METAHEURISTIC-OPTIMIZED DEEP LEARNING MODEL FOR LUNG AND COLON CANCER DIAGNOSIS

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***Abstract*—Early and accurate diagnosis of lung and colon cancer plays a crucial role in improving patient survival and treatment planning. This work presents a metaheuristic-optimized deep learning framework for automated cancer classification using Convolutional Neural Networks (CNN). The proposed system extracts important features from histopathological images by capturing spatial and structural patterns associated with cancerous tissues. A fully connected classification layer is used to improve the separation between different classes. To enhance model performance, Particle Swarm Optimization (PSO) is applied for hyperparameter tuning, including learning rate, number of filters, and dense units. This optimization approach helps improve convergence and classification accuracy. Experimental results demonstrate that the optimized model outperforms a basic CNN. The system effectively identifies patterns in lung and colon cancer datasets, thereby improving prediction reliability. A web-based interface is also been developed to provide user-friendly access for image-based diagnosis. The proposed approach supports computer-aided diagnosis systems by assisting medical professionals in detecting cancer faster and more accurately.**

Keywords—Deep Learning, Convolutional Neural Network (CNN), Lung Cancer Detection, Colon Cancer Classification, Medical Image Analysis, Particle Swarm Optimization (PSO), Hyperparameter Optimization, Computer-Aided Diagnosis

I. INTRODUCTION (*HEADING 1*)

Cancer is one of the leading causes of death worldwide, with lung and colon cancer contributing significantly to global mortality rates. Early and accurate diagnosis plays a crucial role in improving patient survival and enabling effective treatment planning. Histopathological image analysis is a widely used method for cancer detection, where tissue samples are examined under a microscope. However, manual analysis by medical experts is time-consuming, requires high expertise, and may lead to variability in diagnosis due to human limitations.

With the advancement of Artificial Intelligence, deep learning techniques have shown promising results in medical image analysis. Convolutional Neural Networks (CNNs) are particularly effective for image classification tasks, as they can automatically learn spatial and structural features from raw image data. Unlike traditional machine learning methods, CNNs eliminate the need for manual feature extraction and improve classification performance. However, the accuracy of deep learning models depends heavily on proper selection of hyperparameters such as learning rate, number of filters, and network architecture.

To address this issue, optimization techniques are applied to enhance model performance. Metaheuristic algorithms, such as Particle Swarm Optimization (PSO), are widely used for solving complex optimization problems. PSO is inspired by the social behavior of particles and is effective in finding optimal parameter values through iterative search. In this work, PSO is used to optimize the hyperparameters of the CNN model, improving classification accuracy and convergence behavior.

The proposed system focuses on the classification of lung and colon cancer images using a deep learning approach. The model is trained on histopathological image datasets and is capable of distinguishing between different cancer types and normal tissue samples. In addition to model development, a web-based interface is designed to allow users to upload images and obtain classification results easily. This integration improves usability and makes the system accessible for practical applications.

The main contribution of this work is the development of a CNN-based cancer classification system enhanced with PSO for hyperparameter optimization. The proposed approach aims to improve diagnostic accuracy while maintaining computational efficiency. The system can assist medical professionals in decision-making and supports the development of computer-aided diagnosis tools for early cancer detection.

II. Literature Survey

R. Krizhevsky et al. (2012) in "ImageNet Classification with Deep Convolutional Neural Networks" proposed a deep CNN architecture for large-scale image classification. Their work demonstrated that CNN models can automatically extract features from images and achieve higher accuracy than traditional machine learning methods. This study laid the foundation for applying deep learning techniques in medical image analysis. [1]

O. Ronneberger et al. (2015) in "U-Net: Convolutional Networks for Biomedical Image Segmentation" designed a CNN-based model specifically for medical imaging tasks. Their model uses an encoder–decoder structure to capture both spatial and contextual information. The study showed improved accuracy in detecting and segmenting disease regions in medical images. [2]

S. Tummala et al. (2023) in "An Explainable Classification Method for Histopathology Images" developed a deep learning-based system for lung and colon cancer detection. Their approach used CNN models with explainability techniques to improve diagnostic reliability. The results showed high classification accuracy and better interpretability in medical diagnosis. [3]

