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Development of an Improved Mayfly Algorithm Based Convolutional Neural Network for Pulmonary Diseases Recognition System

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Abstract
Pulmonary diseases impact the respiratory system. Convolutional Neural Network (CNN) is used for detection and recognition of pulmonary diseases; however, it suffers from hyperparameter selection and overfitting problems. Existing optimization techniques such as the Mayfly Algorithm (MA) also require initial parameter tuning and exhibit slow convergence behaviour. This research developed a Roulette Chaotic Mayfly Algorithm (RCMA) based on CNN (RCMA-CNN) for pulmonary diseases recognition. X-ray images including normal and pulmonary diseases cases were obtained from Kaggle and pre-processed for the desired image quality. The RCMA was formulated using Roulette wheel selection to model attraction deterministically and Chaotic Sinusoidal Map Function to balance exploration and exploitation in the MA. RCMA was applied to optimize CNN hyperparameters including number of layers and batch size at the convolutional layer. This was implemented in MATLAB (R2020a) and compared with MA-CNN and CNN in terms of false positive rate, sensitivity, specificity, accuracy and recognition time. At optimal threshold of 0.75, RCMA-CNN gave false positive rate of 1.43%, sensitivity of 98.06%, specificity of 98.57%, and accuracy of 98.32%. RCMA-CNN recorded a recognition time of 76.81 seconds, which was better than that of MA-CNN and CNN. The RCMA-CNN model significantly outperformed both MA-CNN and standard CNN.

Keywords: *Convolutional Neural Network, Hyperparameters, Mayfly Algorithm, Pulmonary Diseases, Roulette Chaotic Mayfly Algorithm*

1. Introduction

Pulmonary diseases are putting even the best healthcare systems across the world under tremendous pressure [7] Pulmonary diseases have become apparently a fatal Severe Acute Respiratory Syndrome (SARS) infection over the last six (6) years [8, 14] It has seriously threatened human life and health worldwide. The early recognition of this type of diseases will help in relieving pressure on the healthcare systems [7, 10]. Furthermore, early and automatic diagnosis of pulmonary diseases may be beneficial to countries for timely referral of the patient to quarantine, rapid incubation of serious cases in specialized hospitals, and monitoring of the spread of the disease [2].

Effective screening and diagnosis are crucial in combating pulmonary diseases, and among various technologies such as Imaging, Serology, Reverse Transcriptase-Polymerase Chain Reaction (RT-PCR), and Droplet Digital-PCR (ddPCR), chest X-ray imaging remains a valuable diagnostic tool. Computer-aided diagnosis of chest X-ray images offers essential support to medical experts by reducing their workload [13]. The availability of public X-ray

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datasets from both healthy individuals and patients since March 2020 has enabled researchers to identify patterns for automated disease detection. Recognizing lung cancer, pneumonia, and COVID-19 from X-ray images is life-saving, particularly in regions with limited access to laboratory kits [11]. Considering the high cost and time requirements of traditional testing, Artificial Intelligence (AI) and deep learning approaches have become vital tools for assisting doctors in the timely and accurate diagnosis of pulmonary diseases [2].

A respiratory condition known as pneumonia results in inflammation of one or both lungs and produces symptoms like fever, chest pain, coughing, and difficulty breathing (dyspnea). Early identification is crucial for treating pneumonia effectively and improving patient outcomes. [5]. This is significant because the disease is still rampant in various parts of the world, and effective diagnosis is critical. Therefore, the use of AI-based automated high-accuracy technologies may provide valuable assistance to doctors in diagnosing pulmonary diseases. Deep Learning such as Convolutional Neural Network (CNN) yielded promising results in classifying radiological images. The challenges in the hyperparameter selection when trained with CNN can be solved using an optimization technique.

The Mayfly Algorithm (MA) is an optimization technique inspired by the social behavior of mayflies, and particularly from their mating process. After hatching from the egg, mayflies are considered adults, and the fittest individuals survive regardless of their lifespan. In the optimization process, the position of each mayfly in the search space represents a potential solution to the problem [15]. The Mayfly Algorithm (MA) was introduced to improve the Convolutional Neural Network. Exploring novel optimization methods tailored to pulmonary disease recognition systems, such as the Roulette Chaotic Mayfly Algorithm (RCMA) is an unexplored area. This research demonstrated that the Optimized technique outperformed the Convolutional Neural Network and is recommended for applications in detecting healthy patients and pneumonia, lung cancer and covid-19 patients from the X-ray images.

2. Related Works

Hussain *et al.*, [6] developed an AI-based imaging analysis tool to classify pulmonary diseases using chest X-ray images. They analyzed 130 public CXR datasets, extracting texture and morphological features, and applied five supervised machine learning algorithms for both binary and multi-class classification, showing promising performance in distinguishing COVID-19 from other pulmonary diseases.

Vaid *et al.*, [12] utilized convolutional neural networks (CNNs) with transfer learning to detect COVID-19 from chest radiographs. Their model achieved high accuracy (96.3%) while minimizing manual intervention from radiologists, highlighting the potential of CNNs for automated pulmonary disease detection.

