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An optimal model for classification of lung cancer using grey wolf optimizer and deep hybrid learning

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ABSTRACT

In recent years, metaheuristic methods have shown major advantages in the field of feature selection due to its comprehensibility and possible extensive search competence. However, the majority of evolutionary computation-based feature selection algorithms in use today are wrapper approaches, which are expensive to compute, particularly for extensive biomedical data. Developing an effective evaluation strategy is crucial for significant reduction of computational cost. The proposed framework extracts deep feature from ResNet-50 and VGG-16 based convolutional neural models with initial segmentation process based on marker-controlled watershed method. Next the feature reduction is a two-fold approach with principal component analysis applied to reduce the dimensionality of large feature space from convolutional neural network (CNN) models as first step. The second step is optimal feature subset selection using a swarm intelligence method referred as modified grey wolf optimization. Finally, the selected feature subset is fed to various machine learning classifiers. The experimental result reveals that the proposed algorithm outperforms the other state-of-the-art methods with classification accuracy of 96.56%, thus upholding the dependability of the approach.

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1. INTRODUCTION

According to GLOBOCAN 2020 statistics released by the international council for research on cancer, lung cancer remained the leading cause of cancer-related fatalities. Lung cancer claimed the lives of around 1,796,144 persons in 2020, or 18% of all cancer-related fatalities [1]. Early detection of lung cancer is a successful strategy to lower mortality, increasing patient 5-year survival rates from 18.6% to 56% [2]. However, a lot more clinically relevant computerized tomography (CT) scans have been produced recently, which has put pressure on clinicians due to the surge in lung cancer incidence and the wider public concern on health. Due to variations in the diagnosis and treatment levels of doctors with diverse levels of seniority, different physicians are likely to reach different diagnostic findings for the same CT scan. The lung computer aided diagnosis (CAD) system can help physicians acquire objective diagnostic findings and significantly reduce missing and erroneous nodule detection [3]. Image preprocessing, lung segmentation, region of interest, feature extraction, and lung cancer classification are often included in the traditional lung CAD system. The lung CAD system relies on feature extraction as a critical component. Traditional CAD systems primarily rely on the expertise of medical professionals; extract subordinate visual features from lung nodule images, such as texture specifics and morphological luminance, and incorporate them into a machine learning based classifier for detection [4], [5].

Deep learning has superseded traditional methods for extracting features from medical imaging data in recent years. It can extract multiple feature levels from various depth layers, making it better suitable for the processing and analysis of medical pictures. Due to its superior performance, the convolutional neural network (CNN) offers the broadest application range among them [6]. The characteristics that a single model can obtain can approximate visual data to some extent, but they may be deficient in showing some subtleties. The ultimate choice can benefit from feature fusion, which can generate a lower-dimensional and more relevant feature vector set from various feature sets. Due to high dimensional data involved in the field of biomedical image processing, existing feature selection methods leads to high computational cost. Owing to its simplicity and potential for global search strategy, evolutionary algorithms [7], [8] have demonstrated significant advantages in the field of feature selection in recent years. When fed with "less" data, the final classification or grouping layer of a deep learning model powered by fully connected neural network layers may overfit. Additionally, these models typically call for the irrational use of computing resources that are uncommon in conventional machine learning techniques. To overcome these limitations, deep hybrid learning (DHL) model [9] have emerged, which merges various technologies with magnificent performance, primarily based on deep learning-based feature extraction and traditional machine-based learned classifiers are presented in cascade, boosting the model's flexibility in classification performance.

This work, which is based on the DHL model, focuses on five crucial lung CAD system algorithms: segmentation, feature extraction, feature fusion, optimal feature selection and classification.

- First the segmentation of lung CT scans is performed using marker-controlled watershed method.
- Deep features are extricated from ResNet-50 and VGG-16 models and dimensionality of the features extracted is extensive and thus principal component analysis (PCA) is used to reduce the dimensionality while retaining the significantly discriminant features. It also helps in the identification of related attribute values, which helps identify a particular subset of salient elements that might improve recognition rate.
- The generated feature subset enables speedy convergence and minimizes computation when used as the input to the grey wolf optimizer (GWO).
- The grey wolf optimizer (GWO), an evolutionary optimization algorithm inspired by nature, is used to select best attributes, which are then fed to a different machine learning classifiers, including the k-Nearest Neighbor, support vector classifier, decision tree, gradient boosting, and random forest classifiers.