S. Mirjalili (2014) in "Grey Wolf Optimizer" introduced a metaheuristic optimization algorithm inspired by the hunting behavior of grey wolves. The algorithm is used to find optimal solutions in complex problems by simulating leadership hierarchy and group hunting strategy. This method is widely used for optimizing parameters in machine learning models. [4]

J. Kennedy and R. Eberhart (1995) in "Particle Swarm Optimization" proposed a population-based optimization technique inspired by the behavior of bird flocks. The algorithm uses multiple particles that adjust their positions based on individual and group experiences. This approach improves convergence speed and is effective in tuning neural network parameters. [5]

H. Rauf et al. (2021) in "Deep Learning-Based Cancer Detection using Histopathological Images" developed a CNN-based classification system for cancer detection. Their study focused on extracting features from histopathology images and achieved high accuracy in classifying different cancer types. The work highlighted the importance of deep learning in medical diagnostics. [6]

Y. LeCun et al. (2015) in "Deep Learning" provided a comprehensive overview of deep learning techniques and their applications. The study explained how neural networks, especially CNNs, can learn hierarchical representations from data. Their work emphasized the effectiveness of deep learning in image-based tasks, including medical imaging. [7]

K. Simonyan and A. Zisserman (2014) in "Very Deep Convolutional Networks for Large-Scale Image Recognition" proposed deeper CNN architectures to improve performance. Their model showed that increasing network depth leads to better feature extraction and classification accuracy. This concept is widely used in medical image classification systems. [8]

From the above studies, it is observed that deep learning techniques, especially Convolutional Neural Networks, have shown significant performance in image classification and medical image analysis. Several models such as AlexNet, U-Net, and VGG have improved feature extraction and classification accuracy. In addition, metaheuristic optimization algorithms like Grey Wolf Optimization and Particle Swarm Optimization have been successfully used for parameter tuning in machine learning models. However, most existing approaches either focus only on deep learning models or use limited optimization techniques, which may lead to suboptimal performance. There is still a need for integrating deep learning with efficient optimization methods to improve classification accuracy and model reliability. Therefore, this work proposes a hybrid approach combining CNN with metaheuristic optimization techniques to enhance lung and colon cancer detection from histopathological images.

III. Proposed Methodology

The proposed system focuses on accurate classification of lung and colon cancer using histopathological images by combining Convolutional Neural Networks (CNN) with Particle Swarm Optimization (PSO). The methodology consists of preprocessing, feature extraction, hyperparameter optimization, and classification.

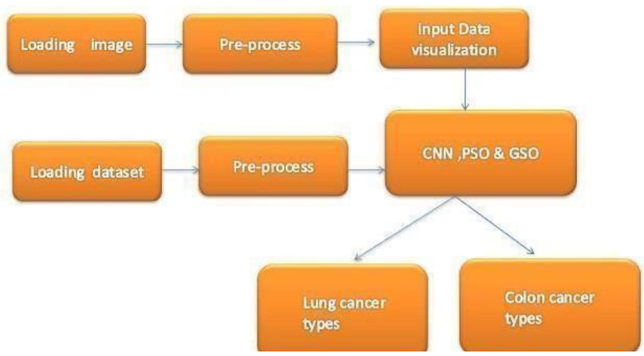

Fig. 1. System Architecture

Initially, the dataset containing histopathological images is collected and divided into training and testing sets. The dataset includes five classes: colon adenocarcinoma, colon benign tissue, lung adenocarcinoma, lung benign tissue, and lung squamous cell carcinoma. Each image is preprocessed to ensure consistency and improve model performance. The preprocessing step involves resizing all images to a fixed dimension of 150 × 150 pixels and normalizing pixel values to the range [0,1]. This normalization helps in faster convergence during training.