Goel *et al.*, [4] introduced an optimized CNN, OptCoNet, for automatic COVID-19 diagnosis from CXR images. Using the Grey Wolf Optimizer for hyperparameter tuning, their model achieved 97.78% accuracy with improved sensitivity and specificity, outperforming standard CNNs.

Nahiduzzaman *et al.*, [9] proposed ChestX-ray6, a lightweight CNN for detecting six pulmonary diseases, achieving 97.94% accuracy in binary classification. The model is compact and shows potential for deployment in mobile or point-of-care settings, emphasizing practicality alongside performance.

An *et al.*, [1] combined EfficientNetB0 and DenseNet121 for pneumonia detection in chest X-rays. Their model achieved 95.19% accuracy, 98.38% precision, and 0.9564 AUC, suggesting strong potential for clinical decision support in pulmonary disease diagnosis.

CNN suffers from hyperparameter selection problems, which can be solved using optimization techniques such as genetic algorithm and mayfly [7]. The hyperparameters of CNNs have a significant impact on the network's performance, so they directly control the training process. The selection of suitable hyperparameters plays an important role in the training of the CNN. In addition, CNNs are powerful, but they often require high computational time due to substantial high storage and computational resources. The increased computational cost can be attributed to the increased width (numbers of filters), depth (number of layers), smaller strides, and their combinations [6]. The recent Mayfly Algorithm still suffers from initial parameter tuning and has slow convergence behaviour [15].

Hence, this study developed an improved Mayfly Algorithm using Roulette wheel selection and Chaotic theory called (RCMA) to resolve the problem of slow convergence in existing MA. It furthers employed RCMA to select appropriate CNN hyperparameters such as number of layers, number of filters, filter size and batch size, which has resolved CNN hyperselection problem and reduced computational time.

3. Methodology

3.1 The Research Approach

The X-ray images, including normal and pulmonary disease cases, were acquired from the Kaggle repository. The dataset contains Chest X-ray images of COVID-19, pneumonia, lung cancer, and normal cases. The images were pre-processed to obtain the desired quality, followed by segmentation for further analysis. A Roulette Chaotic Mayfly Algorithm (RCMA) was developed by applying the roulette wheel selection procedure to model the attraction process as a deterministic process, assisting the standard MA, and incorporating a Chaotic Sinusoidal Map Function to establish a balance between exploration and exploitation. The RCMA was utilized to optimize CNN hyperparameters such as the number of layers and batch size at the convolutional layer. The segmented results were then presented to the RCMA-CNN for feature extraction and recognition of pulmonary diseases, including lung cancer, pneumonia, and COVID-19. The performance of the developed technique was evaluated using accuracy, specificity, sensitivity, false positive rate, and computation time. Figure 1 depicts the framework diagram to illustrate the entire methodology.

Image Acquisition

The dataset used in this study was collected from a Comprehensive Dataset for AI-driven Analysis of Chest X-ray Images consisting of COVID-19, pneumonia, lung cancer, and normal cases available via www.kaggle.com. A total of 2,575 pulmonary disease cases were initially analyzed, including 650 COVID-19 cases, 605 lung cancer cases, 600 pneumonia cases, and 720 normal cases. Data augmentation techniques such as flipping and rotation were applied to each category of pulmonary disease, increasing the dataset to 1,950 COVID-19 cases, 1,815 lung cancer cases, 1,800 pneumonia cases, and 2,160 normal cases, resulting in a total of 7,725 pulmonary disease cases. This expanded dataset provided a more robust and diverse set of training samples, enhancing the model's ability to generalize and accurately diagnose various pulmonary conditions. The model development and evaluation process utilized 5,831 cases (75% of the dataset) for training and 1,894 cases (25% of the dataset) for testing through a random sub-sampling cross-validation method. This data allocation ensured sufficient information for model training and a reliable assessment of its performance on unseen data, thereby facilitating a comprehensive evaluation of the model's accuracy and reliability in diagnosing different pulmonary diseases.

Image Preprocessing

Image preprocessing plays an important role in training the model, conforming to system requirements. The acquired images underwent preprocessing stage, which involves image resizing, image enhancement and segmentation. Image resizing ensures that all

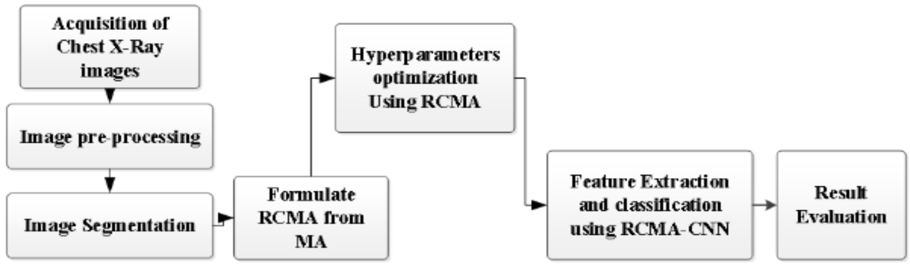


Figure 1: The framework diagram of the methodology

pulmonary disease images have uniform dimensions, which is necessary for consistent input into the deep learning model and reduces computational complexity. Image enhancement improves the visual quality of the images by increasing contrast and highlighting important lung structure details. In this study, histogram equalization was used to enhance lung features for better feature extraction. Segmentation isolates the region of interest (the lung area) from the background or unwanted parts of the image. Using the Sobel-edge detection algorithm, the boundaries of the lung region were clearly defined for accurate analysis.