The remainder of the paper is organised as shown in: section 2 discusses the proposed methodology and various algorithms used. Section 3 discusses the details of dataset, simulation and analysis of results. The conclusion and scope for future work is discussed in section 4.

2. METHOD

The framework of the proposed deep hybrid learning model is as shown in Figure 1. The model has preprocessing, segmentation, feature extraction, featured fusion methods. The fused features are optimized using evolutionary methods and fed to supervised based classifiers.

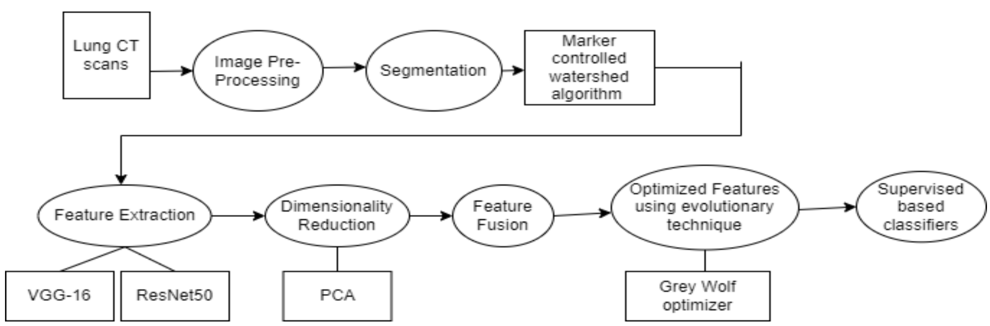


Figure 1. Proposed methodology

2.1. Segmentation

The marker-controlled watershed [10] segmentation method has been proven to be a reliable and flexible method for dividing objects with closed outlines when the boundaries are represented by ridges. The marker image used for watershed segmentation is a binary image with either standalone marker points or larger marker regions, where each associated marker is positioned inside an object of interest. This can enhance the precision of radiologist's diagnosis.

2.2. Deep feature extraction
The arduous process of extracting features from a huge dataset might include human biases, lowering the quality of the features and ultimately impairing the classification task. Greater rates of misclassification might be the result of the extraction of duplicate features. The deep features from CNN classifiers [11] are therefore extracted in this work. By utilizing backpropagation to obtain the essential characteristics, deep learning models simplify the laborious process of using hand-crafted features. Using VGG-16 and ResNet-50, we retrieved features from the ultimate layer of the models for the present research.

2.2.1. VGG-16
The inclusion of 3*3 convolution layers, which significantly improved network performance while making the network deep, is one of the primary features of visual geometry group (VGG) nets [12]. The full net is made up of 3*3 responsive filters, with strides of 1. Because it uses more memory in these circumstances, local response normalization (LRN) is not employed in VGG nets. A very large number of weight layers can be used because of small sized convolution filters supported by VGG, which leads to increase in performance. The input has a shape of 224×224×3. In the present work, VGG-16 model is fine tuned including stochastic gradient descent (SGD) optimizer and rectified linear unit (ReLU) activation function [13].

2.2.2. ResNet-50
The ResNet-50 design [14] has incorporated residual skip connections that facilitate network training. Because of the embedding of the skip connections, very deep networks may be handled with little computational expense, and the gradient vanishing problem is also resolved at the same time. The ResNet-50 model has 224*224*3 sized inputs, an adam optimizer, and sigmoid activation function.

2.3. Dimensionality reduction and feature fusion
In the proposed approach, a feature map of 7*7*512 is obtained after the stack of convolution and max-pooling layer from VGG-16 model. Next output is flattened to produce 1*25088 feature vector. The feature layer of 7 * 7 *2048 is obtained by feature extraction from Stage2 to Stage5 in ResNet-50 and the last full connection layer is eliminated. The number of network parameters is significantly reduced when the collected CT image features are tiled by adding an average pooling layer. The features excerpted from ResNet-50 and VGG-16 are huge with 25,088 and 1,00,352 features respectively. Hence principal component analysis (PCA) is applied on each model to procure nominal feature subset from the fused set. PCA with threshold value set to 99 is used, which means that 99% of the data variance in the reduced feature vector is maintained. The reduced features from both the models are fused.

