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PAPER

Enhancing Lung Cancer Detection in CT Imaging through Wavelet Multi-Layer Perceptron and Dragonfly Algorithm Optimization

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ABSTRACT

Globally, lung cancer continues to be the primary cause of cancer-related mortality. Reducing the death rates associated with this dangerous illness requires prompt, precise diagnosis and efficient treatment. An enhanced deep learning (DL) framework for lung cancer classification utilizing computed tomography (CT) scan images is presented in this paper. A multi-layer perceptron (MLP) is used for classification after a variety of picture preparation techniques, including wavelet transformations and Canny edge detection, are used to improve feature extraction. Additionally, the dragonfly algorithm (DA) is used to increase the optimization. This approach's remarkable 98.6% accuracy rate shows how reliable and successful it is in identifying lung cancer.

KEYWORDS

lung cancer, deep learning (DL), wavelet transform, multi-layer perceptron (MLP), dragonfly algorithm (DA)

1 INTRODUCTION

As one of the primary causes of cancer-related death, lung cancer is a major global health concern. Since early diagnosis frequently results in more successful treatment options, timely detection of lung cancer is essential to improving patient survival rates. Because computed tomography (CT) scans can produce high-resolution pictures, they are essential for detecting lung nodules and cancers. But because it takes a lot of time and is inconsistent to interpret these images manually, there is a need for automated methods that can improve diagnostic precision.

Treatment outcomes for lung cancer are greatly enhanced by early identification. The American Cancer Society [1] reports that patients with lung cancer who receive an early diagnosis may have a 56% five-year survival rate. In comparison, patients with advanced-stage diagnoses have only a 5% chance of survival.

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Therefore, there is an urgent need for techniques that can use effective image analysis to enable early detection and precise diagnosis. The gold standard for detecting lung cancer is CT imaging. Due to its great spatial resolution, tiny nodules that might represent signs of lung cancer in its early stages can be seen. Numerous studies have shown how well CT scans can detect problems in the lungs. For example, a study [2] demonstrated that low-dose CT screening, as opposed to routine chest X-rays, could considerably lower lung cancer mortality.

Machine learning is a rapidly developing field of study with enormous potential, particularly in the area of medical diagnosis [3]. The investigation of gene expression patterns associated with the advancement of disease is highly significant for the fields of biological and clinical sciences. In particular, convolutional neural networks (CNNs) and DL have revolutionized the field of medical picture processing [4]–[7]. Due to CNNs' proficiency with automatic feature extraction, manual feature engineering is no longer as necessary. Several research utilizing CNNs have revealed encouraging outcomes for lung cancer screening [8]. A DL model developed in [9] was able to identify lung cancer from chest X-rays with an accuracy that was on par with radiologists. Recent developments include a deep neural network [10] that successfully conserved object features and a CapsNet-based detection system [11] that obtained excellent accuracy in classifying lung cancer. DL is becoming increasingly important in lung cancer segmentation, detection, and classification, as evidenced by the numerous studies and reviews that have emphasized its critical importance in these areas [12].

Wavelet transforms offer an analysis with several resolutions, enabling the dissection of pictures into distinct frequency components. This feature can improve the detection of small features in medical imaging, which makes it extremely helpful. In the study [13], used wavelet transforms to show that better feature extraction from lung CT images improved classification accuracy. A feedforward neural network with numerous layers of nodes, the multi-layer perceptron (MLP) can learn intricate mappings from inputs to outputs. MLPs have been effectively used to classify lung nodules based on extracted attributes in the context of lung cancer screening. The efficacy of MLPs in conjunction with wavelet-based features to achieve high classification accuracy for lung cancer detection was demonstrated in a study conducted [14].

Optimizing hyperparameters is essential to enhancing DL model performance. Conventional techniques like random and grid search can be computationally costly and ineffective. More advanced optimization algorithms have recently been proposed, such as the Dragonfly algorithm (DA). The DA is useful for optimizing multimodal functions and is modeled after the group behavior of dragonflies. The use of DA in hyperparameter optimization for DL models was shown in [15], who reported faster convergence and increased accuracy. Integration of MLPs, wavelet transforms, and optimization strategies for improved lung cancer detection has been investigated in a number of research. In [16], presented a system that combines genetic algorithm-optimized wavelet-based feature extraction with MLP classification in a thorough investigation. Their results demonstrated the benefits of integrating various approaches, showing a notable improvement in detection rates.

1.1 Problem definition

The goal of this work is to automatically classify lung cancer cases using DL methods and images from CT scans. Because of its high-resolution images, CT scans are crucial for the detection and treatment of lung cancer; yet, manual processing can be laborious and unpredictable. The objective of automating this procedure is to lessen the amount of work radiologists have to do while simultaneously increasing diagnostic precision and producing more effective and reliable outcomes in clinical settings.

