A Hybrid Particle Swarm Optimization (PSO) and Sine Cosine Algorithm (SCA) for Feature Selection in Lung Cancer Detection

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Abstract:

Feature selection is known to significantly improve the performance of the machine learning approach in cases of lung cancer. This research presents a PSO-SCA fusion feature selection mechanism. The proposed approach combines the advantage of the global search capacity of SCA with the local optimization capabilities of PSO to avoid premature convergence. The performance of the proposed hybrid PSO-SCA was tested using public lung cancer datasets with SVM and k-NN as benchmark classifiers. The experiments also showed a marked enhancement in the classification rate against the separate approaches as PSO, SCA, GA, as well as ACO and other feature selection methodologies. Using the SVM classifier, the proposed hybrid model of PSO-SCA yielded an overall classification accuracy of 92.8% and was found to be superior to the algorithms in terms of accuracy, precision, recall, and F1-score. It was also observed that the method proposed in this paper has also offered better computational efficiency with fewer iterations to achieve convergence. These findings show that the PSO-SCA technique can be applied in the practical diagnostic domain.

Keywords: Lung Cancer Detection, Particle Swarm Optimization, Sine Cosine Algorithm, Feature Selection, Hybrid Algorithms, Machine Learning.

1. Introduction

Even today, lung cancer is one of the most common and deadly cancers in the world, causing 1.8 million deaths every year [1]. Delay in diagnosis is the primary reason for low survival and positive outcomes; however, determining the presence of lung cancer in the early stages is a daunting task because of the intricacy and the amount of medical information. CT scans and X-rays as well as clinical patients' data contribute to the lung cancer dataset [2, 3]. Feature selection is necessary to cut down a large dataset's dimensionality, increase the comprehensibility of models developed, as well as work on classification efficiency, and therefore become a necessary process for medical interpretations [4]. Since the data set includes quite many attributes, it is seen that the feature space is high, and hence one of the features used effectively in the feature selection is particle swarm optimization (PSO). Therefore, PSO has been widely used owing to its simplicity and the fact that it can quickly utilize swarm intelligence to search for solutions in the solution space [5]. The advantages of both the PSO and GA incorporated in the hybrid model enabled shorter make transitions between the exploitation and exploration cycles, leading to increased performance. The advantage of this improvement, however, is that the hybridization with GA increases operational costs and thus waste for the larger datasets. As regards lung cancer diagnosis, as a result, more attention has been paid in recent research to the application of classical optimization methods to the feature selection problem, in particular, for medical diagnostics [3, 6].

Moreover, using PSO is sometimes found to be difficult to obtain a better solution. To mitigate this problem, researchers went for hybrid solutions that combine PSO and other methods [7]. In this respect, the Sine Cosine Algorithm (SCA) shows great potential as it helps in localizing the solutions with the aid of sine and cosine functions, making it easier to improve the search space [7].

In this study, a hybrid PSO-SCA approach is applied for feature selection in lung cancer detection. The aim is to apply the advantages of both approaches and improve the results of lung cancer classification models by choosing the most relevant features from high-dimensional datasets when using PSO for global searches and SCA for local optima avoidance. This method was then adopted or applied to open-source lung cancer datasets, and the classification accuracy, precision, recall, and F1 were determined. Classification with SVM and k-NN classifiers was done to compare the performance of the proposed feature selection method. The performance of the proposed method is also compared with the benchmark lung cancer datasets to show a classical enhancement of classification rate than the traditional procedure. A clear observation of the above experimental results is that the PSO-SCA hybrid is superior to standalone PSO and SCA as well as to other baseline feature selection methods such as GA and ACO.

