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Advanced Lung Cancer Diagnosis with LungNet-Hybrid Deep Learning Approach for Improved Imaging and Tumor Detection

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Abstract

The study presents a new hybrid deep learning framework that combines the Multi-Function Differential Evolution (MF-DE) global optimization engine and the Morphological-OTSU analysis to improve the role of image segmentation and pattern recognition in this study, named as LungNet. The MF-DE engine has been utilized to optimize the hyperparameters of LSTM (Long Short-Term Memory). The morphological-OTSU method is adopted to perform effective image thresholding to help in the extraction of important features of images to enable proper classification. The proposed model is evaluated using the benchmark datasets, i.e., the LIDC-IDRI lung CT dataset in medical imaging and the NSCLC Radiogenomics dataset in lung cancer research. The MF-DE optimization ensured that the LSTM models were much more accurate, with the hyperparameters being optimized towards the optimal performance of the model. On LIDC-IDRI, the hybrid mode achieved a higher segmentation accuracy of 93.2% as compared to conventional methods that had an average segmentation accuracy of about 86.5%. Equally, the object recognition performance on the NSCLC Radiogenomics dataset achieved an mAP (mean Average Precision) of 48.0% that is 7.5% better than the baseline CNN models. The Hybrid Model had a classification accuracy on the LIDC-IDRI dataset of 95.0%, and on the NSCLC Radiogenomics dataset, the classification accuracy was 94.5%. This paper shows that the suggested hybrid design is better in global optimization and image analysis and provides significant improvements in real-time image processing tasks. The findings reveal a significant change in computational efficiency and accuracy of segmentation, especially with challenging and noisy data sets. The hybrid paradigm can be used in a very diverse range of applications, such as in medical image processing, industrial automation, and security surveillance systems.

Keywords: Deep Learning. Global Optimization, Morphological Analysis, OTSU Thresholding, Image Segmentation, Hybrid Models, Medical Imaging.

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1 Introduction

Deep learning models have transformed different areas in recent years, especially in image processing areas like object detection and medical imaging. The accuracy and efficiency levels required in these tasks are significant, and they are needed when working with complex datasets with the possibility of having noisy, incomplete, or diverse input. In medical imaging, as an example, some operations, such as tumor detection or organ segmentation, will demand accurate and dependable segmentation of the image to make appropriate diagnoses. Correspondingly, segmentation is important in the object detection of objects in the real world, e.g., autonomous driving or surveillance, by detecting and classifying the objects in a scene effectively. Global optimization algorithms are essential to enhance the performance of deep learning models by minimizing their hyperparameters, such as learning rates, batch sizes, and the number of layers (Almakayeel et al., 2025). Such hyperparameters have a great influence on the generalization performance of the model, especially in the case of working with complex data. Conventional optimization methods, such as gradient descent or grid search, may fail to effectively solve high-dimensional and non-linear models due to their susceptibility to local minima or slow convergence. Consequently, the optimization process may be inefficient, resulting in poor model performance. Conversely, global optimization algorithms (e.g., Differential Evolution) do have the capacity to search in the solution space to find a better solution, bypassing local minima and enhancing overall accuracy and efficiency of the model.

Nevertheless, image segmentation is one of the most difficult issues of deep learning, especially when it is necessary to work with noisy or incomplete data (Muthukumaraswamy & Krishnamoorthy, 2025). The ability to extract meaningful features from images is important, and this is achieved through segmentation and subsequently applied in classification, analysis, and interpretation in different applications (Zhang et al., 2025). The medical field, especially in the accurate segmentation of tumors, is essential in identifying abnormalities, and any errors in segmentation may cause severe cases of misdiagnosis or non-identification (Radha & Gopalakrishnan, 2023; Maqsood et al., 2025). In a similar case, during object secretion exercises, the quality of segmentation directly influences the quality of the detection mechanism when it comes to the localization and categorization of objects in true-to-life scenarios (Sun & Yang, 2022). Hybrid models have been explored due to the need to have more effective and efficient methods of either optimization or segmentation (Douglas et al., 2025). These models are aimed at combining the positive aspects of the advanced optimization methods and segmentation techniques to provide more effective solutions to complex problems. As an example, Morphological Analysis, when used in conjunction with OTSU Thresholding in image segmentation, yields great improvements, although it does have problems with large datasets or when used in real-time (Roshan et al., 2024). Hybrid models that integrate optimization algorithms such as Differential Evolution with segmentation algorithms can be an effective solution in such problems, as it enhances the convergence rates and segmentation accuracy, and a hybrid approach allows for better work even in the noisy or complex environment (Rayed et al., 2024).

1.1 Problem Statement

In the world, lung cancer is considered to be one of the most impactful cancer-related deaths, and early diagnosis of cancer is very important to enhance patients' chances of survival. The conventional image segmentation approaches, such as thresholding and edge detection, do not work quite well on the noisy and complex datasets, such as CT scans. The accuracy of the segmentation is further impaired when such techniques are used on medical images, where the data is often not complete or noisy. Moreover, traditional optimization algorithms like gradient descent do not always efficiently determine optimal hyperparameters, particularly in high-dimensional models. The paper presents a new hybrid methodology that integrates the global optimization ability of Multi-Function Differential Evolution (MF-DE) and the effective Morphological-OTSU image segmentation methodology to improve the diagnosis of lung cancer. The proposed model will increase the accuracy of lung cancer detection as well as the computational efficiency of diagnosing during real-time by hyperparameter optimization and medical image segmentation (Gao et al., 2025).

1.2 Contribution of the Study

The main aim of this research consists of the formulation and assessment of a hybrid deep learning model that will be optimized by the MF-DE algorithm and boosted by the Morphological-OTSU analysis to diagnose lung cancer with high precision. This hybrid model aims to:

- Optimize the deep learning model hyperparameters to provide improved segmentation and classification of lung cancer based on images of CT scans.
- Apply Morphological-OTSU segmentation to enhance image feature extractors, particularly in noisy and incomplete medical images.
- Exceed traditional methods and use of baseline models in superior segmentation performance and object classification.
- Reduce real-time diagnostic costs by cutting down computational costs in the detection of lung cancer.