1.2 Research contributions

The major contributions in the paper are as followed:

- **Advanced pre-processing techniques:** The technique uses Canny edge detection and wavelet transforms to improve picture quality, which makes it easier to extract important characteristics from CT scan images.
- **Feature extraction and analysis:** A structured approach to feature selection is demonstrated by the extraction of significant statistical features, such as mean, standard deviation, energy, and entropy, to offer relevant input for the classification model.
- **Hyperparameter optimization:** The work uses the DA to improve the MLP hyperparameters, demonstrating a novel use of algorithms inspired by nature to enhance the performance of DL models.
- **High classification accuracy:** The MLP shows that the suggested DL framework for lung cancer diagnosis is effective, as seen by its remarkable 99.82% accuracy in both training and testing phases.
- **Framework for future research:** The results point to a solid future direction for the creation of automated diagnostic tools. To improve classification accuracy and durability, future work will concentrate on growing the dataset, investigating more intricate neural network topologies, and incorporating fresh approaches to image pre-processing.

The paper's structure is organized as follows: An overview of relevant literature is provided in Section 2. Section 3 presents the proposed work comprising integration of wavelet-based multi-layer perceptron (WMLP) and DA. The test results and their analysis are included in Section 4. Ultimately, the study's conclusions are presented in Section 5.

2 LITERATURE REVIEW

Using DL architectures to detect and diagnose lung cancer entails a number of complex phases, each with a specific function. The first step in this process can be characterized as image preparation. Highlighting the region of interest (ROI) in lung CT scan pictures is the main goal of this early stage. Consistent image intensity levels are guaranteed by techniques such as intensity normalization, while noise and unnecessary details can be removed by cropping image values.

Initially, conventional machine learning (ML) models were used for lung cancer diagnosis. In order to categorize lung nodules as benign or malignant, researchers investigated a variety of feature extraction and classification strategies, including tools like support vector machines (SVMs) and decision trees. In [17], used SVM to categorize lung lesions based on a number of radiomic features taken from CT scans, and they achieved an amazing 90.3% accuracy rate in identifying malignant nodules. Traditional computer-aided detection (CAD) systems still had a lot of drawbacks in spite of these improvements. Redundancy in extracted features resulted from the handcrafted features' frequent lack of generalizability and consistency in these systems. Although the goal of this redundancy was to increase efficiency, it actually increased computational complexity and frequently made many features obsolete.

Significant progress in medical image analysis was made with the introduction of DL CAD systems. Due to their capacity to automatically extract features from unprocessed data, DL techniques—particularly CNNs and other deep neural network architectures—have become more and more popular among academics studying medical imaging. Since DL models have shown more accuracy than previous ML approaches, they have become the predominant method for diagnosing lung cancer. Different approaches have been investigated in the field of 2D DL architectures. A noteworthy method is the multi-view 2D CNN model, which accepts as input 2D slices of a CT scan taken from several perspectives. Research [18] and [19] revealed accuracy of almost 95% and sensitivity rates of about 81%, respectively.

Patch-based CNN models provide another novel strategy in 2D DL approaches. From CT scans, these models identify small image patches and classify them as either nodules or non-nodules. This approach was proven in [20], who used only nodule patches to classify nodules with an accuracy of 86.84%. These developments have demonstrated how well 2D DL models work to improve lung cancer diagnosis and detection. Even with their advantages, 2D DL models are not as good as 3D models at precisely identifying small nodules or pinpointing their location within the lung. This restriction results from 2D models' incapacity to accurately capture the volumetric data included in 3D scans.

Lung cancer diagnosis has advanced significantly as a result of the creation of 3D CNN models. In contrast to 2D models, 3D CNNs may receive whole CT scan volumes as input, which enables them to record volumetric information that is essential for locating and categorizing lung nodules. A 3D CNN was trained in [21] to identify and categorize lung nodules, outperforming previous techniques in terms of sensitivity and precision. In a similar vein, [22] used a 3D CNN to predict malignancy and locate nodules.

A deep residual learning approach for lung cancer identification was presented [23]. UNet and ResNet models are used to identify features that are suggestive of malignancy. However, the model's performance was hampered by forecast accuracy constraints. Although the model experienced overfitting, in [24], the DL approach used CT scans as a set of states and included reinforcement learning for continuous improvement. The advantage of examining individual slices as well as the full 3D volume of a CT scan is provided by a hybrid technique that combines 2D and 3D CNNs. Based only on 3D CNNs, [25] created a unique CAD approach for low-dose CT image-based lung cancer detection. In the LUNA16 and Kaggle Data Science Bowl competitions, this method performed exceptionally well in the lung nodule detection and malignant classification tasks, highlighting the connection between the detection and diagnostic processes for improved dependability.