3.2 Development of pulmonary diseases recognition system using RCMA-CNN

The main aspect of this scheme is the development of a method for classifying Chest X-ray images using deep learning Convolutional Neural Networks (CNN). The images were categorized into lung cancer, pneumonia, and COVID-19 classes, where the input images produced accurately classified outputs. CNN was fine-tuned using the Roulette Chaotic Mayfly Algorithm (RCMA), allowing the network to be retrained with Chest X-ray images for precise classification results. This approach enhanced the efficiency of the pre-trained VGG-19 network by optimizing key hyperparameters such as the number of layers, filters, and batch size through RCMA. After the convolutional and pooling layers, fully connected layers were used to combine the extracted features, followed by a SoftMax layer that generated the final classification output. This structure enabled the study of nonlinear combinations of extracted features, ensuring effective and accurate classification of pulmonary diseases.

The optimization of hyperparameters in pre-trained CNN architectures plays a vital role in improving their adaptability and performance. RCMA was integrated into the CNN framework to overcome the limitations of fixed hyperparameters in pre-trained networks. The algorithm optimized parameters such as batch size, dropout rate, number of convolutional layers, filter sizes, and the number of filters per layer by generating populations of male and female mayflies, each representing potential CNN configurations. These configurations were evaluated iteratively, updating their positions based on the best individual (pbest) and global (gbest) results until convergence toward the optimal CNN setup was achieved. Although computationally intensive, this process significantly enhanced model efficiency and predictive accuracy. During the learning phase, the optimized VGG-19-based CNN architecture efficiently classified chest X-ray images of pneumonia, lung cancer, and COVID-19. The final RCMA-CNN model demonstrated a strong capability in accurately recognizing pulmonary diseases, offering a reliable and effective framework for medical image analysis and diagnosis.

3.3 Implementation of RCMA-CNN for Pulmonary Diseases Recognition System

The implementation of RCMA-CNN for Pulmonary Diseases Recognition System was carried out using MATLAB R2020a. An interactive Graphic User Interface (GUI) application was developed with an online database using toolboxes such as image processing and computer vision as well as optimization in MATLAB 2020a. The MATLAB software package was used for the implementation on a HP computer system with Windows 10Pro, Intel® Core i7-7600U 7th Gen CPU@2.90GHz, 16.0GB, 64-bit O.S, 500GB configuration.

3.4 Evaluation Measure

The performance of the developed technique under study for the recognition of pneumonia, lung cancer and Covid-19 was evaluated based on False Positive Rate (FPR), sensitivity, specificity, precision, accuracy and prediction time. Confusion matrix was used to determine the values of the performance metrics. It contains “True Positive (TP), False Positive (FP), False Negative (FN) and True Negative (TN)”.

False-Positive Rate (FPR): The number of negative observations the model incorrectly predicted as positive. It is based on how many actual negatives the model predicted incorrectly.

$$\text{False Positive Rate} = \frac{\text{FP}}{\text{TN+FP}}\ X\ 100\% \quad (3.1)$$

Sensitivity: This is the metric that evaluates a model's ability to predict true positives of each available category. It is the ratio of the correctly positive (+ve) labelled by our program to all who are pneumonia, lung cancer, and COVID-19 positive in reality. Sensitivity answers the following question: Of all the people who have pneumonia, lung cancer, and COVID-19 positive, how many of those we correctly predicted.

$$\text{Sensitivity} = \frac{\text{TP}}{\text{TP+FN}}\ X\ 100\% \quad (3.2)$$

Specificity: This is the correctly negative (-ve) labelled by the program to all who are healthy. Specificity answers the following questions: Of all the healthy people, how many of those did we correctly predict?

$$\text{Specificity} = \frac{\text{TN}}{\text{TN+FP}}\ X\ 100\% \quad (3.3)$$

Precision: This is the ratio of True Positives to all positive predictions made by the model. A low precision value indicates a higher number of false positives. This metric reflects how effectively the model identifies the positive class, showing how many of its positive predictions are actually correct. Using this metric alone for optimization focuses on minimizing false positives.

$$\text{Precision} = \frac{\text{TP}}{\text{TN+FP}}\ X\ 100\% \quad (3.4)$$

Accuracy: This is the total number of correct predictions divided by the total number of predictions made for a dataset.

$$\text{Accuracy} = \frac{\text{TP+TN}}{\text{TP+TN+FP+FN}}\ X\ 100\% \quad (3.5)$$

Intersection Delay Index (IDI): Intersection Delay Index is a normalized measure used to evaluate the overall delay efficiency of the junction. AVD = average vehicle delay (as previously defined), and C = cycle time (total duration of one full signal cycle). A lower IDI reflects a more efficient intersection with minimal delays relative to the signal cycle length.