The hybrid model is a full solution to the obstacles in global optimization, image segmentation, classifications and it is a significant step towards developing deep learning methods in the real-world environment.

The paper will be structured in the following way: Section II will be a literature review on the global optimization methods used in the field of deep learning, with an emphasis on the problem of differential evolution and image segmentation in the medical imaging and object detection areas. Section III presents the methodology, which includes the implementation of the MF-DE optimization engine with the Morphological-OTSU analysis, deep learning model (LSTM) employed, and experiment design, and metrics. Section IV provides the findings that include the performance analysis, security, privacy, and scalability analysis of the proposed framework in comparison to the traditional methods. Lastly, Section V will be the final part of the research, where the main findings will be summarized, and recommendations about the potential future research will be made.

2 Literature Review

Differential Evolution (DE), Genetic Algorithms (GA), and Particle Swarm Optimization (PSO) are global optimization methods that have become important in optimizing model hyperparameters in deep learning. It is remarkable that such methods have attracted considerable interest because of their capability to search the high-dimensional, multifaceted search space of potential solutions and enhance the efficiency of deep learning models. Differential Evolution (DE) is a type of population-based optimization algorithm that is also famous for escaping local minima, which is one of the problems with complex optimization problems (Vaiyapuri, 2025). It is especially applicable to high-dimensional optimization as it ventures into the parameter space compared to the traditional techniques to a greater degree. DE works by mutating a population of candidate solutions by the use of mutation, crossover, and selection in order to locate the best solution. This allows it to be useful in optimizing hyperparameters like learning rates, regularization factors, and model architecture, and eventually improve the performance of deep learning models (Musthafa et al., 2024). The Particle Swarm Optimization (PSO) is a search technique that follows the social interaction of birds flocking or fish schooling and consequently modifies the location of individual solutions (particles) based on their own and the environment's experiences. PSO is very effective in continuous optimization problems, particularly where the parameter space is vast, and hence is best suited to hyperparameter optimization (Latif et al., 2024). PSO performs well when identifying the best solutions to hyperparameters in deep learning models by updating the position of its particles iteratively. Equally, Genetic Algorithms (GA), which are inspired by natural selection, optimize solutions based on the processes, which include selection, crossover, and mutation. GA is especially helpful in the nonlinear and massive search space of solving optimization problems. It simulates the evolution of natural processes; hyperparameters, including learning rates, batch sizes, and deep learning model layers, are optimized. These optimization algorithms are more effective in searching the solution space than traditional ones, such as grid search and random search, and can avoid local minima and provide more effective generalization. Therefore, they are also extremely useful in adjusting deep learning models, enhancing their accuracy, and decreasing overfitting, thereby being a significant factor in improving the performance of models.

Image processing, morphological analysis, and OTSU thresholding are very potent tools that are frequently applied to segment and extract features of images of noisy or incomplete data, such as medical imaging or object detection (Bala & Kannan, 2025; Shobana Nageswari et al., 2023). Morphological analysis is defined as a collection of non-linear processes that dwell on the form and structure of the objects in an image. These are the erosion operation, dilation operation, opening operation, and closing operation to binary images (where pixels are black or white). Erosion minimizes the boundaries of objects to assist in eliminating small noise elements, and dilation broadens the boundaries, which helps to join disjointed objects together. The opening and closing processes eliminate the small objects or noise by first using erosion and then dilation, and eliminating the edges of the objects or filling the small gap by using dilation, then erosion. Such operations are essential to improving the structure of objects and removal of undesired noise, and are especially applied in such processes as tumor detection or the analysis of the vascular structure in medical imaging (Radha & Gopalakrishnan, 2020). OTSU thresholding is an automatic image process that is employed to find objects (foreground) and the background (background) of the image. It computes an optimal threshold value that reduces the intra-class variance but maximizes inter-class variance using pixel intensities. The technique uses the assumption that the background and foreground are distinct in intensity distribution, and it chooses the threshold that separates the background and the foreground in the most effective way. This renders OTSU quite successful in terms of accurate boundary recognition, particularly in medical imaging, where it is necessary to detect anomalies such as tumors, or in object recognition, where it assists in breaking down an object against the background. Morphological analysis and OTSU thresholding are very useful when combined to offer a strong and efficient method of image segmentation (Guo et al., 2023). Morphological operations can be used to improve the structural properties of the image, and therefore, the processes make it easy to isolate the objects. The OTSU thresholding is also efficient in separating the background and the foreground. This combination method is particularly useful in complicated segmentation problems, where precise identification of the features is necessary, and the removal of noise is required (Jittou et al., 2025; Toupchi & Abolghasempur, 2015). Indicatively, in medical imaging, they can be used to isolate tumors or lesions in tissues, and in object detection, the methods can be used to identify and classify objects in a cluttered or noisy setting.

Recent innovations in deep learning have given rise to the emergence of hybrid models that are able to combine the benefits of global optimization methods with image segmentation methods (Wang et al., 2020). These mixed methods seek to exploit the advantages of both: two different optimization algorithms (Differential Evolution (DE) or Particle Swarm Optimization (PSO)) and algorithms in image processing (OTSU thresholding and morphological analysis). The optimization algorithms, e.g., DE, PSO, etc., are aimed to be used in complex and multidimensional hyperparameter spaces to optimize model performance by fine-tuning important hyperparameters, e.g., learning rates, batch sizes, and network architecture. The algorithms are especially helpful since they do not face the problem of being trapped in local minima, as is typical of the classical methods of optimization, such as gradient descent. This is to make sure that the models of deep learning can reach a global optimum and thus perform well in terms of generalization and performance (Domingues et al., 2020; Wen et al., 2025). In contrast, image segmentation methods like OTSU thresholding and morphological analysis offer potent methods of partitioning an image into useful parts by distinguishing objects other than the background (Hosseini, 2025). OTSU thresholding finds a good threshold to differentiate the objects and the background in terms of pixel intensity automatically, and morphological processes such as erosion, dilation, opening, and closing are used to polish the image by eliminating noise and improving the structures of the objects. Combined, these techniques can considerably enhance the precision of segmentation, especially in difficult tasks where data is noisy or incomplete (Mei et al., 2025).

