Optimizing Neural Network Performance for Colon Cancer Detection with the Addax Optimization Algorithm

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Abstract: One of the primary cancers in the world causing cancer related deaths is Colon Cancer. To improve the patient survival rate, it is very important to predict it well before in time with great accuracy. The proposed paper using the concept of Addax Optimization Algorithm to optimize the neural networks for predication of colorectal cancer. The AOA is incorporated for fine tuning of hyperparameters as well as optimize the performance of neural networks by improving the accuracy and dropping the computational cost. The application of this proposed algorithm is used for good health and wellbeing by enhancing medical diagnostics and by leveraging advanced AI driven optimization techniques for industry, innovation and infrastructure. The experimental results shows that the proposed approach outperformed conventional models with respect to classification accuracy, precision, recall and F1 score.

Keywords: Convolutional Neural Network, Addax Optimization Algorithm, Opposition based Learning, Medical Diagnosis, Healthcare System, Colon cancer detection.

Introduction

Colon cancer is among the most prevalent forms of cancer in the world. Detecting it early is critically important to reduce mortality rates. Even with substantial advancements in medical investigations, early detection of colon cancer remains difficult due to its elusive nature. Conventional methods of identifying colon cancer, such as through tissue samples and imaging, need manual testing to a large extent. This could be time-consuming, prone to errors, and might not be entirely accurate all the time. To address all these issues, machine learning (ML) processes, particularly artificial neural networks (ANNs), have been observed to be excellent chances to recognize elusive patterns in large databases.

Neural networks are in general hyperparameter-sensitive with respect to selection processes such as weights, learning rates, and architectures. These affect their performance significantly. Optimization of these parameters is critical to rendering neural networks accurate and reliable. The Addax Optimization Algorithm (AOA) is a nature-inspired algorithm that has been used as an effective method of enhancing machine learning models in recent times. AOA is inspired by the hunting behavior of the Addax antelope

and has been found to perform better than some other optimization strategies in various cases, particularly to optimize complex functions and enhance the performance of machine learning models.
This study examines how the Addax Optimization Algorithm can be used to improve the performance of neural networks in detecting colon cancer. Using AOA to train the neural network, we aim to make the model able to detect patterns in medical data. This should result in more accurate and dependable predictions of colon cancer. The study will also examine how efficient the Addax Optimization Algorithm performs compared to other algorithms such as Genetic Algorithms (GA) and Particle Swarm Optimization (PSO) in terms of diversity and convergence.
Recent studies have explored comparable areas for utilizing optimization techniques to improve neural networks in the medical field. For instance, Zhang et al. (2022) [1] employed hybrid optimization techniques such as particle swarm optimization and neural networks to improve cancer detection accuracy. Furthermore, a hybrid model incorporating extreme gradient boosting (XGBoost) and genetic algorithms has proven tremendous possibilities in cancer classification [2]. Other research has effectively used hybrid optimization strategies to increase the performance of deep learning models in a variety of medical applications, such as breast cancer and brain tumour detection [3], [4]. In this context, our approach employs AOA to fine-tune neural networks, specifically targeting colon cancer detection, with the goal of boosting the accuracy, efficiency and generalization.

Related work

In recent years, various optimization algorithms have been explored to enhance machine learning models for cancer detection. The integration of these algorithms with neural networks has led to significant improvements in performance, particularly in terms of accuracy, convergence speed, and generalization. A few notable examples of these advancements are discussed below.

Table 1. Literature survey on Various Optimization Algorithms used to enhance neural network models

