KAMPALA INTERNATIONAL UNIVERSITY

KIU
Journal of Science, Engineering and Technology

KJSET Research Article

Convolutional Neural Networks architectures for lung classification

[1]O. E Makinde*, [2]D.A. Omideyi, [3]M. O Oyediran

[1]oe.makinde@acu.edu.ng, [2]mo.oyediran@acu.edu.ng, [3]da.omideyi@acu.edu.ng

[1,2] Department of Computer Sciences, Ajayi Crowther University, Oyo.

[3] Department of Computer Engineering, Ajayi Crowther University, Oyo.

Paper history:
Received 22 April 2026
Accepted in revised form 28 May 2026

Keywords
Convolutional Neural Network, Mayfly Algorithm, Chest X-ray Images, Lung Disease Classification, Deep Learning.

Abstract

The increasing prevalence of lung-related diseases such as COVID-19, pneumonia, and tuberculosis has necessitated the development of intelligent diagnostic systems for early detection and classification using Chest X-ray images. This study focused on the development of a deep learning-based lung disease classification framework using Convolutional Neural Networks (CNN) integrated with the Mayfly Optimization Algorithm (MA). This study objectives are to: (i) acquire and pre-process Chest X-ray image datasets for lung disease detection, (ii) perform image segmentation and feature extraction using CNN architecture, (iii) optimize CNN hyper-parameters using the Mayfly Algorithm, and (iv) evaluate the performance of the developed CNN-MA model in comparison with the conventional CNN classifier. The study adopted deep learning techniques for lung disease classification using Chest X-ray images. A total of 2,820 Chest X-ray images comprising 1,414 COVID-19 positive and 1,406 non-COVID images were obtained from publicly available medical image repositories. The dataset was partitioned into 60% training and 40% testing sets using random sampling cross-validation. Data preprocessing techniques such as image resizing, histogram equalization, augmentation, segmentation, and feature extraction were performed. The CNN architecture was integrated with the Mayfly Algorithm for hyper-parameter optimization and feature selection. Performance evaluation was conducted using False Positive Rate (FPR), Sensitivity, Specificity, Accuracy, and Recognition Time. This findings revealed that: (i) the conventional CNN classifier achieved an accuracy of 90.16%, sensitivity of 89.96%, specificity of 90.36%, and FPR of 9.64%; (ii) the developed CNN-MA classifier achieved an improved accuracy of 96.19%, sensitivity of 95.95%, specificity of 96.43%, and FPR of 3.57%; (iii) the CNN-MA classifier recorded a faster recognition time of 89.54 seconds compared to 101.00 seconds for the conventional CNN; and (iv) the optimal CNN-MA configuration consisted of 3 convolutional layers, 128 filters, filter size of 6×6, and batch size of 155. This study concluded that the integration of the Mayfly Optimization Algorithm with CNN significantly improved lung disease classification performance by enhancing feature optimization, reducing false positive rates, and improving classification accuracy. This study recommended the adoption of intelligent MA-CNN frameworks for automated lung disease diagnosis in healthcare systems. However, this study was limited to publicly available Chest X-ray datasets and binary classification of lung diseases.

1.0 Introduction

Lung diseases such as COVID-19, pneumonia, tuberculosis, and other respiratory infections remain major global health challenges responsible for high mortality and morbidity rates worldwide. Early and accurate diagnosis of these diseases is essential for effective treatment and clinical management, particularly in developing countries where healthcare resources and expert radiologists are limited (World Health Organization [WHO], 2024). Chest X-ray imaging has become one of the most widely used diagnostic tools for detecting lung abnormalities because of its affordability, accessibility, and rapid imaging capability (Rajpurkar et al., 2022).

Despite the usefulness of Chest X-ray imaging, manual interpretation by radiologists is often time-consuming, subjective, and prone to diagnostic errors due to the complexity and similarity of lung disease patterns (Apostolopoulos & Mpesiana, 2023). Consequently, researchers have increasingly adopted deep learning techniques to improve the accuracy and efficiency of medical image analysis. Among these techniques, Convolutional Neural Networks (CNNs) have demonstrated remarkable success in automated image classification and feature extraction because of their capability to learn discriminative image patterns directly from medical images (Albahli et al., 2024).