2.4. Optimal feature selection
In the past two decades, there has been a phenomenal growth of evolutionary optimization algorithms that are inspired by nature. These algorithms are known to give the best results for the considered challenges. It has been observed that researchers use bio-inspired meta-heuristic algorithms such the genetic algorithm [15], [16], ant colony optimization [17], particle swarm optimization [18], bacteria foraging algorithm [19], particle swirl algorithm [20] and others to identify the best solution to a variety of issues. The benefits of these algorithms are pliability, evasion of local and global optima, and quicker convergence. These algorithms were followed by the creation of GWO, which was motivated by the leadership and natural hunting techniques of gray wolves. The top tier of their rigid social structure, the alpha wolf, is followed by the grey wolves. The dominant wolf in the pack may not always be the strongest or fittest, but capable of regulating the entire pack. The alpha wolves make the major choices, often assisted by the beta wolves.

They play a significant role in sustaining the pack as a whole and are typically the fittest contenders for alpha if the alpha gets old or feeble. The wolves at next lower level are classified as deltas and they are particularly vital to the pack’s decision making and other crucial processes. Omega is the last and least significant group in the pack and frequently served as scapegoat. Thus, a dominance hierarchy is used to build the whole pack. Below is the description of the mathematical model for the optimization phases to their hunting method.

In the mathematical design of GWO, alpha ($\propto$) is regarded as the top wolf. The second and third best wolves, respectively, are beta (β) and delta (δ). Omega (ω) is the phrase used to refer every other wolf [21]. Encircling prey should be the initial step in the wolf packs hunting strategy. As shown in (1) to (4) demonstrate how the pack may update its location in relation to the prey at any random location where iter represents the most recent iteration.

$$\vec{X} = \left|\overrightarrow{M}.\ \overrightarrow{Y_p}(iter) - \vec{Y}\ (iter)\right| \tag{1}$$

$$\vec{Y}(iter+1) = \overrightarrow{Y_p}(iter) - \vec{N}.\vec{X} \quad (2)$$

The position of the prey is indicated by $\overrightarrow{Y_p}$, the position of a grey wolf as $\overrightarrow{Y_p}$, and M and N are coefficient vectors that are calculated using:

$$\vec{N} = 2\vec{d}.\overrightarrow{rand_1} - \vec{d} \quad (3)$$

$$\vec{M} = 2.\overrightarrow{rand_2} \quad (4)$$

here, $rand1$ and $rand2$ are randomly produced vectors in [0, 1]. Iteratively, components d linearly decreases from 2 to 0 over time. The pack's grey wolves of the, are more knowledgeable about the location of potential prey. The first three top solutions are therefore preserved, which places stress on the remaining search agents to change their rankings to match the top three as per the equations given from (5) to (11):

$$\overrightarrow{X_\propto} = |\vec{M}_1.\vec{Y}_\propto - \vec{Y} \quad (5)$$

$$\overrightarrow{X_\beta} = \left|\vec{M}_2.\vec{Y}_\beta - \vec{Y}\right| \quad (6)$$

$$\overrightarrow{X_\delta} = |\vec{M}_3.\vec{Y}_\delta - \vec{Y} \quad (7)$$

$$\overrightarrow{Y_1} = \vec{Y}_\propto.\vec{N}_1 - \vec{X}_\alpha \quad (8)$$

$$\overrightarrow{Y_3} = \vec{Y}_\delta.\vec{N}_3 - \vec{X}_\delta \quad (9)$$

$$\vec{Y}(\text{iter+1})=\frac{\overrightarrow{y1}+\overrightarrow{y2}+\overrightarrow{y3}}{3} \quad (10)$$

where Xα, Xβ and Xδ are the first three top solutions found in the pack at a certain iteration iter. The last stage involves GWO changing the parameter z that controls how exploitation and exploration are adjusted. The parameter d is changed according to (12) per iteration, ranging from 2 to 0.

$$\vec{z} = 2 - it\frac{2}{Max_{it}} \quad (12)$$

Where it is the current iteration and Maxit is the maximum number of iterations permitted for optimization.