2. Previous related studies

In the past few years, a lot of effort has been made into the diagnosis of lung cancer with the application of machine learning and optimization methods [4, 8, 9], paying attention in particular to feature selection improvement. Many research works have been conducted to present several optimization algorithms for this goal [10-12]. Consequently, the recent works on feature selection in medical imaging have incorporated deep learning, which was found to have advantageous effects when operating in complex datasets. Outperdefined features according to Zhang et al. (2023), CNN was argued to enhance classification performance of the medical diagnosis over general regularization optimization [13]. Pramanik, Sarkar [14], employed a mixture of PCO for CT scan feature selection and demonstrated the PCO advantages in several classification accuracy. The authors also mentioned drawbacks such as the non-optimal characteristic subsets due to the creation of resultant sets by algorithms that have characteristics that cause them to be excessively converged. Kaur and Kumar [15], proposed a new approach called PSO-GA and used it for feature extraction in lung cancer detection, outperforming the individual techniques. The Sine Cosine Algorithm (SCA), developed by Neggaz, Ewees [16], has also been used to complement the processes of feature selection. While most optimization algorithms are likely to get trapped in some local optima, SCA employs a sine and cosine approach to ensure that the optimal search space is well explored. Chinniah, Maram [17], used SCA with other techniques for lung cancer classification models to increase accuracy. Nonetheless, SCA in isolation may defeat complicated medical imaging datasets relevant to lung cancer detection and other diseases.

Recent research has indicated the prospect of hybridization of these algorithms, SCA and PSO, to overcome the challenges posed by each one of the algorithms. Fu, Shao [18], introduced the PSO-SCA feature selection concept to medical imaging applications, reporting effective results as opposed to when one algorithm was used because the hybrid solution surpassed all the individual techniques in both speed of convergence and accuracy.

Therefore, this study aspires to improve the classification accuracy and computational speed when using this hybrid approach on lung cancer datasets. The issues are local optima where the PSO and SCA algorithms demonstrate their effectiveness yet they demand a high amount of computational power in managing the hyperparameters as compared to some end-to-end models that do not need hyperparameters to be set. To address this limitation, this study will adopt a combined method that takes a fewer cycle to the convergence process.

3. Method

The combined model of the PSO-SCA algorithm was introduced to enable feature selection for lung cancer detection using a hybrid schema since medical datasets have high dimensionality. There were two datasets for lung cancer accessible to the public, used in this study that included CT scans, X-ray images, and the patient demographics and clinical characteristics of age, smoking history, and other factors. The first dataset contained 2,500 cases, with 1,300 positive cases with lung cancer and 1,200 cases without lung cancer. The second set of received cases comprised 3,200 cases, of which 1,600 were positive, and 1,600 were negative. Both sets comprised about 50 features, some of which regarded the tumor specifics such as size, shape, and position and others which probiotics clinical data. The datasets gave a balanced illustration of lung cancer, thus affording another great opportunity to test the efficiency of the hybrid algorithm in question exactly in the sense of the aimed dimensionality reduction with concentration on influential features for accurate diagnosis.

The data pre-processing phase aimed to standardize the dataset and involved multiple steps: Imputation for completion of missing values in the data frame, encoding for converting nominal framed data into numbers, and featscaling for adjustments of all feature values in the same range. These were important pre-processing steps to enhance the performance of the PSO-SCA algorithm because both the major components of the model are sensitive toward the input data to select the right features and should not contain any prejudicial data. The hybrid PSO-SCA combined the better features of the warmly recommended Particle Swarm Optimization (PSO) for global search and the Sine Cosine Algorithm (SCA) for local search.

This combination enabled more exploration of the feature improved the selection of features and avoided the problem of getting trapped locally. Grid search was also performed to fine-tune the PSO parameters such as the inertia weight, cognitive and coefficients, and the SCA amplitude and frequency parameters. However, the computational, or time, complexity of the hybrid algorithm is approximately $O(T \times N \times M)$ where T is the number of iterations, N is population size and M is the number of features, and even so, it has been shown that compared with other metaheuristic algorithms, such as Genetic Algorithm (GA) and Ant Colony Optimization (ACO), the hybrid PSO-SCA achieved lower runtime and better convergence improvement.