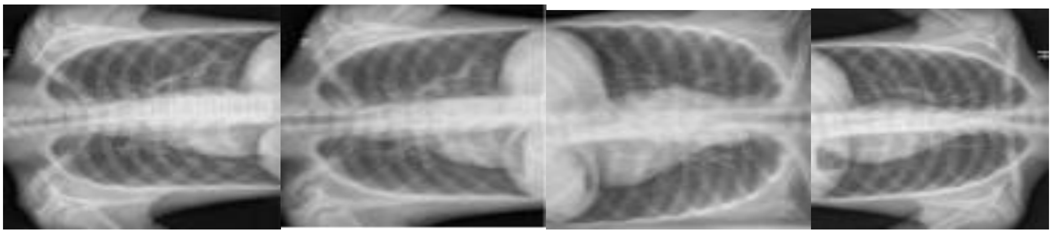
$$\text{Computational Time} = \frac{\text{No.of recognised pulmonary disease images}}{\text{Total number of pulmonary disease images}}\ X\ \text{Time Taken} \quad (3.6)$$

4. Results and Discussion

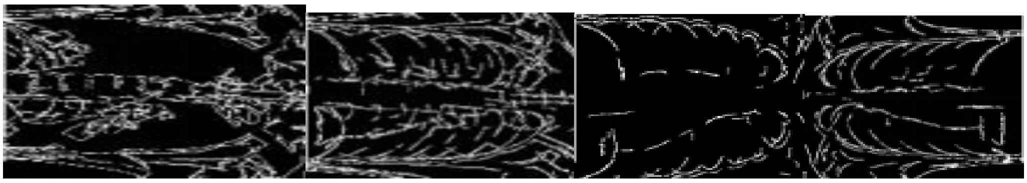
A total of 7,725 cases were collected. The dataset consisted of 1,950 COVID-19 cases, 1,815 lung cancer cases, 1,800 pneumonia cases, and 2,160 normal cases. To train and evaluate the model, 5,831 cases were randomly assigned to the training set, using random sub-sampling cross-validation and 1,894 cases were reserved for the testing set. Using this distribution, the model was trained on a significant portion of the data, enabling it to learn from various pulmonary conditions. The remaining data in the testing set provided a strong foundation for evaluating the model's ability to accurately predict outcomes in unseen cases, ensuring its reliability in real-world use.

The CNN, MA-CNN, and RCMA-CNN classifiers were evaluated on their ability to diagnose pulmonary diseases; lung cancer, pneumonia, and COVID-19 using chest X-ray images. The preprocessed and segmented images used in the study are shown in Figure 2. The Graphical User Interface (GUI) for training, testing, and classifying lung chest X-ray images based on pulmonary disease is presented in Figures 3, Figure 4, and Figure 5, respectively.
The system's performance was evaluated using the following metrics: False Positive Rate (FPR), Accuracy (ACC), Sensitivity (SEN), Specificity (SPEC), and recognition time. These metrics were analyzed for different average threshold values (0.25, 0.35, 0.50, and 0.75) at various pixel resolutions. The study used a 75/25 train-test split with random sampling cross-validation.

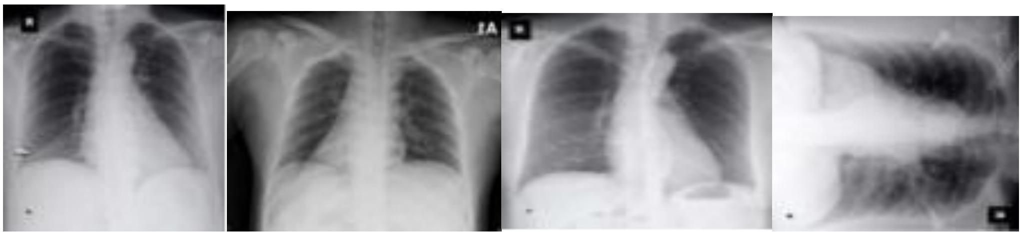
The optimization of the MA and RCMA algorithms on the CNN involved experimenting with different filter sizes, numbers of filters, Convolutional layers, and batch sizes. The optimization process, using recognition rate as the objective function which is inversely proportional to the fitness value of MA and RCMA. After 30 iterations, the MA and RCMA achieved recognition rates of 99.12% and 99.91%, respectively, with the optimal CNN configurations being 17 convolutional layers, 256 filters per layer (5×5), and batch size 256 for MA, and 19 convolutional layers, 256 filters per layer (3×3), and batch size 128 for RCMA.