2.4.1. Psuedocode of the grey wolf optimizer

The pseudocode of grey wolf optimizer is dicussed in this section. Popoulation size, maximum iterations, lower and upper curb are initialized. In GWO, α, β, and δ lead ω wolves toward the areas of the search space that are promising for finding the optimal solution.

```
Begin
Initialize ps, mi, low and up where
ps: size of population;
mi: maximum iterations;
low: lower curb;
ub: upper curb;
Setup the initial point of grey wolves with low and ub;
Set a , N⃗, M⃗;
Assess the strength of each grey wolf;
α = the fittest wolf;
β= the second finest wolf;
δ = the third finest wolf;
While k<mi
   for i=1 : ps
     Revise the locale of the current grey wolf by Eq. (11);
  end for
  Revise a, N⃗, M⃗;
 Evaluate the fitness of all grey wolves;
  Revise α , β, δ;
  k=k+1;
end while
```

```
Return α ;
End
```

2.5. Machine learning classifiers

The last step is to fit the best features to the classifiers for the categorizing task after selecting the finest features. To train the network, the retrieved features are used in the learning process. This hybridized model employs powerful machine-learning techniques to exploit their full potential for classification task. A radial basis function-based support vector classifier [22], decison tree, random forest, gradient boosting, k-nearest neighbor classifier [23] are used as classifiers.

3. RESULTS AND DISCUSSION

3.1. Dataset and Simulation details

The primary data source set is the Kaggle data science bowl (DSB) 2017 patient lung CT scan dataset [24]. Total 1211 CT scans are considered, which is partitioned into a training set with a size of 968 and a test set with a size of 243. The data for each patient comprises of a CT scan and a label (0 for no cancer, 1 for cancer). The CT scan data for each patient comprises of a varying number of images (usually between 100 and 400, with each image being an axial slice) at a resolution of 512*512 pixels. The model is experimented using google colaboratory with Python 3 Google compute engine backend (GPU), CUDA Version: 11.2, Nvidia smi. The values for various parameters of GWO used in proposed method is as shown in Table 1.

Table 1. Parameter setting for the GWO

Parameter	Value
Iterations	100
Wolves	5
Dimension	20
Search domain	[0,1]
lb	-1.28
ub	1.28

3.2. Evaluation metrics

The different evaluation metrices considered are accuracy, precision, recall and F1-score. Total accuracy is the ratio of correctly labelled cancer subjects to total cancer subjects. It is calculated as stated in (13). Precision is the ratio of correctly positive labelled cancer subjects to total positive labelled cancer subjects. It is as stated in (14). Recall is the ratio of positive labelled cancer subjects to all cancer subjects. It is as stated in (15). F1 Score is best if there is some sort of balance between precision (p) and recall (r) in the system. F1 score is stated in (16).

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \tag{13}$$

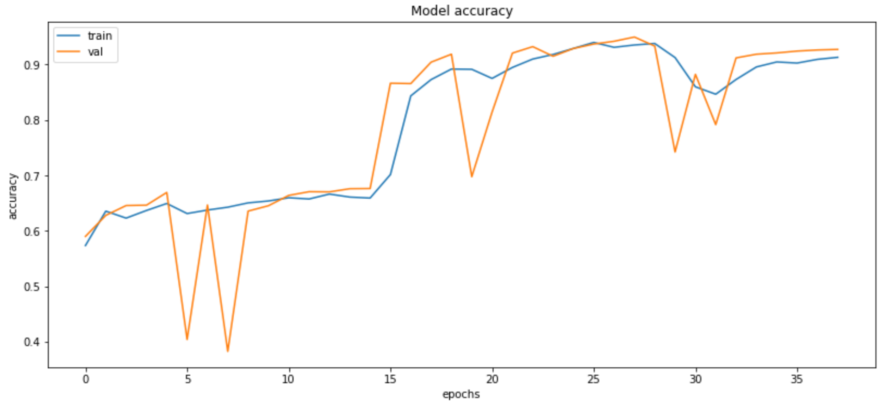
$$Precision = \frac{TP}{TP+FP} \tag{14}$$