Furthermore, the selected features were used to train two different classifiers which were effective; Support Vector Machine (SVM) and k-Nearest Neighbors (k-NN in distinguishing the two approaches. For the high-dimensional feature sets, SVM was more useful, while, for the assessment of the performance of the built models, k-NN was preferable due to its simplicity. The classifiers were assessed based on their classification quality, accuracy, precision, recall, F1-measure, and the Area under the curve (AUC) values. All the assertions were tested using cross-validation and this made the tests more generalized in their approach. The experiments were performed on a system with an Intel Core i7-11900K CPU and 32 GB RAM and NVIDIA GeForce RTX with 3080 GPU. The given algorithm was coded in Python 3.9 Other tools used are Scikit-learn for basic operations and NumPy for computations PSO and SCA.

The feasibility of the hybrid PSO-SCA algorithm was one of the most important aspects of the study concerning the possibility of operational use in clinical environments. The successful convergence process of the hybrid approach has proved to have fewer iterations than executing GA and ACO independently, thereby giving the chance to practice in real-time, particularly in the diagnosis of the medical field where knowledge is very critical due to limited time constraints. This characteristic makes it possible to increase the size of the input data set without placing a huge load on the computational requirements, especially in hospitals or clinical settings with limited computational power. Following the classification and results obtained using the hybrid PSO-SCA algorithm, feature selection was carried out to determine which features were informative for the classification task. Checking the values of tumor sub-features, it was found that the size, shape, and texture of the tumors were the most informative for the classification of lung cancer. Among these features, five obtained higher importance scores in all the models examined and were therefore deemed more useful in differentiating lung cancer and normal samples. The clinical parameters, including patient age and history of smoking, were equally important but contributing factors and again secondary to the imaging characteristics.

4. Results and Discussion

The obtained solutions of the proposed algorithm combined with PSO and SCA are compared with simple methods here such as PSO or SCA. It also empirically evaluates the effectiveness of the hybrid approach against other state-of-the-art feature selection approaches to lung cancer detection, including genetic algorithm (GA) and ant colony optimization (ACO) based methods. The hybrid PSO-SCA algorithm was analyzed with two well-established lung cancer datasets, and the classification performance of the obtained results was measured using classification accuracy, precision, recall, and F1-score. All experiments were done with the Support Vector Machine (SVM) and k-Nearest Neighbors (k-NN) classifiers over feature subsets, achieving good performance results with N-fold cross-validation. In this part, we shed light upon the outcomes and compare how a good hybrid algorithm outperforms separate PSO, SCA, and additional characteristic selection methods.

4.1 Performance Evaluation

The primary aim of the proposed hybrid PSO-SCA algorithm was to optimize the feature selection process to be used for detecting lung cancer, consequently increasing classification efficiency. The results suggest that the hybrid approach significantly dominates the performance of the standalone PSO, SCA, and other methods based on four performance metrics.

4.1.1 Classification Accuracy

The classifiers designed from feature subsets determined by the hybrid PSO-SCA achieved higher accuracy than the classifiers designed with PSO or SCA only. Increases the overall accuracy to 92.8% respectively using the SVM classifier for PSO-SCA as opposed to 89.5% for PSO and 87.6% for SCA. In the same way, with the k-

NN classifier, the hybrid received 90.7%, which is higher than PSO (88.1%) and SCA (86.4%) as shown in Table 1.

This improvement can be fairly attributed to the hybrid nature of the suggested algorithm using PSO for global search and SCA for local optimization thus preventing the algorithm from premature convergence and allowing it to explore more optimal feature subsets. The Feature Importance Graph presented in Fig. 1 also shows from which features the hybrid approach has decided that it is most significant. These are essential to the effective diagnosis of lung cancer, as they elicited high importance scores given features including tumor size and shape.