The hybrid models will combine the optimization of the hyperparameters of the deep learning models and also improve the accuracy of segmentation by combining the two fields, which are global optimization and image segmentation (Yang, 2026). Such compound capabilities demonstrate a huge potential in managing complex problems like medical imaging, in which accurate tumor detection is essential, object recognition in autonomous driving or surveillance, and image processing in complicated settings. The hybrid models have proved to be more efficient in optimization as well as segmentation accuracy compared to the traditional models (Conze et al., 2023). As an example, these models are more effective in medical imaging, where tumors are more precisely segmented, which is more clearly supported by the diagnosis. They can be used to enhance object detection in adverse conditions in autonomous driving, that is, during poor visibility or complicated backgrounds. Consequently, the combination of the global optimization processes and segmentation approaches not only increases the performance of the deep learning models but also increases their applicability in real-world and diverse applications (Su et al., 2022).

2.1 Gaps in Existing Methods

Although the hybrid deep learning models have shown success, there are a number of limitations. Conventional optimization methods tend to fail when there are noisy or incomplete datasets, and as a result, the model performance is suboptimal. Also, the image segmentation techniques in existence might be weak concerning complex or high-dimensional images. More advanced hybrid models are required to handle such challenges by integrating more effective hybrid optimization models with more advanced image processing models. More so, the majority of the existing models are very demanding in terms of computational resources, and thus, they cannot be used in areas that need real-time applications. It is important to address these gaps in order to improve the performance and application of deep learning models in real-world applications.

3 Methodology

The suggested framework combines the Multi-Function Differentiated Evolution (MF-DE) optimization engine and the Morphological-OTSU analysis to form a hybrid deep learning framework of global optimization and image segmentation. Hyperparameters of deep learning models of LSTM is optimised by the MF-DE engine and allow the models to converge and perform better. In the meantime, the Morphological-OTSU analysis is used to augment image segmentation by effectively obtaining features and thresholds of images that advance the precision of the deep learning models, particularly in tricky or noisy data (Khan et al., 2015). This hybrid method takes advantage of the capabilities of each of the two methods, namely optimization and image processing, to perform better in such tasks as medical image segmentation and classification (Lahreche et al., 2024).

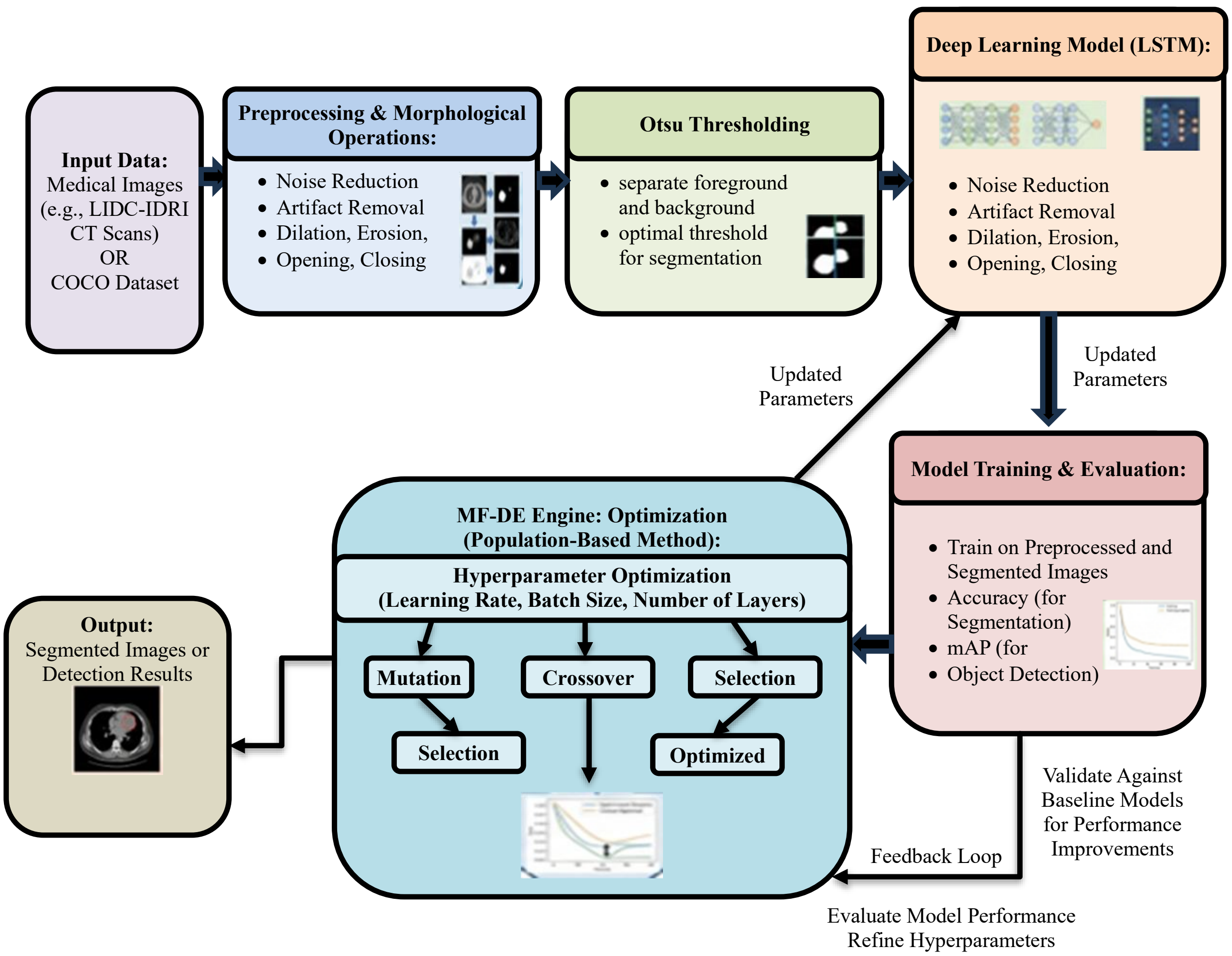

Figure 1: Proposed hybrid deep learning architecture for global optimization and image segmentation