A lung nodule identification system based on a generative adversarial network (GAN) improved by the sine cosine sailfish (SCSF) algorithm was introduced [26]. On the LIDC-IDRI dataset, the system achieved 94.74% accuracy for initial classification and 95.64% accuracy for secondary classification. In a similar vein, [27] presented the multivariate Ruzicka regressed extreme gradient boosting data classification

(MR-RXGBDC) approach, which by combining a variety of datasets and exceeding alternatives by 9% in accuracy, improved the efficiency and accuracy of lung cancer prediction. In [28], introduced WS-LungNet, a two-phase weakly-supervised network intended for lung cancer detection and diagnosis, in order to address issues with CT image annotation. With an accuracy of 85.72%, the network uses a cross-nodule attention (CADx) to assess malignancy at the patient level.

The authors in [29] presented a set of DL models that combine ensemble learning with deep transfer learning. ResNet152, DenseNet169, and EfficientNetB7 were used to improve the categorization of lung nodule severity, with an astounding accuracy of 97.23%. In [30], improved lung cancer detection while preserving patient privacy by combining blockchain technology, DL algorithms, and federated learning (FL). Using CapsNets for local mode classification, this framework—dubbed FBCLC-Rad—achieved an accuracy of 99.69% on a number of datasets. Using YOLOv4 and a region-based active contour model, [31] created an automated method to recognize, define, and reconstruct non-small cell lung cancer (NSCLC) tumors in three dimensions. During testing, this method had a DSC of 92.19%, indicating a noteworthy level of tumor segmentation accuracy. GUNet3++ is an evolutionary method that uses multi-scale skip connections to improve contextual data collection, as suggested in [32]. For lesions with irregular borders, this method produced a DSC of 0.978, demonstrating the usefulness of evolutionary algorithms in DL architecture optimization. The visual geometry group-capsule network (VGG-CapsNet), a DL capsule neural network (CapsNet) that [33] presented, achieved an AUC of 0.980 and 98.61% accuracy for lung cancer classification on the LIDC-IDRI datasets.

A four-phase decision support system employing an advanced marine predator algorithm with SVM for noise removal, enhancement, feature extraction, and classification was presented in [34]. 93.3% accuracy was attained by their method on the LIDC-IDRI database. The LCD-CapsNet system was created in [35] to effectively classify lung cancer using CT imaging by combining CNN and CapsNet architectures. With this architecture, the LIDC-IDRI dataset yielded 94% overall accuracy, 95% precision, and 94.5% recall while maintaining spatial dependability. Using the LIDC-IDRI dataset, [36] developed a BDHOA-based DCNN that improved lung cancer detection precision, obtaining accuracy rates of 92.43%, sensitivity of 94.21%, and specificity of 89.15%.

3 PROPOSED WORK

The working of the proposed system is shown in Figure 1. The proposed work combines the WMLP with the dragonfly algorithm (DA) for optimization. Machine learning models can perform much better when WMLP and DA are combined, especially for image classification tasks. The process starts with the Haar wavelet transform, which generates wavelet coefficients representing different frequency components. From these, features like mean, standard deviation, energy, and entropy are extracted. Initially, the WMLP is trained using these features. Then, DA optimizes the learning rate and hidden neurons for improved performance. The WMLP is retrained with these optimized parameters. Finally, the model is evaluated using metrics like accuracy, precision, recall, F1-score, and AUC to assess its effectiveness.