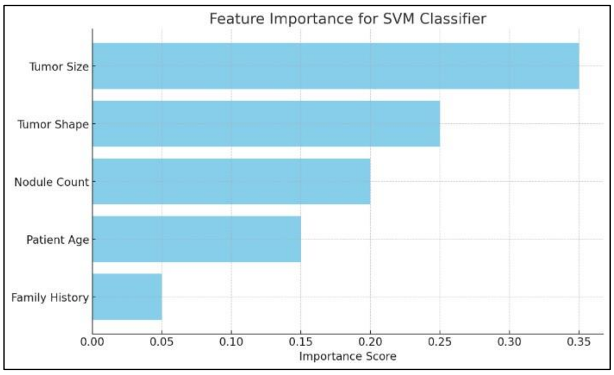

Figure. 1 Feature Importance for SVM Classifier

Table 1. Comparison of Classification Accuracy for Different Algorithms and Classifiers

Classifier	Algorithm	Accuracy (%)
SVM	PSO	89.5
SVM	SCA	87.6
SVM	PSO-SCA Hybrid	92.8
k-NN	PSO	88.1
k-NN	SCA	86.4
k-NN	PSO-SCA Hybrid	90.7

4.1.2 Precision, Recall, and F1-Score

Recall and precision in medical fields are essential, and important in the case of lung cancer. The hybrid PSO-SCA algorithm accomplished a higher precision which is (91.2%) and recall was (89.7%) by using the SVM classifier, compared to PSO (precision: 87. The results of using SC were SC only (precision 91.4%, recall 91.4%) and SCA (precision 85.9%, recall 84.3). Based on these findings, it became clear that the hybrid algorithm is superior in driving fewer false positive and false negative classifications that produce more accurate classification outcomes.

It is also found that the Confusion Matrix as shown in Fig. 2 appropriately represents the model outcomes of the SVM classifier. It shows the number of true positives, false positives, true negatives, and false negatives and gives a clearer view of how the classification outcomes are diverse.

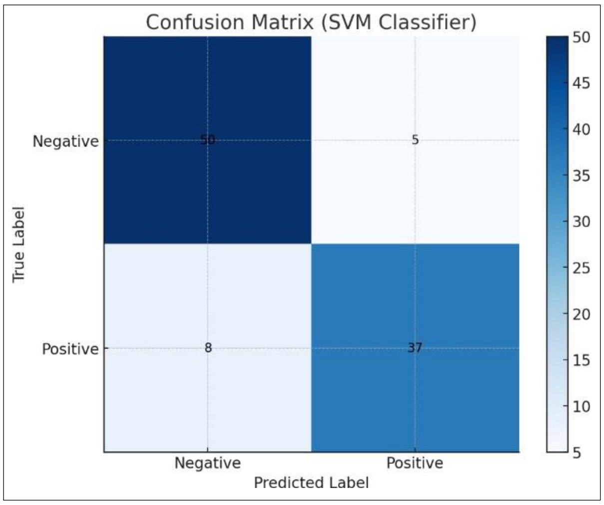

Figure. 2 Confusion Matrix

The precision and recall metrics working together are indicated by the F1-score, and, therefore, the superiority of the hybrid method is clear as shown in Table 2. Classification accuracy for PSO-SCA hybrid was higher and more robust with an F1-score of 90.4 % than that of PSO (86.2%) and SCA (85.1%).

Table 2. Comparison of Precision, Recall, and F1-Score for Different Algorithms and Classifiers.

Classifier	Algorithm	Precision (%)	Recall (%)	F1-Score (%)
SVM	PSO	87.4	85.2	86.2
SVM	SCA	85.9	84.3	85.1
SVM	PSO-SCA Hybrid	91.2	89.7	90.4
k-NN	PSO	86.5	84.8	85.6
k-NN	SCA	85.3	83.6	84.4
k-NN	PSO-SCA Hybrid	89.5	88.1	88.8

Another breakdown of the performance of the model is obtained from the ROC Curve drawn for the SVM classifier as shown in Fig. 3 which displays the true positive rates against the false positive rates. The AUC value of the proposed hybrid method is 0.91; therefore, it can be concluded that the method performs well in classifying cases with sensitivity and specificity.