Optimization Algorithm	*Key Features*	*Advantages*	*Limitations*
Genetic Algorithm (GA)[1]	Inspired by natural selection, used for feature selection and weight optimization	Effective in searching large spaces, widely adopted	High computational complexity, slow convergence
Particle Swarm Optimization (PSO)[2]	Based on swarm intelligence, optimizes hyperparameters	Fast convergence, simple implementation	May converge prematurely in complex search spaces
Whale Optimization Algorithm (WOA)[3]	Mimics whale hunting behavior for optimization	Strong balance between exploration and exploitation	Struggles with fine-tuning parameters in high-dimensional problems
Grey Wolf Optimizer (GWO)[4]	Inspired by the leadership hierarchy of	Effective in balancing exploration and	Can get trapped in local optima

	grey wolves	exploitation	
Ant Colony Optimization (ACO)[5]	Simulates ant foraging behaviour	Efficient in combinatorial problems	Computationally expensive, requires extensive parameter tuning
Harris Hawks Optimization (HHO)[6]	Mimics hawks' attacking strategy	Dynamic and adaptive exploration-exploitation	Sensitive to parameter settings
Aquila Optimizer (AO)[7]	Inspired by the hunting strategy of eagles	Fast convergence, effective in high-dimensional problems	Limited applications in deep learning
Addax Optimization Algorithm (AOA)	Mimics addax antelopes' foraging behavior	Efficient balance between exploration and exploitation, robust convergence	Underexplored in deep learning applications
Moth Flame Optimization (MFO)[9]	Mimics moths navigating using the moonlight	Strong exploration capabilities	May have slow convergence
Sine Cosine Algorithm[10] (SCA)	Uses sine and cosine functions for position updates	Simple implementation, effective in global optimization	May get trapped in local minima
Butterfly Optimization Algorithm [11](BOA)	Inspired by the foraging behavior of butterflies	Effective balance between exploration and exploitation	Sensitive to parameter tuning
Cuckoo Search Algorithm (CSA)[12]	Based on cuckoo birds' egg-laying strategy	Strong global search ability	High computational cost in some cases

Methodology

The proposed work employ AOA with Convolutional neural networks (CNN) for the optimization of weight and hyperparameters to improve the classification accuracy of colon cancer. Addax Optimization algorithm mimics the behavior of addax antelopes in hunt of best food resources, which can be useful in exploration and exploitation process of hyperparameter tuning. The proposal can be contributed to enhance the early cancer detection and some other medical diagnostics.

Proposed Work

The proposed method integrates AOA with a convolutional neural network (CNN) to optimize hyperparameters and improve colon cancer classification accuracy. The Addax Optimization Algorithm mimics the behavior of addax antelopes in search of optimal food sources, which is translated into exploration and exploitation in hyperparameter tuning. The workflow consists of the following steps and contributes to SDG3 by enhancing early cancer detection and SDG9 by employing AI-driven innovation:-- --

```
BEGIN

1. Load Colon Cancer Dataset
  - Preprocess (resize, normalize, augment)
  - Split into training and testing sets

2. Initialize Parameters:
  - Population size (N), Max iterations (T), Dimension of solution (D)
  - Define Upper Bound (UB) and Lower Bound (LB) for each hyperparameter

3. Initialize Population (X):
  FOR each candidate i in 1 to N DO
     X[i] ← Random vector in range [LB, UB]
     X_opp[i] ← UB + LB - X[i]   // Apply Opposition-Based Learning (OBL)
     Evaluate fitness of X[i] and X_opp[i] via CNN
     Keep the better one in X[i]
  END FOR

4. Optimization Loop (for t = 1 to T):
  Identify the best solution X_best with highest fitness

  FOR each candidate i in 1 to N DO
     IF t < T/3 THEN
        // Exploration Phase
        X_new ← X[i] + rand() * (UB - LB)
     ELSE IF T/3 ≤ t < 2T/3 THEN
        // Transition Phase
        X_new ← X[i] + β * (X_best - X[i])
     ELSE
        // Exploitation Phase
        X_new ← X[i] + γ * (X_best - X[i])
     END IF

     // Clamp X_new within bounds
     X_new ← min(max(X_new, LB), UB)

     // Apply OBL to new solution
     X_opp ← UB + LB - X_new

     // Evaluate fitness of X_new and X_opp using CNN
     Replace X[i] with the better of the two solutions
  END FOR

  Update X_best if better solution found
END FOR

5. Train Final CNN Model Using X_best (optimal hyperparameters)
  - Evaluate on test set
  - Compute Accuracy, Precision, Recall, F1-score

6. Output Trained CNN Model and Metrics

END
```

Figure 1. Pseudo code of proposed optimization of neural network for colon cancer detection

Figure 1 shows the pseudo code of the proposed model. The first step is data collection and preprocessing in which histopathological images get normalized for feature extraction process. Then data augmentation is applied to improve the generalization in dataset. Then the data import to CNN model and adjust the parameters. AOA is applied to CNN for hyperparameters optimization.