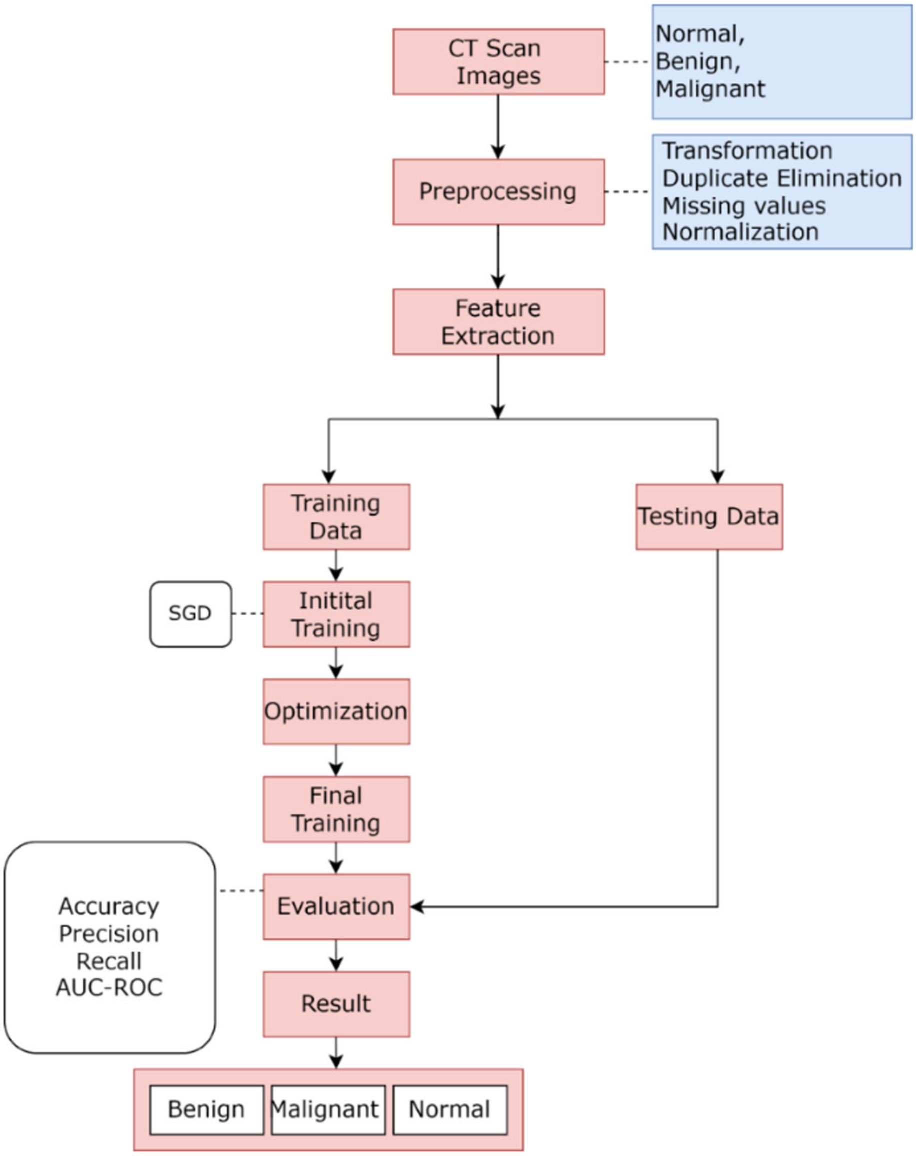

Fig. 1. Working of proposed system

3.1 Dataset description

The dataset for this study was meticulously curated to encompass a broad range of lung cancer presentations. There are 1,097 CT scan images in total, of which 416 are normal, 120 benign, and 561 malignant instances. The purpose of this Kaggle dataset is to facilitate in-depth training and assessment of the suggested approach.

3.2 Data pre-processing

The dataset was thoroughly cleaned in order to improve its quality. To guarantee a solid basis for analysis, this required eliminating duplicate entries and taking care of any missing values. In order to simplify calculations and preserve uniformity, every image was transformed into grayscale. This transformation helps to remove the extra complexity of color channels from the data while also simplifying it and allowing attention to be drawn to the important aspects. Subsequently, the images were resized to a uniform 128×128 pixel size in order to guarantee the neural network's uniform input dimensions and enable effective processing during training. After that, the pixel values were normalized, scaling them to a range of [–1, 1], which aids in quickening the neural network's convergence and enhances performance all around.

3.3 Data augmentation

Numerous data augmentation methods, most notably wavelet transforms and Canny edge detection, were used to enhance the dataset. Multiple edge-detected versions of the photos were produced by applying different threshold settings to the Canny edge detection algorithm. This method enhances the richness and variability of the information by efficiently capturing a variety of details and edges. Additionally, pictures were divided into several frequency components using wavelet transformations. A more thorough depiction of the image is made possible by this decomposition, which highlights both low- and high-frequency components. The model can access a wider range of data by examining these frequency components, which can be important for applications requiring in-depth feature extraction. By offering a variety of inputs, the combination of these methods not only expands the dataset but also helps to improve model performance. These adjustments improve the model's capacity to identify structures and patterns in the images, which in turn improves generalization and prediction accuracy. By putting these augmentation tactics into practice, you can make sure the model is exposed to many viewpoints on the data, which will increase its accuracy and robustness in practical situations.

3.4 Feature extraction

Wavelet transforms were used to extract multi-resolution features from the images in addition to these preprocessing processes. Wavelet transforms extract both spatial and frequency information from input images by breaking them down into different frequency components. Four sets of coefficients are produced by this decomposition: the approximation (cA), the vertical detail (cV), the horizontal detail (cH), and the diagonal detail (cD). Statistical features like mean, standard deviation, energy, and entropy can be obtained using these coefficients.

3.5 Initial training of WMLP

The wavelet-based MLP, or WMLP, is made to take use of wavelet transformations' advantages in feature extraction. The three layers of MLP are input layer, the hidden layer, and the output layer. The input layer is with 6,384 neurons, matching the images of size 128×128. The Hidden layer is with 100 neurons and an output layer with 3 neurons representing the three categories of benign, malignant, and normal.