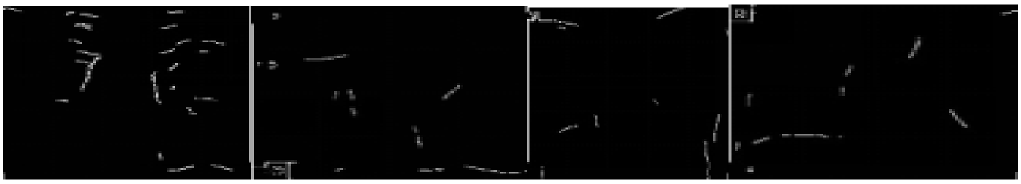
(a) Original Image Positive



(b) Pre-processed Image Negative



(a) Original Image Positive



(b) Pre-processed Image Negative

Figure 2: Original and Pre-processed images

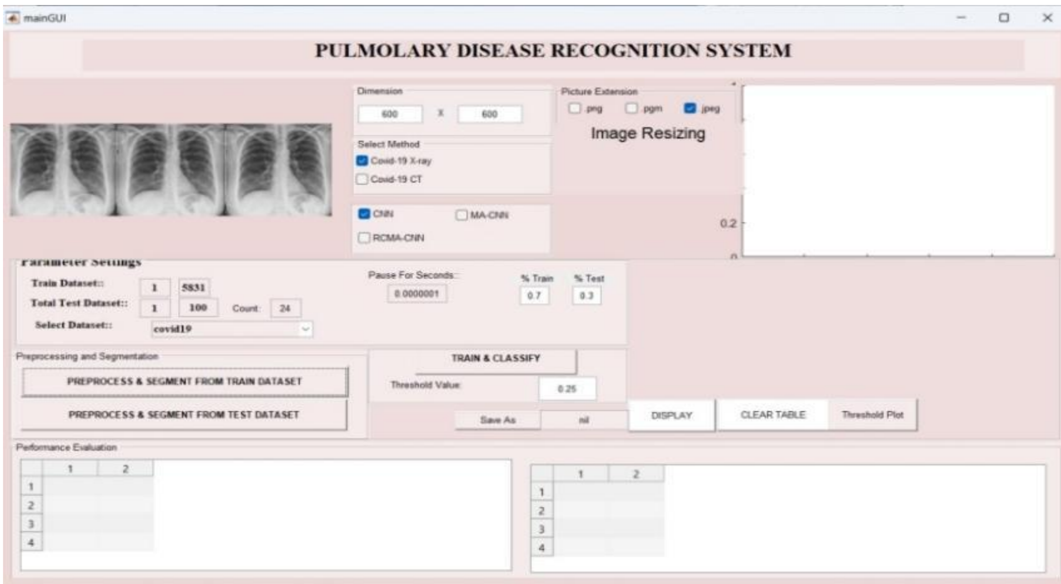


Figure3: Graphical User Interface (GUI) showing training phase

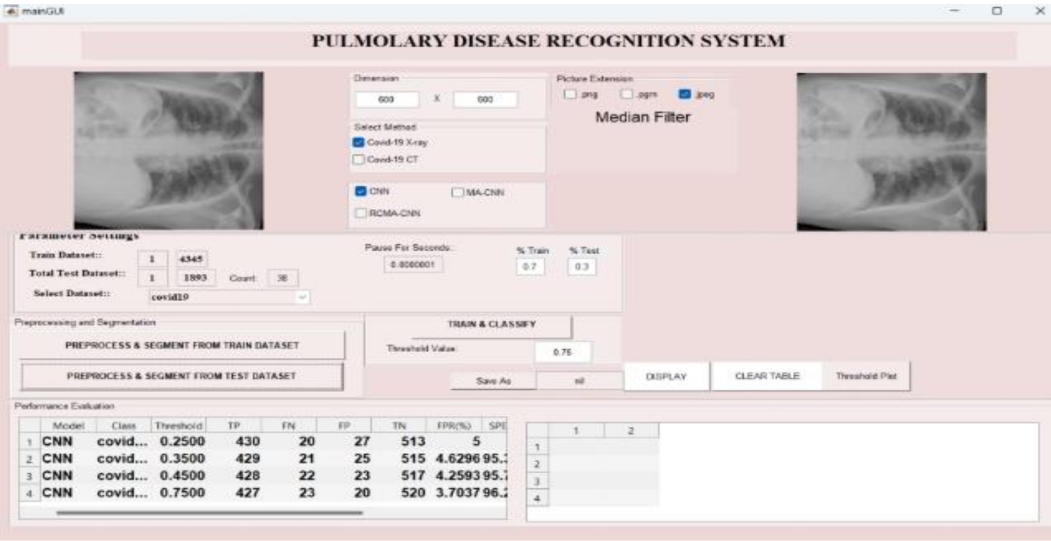


Figure 4: Graphical User Interface (GUI) showing testing phase and Classification