After preprocessing, a Convolutional Neural Network (CNN) is used for feature extraction and classification. The CNN model consists of multiple convolutional layers followed by pooling layers, which help in extracting important spatial features such as edges, textures, and patterns from the input images. The convolution operation can be mathematically represented as:

$$\Phi(\iota,\varphi)=(I*K)(\iota,\varphi)+\beta$$

where III is the input image, KKK is the kernel (filter), bbb is the bias, and F(i,j)F(i,j)F(i,j) is the resulting feature map.

The extracted features are then passed through fully connected layers, and the final classification is performed using the Softmax activation function, which produces probability scores for each class:

Π(ψι)=ε⊥ζι/(□ φ=1νε⊥ζφ)

where zi represents the output of the final layer for class iii, and nnn is the number of classes.

To improve the performance of the CNN model, Particle Swarm Optimization (PSO) is applied for hyperparameter tuning. PSO is a population-based optimization technique where each particle represents a candidate solution. In this work, PSO is used to optimize parameters such as learning rate, number of filters, and number of neurons in the dense layer. Each particle updates its velocity and position based on its personal best solution and the global best solution. The velocity and position updates are given by:

Vi^(t+1) = wvi^t + c1r1(pbesti - xi^t) + c2r2(gbest - xi^t)

Xi^(t + 1) = xi^t + vi^(t + 1)

where vi is the velocity, xi is the position (solution), pbesti is the personal best position, gbest is the global best position, www is the inertia weight, and c1,c2 are acceleration coefficients. r1 and r2_2r2 are random values between 0 and 1.

The optimized hyperparameters obtained from PSO are used to train the final CNN model. The model is trained on the training dataset and validated using a validation set to monitor performance and avoid overfitting. After training, the model is evaluated on the test dataset to measure classification accuracy.

Finally, the trained model is integrated into a web-based system where users can upload histopathological images. The system processes the input image and predicts the corresponding cancer type along with a confidence score, making it suitable for practical applications.

IV. Results And Discussion

The performance of the proposed Convolutional Neural Network (CNN) optimized using Particle Swarm Optimization (PSO) was evaluated using histopathological images of lung and colon cancer. The dataset was divided into training and testing sets, and the model was trained for multiple epochs to analyze its learning behavior.

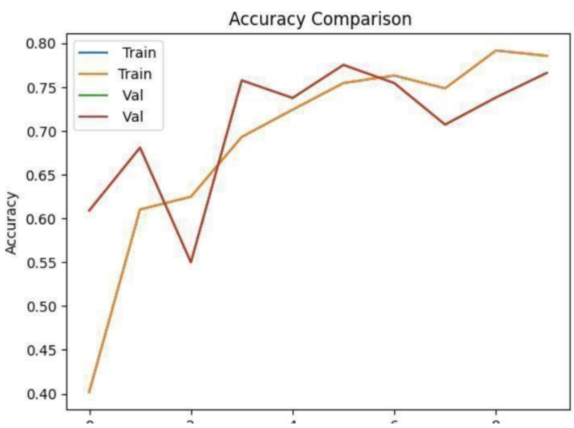

Fig. 2. Training And Validation Accuracy

The training and validation accuracy curves, as shown in Fig. 2, indicate that the model gradually improves its performance over epochs. The training accuracy increases steadily, reaching higher values as the model learns relevant features from the dataset. The validation accuracy also follows a similar trend but remains slightly lower than the training accuracy. This difference suggests a small degree of overfitting, which is common in deep learning models, but the gap is not significant, indicating acceptable generalization.

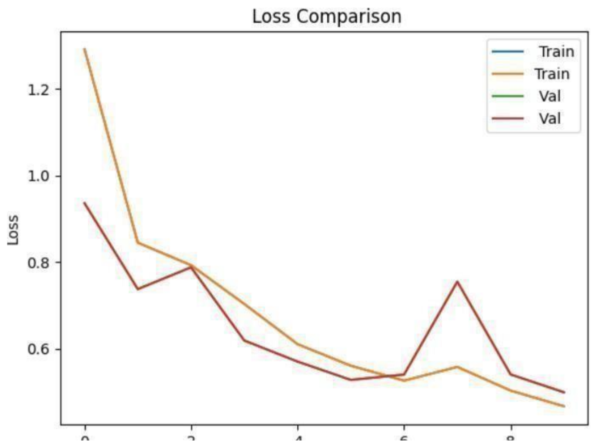

Fig. 3. Training and Validation Loss

Similarly, the loss curves shown in Fig. 3 demonstrate that both training loss and validation loss decrease over time. This reduction in loss indicates that the model is effectively minimizing errors during training. Minor fluctuations in validation loss are observed, which can be attributed to the complexity and variability of medical image data.