The extracted features are fed to a single hidden layer MLP that further produces to output layer. The input is divided into one of the three classes by the output layer using the softmax function, while the hidden layer uses the ReLU (rectified linear unit) activation function. This method efficiently distinguishes between benign, malignant, and normal tissues, improving the detection of lung cancer by combining wavelet-based feature extraction with MLP classification.

Initially, stochastic gradient descent (SGD) was used to train the MLP model, with a learning rate of 0.01. Thirty percent of the dataset was set aside for testing, while seventy percent was placed aside for training. The training data was arranged into batches of 256 photos in order to maximize the training process. The MLP was fed the input for each batch in order to produce output probabilities. Next, by contrasting these anticipated probabilities with the actual labels, the cross-entropy loss was calculated.

The gradients of the loss with respect to the model parameters were computed by backpropagation. The model's parameters were updated in order to minimize the loss function based on these gradients. To encourage convergence, this training cycle was repeated 100 times. Table 1 provides a clear picture of the major components utilized in the MLP model by summarizing the parameters and their configurations.

Table 1. Initial hyper-parameters for WMLP

Parameter	Value
Optimizer	SGD
Batch size	256
Learning rate	0.01
Random seed	1
Loss function	Cross entropy
Num epochs	10
Hidden layers	100
Num features	128×128
Num class	3

3.6 Model optimization using DA and retraining the WMLP

The DA is an optimization method inspired by nature that simulates the swarming behaviors of dragonflies. The five essential components of the swarming behavior of dragonflies—separation (to prevent crowding), alignment (to synchronize direction), cohesiveness (to preserve group structure), attraction to food sources, and diversion from threats—are the inspiration for the dragonfly algorithm.

The learning rate and the number of hidden neurons is the two main hyperparameters of the WMLP that are optimized using the DA. The purpose of the DA is to maximize validation accuracy by minimizing its objective function, which is defined as the negative validation accuracy. To maximize the performance of the model, the method iteratively modifies the hyperparameters, such as learning rate and hidden neuron count. A population of dragonflies is initialized, their fitness is assessed based on classification accuracy, and they iteratively update their positions and velocities. By avoiding local minima and striking a balance between exploration and exploitation, this method efficiently searches the hyperparameter space. Table 2 summarizes important DA configurations, such as population size and search bounds. The WMLP is trained again based on the optimized parameters received from dragonfly algorithm.

Table 2. Configurations used in dragonfly algorithm

Parameter	Value
Objective Function	Rastrigin Function
Upper Bound (ub)	5.12/[0.1, 200]
Lower Bound (lb)	–5.12/[0.0001, 10]
Dimensions (dim)	10/2
Maximum Iterations (max iter)	100/2
Population Size	30/10
Population Initialization	Uniform Distribution
Velocity Initialization	Zeros
Best Fitness	Initialized to Infinity
Best Solution	Initialized to First Individual

3.7 Model evaluation metrics

In order to validate the efficacy of the DA-optimized wavelet WMLP for lung cancer detection and classification from CT scans, we comprehensively evaluate a variety of metrics. These metrics are necessary for a thorough assessment of the diagnostic accuracy and error types of the model. The performance evaluation metrics used in the study are as follows:

- **Confusion matrix:** A confusion matrix summarizes true positives (accurately identified cancers), true negatives (accurately identified non-cancers), false positives (inaccurately identified cancers), and false negatives (missed cancers) in order to assess the effectiveness of classification models in lung cancer detection. This thorough analysis helps you comprehend the advantages and disadvantages of the model.
- **Accuracy:** The percentage of correctly diagnosed cases (malignant and benign) relative to the total number of cases is used to determine the accuracy of lung cancer detection. Although a valuable measure, it could be deceptive in unbalanced datasets where benign cases predominate, necessitating the employment of additional metrics to guarantee accurate cancer detection.

$$Accuracy = \frac{Number\ of\ Correct\ Predictions}{Total\ Number\ of\ Predictions} \quad (1)$$

- **Loss:** When it comes to lung cancer diagnosis, loss functions measure the discrepancy between expected and real cancer outcomes. During model training, popular loss functions such binary cross-entropy direct the optimization process. Reducing loss enhances the predicted accuracy and dependability of the model in identifying lung cancer.

$$Loss = \frac{\sum Errors}{Total\ Number\ of\ Predictions} \quad (2)$$

- **Precision:** Accuracy of favorable predictions is indicated by precision in lung cancer detection. The ratio of true positives to the total of true positives and false positives is used to compute it. To minimize needless worry and additional testing for patients, high precision is essential in confirming that the majority of detected tumors are, in fact, malignant.