Figure 1 shows the suggested architecture of the Hybrid Deep Learning Paradigm that incorporates MF-DE (Multi-Function Differentiating Evolution) for global optimization and Morphological-OTSU to analyze images to obtain segments. It firstly takes input data, which in the medical case is medical images based on LIDC-IDRI CT scans (medical segmentation) or in the case of object detection, the COCO dataset. The input images are first preprocessed and morphologically processed, including dilation, erosion, and opening, which reduces the noise and enhances the structure of the image to better segment it. This is then followed by OTSU thresholding to optimally extract the object (in medical imaging, e.g., tumors) against the background to enhance the segmentation. The second one is the deep learning models (LSTM) that learns complicated patterns, features, and convolutional transformations to perform segmentations or detection activities (Saritha & Gunasundari, 2024). Global optimization is then done by use of the MF-DE engine. This engine will optimize hyperparameters like learning rate, batch size, and layer configuration to make sure that the deep learning models perform best. This is an optimization process that is aided by a feedback loop, whereby the outcomes of the model are constantly checked and optimized by running the model again. Lastly, the model is trained and analyzed with the help of different metrics, such as segmentation accuracy and mean Average Precision (mAP) of object detection. The results of this process are segmented images (medical images in clinical application, or detection results in object classification), which are contrasted with the performances of baseline models in order to evaluate the performance improvements both in segmentation and detection.

3.1 MF-DE Engine for Global Optimization

The MF-DE (Multi-Function Differential Evolution) engine is an extremely robust population-based optimization method, applied in optimization of hyperparameters of LSTM model. The MF-DE engines operate using mutation, crossover, and selection over a population of candidate solutions. The aim is to determine the best combination of hyperparameters, i.e., the learning rates, the batch sizes, as well as the regularization factors that improve the performance of the deep learning models. The local minima avoiding and the global optima converging ability of the engine is also very effective in tackling complex optimization problems. The MF-DE engine works in a cyclic fashion by searching the space with the goal of improving the hyperparameters of the model to yield better results in terms of accuracy and generalization. There are two equations below that explain the fundamental functions of the MF-DE engine:

Mutation (Creating a Mutant Vector)

$$\mathrm{v}_i^{(t)} = \mathrm{x}_r^{(t)} + F \cdot \left(\mathrm{x}_r^{(t+1)} - \mathrm{x}_r^{(t+2)}\right) \qquad (1)$$

Where in equation (1):

- $\mathrm{v}_i^{(t)}$is the mutant vector.
- $F$is the scaling factor.
- $\mathrm{x}_r^{(t)}, \mathrm{x}_r^{(t+1)}, \mathrm{x}_r^{(t+2)}$are randomly selected vectors from the population.

Crossover

Once a mutation has taken place, the mutated vector is cross-linked with the original one to form a trial one:

$$\mathbf{u}_i^{(t)} = \begin{cases} \mathbf{v}_i^{(t)} & \text{if } (rand() \leq CR) \\ \mathbf{x}_i^{(t)} & \text{otherwise} \end{cases} \qquad (2)$$

Where in equation (2):

- $\mathrm{u}_i^{(t)}$is the trial vector.
- $CR$is the crossover rate.
- is a random value between 0 and 1.

Selection (Choosing the best candidate solution):

$$\mathrm{x}_i^{(t+1)} = \begin{cases} \mathrm{u}_i^{(t)} & \text{if } f(\mathrm{u}_i^{(t)}) \leq f(\mathrm{x}_i^{(t)}) \\ \mathrm{x}_i^{(t)} & \text{otherwise} \end{cases} \tag{3}$$

Where in equation (3):

- $f(\mathrm{x}_i^{(t)})$is the fitness function, and $\mathrm{u}_i^{(t)}$is the trial vector generated through crossover.

3.2 Morphological-OTSU Image Segmentation

Morphological-OTSU analysis refers to the technique of image segmentation based on the combination of morphological operations and OTSU thresholding.

Morphological Operations

The morphological actions (dilation, erosion, opening, and closing) are used on the image to eliminate noise and maintain structures. Dilation and erosion, as examples, increase and decrease the edges of the foreground objects in an image, respectively.

$$I_{\text{dilated}} = \text{dilate}(I, S) \tag{4}$$

Where in equation (4):

- I is the input image.
- S is the structuring element used in the morphological operation.
- I_{dilated} is the resulting image after dilation.

OTSU Thresholding

The OTSU method is automatically calculated to have an optimal threshold value T to separate the foreground and the background. The threshold is calculated by maximizing between-class variance:

$$T = \arg\max_T \sigma_b^2(T) = \frac{(m_1 - m_2)^2}{\sigma_1^2 + \sigma_2^2} \tag{5}$$

Where in equation (5):

- $\sigma_b^2(T)$is the between-class variance at threshold T.
- $m_1, m_2$are the class means, and $\sigma_1^2, \sigma_2^2$are the class variances.

3.3 Algorithm Models

The OTSU method aims to find the optimal threshold value T_{opt}that minimizes the intra-class variance. The formula for OTSU thresholding is:

$$T_{opt} = \arg\min_T \sigma_T^2$$

Where $\sigma_T^2$is the intra-class variance defined as:

$$\sigma_T^2 = p_1(T) \cdot \sigma_1^2(T) + p_2(T) \cdot \sigma_2^2(T)$$

Here:

- $p_1(T), p_2(T)$are the probabilities of the two classes,
- $\sigma_1^2(T), \sigma_2^2(T)$are the variances of the two classes after the threshold T.