The addax antelopes randomly explore different regions, corresponding to a broad search for hyperparameter values (exploration phase) by using the following equation:

$$X_i^{t+1} = X_i^t + r.(UB - LB) \qquad (1)$$

Where r is the random variable ranges (0,1).

X_i^{t+1} is the updated position of the ith solution (or candidate hyperparameter set) at iteration t+1.

X_i^t is the current position of the ith solution at iteration t.

When iterations progress, then the search area become narrow that means the addax moving toward promising food sources (transition phase).

$$X_i^{t+1} = X_i^t + \beta.(X_{best} - X_i^t) \qquad (2)$$

Where β is control parameter that influences how much the agent moves towards the best solution.

The addax focuses on refining the best solution, like fine-tuning the hyperparameters to maximize model performance (exploitation phase).

$$X_i^{t+1} = X_i^t + \gamma.(X_{best} - X_i^t) \qquad (3)$$

Then model training and evaluation takes place where the CNN model is trained using AOA.

AOA simulates the adaptive foraging behavior of Addax antelopes in desert environments. The algorithm balances exploration and exploitation using inertia weight and dynamic adaptation coefficients. So the objective function for the same is as follow:

$$\min_{\theta} L_{val} = 1 - Accuracy_{val}(\theta) \qquad (4)$$

Where θ represents the hyperparameters.

Following neural network training and optimization with various algorithms—including the baseline CNN, GA-CNN, AOA-CNN, and the proposed AOA-OBL-CNN—the model's classification performance is evaluated using standard evaluation metrics: accuracy, precision, recall, and F1-score. These measures provide a thorough understanding of how well the algorithm separates malignant and non-cancerous samples.

By incorporating all four criteria, the evaluation avoids depending just on accuracy, which can be misleading in imbalanced datasets, and assures that the model is robust, trustworthy, and appropriate for clinical applications. These findings also enable to fairly compare various optimization strategies and confirm the AOA-OBL-CNN model's supremacy in this task.