$$Recall = \frac{TP}{TP+FN} \tag{15}$$

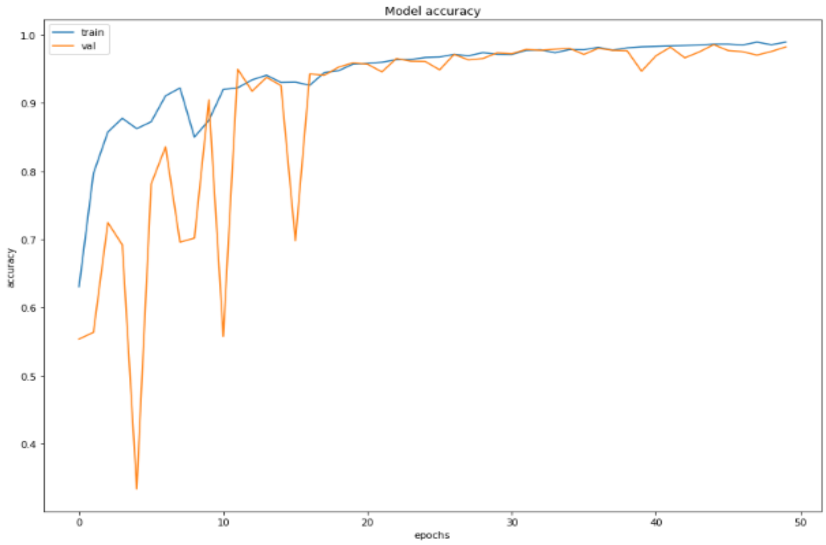
$$F1-Score = \frac{2*Recall*Precision}{Recall+Precision} \tag{16}$$

3.3. Graphs

The model accuracy (Figure 2) of VGG-16 and ResNet-50 used for feature extraction is 96% and 98% respectively as represented in Figure 2(a) and 2(b). The evaluation metrics for different supervised learning classifiers used in the proposed method are compared with train-test split ratio of 60:40, 70:30, and 80:20 as shown in Figure 3, Figure 4 and Figure 5 respectively. The proposed model outperforms with accuracy of 96.56% when compared with existing approaches as shown in Table 2.



(a)



(b)

Figure 2. Model accuracies, (a) accuracy of VGG-16 and (b) accuracy of ResNet-50 model

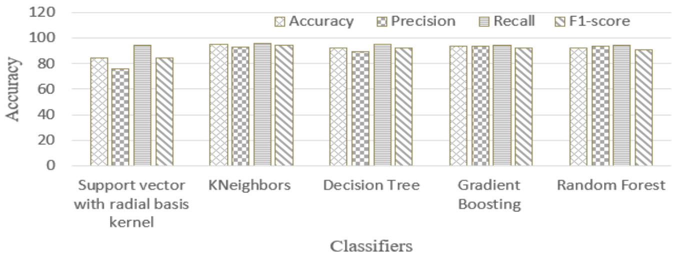


Figure 3. Key performance indicators for classifiers with 60:40 train and test ratio

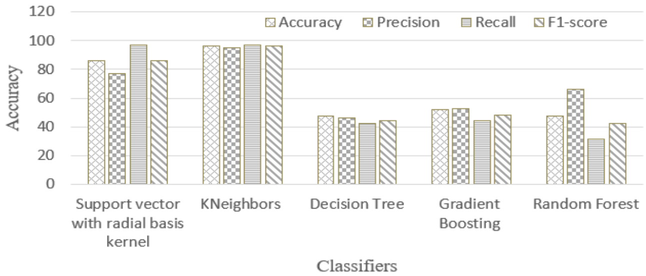


Figure 4. Key performance indicators for classifiers with 70:30 train and test ratio

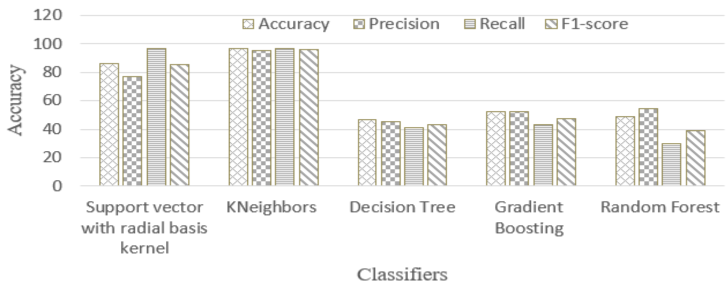


Figure 5. Key performance indicators for classifiers with 80:20 train and test ratio

Table 2. Comparison of proposed model with state-of-art models

References	Year	Methods	Accuracy %
Shi *et al*. [25]	2019	VGG-6 features+ SVM classifier	87.8
Mastouri *et al.* [26]	2020	Two-stream CNNs (VGG-16 and VGG-19) + SVM	91.99
Chang *et al.* [27]	2021	handcrafted features + VGG-16 + Cascade + Hybrid Swarm Intelligence Optimization for MKL-SVM	95.88
Proposed model	2022	Fused features of VGG-16 and ResNet-50 +PCA+GWO+k-Nearest Neighbor	96.56%