$$Precision = \frac{True\ Positives}{True\ Positives + False\ Positives} \tag{3}$$

- **ROC:** The ROC curve, which shows the trade-off between sensitivity (true positive rate) and false positive rate across different thresholds, is essential for evaluating lung cancer detection models. The area under the curve (AUC) offers a thorough evaluation of the performance of the model and helps determine the best detection thresholds.
- **Recall:** The model's recall, or sensitivity, in the identification of lung cancer indicates its capacity to recognize every real cancer case. The ratio of true positives to the total of false negatives and true positives is used to compute it. High recall is essential because patient outcomes may suffer greatly if a cancer diagnosis is missed.

$$Recall = \frac{True\ Positives}{True\ Positives + False\ Negatives} \tag{4}$$

- **F1 score:** In detecting lung cancer, the F1 score plays a crucial role by striking a balance between recall and precision. It offers a solitary statistic that reflects the model's capacity to minimize false positives while accurately identifying malignant situations. An improved model, which is essential for a precise diagnosis of lung cancer, is indicated by a higher F1 score.

$$F1\,Score = 2 * \frac{Precision * Recall}{Precision + Recall} \tag{5}$$

4 EXPERIMENTAL RESULTS

The proposed work has been implemented using various libraries, and functions used are listed in Table 3. The experimentation has been carried out as per the detailed discussions in the Section 3. The dataset has all three classes, such as Benign, Malignant, and Normal. The entire dataset is divided as 70% for training and 30% for testing, where the training is carried out twice, i.e., before and after optimization.

Table 3. Functions and libraries used for experimentation

Operation	Function used	Library
Transformation	transforms.Resize	torchvision
Normalization	transforms.Normalize	torchvision
Wavelet transforms	pywt.dwt2	PyWavelets
Canny edge detection	cv2.Canny()	OpenCV
Hidden layer	ReLU	
Output layer.	Softmax	

Strong classification performance for benign, malignant, and normal patients is revealed by the confusion matrix, as shown in Figure 2. With 561 malignant and 118 benign true positives, the model shows good accuracy and dependability.

The two benign instances that were mistakenly diagnosed as cancer draw attention to a small but important worry about false negatives, which can have a big impact on healthcare. On the other hand, the lack of false positives suggests the model does a good job of differentiating across groups. While the model functions well overall, improving diagnosis accuracy and patient outcomes in clinical settings still depends on minimizing misclassifications, particularly in key areas.

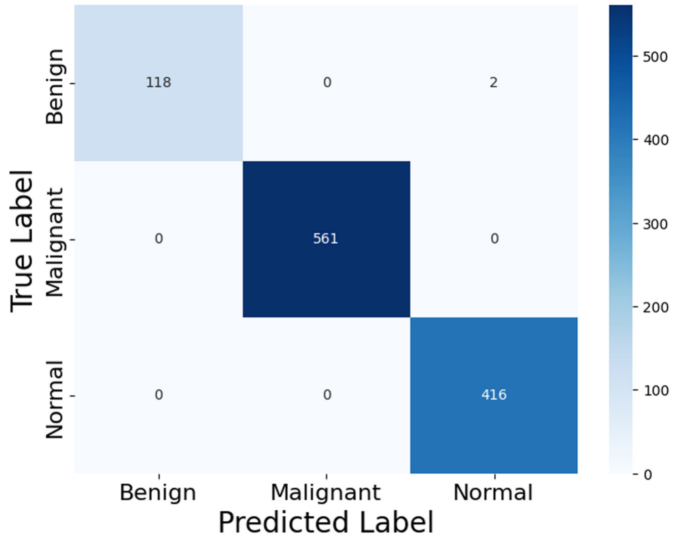

Fig. 2. Confusion matrix on the considered dataset

Based on the analysis, the model performs flawlessly in terms of classification, obtaining 100% accuracy on both training and test datasets, as shown in Figure 3. Benign, malignant, and normal ROC curves show perfect metrics, with a 0.0 false positive rate and a 1.0 true positive rate, respectively, for each class. This suggests that every positive case has been accurately discovered and has not been misclassified. Although these are amazing results, there is a possibility of overfitting. Sustained validation of the model across various datasets will be necessary to guarantee its resilience and efficacy in practical clinical settings. All things considered; the results highlight remarkable diagnostic abilities.