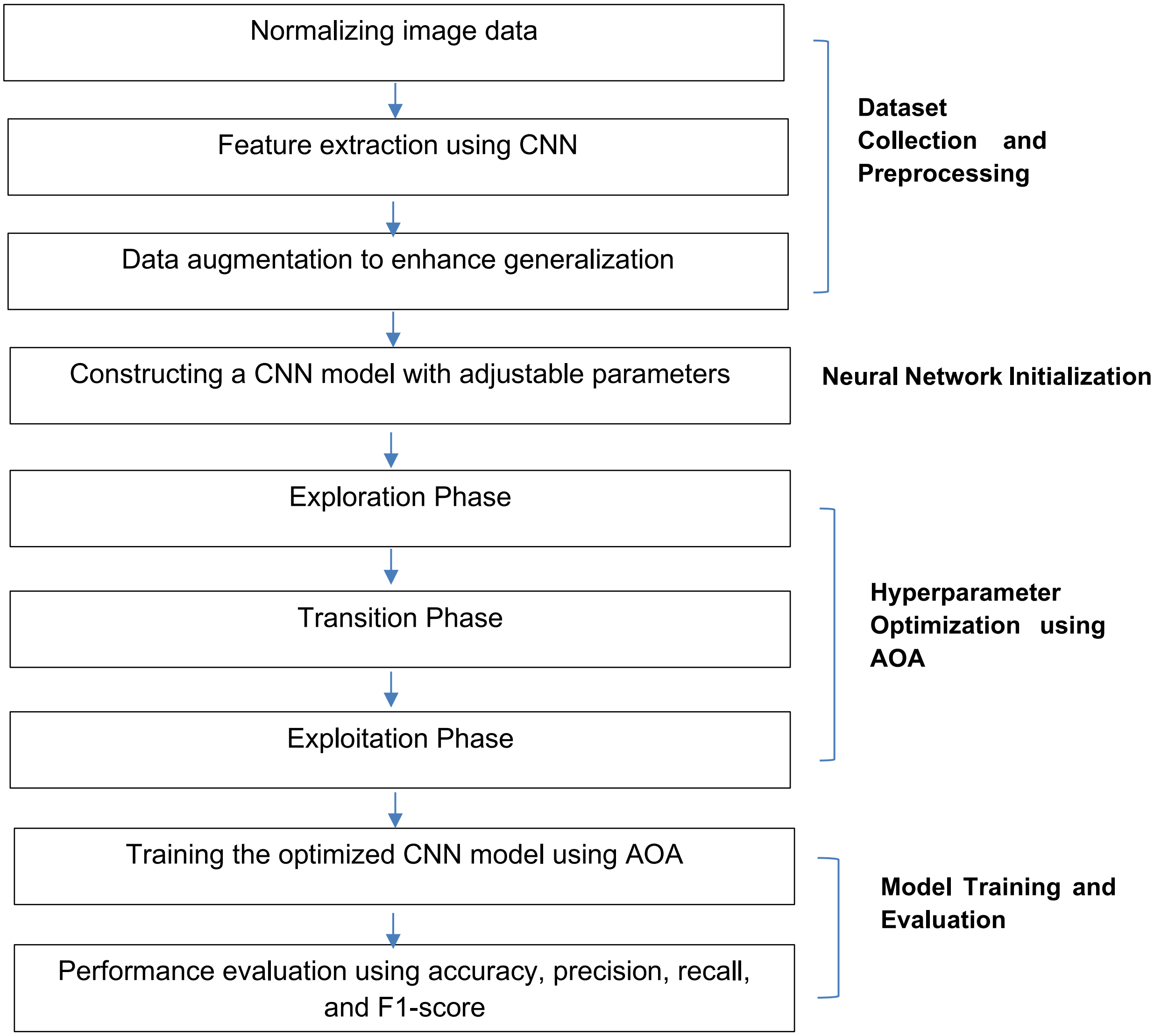

Figure 2. Flow chart of proposed model

Figure. 2 shows the flow of execution for the proposed model. the flow chart majority divided into four phases. The first phase is data collection and preprocessing where the images from the dataset used to get normalized, then the process of feature extraction is done and at the end data argumentation is done. The second phase of flow chart consists of initializing neural network with adjustable parameters. The third phase AOA takes place where the hyperparameter are get optimize using various step of AOA. And last phase explores training and evaluation of the model.

Experimental setup

For the proposed model, the parameter setting is given in table 2 where it shows population size, number of iterations, dataset split information, number of epochs, size of the image and loss function used for implementation.

Table 2. parameter setting for AOA-OBL-CNN

PARAMETER	*VALUE*
Population size	20
Iterations	50
Dataset split	70% Train, 15% Val, 15% Test
Epochs	50
Image size	128×128
Loss function	Categorical Crossentropy

CNN Architecture (Kept constant across all models)

- Input: 128x128x3
- Conv2D → ReLU → MaxPooling (×3 blocks)
- Flatten → Dense(128) → ReLU → Dropout(0.5)
- Output Layer: Dense(1) → Sigmoid

Results and discussion

The section represents the outcomes of the experiment. Here Addax Optimization Algorithm (AOA) is applied on neural network to optimize the parameters of colon cancer detection model. The evaluation of performance of the model is done on the bases of various metrics, such as accuracy, precision, recall, and F1-score. The dataset is taken for Kaggle for this study and then comparison is done with state-of-the-art as well as new metaheuristic algorithms like such as Genetic Algorithm (GA), Addax Optimization Algorithm (AOA) and Hybrid Models for better understanding of model performance.