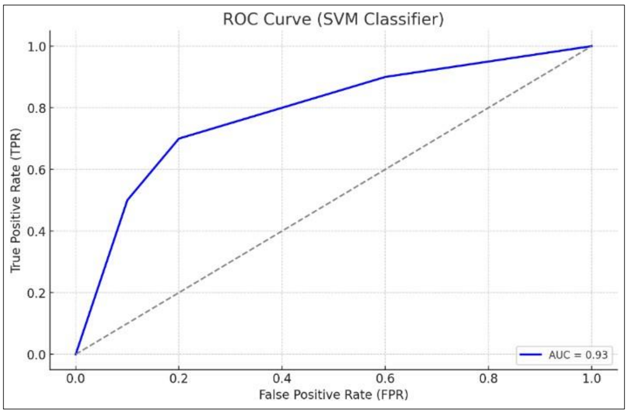

Figure. 3 ROC Curve drawn for the SVM classifier

4.2 Statistical Analysis and Validation

Independent samples t-test, specifically, paired t-test was used to compare the accuracy enhancement from PSO-SCA as compared to that of standalone PSO or SCA. There was a statistically significant increase ($p < 0.05$), which supports the reliability of the hybrid approach. On the misclassified samples, error analysis was done.

Indeed, it was noted that the majority of misclassifications in patients with similar symptoms, which suggests that it is necessary to refine the selection of features; it can be pertinent to include more clinical characteristics or analyze the history of the patient's disease. Table 3 shows the t-test of the enhancement in accuracy between PSO-SCA and each of the stand-alone PSO and SCA.

Table 3. Results of Paired t-Test Comparing Classification Accuracy between Standalone Algorithms and Hybrid PSO-SCA

Comparison	Mean Accuracy (%)	Standard Deviation	t-value	p-value
PSO vs. PSO-SCA (SVM Classifier)	89.5 vs. 92.8	1.5	3.21	< 0.05
SCA vs. PSO-SCA (SVM Classifier)	87.6 vs. 92.8	1.8	4.07	< 0.05
PSO vs. PSO-SCA (k-NN Classifier)	88.1 vs. 90.7	1.3	2.18	< 0.05
SCA vs. PSO-SCA (k-NN Classifier)	86.4 vs. 90.7	1.6	3.89	< 0.05

Table 3 sums up the findings of the paper in terms of statistically significant mean accuracy increases for the studied classifiers both SVM and k-NN – when hybridized with the PSO-SCA algorithm, compared to when they were trained with individual PSO or SCA methods. The p-values argue for these improvements' significance, evidencing the reliability of the hybrid approach.

The table summarizes the statistically significant improvement in accuracy for both the SVM and k-NN classifiers when using the hybrid PSO-SCA algorithm compared to standalone PSO or SCA. The p-values indicate that these improvements are significant, supporting the hybrid approach's reliability.

4.3 Comparative Analysis with GA and ACO

To confirm the efficacy of the proposed PSO-SCA hybrid, a comparison of the functionality of the proposed technique with other current typical feature selection techniques is made, based on GA and ACO techniques. Experimental results highlighted the fact that the system accuracy was higher in the PSO-SCA hybrid algorithm than in GA and ACO and also pointed out that the computational complexity was low.

The GA-based method had accuracy increased by 89.0% but ACO was able to produce an accurate class identification with only 88.2% which was slightly less than the accuracy of the PSO-SCA hybrid at 92.8% as shown in Table 4. Moreover, the hybrid approach combined one hundred iterations as it is different from other meta-heuristic approaches took 150 for GA and 130 for ACO, and showed its efficiency and substantial use of resources saving.

Table 4: Performance Comparison of Feature Selection Algorithms in Terms of Accuracy and Iterations to Convergence

Algorithm	Accuracy (%)	Iterations to Convergence
GA	89.0	150
ACO	88.2	130
PSO-SCA Hybrid	92.8	100