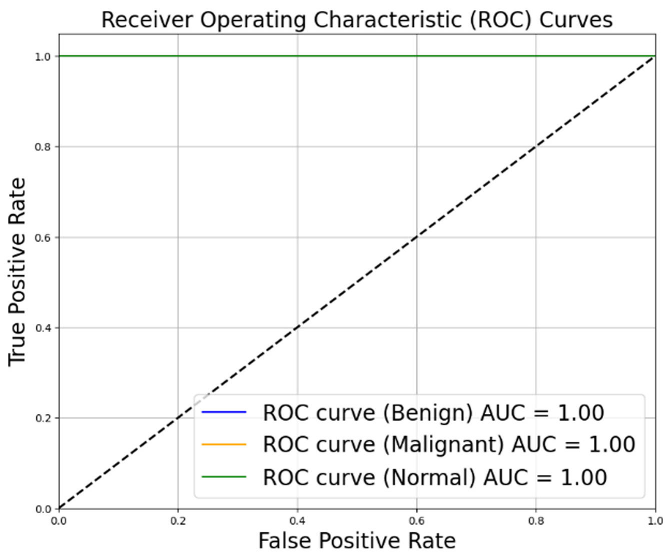

Fig. 3. ROC-AUC results for all three cases

Model performance was significantly impacted by data augmentation, which resulted in major improvements in accuracy and robustness. The training accuracy of models trained using enhanced datasets increased significantly, from 90% to 99%. Additionally, with the implementation of various data augmentation approaches, test accuracy significantly increased from 88% to 98.6%. These results demonstrate how well data augmentation works to enhance model generalization and reduce overfitting, which eventually improves performance in practical settings. This illustrates how important data augmentation is to creating trustworthy machine learning models for applications such as CT imaging lung cancer detection, as shown in Figures 4 and 5.

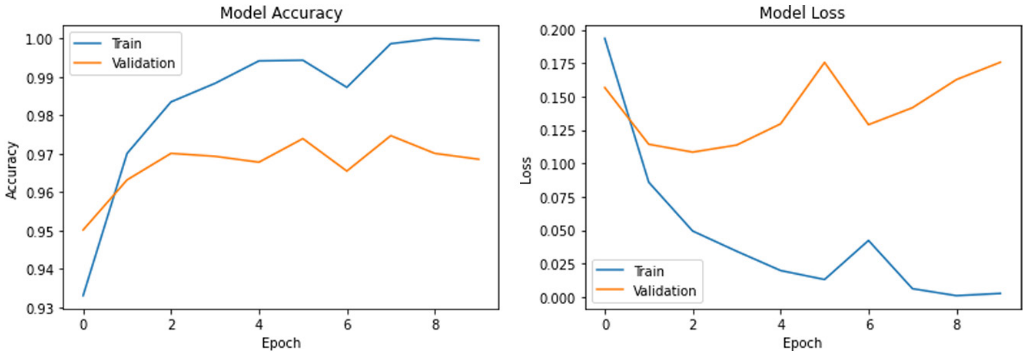

Fig. 4. Accuracy and loss before applying dragonfly algorithm

The overall accuracy and loss metrics throughout 50 epochs are shown in Figure 6. It is showing the accuracy trends and the associated loss values; these visualizations show how well the model performed throughout training. By examining these numbers, one can gain knowledge about how the model learns and evaluate its stability and efficacy in lung cancer classification.