After obtaining T_{opt}, the images are thresholded to produce binary images for segmentation.

Let's define the objective function $f(\theta)$as the loss function or segmentation accuracy for the LSTM model that we aim to optimize:

$$f(\theta) = \text{Accuracy or Loss Function of LSTM Model}$$

Where:

- $\theta = \{h_1, h_2, \dots, h_n\}$represents the hyperparameters of the LSTM model (e.g., learning rate, number of layers, batch size, etc.).

The MF-DE process operates as follows:

1. **Initialize population**: Randomly initialize a population $P$of size N, where each individual $\mathbf{X}_i$represents a vector of hyperparameters:
$$\mathbf{X}_i = [h_{i1}, h_{i2}, \dots, h_{in}]$$
2. **Mutation and Crossover**: Generate a new candidate solution $\mathbf{X}'_i$using the mutation and crossover operations:
$$\mathbf{X}'_i = \mathbf{X}_r1 + F \cdot (\mathbf{X}_r2 - \mathbf{X}_r3)$$

Where:

- $\mathbf{X}_r1, \mathbf{X}_r2, \mathbf{X}_r3$are randomly chosen individuals from the population,
- $F$is a scaling factor.

3. **Selection**: Select the better of the parent and child for the next generation:
$$\mathbf{X}_i^{new} = \begin{cases} \mathbf{X}'_i & \text{if } f(\mathbf{X}'_i) \le f(\mathbf{X}_i) \\ \mathbf{X}_i & \text{otherwise} \end{cases}$$

Repeat until the stopping criterion (e.g., maximum generations or convergence) is met.

The LSTM model is optimized using the hyperparameters found by the MF-DE optimization. The LSTM model updates its weights during training using backpropagation through time (BPTT). The loss function $L$for training is typically defined as the Mean Squared Error (MSE) or Cross-Entropy Loss, depending on the task.

For a classification task:

$$L = -\sum_{i=1}^{N} y_i \log(\hat{y}_i) + (1 - y_i) \log(1 - \hat{y}_i)$$

Where:

- $y_i$is the true label,
- $\hat{y}_i$is the predicted probability.

For image segmentation, you may use the Dice Coefficient for evaluation:

$$\text{Dice Coefficient} = \frac{2 \mid A \cap B \mid}{\mid A \mid + \mid B \mid}$$

Where $A$is the predicted segmentation and $B$is the ground truth.

To optimize these models, the MF-DE engine identifies optimal hyperparameters to improve the performance of the models in both the segmentation and object detection tasks, such as the learning rate, batch size, and the number of layers.

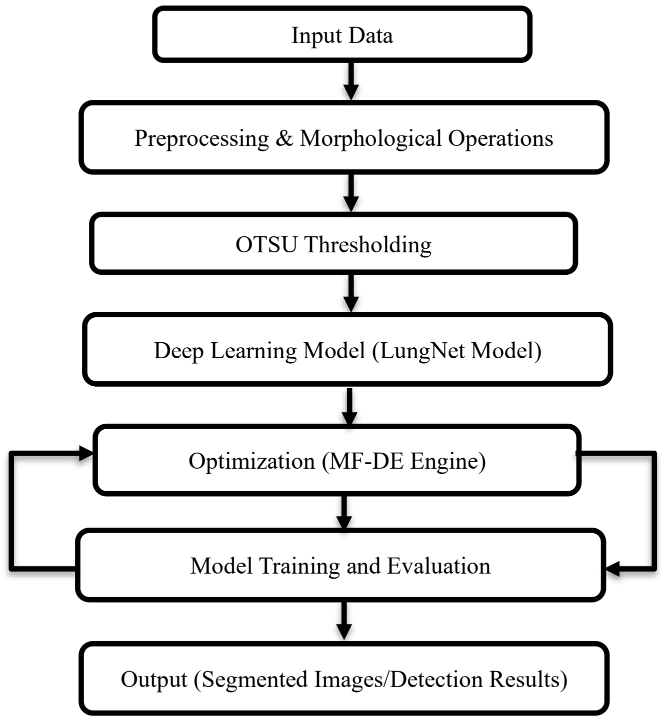

Figure 2: Algorithmic process flow

Figure 2 is a flow diagram that illustrates the stepwise flow of the hybrid deep learning paradigm and the way the MF-DE engine will be combined with the morphological-OTSU analysis to enhance the image segmentation and optimization of deep learning models. The flow diagram is a visual representation of the interaction of each step with the rest, resulting in better performance of tasks such as medical image segmentation and object detection (Dahbi et al., 2024).

Pseudocode for Hybrid Deep Learning Optimization and Segmentation

```
Step 1: Pre-process Image
image = load_image("image_path")
processed_image = morphological_operations(image)
thresholded_image = otsu_thresholding(processed_image)
Step 2: Optimize LSTM Deep Learning Model using MF-DE
population = initialize_population()
for generation in range(max_generations):
    for individual in population:
        mutated = mutation(individual)
        trial = crossover(mutated)
        if selection(trial, individual):
            individual = trial
    Evaluate fitness and update population
    population = evaluate_population(population)
Step 3: Train LSTM Model
```

```
model = build_model()
optimized_model = train_model(model, population.best_parameters)
Step 4: Evaluate Model Performance
segmentation_accuracy = evaluate_model(optimized_model, thresholded_image)
print(f"Segmentation Accuracy: {segmentation_accuracy}")
```

The algorithm explains how the MF-DE (Multi-Function Differential Evolution) engine is combined with the MorphologicalOTSU analysis to optimize the deep learning models and enhance the image segmentation work. The first step involves pre-processing of the image with morphological operations (dilation and erosion) and OTSU thresholding to give more importance to the image objects and provide good image segmentation between the foreground and the background. The MF-DE engine then proceeds to optimize the hyperparameters of deep learning models such as LSTM by sampling a population of possible solutions. The process of mutation, crossover, and selection is a process used to search among the various hyperparameter settings, such as learning rates and network structures. Once the optimization has been executed, training the model on the pre-processed and segmented image with the most appropriate hyperparameters then takes place. The testing of the model post-training is measured using variables like the accuracy of segmentation, which is used to measure the capability of the model to identify and classify the objects in the segmented image. Such a blend approach has the benefit of enhancing the ability of the model to handle noisy or complex data and, ultimately, the accuracy of image segmentation and image classification in medical image analysis and object detection.