Comparison of Model Performance

Table 3 shows the performance metrics of the optimized neural network models using different optimization algorithms. The models were evaluated on the accuracy, precision, recall, and F1-score. The results indicate that the neural network optimized using not only AOA but also AOA-OBL outperforms the models optimized with other algorithms.

Table 3. Performance Comparison of various Optimization Algorithms with CNN

MODEL	**ACCURACY (%)**	**PRECISION (%)**	**RECALL (%)**	**F1-SCORE (%)**
CNN	90.0	88.5	91.2	89.8
GA-CNN	92.4	91.0	93.1	92.0
AOA-CNN	94.8	94.0	95.2	94.6
AOA-OBL-CNN	96.5	96.2	96.8	96.5

The table 3 explains the experimental outcome of the proposed method, which combines the Addax Optimization Algorithm (AOA) with Opposition-Based Learning (OBL) to fine-tune a Convolutional Neural Network (CNN) for colon cancer detection. AOA-OBL-CNN model achieved the highest scores across all major classification metrics—accuracy, precision, recall, and F1-score. These metrics suggest that the model not only correctly identifies most cancer cases (high recall) but also avoids false positives (high precision), resulting in a robust and reliable classifier (high F1-score and accuracy). If it compares with other models, it shows that hybrid model performs better than standard CNNs and CNNs optimized using Genetic Algorithm (GA) or AOA alone, showing the added value of integrating OBL.

Additional the model supports the goal of good health and well-being by offering enhanced diagnostic accuracy, potentially leading to earlier and more reliable detection of colon cancer, improving patient outcomes. Not only this but also it utilizes cutting-edge AI techniques like metaheuristic optimization (AOA) and neural networks, pushing the boundaries of technological innovation in healthcare.

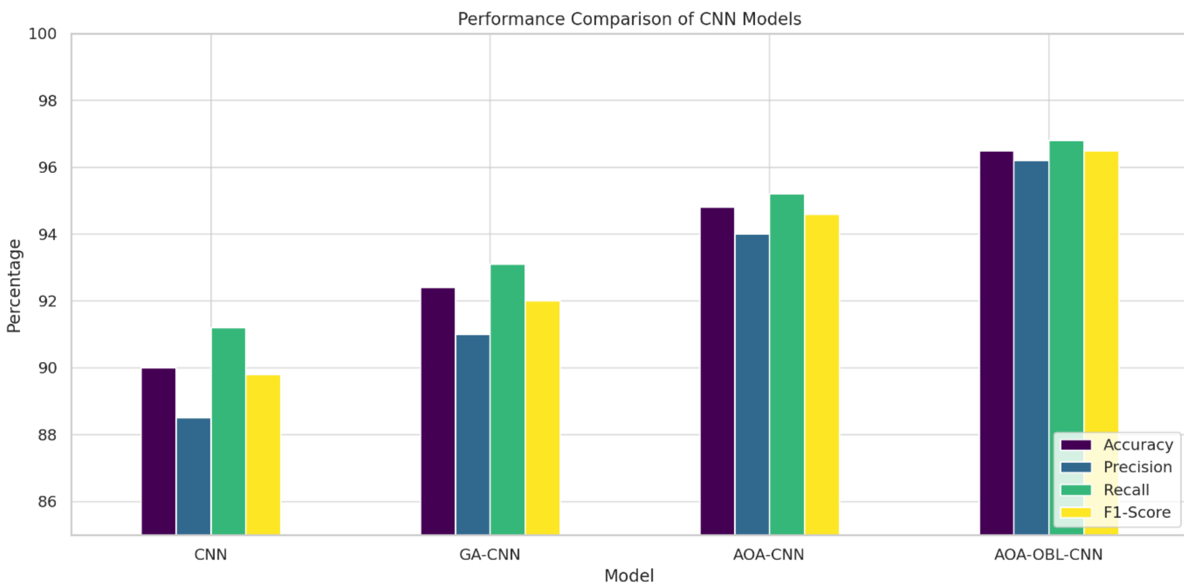

Figure 3. Comparative analysis graph of various CNN variants for colon cancer detection