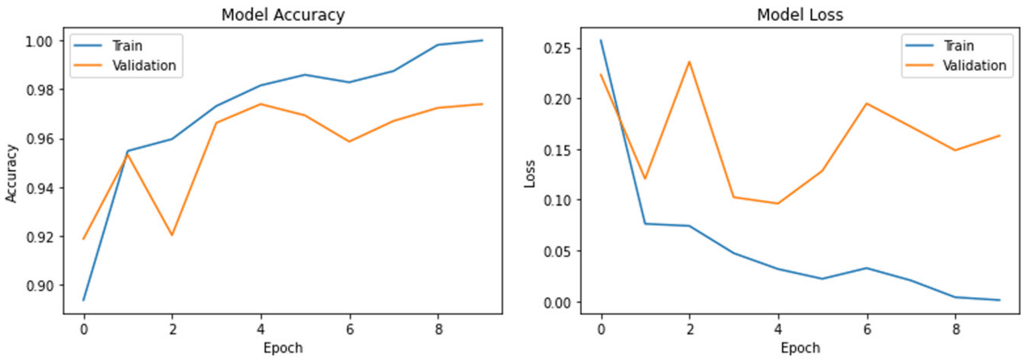

Fig. 5. Accuracy and loss after applying DA

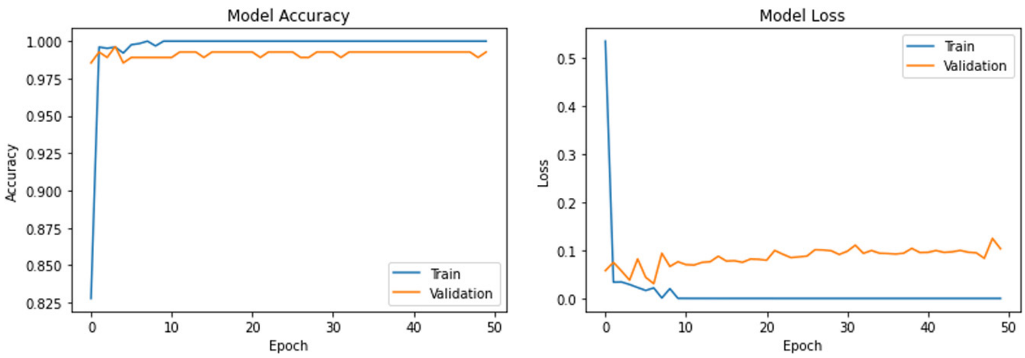

Fig. 6. Model training and validation accuracy

The analysis of results compared with the works carried out in [37], [38], and [39] are shown in Table 4. With matching precision, recall, and F1-score values of 0.86, the MLP attained an accuracy of 88%. With an accuracy of 91.26%, the VGG19 model in conjunction with ANN transfer learning demonstrated better outcomes. A hybrid strategy combining CNN, ResNet-50, Inception V3, and Xception achieved 92% accuracy, further improving performance. With an outstanding accuracy of 98.6%, high precision, recall, and F1-score of 0.99, the suggested WMLP optimized with the DA far beat the other models. These findings demonstrate the model's high robustness and dependability in identifying cases of lung cancer. The efficiency of the suggested methodology in correctly identifying lung cancer from CT scans is highlighted by the high scores obtained across several measures. This result demonstrates the WMLP approach's potential as a useful tool for improving diagnostic precision and assisting with clinical decision-making in the field of medical imaging.

Table 4. Comparative analysis

Paper & Year	Used Model	Accuracy %	Precision	Recall	F1-Score
[37] 2024	MLP	88	0.86	0.86	0.86
[38] 2024	VGG19 & ANN TL	91.26	0.91	0.91	0.91
[39] 2024	CNN, ResNet-50, Inception V3, Xception	95	0.97	0.97	0.97
Proposed model	Wavelet-MLP Optimised with DA	98.6	0.99	0.99	0.99

The Figure 7 shows how a WMLP in conjunction with DA Optimization can effectively forecast and classify lung cancer into normal, malignant, and benign categories. By improving feature extraction and model accuracy, our method helps patients with lung cancer receive more accurate diagnoses and more effective treatment plans.

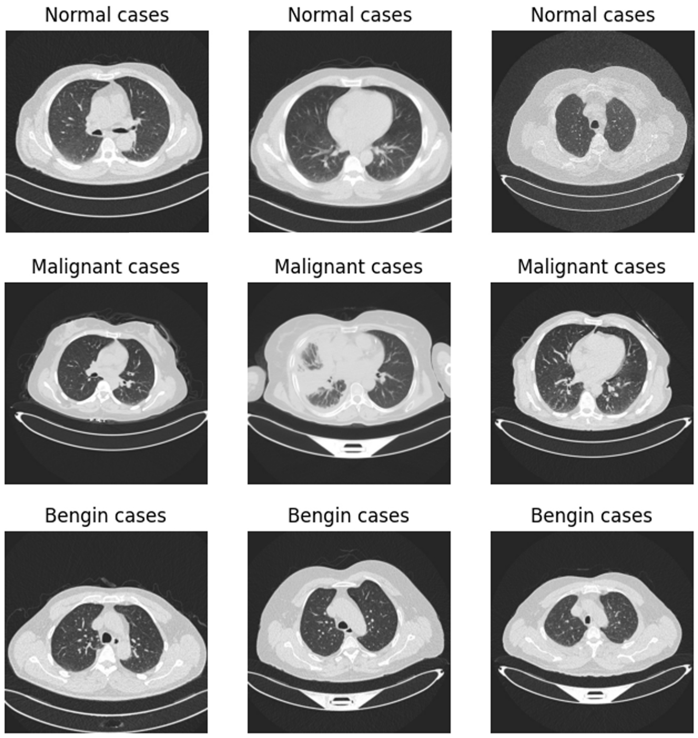

Fig. 7. Predicted labels

5 CONCLUSION

In this work, we introduced a novel DL framework that uses a WMLP improved by the DA to diagnose lung cancer from CT images. By using sophisticated picture preprocessing methods, including wavelet transformations and Canny edge detection, this technology was able to classify lung cancer with an astounding 98.6% accuracy rate. Nonetheless, the study noted many drawbacks, such as a small and uniform dataset that would impair the generalizability of the model. Future studies should investigate different preprocessing techniques and evaluate the model using bigger, more varied datasets. Its clinical application will also be improved by tackling the computational complexity of the DA optimization and broadening the classification framework.

Finally, to guarantee the model's performance in practical situations and enable its incorporation into standard diagnostic procedures, prospective validation via clinical trials is required.

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