long-range interactions, and adaptive weight optimization through the Draco Lizard Optimizer. The drawbacks include the high level of computation and the increased time of training on large datasets. Future research will center on the implementation of the model with blockchain technology to realize safe, irreversible medical data sharing, the model to multimodal imaging data, enhancing computational efficiency, and allowing real-time clinical implementation to carry out the diagnosis of pulmonary disease faster, more accurately and reliably.

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