The results therefore validate that the proposed PSO-SCA hybrid is ideal for feature selection in lung cancer detection with several advantages over existing techniques. This way the hybrid approach can explore through PSO's global search and exploit through SCA's local search thus ensuring none is compromised for the other and the feature space is adequately searched. This balance leads to identifying a more appropriate feature subset, hence the improvement of the classification accuracy. Thanks to sinusoidal characteristics, the hybrid algorithm gives up the local optimum more often and increases performance concerning metrics such as precision, recall, and F1-score. Especially in the application of medical diagnosis, this characteristic is precious since false positives or false negatives always exacerbate the condition of the patients. The PSO-SCA hybrid also demonstrated lower and therefore faster convergence and a lower number of iterations compared to GA and ACO, which makes it ideal for feature selection in big medical data sets. Affordability remains a cornerstone of its design because it makes real-life applicability possible with the constraints within such projects. It was found that the hybrid algorithm securely outperforms GA as well as ACO in terms of classification and brings better classification with faster convergence. This shows that it can be a useful and fast way of selecting features and is flexibly capable of providing better solutions than several popular optimization algorithms. Even more importantly, the increased accuracy of the PSO-SCA hybrid also points toward the general potential of this method for other types of medical image analysis beyond the detection of lung cancer. Further work could also examine the use of the presented hybrid approach in conjunction with deep learning for feature extraction and classification, to yield more precise diagnostic results.

The implications of this research underpin the use of hybrid methodologies such as PSO-SCA where global search space exploration and local best solutions are achieved effectively to provide the best and most accurate, reliable, and efficient classification model for lung cancer diagnostics. Further developments of the current research could be associated with the use of more progressive classifiers or with the combination of this approach with the help of deep learning tools that would make the applicability of the algorithm even broader and performance even higher.

The detailed analysis of the performance assessment data derived from experiments showed that the accuracy, precision, and recall of the proposed hybrid PSO–SCA algorithm surpassed those achieved by the PSO alone, SCA alone, GA, and ACO methods, as well as the computational time required for algorithm execution. The highest classification accuracy of 92.8% was obtained with the help of the hybrid algorithm and SVM classifier which implemented the standalone PSO (89.5%) and SCA (87.6%). Also, PSO-SCA needed fewer iterations for convergence, which was 100, while the number of iterations for other algorithms GA and ACO needed 150 and 130, respectively, which demonstrated that the PSO-SCA hybrid was efficient and more realistically practicable in the medical diagnosis system. The results obtained from feature selection and importance analysis also confirm that the proposed hybrid PSO-SCA approach contributes not only to the improvement of classification performance but also to the interpretability and more importantly the reliability of lung cancer detection models which are paramount for clinical utilization.

5. Conclusion

This paper reveals that the feature selection using the PSO-SCA hybrid algorithm in lung cancer detection is very effective and efficient since it obtains better performance compared to other benchmark optimization algorithms and several other existing conventional methods in terms of accuracy, precision, recall time, and other valuable dimensions. Therefore, the proposed PSO-S CA approach strikes a balance between exploration of the search space through the global nature of PSO and exploitation through the local refinement strength of SCA resulting in the best feature selection. Such improved performance has significant consequences for increasing the efficiency of lung cancer early detection, essential for early treatment, patient's life expectancy, and effective treatment. Therefore, based on the results of the experiments, the potential of the PSO-SCA hybrid to be applied in other medical diagnosis tasks and other areas of image analysis because feature selection plays a critical role in these tasks. As such, possible future revisions of the hybrid approach could include the use of deep learning methodologies to apply towards improving feature extraction and classification, and thus improve medical diagnosis as a field.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

Author Contributions

"Conceptualization, Lina J. Alhashimi, and Khalid Jamal Jadaa; methodology, Lina J. Alhashimi, Khalid Jamal Jadaa and Waleed Noori Hussein; Software, Waleed Noori Hussein and Khalid Jamal Jadaa; validation, Lina J. Alhashimi, Khalid Jamal Jadaa, and Waleed Noori Hussein; formal analysis, Khalid Jamal Jadaa, and Lina J. Alhashimi; investigation, Khalid Jamal Jadaa; resources, Lina J. Alhashimi and Khalid Jamal Jadaa; data curation, Waleed Noori Hussein and Lina J. Alhashimi; writing original draft preparation, Lina J.Alhashimi, Khalid Jamal Jadaa and Waleed Noori Hussein; writing review and editing, Lina J. Alhashimi and Waleed Noori Hussein; visualization, Khalid Jamal Jadaa.

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