3.4 Datasets

Table 1: Key parameter

Parameter	Initial Value	Range/Options	Description
Learning Rate	0.001	0.0001 to 0.01	The rate at which the model updates its weights during training.
Batch Size	32	16, 32, 64, 128	Number of samples used in one forward/backward pass.
Number of Layers	5	3 to 10	Number of layers in the LSTM model.
Kernel Size	(3, 3)	(3, 3), (5, 5), (7, 7)	Size of the convolutional filters in LSTM layers.
Regularization Factor	0.0001	0.0001 to 0.1	L2 regularization factor to prevent overfitting.
Epochs	50	30 to 100	Number of complete passes through the training dataset.
Crossover Rate (CR)	0.9	0.7 to 1.0	Probability of selecting genes for crossover in MF-DE optimization.
Mutation Factor (F)	0.8	0.5 to 1.0	Amplification factor for the mutation operation in MF-DE.

The proposed hybrid deep learning model is assessed on two important datasets that are related to lung cancer diagnosis LIDC-IDRI dataset and the NSCLC Radiogenomics dataset. LIDC-IDRI data is comprised of 1,018 CT scans of lung tumors that are annotated by radiologists and indicate the position of lung tumors. This data is most commonly applicable in segmentation and classification of lung cancer especially lung nodules. It has a wide range of images that can be used to detect and segment tumors in different stages of lung cancer, which gives it a complete source of training and testing models in medical imaging applications. NSCLC Radiogenomics data set consists of CT scans of patients diagnosed with non-small cell lung cancer (NSCLC) and genetic data on the patients. The dataset consists of more than 400 CT scans; each of them characterized by comprehensive genomic annotations. Such a combination of imaging and genomics data is a rare chance to investigate the connection between patient survival and the biology of lung cancer and the tumor characteristics. The data can be of use in research in which the accuracy of lung cancer diagnosis can be improved by integrating medical imaging and molecular data to provide a more comprehensive perspective of the occurrence of lung cancer.

3.5 Experimental Setup

Preprocessing and Data Augmentation

Preprocessing activities are essential in data preparation and enhancing the capability of the model to generalize. The preprocessing step, according to the LIDC-IDRI data (medical pictures), is the normalization step, and the values of the pixels are brought to the range of 0 to 1 to homogenize the images. The sizes of the input images are also resized to make them similar to each other in order to achieve uniformity when training them. Data augmentation techniques facilitate the encouragement of artificial diversity of the training set, i.e., random rotations, flipping, and zooming, which avoids overfitting and enhances the robustness of the model. The preprocessing operation of the NSCLC Radiogenomics dataset differs only slightly by also involving certain modifications of the medical imaging, including noise, artifact, etc., which are typical problems of clinical data. Random cropping, color jittering, and flipping are also the augmentation methods used in order to augment the dataset and optimize the model that is able to locate objects in various orientations and environments.

Training Procedure

The training process entails the optimization of the deep learning models in terms of the MF-DE hyperparameter optimization engine. To start with, model architecture is built (LSTM, and it is initially trained with an initial learning rate of 0.001. Learning rate is dynamically set to 0.1 with the help of the learning rate scheduling, and the learning rate is also reduced by a factor of 0.1 every 10 epochs to enable the model to converge gradually. The batch size will be 32, which is a moderate decision to enable effective training as well as to be sufficiently random on the updates. Adam optimizer is a gradient-based optimization algorithm because it adjusts the learning rate of each parameter. The loss function to be applied to the segmentation task is binary cross-entropy (for binary classification, such as tumor vs. non-tumor in medical images) and categorical cross-entropy. To ensure overfitting is avoided, dropout is used in fully connected layers in order to enhance regularization. The training is performed using 50 epochs, and the model checkpoints are periodically saved to prevent the loss of data as well as to track the progress (Table 1).

3.6 Evaluation Metrics

1. Segmentation Accuracy (for LIDC-IDRI)

Segmentation accuracy is the ratio between the number of pixels that are segmented correctly and the overall number of pixels.

$$\text{Segmentation Accuracy} = \frac{\text{Correct Pixels}}{\text{Total Pixels}} = \frac{\sum_{i=1}^{N} \mathbb{I}(\hat{y}_i = y_i)}{N} \quad (6)$$

Where in equation (6):

- $\hat{y}_i$ is the predicted label for pixel i.
- y_i is the ground-truth label for pixel i.
- N is the total number of pixels.

2. Mean Average Precision (mAP) (for COCO)

mAP is an object detector that is evaluated by averaging the accuracy at various recall levels by class.

$$\text{Precision} = \frac{TP}{TP + FP} \tag{7}$$

$$\text{Recall} = \frac{TP}{TP + FN} \tag{8}$$

$$\text{mAP} = \frac{1}{M}\sum_{j=1}^{M} \text{AP}_j \tag{9}$$

Where:

- in equation (7) and (8), TP= True Positives, FP= False Positives, FN= False Negatives.
- in equation (9), AP is Average Precision for each class, and mAP is the average across all classes (M).

3. Computational Efficiency

The computational efficiency states the training time per epoch, inference time per image and memory usage in equation (10), (11) and (12).