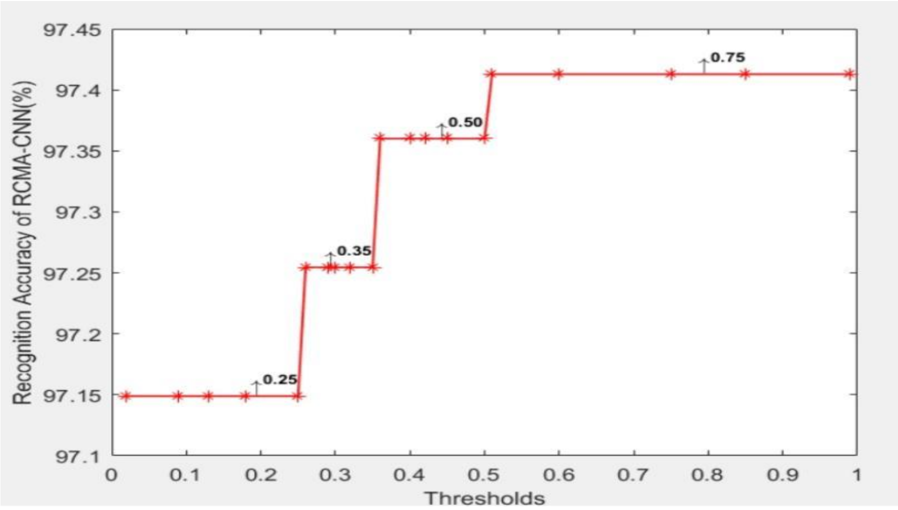


Figure 5: Graph showing choice of threshold used for the evaluation

4.1 Results for CNN

A Convolutional Neural Network (CNN) analysed a dataset of 1,894 cases at the optimal threshold of 0.75, comprising 450 COVID-19, 454 lung cancer, 450 pneumonia, and 540 normal cases. The dataset was divided into three segments for evaluation: COVID-19 vs. Normal, Lung Cancer vs. Normal, and Pneumonia vs. Normal. This structured approach enabled a comprehensive assessment of the CNN's ability to distinguish between normal and diseased cases, effectively demonstrating its diagnostic strength across different pulmonary conditions.

Analysis of CNN with Pneumonia

Table 1 presents the CNN results on 990 chest X-ray images, comprising 450 positive and 540 negative cases. At the optimal threshold of 0.75, the CNN correctly identified 424 positive and 517 negative cases, with 26 false negatives and 23 false positives. The model achieved an average FPR of 4.25%, specificity of 95.74%, sensitivity of 94.22%, and accuracy of 95.05%, with an average classification time of 80.62 seconds.

Table 1: Performance of the CNN technique with pneumonia

Threshold	0.25	0.35	0.50	0.75
TP (positive)	427	426	425	424
FN (negative)	23	24	25	26
FP (positive)	30	28	26	23
TN (negative)	510	512	514	517
SPEC (%)	94.44	94.81	95.18	95.74
SEN (%)	94.88	94.66	94.44	94.22
FPR (%)	5.55	5.18	4.81	4.25
ACC (%)	94.64	94.74	94.84	95.05
Time(sec)	89.93	88.64	86.06	80.62

Analysis of CNN with lung cancer

Table 2 presents the CNN results on 994 chest X-ray images, including 454 positive and 540 negative cases. At the optimal threshold of 0.75, the CNN correctly identified 429 positive and 518 negative cases, with 25 false negatives and 22 false positives. The model achieved an average FPR of 4.07%, specificity of 95.92%, sensitivity of 94.49%, and accuracy of 95.27%, with an average classification time of 79.75 seconds.

Analysis of CNN with COVID-19

Table 3 presents the CNN results on 990 chest X-ray images, comprising 450 positive and 540 negative cases. At the optimal threshold of 0.75, the CNN correctly identified 427 positive and 520 negative cases, with 23 false negatives and 20 false positives. The model achieved an average FPR of 3.70%, specificity of 96.29%, sensitivity of 94.88%, and accuracy of 95.65%, with an average classification time of 84.08 seconds.

Table 2: Performance of the CNN technique with Lung Cancer

Threshold	0.25	0.35	0.50	0.75
TP (positive)	432	431	430	429
FN (negative)	22	23	24	25
FP (positive)	29	27	25	22
TN (negative)	511	513	515	518
SPEC (%)	94.62	95	95.37	95.92
SEN (%)	95.15	94.93	94.71	94.49
FPR (%)	5.37	5.0	4.62	4.07
ACC (%)	94.86	94.96	95.07	95.27
Time(sec)	81.05	88.40	80.77	79.75

Table 3: Performance of the CNN technique with COVID

Threshold	0.25	0.35	0.50	0.75
TP (positive)	430	429	428	427
FN (negative)	20	21	22	23
FP (positive)	27	25	23	20
TN (negative)	513	515	517	520
SPEC (%)	95	95.37	95.74	96.29
SEN (%)	95.55	95.33	95.11	94.88
FPR (%)	5.0	4.62	4.25	3.07
ACC (%)	95.25	95.35	95.45	95.65
Time(sec)	82.71	82.33	80.03	84.08

4.2 Results for MA-CNN

In this study, a Convolutional Neural Network (CNN) optimized with the mayfly algorithm was used to achieve the best settings at a target accuracy threshold of 0.75. The enhanced CNN analyzed 1,894 medical images comprising 450 COVID-19 cases, 454 lung cancer cases, 450 pneumonia cases, and 540 healthy cases. The evaluation focused on three comparisons: COVID-19 vs. Normal with 990 images, Lung Cancer vs. Normal with 994 images, and Pneumonia vs. Normal with 990 images.

Analysis of MA-CNN with Pneumonia

Table 4 presents the results of the MA-CNN technique applied to 990 chest X-ray images, including 450 pneumonia and 540 healthy cases. Optimized with the mayfly algorithm, the model achieved its best performance using 3 convolutional layers, 128 filters per layer, a filter size of 6x6, a batch size of 155, and an optimum threshold of 0.75. At these settings, it correctly classified 431 positive and 524 negative cases, achieving 95.77% sensitivity, 97.03% specificity, and 96.46% accuracy, with a processing time of 61.68 seconds.