Figure 3 consists of CNN which has Baseline performance, GA-CNN which is CNN optimized using Genetic Algorithm, AOA-CNN that is CNN optimized with Addax Optimization Algorithm and last is AOA-OBL-CNN which is CNN optimized using Addax Optimization Algorithm hybridized with Opposition-Based Learning. All the model has four key metrics: AccuracyPrecisionRecallF1 Score.The AOA-OBL-CNN model outperforms others in all metrics, highlighting the effectiveness of the hybrid optimization approach

This bar chart in figure 3 clearly show the Performance Comparison of CNN Models. The chart compares the performance metrics (Accuracy, Precision, Recall, F1-Score) of different CNN-based models. With respect to Accuracy, CNN shows decent performance with ~90% accuracy, Genetic Algorithm improves all metrics moderately with ~92%, Further enhancement through Addax Optimization with ~95% and the Best performance across all metrics with ~96.5%, showing the benefit of combining AOA with Opposition-Based Learning.

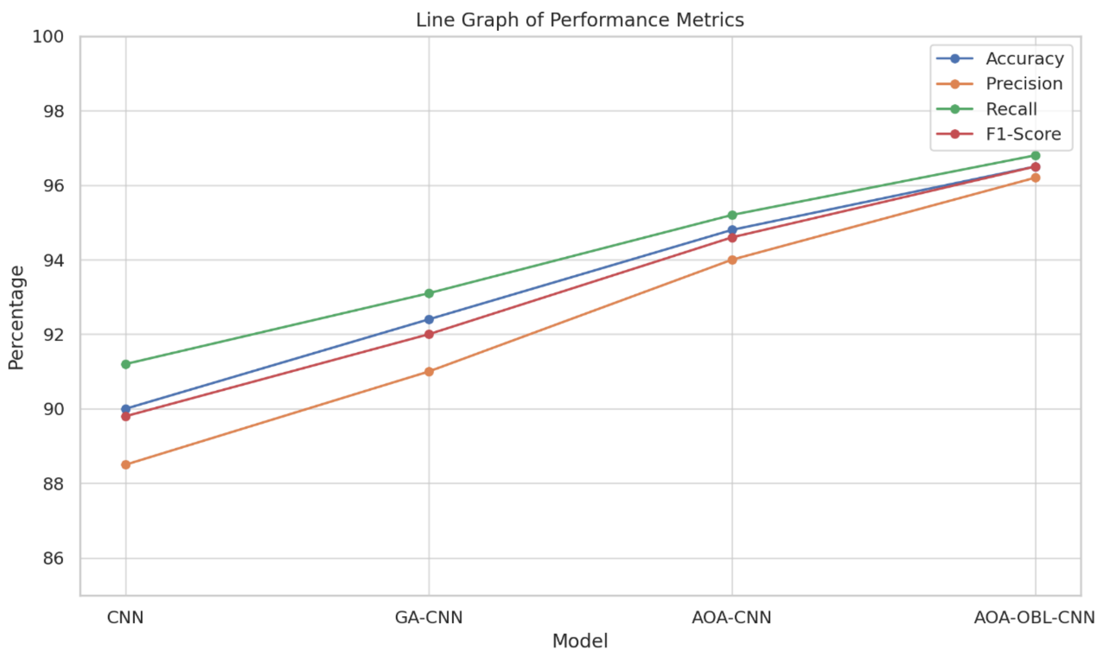

Figure 4. Performance Trends Across Models

Figure 4 depicts how each statistic improves progressively with each model upgrade. A smooth ascending trend implies steady improvement. AOA-OBL-CNN is a strong positive outlier, with large increases in all parameters. It is obvious that hyperparameter tuning using AOA (particularly with OBL) improves model performance significantly.