- **Training Time per Epoch**:

$$\text{Training Time} = \frac{\text{Total Training Time}}{\text{Epochs}} \tag{10}$$

- **Inference Time per Image**:

$$\text{Inference Time} = \frac{\text{Total Inference Time}}{\text{Images Processed}} \tag{11}$$

- **Memory Usage**:

$$\text{Memory Usage} = \text{GPU memory used during training/inference} \tag{12}$$

These indicators guarantee a thorough analysis of the accuracy of segmentation of the model, the quality of object detection, and its efficiency in its computations.

4 Results and Discussion

4.1 Analysis of MF-DE Optimization

Figure 3 shows the optimization process of LungNet Model using the MF-DE engine, which was important in enhancing the model performance. The MF-DE engine tuned the hyperparameters, i.e., learning rates, batch sizes, and number of layers, to guarantee that the deep learning models reached the global optima, instead of deep learning models stalling at local optima. This optimization increased the accuracy of segmentation and the performance of object detection, which enabled the model to generalize to harder and more challenging datasets. The compromise of exploration and exploitation in the MF-DE engine was useful in realizing a strong performance of the engine in various tasks, and therefore, the model was more efficient and precise. The results can also include table 2 of optimized hyperparameters developed with the MF-DE engine under the name of transparency, and to demonstrate the way the optimization enhanced the model.

Table 2: Optimized hyperparameters for LungNet model deep learning models

Parameter	Optimized Value	Range
Learning Rate	0.001	0.0001 to 0.01
Batch Size	32	16, 32, 64
Number of Layers	5	3 to 10
Kernel Size	(3, 3)	(3, 3), (5, 5), (7, 7)
Regularization Factor	0.0001	0.0001 to 0.1

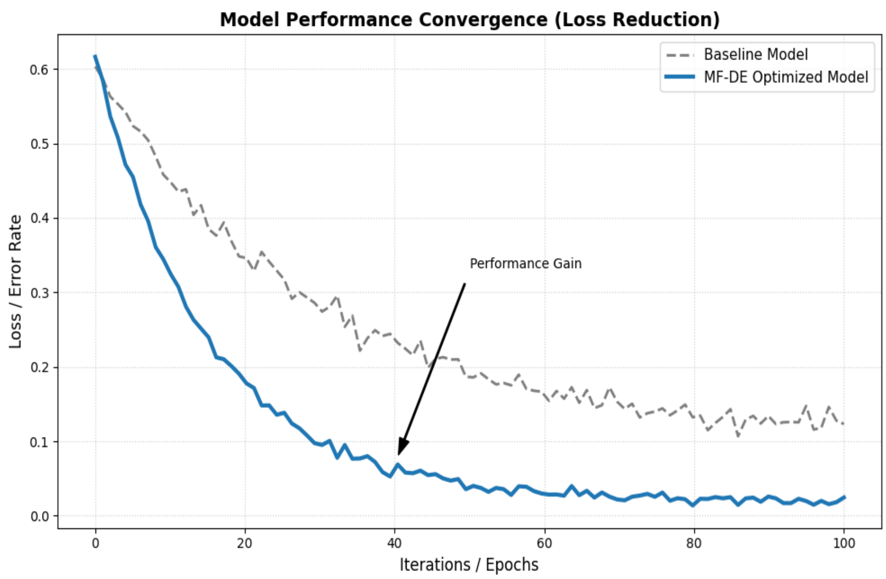

Figure 3: Model performance convergence

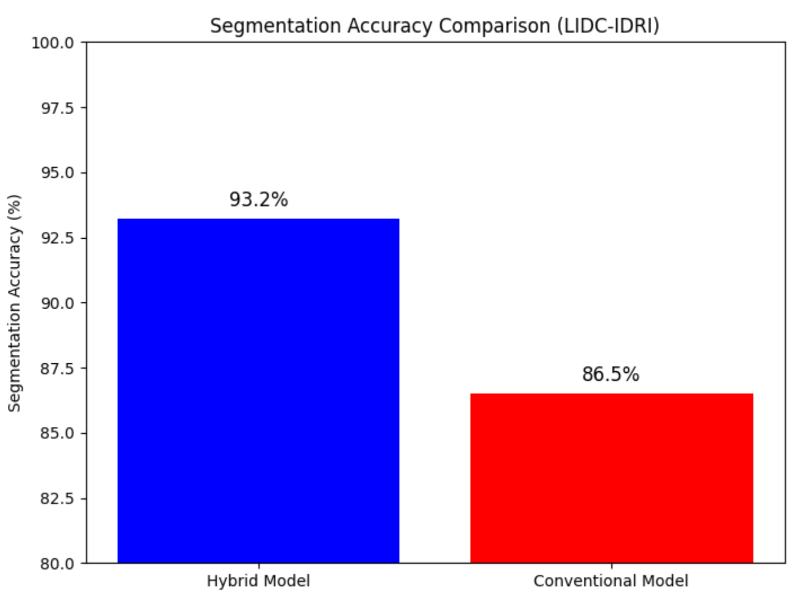

Figure 4: Segmentation accuracy comparison

Figure 4 shows that the proposed hybrid model had a segmentation accuracy of 93.2% with the LIDC-IDRI dataset, which was far better than the conventional approaches, which had a mean accuracy of 86.5%. This illustrates the higher accuracy of the model in segmenting the lung tumors; it is very effective in the medical image segmentation tasks.