4. CONCLUSION

This paper proposes a lung computer aided diagnosis system based on deep hybrid learning model, which sights on classification of lung cancer. The focal points of this model are segmentation, feature extraction, feature fusion, optimal feature selection. First in order to excerpt the features VGG-16 and resnet-50 models are used. Then, through PCA dimensionality reduction and features fusion methods, powerful feature expression potentiality and low-aspect attributes are obtained. Finally, the GWO algorithm's is employed to address the feature selection problem due to its few control parameters, adaptable exploration behavior and ease of use. The optimal feature set is trained and tested with various supervised learning classifiers. Using the kaggle DSB 2017, the experiment reveals that combination of fused VGG-16 and ResNet-50 with grey wolf optimizer and k-nearest neighbor classifier outperforms with accuracy of 96.56% compared to state of art models. The hybrid approach of proposed model has strong reliability. It can successfully eliminate false detection and misclassification by ensuring good classification accuracy. In the future, research can be extended by focussing on building a lightweight network with features excerpted using model pruning technologies. Additionally, sparse statistical knowledge can be used to strengthen the feature fusion method and boost the lung CAD system's efficiency.

REFERENCES

[1] J. Ferlay *et al.*, "Cancer statistics for the year 2020: An overview," *International Journal of Cancer*, vol. 149, no. 4, pp. 778–789, Aug. 2021, doi: 10.1002/ijc.33588.

[2] R. Mastouri, N. Khlifa, H. Neji, and S. Hantous-Zannad, "Deep learning-based CAD schemes for the detection and classification of lung nodules from CT images: A survey," *Journal of X-Ray Science and Technology*, vol. 28, no. 4, pp. 591–617, Aug. 2020, doi: 10.3233/xst-200660.

[3] A. O. de Carvalho Filho, A. C. Silva, A. C. de Paiva, R. A. Nunes, and M. Gattass, "Computer-aided diagnosis of lung nodules in computed tomography by using phylogenetic diversity, genetic algorithm, and SVM," *Journal of Digital Imaging*, vol. 30, no. 6, pp. 812–822, Dec. 2017, doi: 10.1007/s10278-017-9973-6.

[4] C. F. J. Kuo, J. Barman, C. W. Hsieh, and H. H. Hsu, "Fast fully automatic detection, classification and 3D reconstruction of pulmonary nodules in CT images by local image feature analysis," *Biomedical Signal Processing and Control*, vol. 68, p. 102790, Jul. 2021, doi: 10.1016/j.bspc.2021.102790.

[5] X. Pang, Z. Zhao, and Y. Weng, "The role and impact of deep learning methods in computer-aided diagnosis using gastrointestinal endoscopy," *Diagnostics*, vol. 11, no. 4, p. 694, Apr. 2021, doi: 10.3390/diagnostics11040694.

[6] J. Manhas, R. K. Gupta, and P. P. Roy, "A review on automated cancer detection in medical images using machine learning and deep learning based computational techniques: challenges and opportunities," *Archives of Computational Methods in Engineering*, vol. 29, no. 5, pp. 2893–2933, Aug. 2022, doi: 10.1007/s11831-021-09676-6.

[7] R. Cheng and Y. Jin, "A competitive swarm optimizer for large scale optimization," *IEEE Transactions on Cybernetics*, vol. 45, no. 2, pp. 191–204, Feb. 2015, doi: 10.1109/TCYB.2014.2322602.

[8] S. Gu, R. Cheng, and Y. Jin, "Feature selection for high-dimensional classification using a competitive swarm optimizer," *Soft Computing*, vol. 22, no. 3, pp. 811–822, Feb. 2018, doi: 10.1007/s00500-016-2385-6.

[9] D. Sengupta, S. N. Ali, A. Bhattacharya, J. Mustafi, A. Mukhopadhyay, and K. Sengupta, "A deep hybrid learning pipeline for accurate diagnosis of ovarian cancer based on nuclear morphology," *PLoS ONE*, vol. 17, no. 1 January, p. e0261181, Jan. 2022, doi: 10.1371/journal.pone.0261181.

[10] P. Tripathi, S. Tyagi, and M. Nath, "A comparative analysis of segmentation techniques for lung cancer detection," *Pattern Recognition and Image Analysis*, vol. 29, no. 1, pp. 167–173, Jan. 2019, doi: 10.1134/S105466181901019X.