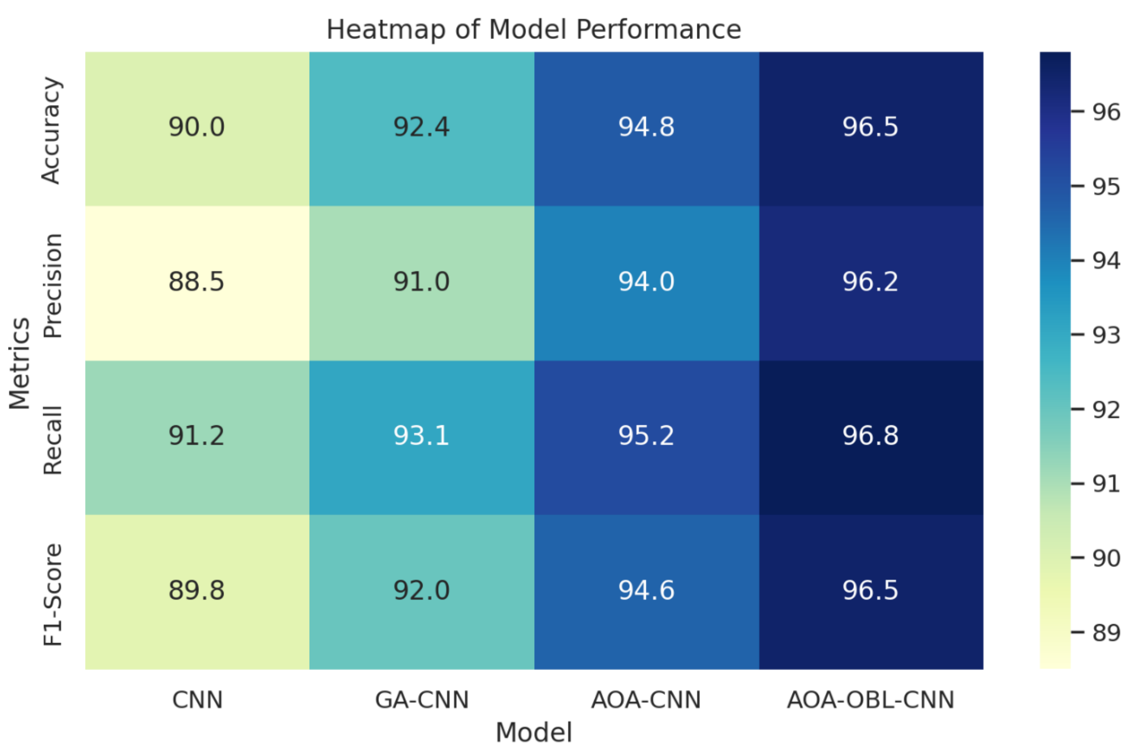

Figure 5. Heatmap of various Models

Figure 5 depicts the metric-wise intensity of several models. The color intensity represents how well each model performs in each statistic. Darker blue tones in the AOA-OBL-CNN row indicate greater overall performance. CNN's lighter tones emphasize its relatively poor performance. AOA-based models particularly with OBL produce significant improvements, making them ideal for medical diagnosis tasks.

Conclusion

This study aimed to increase the diagnostic accuracy of colon cancer detection using convolutional neural networks (CNNs) optimized by metaheuristic algorithms, specifically the Addax Optimization Algorithm (AOA) and its improved variation with opposition-based learning (AOA-OBL). The goal was to overcome the constraints of classic CNN models in medical diagnostics by enhancing their classification performance through intelligent hyperparameter adjustment. Metaheuristic optimization, specifically AOA and AOA-OBL, outperforms both conventional CNNs and alternative evolutionary approaches such as GA. The AOA-OBL-CNN framework has been demonstrated to be extremely effective in clinical applications, with great classification consistency across all performance criteria. The performance improvement is not only statistically significant, but also clinically useful, providing more support for the early and precise identification of colon cancer. Expand the AOA-OBL strategy to include more cancer types (lung, breast, prostate) and imaging modalities (MRI, CT, histology).

The future work could be Investigate hybrid optimization strategies that incorporate AOA with swarm intelligence or gradient-based methodologies. Implement the paradigm in real-time diagnostic systems, with explainability modules for physician assistance. Integrate uncertainty quantification to boost trustworthiness in AI-powered diagnostics.

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