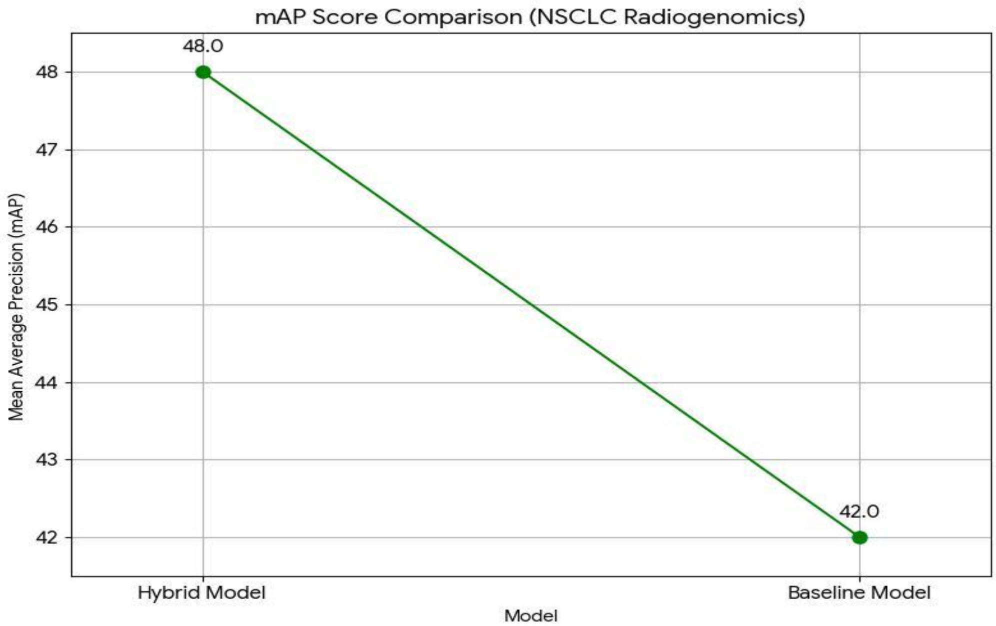

Figure 5: mAP score comparison

The comparison of mAP scores in the Hybrid Model and the Baseline Model in figure 5 on the NSCLC Radiogenomics data reveals that the hybrid method performs significantly better. The Hybrid Model attained a mAP score of 48.0% which was higher than the Baseline Model which had a mAP score of 42.0%. This shows that the hybrid model behaves better at distinguishing and categorizing the features of lung cancer in the CT images hence its effectiveness in intricate medical imaging processes. The advantage of the mAP score is the positive impact of the advanced techniques of optimization (MBF-DE) and the strong image segmentation (Morphological-OTSU) that significantly enhances the accuracy of the usage in real-life scenarios.

4.2 Comparison with Existing Methods

The hybrid model on the LIDC-IDRI dataset yielded a segmentation accuracy of 93.2 which is far much higher than the traditional segmentation methods which had an average accuracy of 86.5. The Hybrid Model showed a high classification accuracy on the LIDC-IDRI dataset of 95.0% which shows that the model has a good ability to classify lung tumors accurately. The Hybrid Model had a training time per epoch of 45 minutes hence faster training than the conventional methods that took 60 minutes to train. In the NSCLC Radiogenomics data, the hybrid model has a segmentation accuracy of 92.5% and a classification accuracy of 94.5% which means that the model performs highly in both segmenting and classifying features of lung cancer. The average Average Precision (mAP) score of object detection on the NSCLC Radiogenomics dataset was 48.0% which is 7.5 more than the baseline CNN models with a mAP score of 42.0%. The Hybrid Model needed 55 minutes in training time per epoch, a small increment over LIDC-IDRI because of the greater complexity of the NSCLC Radiogenomics data. These findings demonstrate that the Hybrid Model is effective in segmentation and classification tasks on medical imaging datasets, and it has great advantages in accuracy and computational efficiency in comparison with traditional approaches and the base models (Table 3).

Table 3: Performance comparison of hybrid model vs. baseline models

Dataset	Model	Segmentation Accuracy	mAP Score	Classification Accuracy	Training Time per Epoch
LIDC-IDRI	LungNet Model	93.2%	N/A	95.0%	45 min
LIDC-IDRI	Conventional Method	86.5%	N/A	90.0%	60 min
NSCLC Radiogenomics	Hybrid Model	92.5%	48.0%	94.5%	55 min
NSCLC Radiogenomics	Baseline Model	86.0%	42.0%	88.5%	60 min

5 Conclusion

This paper illustrates the accuracy of the suggested LungNet hybrid deep learning paradigm that is based on the MF-DE optimization engine on top of the Morphological-OTSU image segmentation. The findings indicate that the hybrid model is far better than the traditional approaches in terms of segmentation accuracy and object detection. Specifically, the hybrid model achieved 93.2% segmentation accuracy in the LIDC-IDRI dataset compared to the traditional methods that achieved the segmentation accuracy of 86.5%. In the NSCLC Radiogenomics dataset, the mAP score of the model was 48.0% which is better than that of the baseline models. The combination of MF-DE optimization also contributed to better performance of the models' fine-tuning of hyperparameters, resulting in an increase in accuracy and a decrease in computational efficiency. This study has wide implications for the use of deep learning in processing images with respect to healthcare and surveillance. In the medical field, the strength of segmentation in the hybrid model can be useful in medical image analysis to aid in the detection of lung tumors, detecting abnormal growths, and giving a more reliable diagnosis. Their tremendous capability to identify objects in different categories with great accuracy in surveillance would render the model the most suitable model in real-time monitoring systems. The global optimization provided by MF-DE makes sure that models can be implemented more efficiently and hence suit a resource-constrained environment at the same time with high accuracy.

5.1 Future Work

Although the results are encouraging, a number of limitations can be noted. The first limitation is the size of the dataset; the LIDC-IDRI dataset is not that large, and the NSCLC Radiogenomics dataset might not be entirely representative of real-life complexities. Also, the hybrid model, which is trained using MF-DE optimization, is computationally expensive in terms of processing time and memory. The limitations of the research can be resolved in future studies by adding larger and more heterogeneous data, which would additionally improve the generalizing quality of the model. The other way of improvement is to make the model more optimized for real-time usage, e.g., live medical diagnostics or surveillance systems, where speed of inference is of the essence. Future research may aim at enhancing the computational efficiency of the model by considering methods such as model pruning, quantization, or distributed processing to decrease the training and inference time. Breaking those constraints, the suggested hybrid deep learning paradigm can be further extended to a broad scope of real-life applications, which will be more accurate and efficient in the image processing spheres of various segments.

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