[11] S. Kothari, S. Chiwhane, S. Jain, and M. Baghel, "Cancerous brain tumor detection using hybrid deep learning framework," *Indonesian Journal of Electrical Engineering and Computer Science (IJEECS)*, vol. 26, no. 3, p. 1651, Jun. 2022, doi: 10.11591/ijeecs.v26.i3.pp1651-1661.

[12] K. Simonyan and A. Zisserman, "Very deep convolutional networks for large-scale image recognition," 2015, doi: 10.48550/arXiv.1409.1556.

[13] Z. Zhu, H. Sun, and C. Zhang, "Effectiveness of optimization algorithms in deep image classification," *arxiv preprints*, Oct. 2021, [Online]. Available: http://arxiv.org/abs/2110.01598.

[14] K. He, X. Zhang, S. Ren, and J. Sun, "Deep residual learning for image recognition," in *2016 IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, Jun. 2016, vol. 2016-Decem, pp. 770–778, doi: 10.1109/CVPR.2016.90.

[15] E. Bonabeu, M. Dorigo, and G. Theraulaz, *Swarm intelligence: from natural to artificial systems*. Oxford University Press, 1999.

[16] I. J. S. Jeya and J. Suganthi, "Watermarking relational databases using genetic algorithm with ring crossover technique," *International Review on Computers and Software*, vol. 9, no. 3, pp. 456–467, 2014.

[17] M. Dorigo, M. Birattari, and T. Stutzle, "Ant colony optimization," *IEEE Computational Intelligence Magazine*, vol. 1, no. 4, pp. 28–39, Nov. 2006, doi: 10.1109/MCI.2006.329691.

[18] J. Kennedy and R. Eberhart, "Particle swarm optimization," in *Proceedings of ICNN'95 - International Conference on Neural Networks*, 1995, vol. 4, pp. 1942–1948, doi: 10.1109/ICNN.1995.488968.

[19] X. Gan and B. Xiao, "Improved bacterial foraging optimization algorithm with comprehensive swarm learning strategies," in *Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)*, vol. 12145 LNCS, 2020, pp. 325–334.

[20] S. Menser and J. Hereford, "A new optimization technique," in *Proceedings of the IEEE SoutheastCon 2006*, 2006, vol. 2006, pp. 250–255, doi: 10.1109/second.2006.1629359.

[21] S. Mirjalili, S. M. Mirjalili, and A. Lewis, "Grey wolf optimizer," *Advances in Engineering Software*, vol. 69, pp. 46–61, Mar. 2014, doi: 10.1016/j.advengsoft.2013.12.007.

[22] S. S. Reddy, N. Pilli, P. Voosala, and S. R. Chigurupati, "A comparative study to predict breast cancer using machine learning techniques," *Indonesian Journal of Electrical Engineering and Computer Science*, vol. 27, no. 1, p. 171, Jul. 2022, doi: 10.11591/ijeecs.v27.i1.pp171-180.

[23] P. Chaturvedi, A. Jhamb, M. Vanani, and V. Nemade, "Prediction and classification of lung cancer using machine learning techniques," *IOP Conference Series: Materials Science and Engineering*, vol. 1099, no. 1, p. 012059, Mar. 2021, doi: 10.1088/1757-899X/1099/1/012059.

[24] Kaggle, "Data science bowl 2017," 2017. [Online]. Available: https://www.kaggle.com/c/data-science-bowl-2017.

[25] Z. Shi *et al.*, "A deep CNN based transfer learning method for false positive reduction," *Multimedia Tools and Applications*, vol. 78, no. 1, pp. 1017–1033, Jan. 2019, doi: 10.1007/s11042-018-6082-6.

[26] R. Mastouri, N. Khlifa, H. Neji, and S. Hantous-Zannad, "A bilinear convolutional neural network for lung nodules classification on CT images," *International Journal of Computer Assisted Radiology and Surgery*, vol. 16, no. 1, pp. 91–101, Jan. 2021, doi: 10.1007/s11548-020-02283-z.

[27] J. Chang, Y. Li, and H. Zheng, "Research on key algorithms of the lung CAD system based on cascade feature and hybrid swarm intelligence optimization for MKL-SVM," *Computational Intelligence and Neuroscience*, vol. 2021, pp. 1–16, Sep. 2021, doi: 10.1155/2021/5491017.

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