Analysis of MA-CNN with Lung Cancer

Table 5 presents the results of the MA-CNN technique applied to 990 lung chest X-ray images, including 450 positive and 540 negative cases. Using the optimal parameters of 3 convolutional layers, 128 filters per layer, a filter size of 6×6, a batch size of 155, and an optimum threshold of 0.75, the model correctly classified 434 positive and 523 negative cases, with 20 false negatives and 17 false positives. At this threshold, the MA-CNN achieved an average FPR of 3.14%, specificity of 96.85%, sensitivity of 95.59%, and accuracy of 96.27%, with a processing time of 59.59 seconds.

Analysis of MA-CNN with COVID

Table 6 presents the results of the CNN technique applied to 990 chest X-ray images, including 450 positive and 540 negative cases across all junctions. Signal Timing Efficiency reached 93.06%, and Green Time Utilization was 83.90%, indicating effective synchronization of signal phases with real-time traffic demand. The Intersection Delay Index values ranged between 0.377 and 1.160, showing smoother flow and reduced congestion. Overall, the SWO-Fuzzy system demonstrated superior adaptability and efficiency, outperforming the traditional FLC in optimizing traffic movement across all junctions.

Table 4: Performance of the MA-CNN technique with Pneumonia

Threshold	**0.25**	**0.35**	**0.45**	**0.75**
TP (positive)	434	433	432	431
FN (negative)	16	17	18	19
FP (positive)	23	21	19	16
TN (negative)	517	519	521	524
SPEC (%)	95.74	96.11	96.48	97.03
SEN (%)	96.44	96.22	96.0	95.77
FPR (%)	4.25	3.88	3.51	2.96
ACC (%)	96.06	96.16	96.26	96.46
Time (sec)	61.83	59.79	61.26	61.68

Table 5: Performance of the MA-CNN technique with Lung Cancer

Threshold	**0.25**	**0.35**	**0.45**	**0.75**
TP (positive)	437	436	435	434
FN (negative)	17	18	19	20
FP (positive)	24	22	20	17
TN (negative)	516	518	520	523
SPEC (%)	95.55	95.92	96.85	96.85
SEN (%)	96.25	96.03	95.81	95.59
FPR (%)	4.44	4.07	3.70	3.1
ACC (%)	95.87	95.97	96.07	96.27
Time (sec)	60.03	60.19	60.10	59.59

Table 6: Performance of the MA-CNN technique with COVID

Threshold	0.25	0.35	0.45	0.75
TP (positive)	435	434	433	432
FN (negative)	15	16	17	18
FP (positive)	22	20	18	15
TN (negative)	518	520	522	525
SPEC (%)	95.92	96.29	96.66	97.22
SEN (%)	96.66	96.44	96.22	96.0
FPR (%)	4.07	3.07	3.33	2.7
ACC (%)	96.26	96.36	96.46	96.66
Time (sec)	60.25	59.81	60.08	59.68

4.3 Results for RCMA-CNN

In this study, an optimal threshold of 0.75 was set, and a Convolutional Neural Network (CNN) fine-tuned using the Roulette Chaotic Mayfly Algorithm (RCMA) was employed to identify the best hyperparameters. The RCMA-optimized CNN analyzed 1,894 cases, including 450 COVID-19, 454 lung cancer, 450 pneumonia, and 540 normal cases. A detailed evaluation was conducted using 990 COVID-19 and normal cases, 994 lung cancer and normal cases, and 990 pneumonia and normal cases, enabling a thorough comparison across disease categories and enhancing the model's accuracy in diagnosing pulmonary conditions.

Analysis of RCMA-CNN with Pneumonia

Table 7 presents the results of the RCMA-CNN technique applied to 990 lung chest X-ray images, including 450 positive and 540 negative cases. Using optimal parameters of 3 convolutional layers, 128 filters per layer, a filter size of 7×7, a batch size of 256, and an optimum threshold of 0.75, the model correctly classified 439 positive and 532 negative cases, with 11 false negatives and 8 false positives. At this threshold, RCMA-CNN achieved an average FPR of 1.48%, specificity of 98.51%, sensitivity of 97.55%, and accuracy of 98.08%, with a processing time of 40.36 seconds

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Table 7: Performance of the RCMA-CNN technique with Pneumonia

Threshold	0.25	0.35	0.45	0.75
TP (positive)	442	441	440	439
FN (negative)	8	9	10	11
FP (positive)	16	13	10	8
TN (negative)	524	527	530	532
SPEC (%)	97.03	97.59	98.14	98.51
SEN (%)	98.22	98.0	97.77	97.55
FPR (%)	2.96	2.40	1.85	1.48
ACC (%)	97.57	97.77	97.97	98.08
Time(sec)	39.94	39.94	39.84	40.36

Analysis of RCMA-CNN with Lung Cancer

Table 8 presents the RCMA-CNN technique results based on 990 lung chest X-ray images, comprising 450 positive and 540 negative cases. Using optimal parameters of 3 convolutional layers, 128 filters per layer, a 7×7 filter size, a batch size of 256, and an optimum threshold of 0.75, the model accurately classified 439 positive and 532 negative cases, misclassifying only 11 positives and 8 negatives. At this threshold, RCMA-CNN achieved an average FPR of 1.48%, specificity of 98.51%, sensitivity of 97.55%, and overall accuracy of 98.08%, completing the classification in 40.36 seconds.