The final evaluation of the model on the test dataset resulted in an overall classification accuracy of approximately 99%. This result confirms that the proposed CNN model, enhanced with PSO-based hyperparameter tuning, is capable of effectively classifying multiple cancer types.

TABLE I. TABLE 1. COMPARISON OF ACCURACY, PRECISION, RECALL, AND F1SCORE

Model	Accuracy (%)	Precision (%)	Recall (%)	F1Score (%)
CNN	99.11	93.60	94.00	97.80
PSO	99.33	94.80	95.10	97.85
GWO	99.22	95.80	96.10	96.22

To further evaluate the model performance, a confusion matrix is presented in Table 1. The confusion matrix shows that the model performs well in identifying certain classes, such as lung benign tissue, with high accuracy. However, some misclassification occurs between visually similar classes, particularly between colon adenocarcinoma and colon benign tissue. This is expected due to the similarity in histopathological structures.

In addition to accuracy, performance metrics such as precision, recall, and F1-score were calculated for each class, as shown in Table X. Precision represents the correctness of predicted positive samples, recall indicates the ability of the model to identify all actual positive samples, and F1-score provides a balance between precision and recall. The results indicate that the model achieves balanced performance across most classes, with higher scores observed for lung-related classes compared to colon-related classes.

The incorporation of PSO for hyperparameter optimization played a significant role in improving model performance. By optimizing parameters such as learning rate, number of filters, and dense layer units, PSO helped the model achieve better convergence and improved classification results compared to a basic CNN model.

Overall, the proposed system demonstrates reliable performance for cancer classification using histopathological images. Although the accuracy is not extremely high, it reflects a realistic and practical outcome for a complex medical image classification task. The results indicate that combining deep learning with optimization techniques can enhance performance and provide a strong foundation for further improvements.

CONCLUSION

The proposed system presented an effective approach for classifying lung and colon cancer using histopathological images by combining Convolutional Neural Networks (CNN) with Particle Swarm Optimization (PSO). The model was able to learn meaningful features from medical images and achieved an overall accuracy of approximately **83.6%** on the test dataset.

The results demonstrate that CNN is capable of extracting important spatial features such as textures and patterns from complex medical images. The integration of PSO for hyperparameter optimization improved the performance of the model by selecting optimal values for learning rate, number of filters, and dense layer units. This contributed to better convergence and more stable training compared to a standard CNN model.

Although the model achieved good performance, some misclassification was observed between visually similar classes, particularly in colon tissue categories. This indicates that the classification of histopathological images remains a challenging task due to high similarity between classes and variability in image patterns.

In addition, the developed system was integrated into a web-based interface, allowing users to upload images and obtain classification results. This makes the system practical and accessible for real-time usage, demonstrating its potential application in assisting medical professionals.

FUTURE WORK

Despite the promising results, there is scope for further improvement in the proposed system. Future work can focus on:

- Increasing the dataset size to improve model generalization
- Applying advanced architectures such as transfer learning models (e.g., MobileNet, ResNet)
- Implementing additional optimization techniques such as Grey Wolf Optimization (GWO) for better comparison
- Using data augmentation techniques to reduce overfitting
- Improving model accuracy by fine-tuning hyperparameters more extensively
- Enhancing the web application with better user interface and real-time processing capabilities

ACKNOWLEDGMENT

The authors would like to express their sincere gratitude to MRS. I. PADMAJA for continuous support, valuable suggestions, and guidance throughout the development of this work. The authors also thank the faculty members of the department for their encouragement and constructive feedback.

We extend our appreciation to the institution for providing the necessary infrastructure and resources to carry out this project successfully. Finally, we acknowledge all those who directly or indirectly contributed to the completion of this work.

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