Analysis of RCMA-CNN with COVID

Table 9 presents the RCMA-CNN technique results based on 990 lung chest X-ray images, including 450 positive and 540 negative cases. Using optimal parameters of 3 convolutional layers, 128 filters per layer, a 7×7 filter size, a batch size of 256, and an optimum threshold of 0.75, the model correctly classified 440 positive and 533 negative cases, with only 10 positives and 7 negatives misclassified. At this threshold, RCMA-CNN achieved an average FPR of 1.26%, specificity of 98.70%, sensitivity of 97.77%, and an overall accuracy of 98.28%, completing the classification in 40.07 seconds

Table 8: Performance of the RCMA-CNN technique with Lung Cancer

Threshold	**0.25**	**0.35**	**0.45**	**0.75**
TP (positive)	448	447	446	445
FN (negative)	6	7	8	9
FP (positive)	14	11	8	6
TN (negative)	526	529	532	534
SPEC (%)	97.40	97.96	98.51	98.88
SEN (%)	98.67	98.45	98.23	98.01
FPR (%)	2.59	2.40	1.48	1.11
ACC (%)	97.98	98.18	98.39	98.49
Time(sec)	40.42	40.23	40.37	40.06

.Table 9: Performance of the RCMA-CNN technique with COVID

Threshold	**0.25**	**0.35**	**0.45**	**0.75**
TP (positive)	443	442	441	440
FN (negative)	7	8	9	10
FP (positive)	15	12	9	7
TN (negative)	525	528	531	533
SPEC (%)	97.22	97.77	98.33	98.70
SEN (%)	98.44	98.22	98.0	97.77
FPR (%)	2.77	2.22	1.66	1.26
ACC (%)	97.77	97.97	98.18	98.28
Time(sec)	40.27	39.93	39.80	40.07

Table 10: Summary of the Performance Evaluation of CNN, MA-CNN and RCMA-CNN

Algorithm	FPR (%)	Sensitivity (%)	Specificity (%)	Accuracy (%)	Time (sec)
RCMA-CNN	1.43	98.06	98.57	98.32	76.81
MA-CNN	3.57	95.95	96.43	96.19	89.54
CNN	9.64	89.96	90.36	90.16	101.00

Comparison Results among CNN, MA-CNN, and RCMA-CNN

Table 10 presents a comparison of CNN, MA-CNN, and RCMA-CNN techniques in classifying pulmonary diseases using chest X-ray images across all performance metrics. At the optimum threshold of 0.75, MA-CNN and RCMA-CNN achieved lower recognition times than the standard CNN. Among the three, RCMA-CNN demonstrated superior performance with 98.32% accuracy, 98.06% sensitivity, 98.57% specificity, a false positive rate of 1.43%, and the shortest recognition time of 76.81 seconds. MA-CNN followed with 96.19% accuracy, 95.95% sensitivity, 96.43% specificity, a false positive rate of 3.57%, and a recognition time of 89.54 seconds, while CNN achieved 90.16% accuracy, 89.96% sensitivity, 90.36% specificity, a higher false positive rate of 9.64%, and the longest recognition time of 101.00 seconds. The improved performance of MA-CNN and RCMA-CNN was attributed to the optimal selection of convolutional layers, filter size, filter number, and batch size by MA and RCMA.

4.4 Discussion of Results

The results described the performance of the three-classifier techniques, showing significant variation in FPR, sensitivity, specificity, and accuracy across CNN, MA-CNN, and RCMA-CNN. At the optimum threshold value of 0.75, the MA-CNN and RCMA-CNN achieved recognition accuracies of 96.19% and 98.32%, respectively, while CNN attained 90.16%. Likewise, MA-CNN and RCMA-CNN recorded false positive rates of 3.57% and 1.43% with recognition times of 89.54 and 76.81 seconds, compared to CNN's 9.64% false positive rate and 101.0 seconds recognition time. The results showed that MA-CNN and RCMA-CNN improved recognition accuracy by 8.16% and 6.03% and reduced FPR by 6.07% and 8.21% over CNN.

These results indicated that MA-CNN and RCMA-CNN are more accurate due to their lower false positive rates and reduced recognition times, enabled by optimal parameter selection such as convolutional layers, filter size, and batch size. Both optimization techniques significantly enhanced CNN's performance by improving recognition accuracy and reducing computational time, aligning with the findings of Fregoso *et al*. (2021). [3] Overall, the study established that RCMA-CNN outperformed MA-CNN based on its superior results.

5. Conclusion

This study developed a pulmonary disease recognition system capable of detecting COVID-19, lung cancer, pneumonia, and normal cases using a Convolutional Neural Network (CNN) optimized with the Roulette Chaotic Mayfly Algorithm (RCMA). The RCMA-CNN achieved superior accuracy, sensitivity, specificity, and faster recognition times compared to traditional CNN and Mayfly-optimized CNN models, demonstrating its reliability and efficiency for medical diagnostics. The findings highlight the RCMA-CNN's potential to enhance clinical decision-making and patient outcomes, while future research should focus on expanding datasets, integrating additional optimization techniques, and conducting real-world clinical validations to further strengthen its robustness and applicability.

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