However, conventional CNN models are associated with challenges such as overfitting, high computational complexity, and difficulty in selecting optimal hyper-parameters for improved classification performance (Sharma & Kumar, 2023). To address these limitations, optimization algorithms have been integrated with CNN architectures to enhance learning efficiency and predictive accuracy. The Mayfly Algorithm (MA), a nature-inspired optimization technique based on the swarming and mating behavior of mayflies, has recently gained attention for its strong exploration and exploitation capabilities in solving complex optimization problems (Zervoudakis & Tsafarakis, 2020).

Therefore, this study focused on the development of a CNN-Mayfly Optimization framework for intelligent lung disease classification using Chest X-ray images. The integration of MA with CNN was intended to optimize hyper-parameters, improve feature selection, reduce false positive rates, and enhance the overall classification accuracy and efficiency of lung disease detection systems.

Aim and Objectives

This study focused on the development of a deep learning-based lung disease classification framework using Convolutional Neural Networks (CNN) integrated with the Mayfly Optimization Algorithm (MA). This study objectives are to: (i) acquire and preprocess Chest X-ray image datasets for lung disease detection, (ii) perform image segmentation and feature extraction using CNN architecture, (iii) optimize CNN hyper-parameters using the Mayfly Algorithm, and (iv) evaluate the performance of the developed CNN-MA model in comparison with the conventional CNN classifier.

2.0 Review of related works

Deep learning techniques has significantly transformed medical image analysis, particularly in the diagnosis and classification of lung diseases using Chest X-ray images. Deep learning models have demonstrated remarkable capabilities in feature extraction, pattern recognition, and disease classification, thereby improving diagnostic accuracy and reducing human errors in clinical practice. This reviews relevant literature related to Convolutional Neural Networks (CNN), Mayfly Algorithm (MA), Chest X-ray imaging, Lung Disease Classification, and Deep Learning techniques applicable to this study.

Convolutional Neural Networks (CNNs) are a class of deep learning architectures specifically designed for image processing and pattern recognition tasks. CNNs utilize convolutional, pooling, and fully connected layers to automatically learn hierarchical image features from raw input data (LeCun et al., 2015). Unlike traditional machine learning approaches that rely on manual feature extraction, CNNs learn discriminative features directly from images, making them highly effective for medical image classification tasks. According to Krizhevsky et al. (2017), CNN architectures have achieved outstanding performance in image recognition due to their ability to capture spatial dependencies and local image patterns. In medical imaging, CNNs have been widely adopted for disease detection, segmentation, and classification because of their robustness and high predictive accuracy (Litjens et al., 2021). Popular CNN architectures such as AlexNet, VGGNet, ResNet, and DenseNet have demonstrated exceptional performance in Chest X-ray image analysis and lung disease diagnosis.

Deep learning is a subset of machine learning that employs multi-layer neural networks for automated learning and data representation. Deep learning techniques have revolutionized healthcare systems by enabling intelligent diagnosis and computer-aided medical decision-making (Goodfellow et al., 2016). Recent studies have shown that deep learning models outperform conventional machine learning methods in medical image analysis due to their capability to learn complex image representations and hidden features (Esteva et al., 2022). In radiological imaging, deep learning approaches have been successfully applied for detecting pneumonia, tuberculosis, lung cancer, and COVID-19 from Chest X-ray and CT scan images (Sharma & Kumar, 2023).

Transfer learning and fine-tuning techniques have further improved deep learning performance by adapting pre-trained models such as VGG-19 and ResNet to domain-specific medical datasets. These approaches reduce training time and improve classification accuracy, especially when limited datasets are available.

Chest X-ray imaging remains one of the most commonly used diagnostic imaging techniques for identifying lung abnormalities due to its low cost, accessibility, and rapid imaging capability (World Health Organization [WHO], 2024). Chest X-ray images provide vital information about lung tissues, airways, and thoracic structures, making them valuable for diagnosing respiratory diseases.

Studies have increasingly employed automated systems for Chest X-ray analysis to overcome challenges associated with manual interpretation, such as diagnostic inconsistency and radiologist fatigue (Rajpurkar et al., 2022). Chest X-ray classification systems based on deep learning techniques have significantly improved disease detection accuracy and reduced diagnosis time.

Lung disease classification involves the identification and categorization of lung abnormalities from medical images. Traditional classification methods relied on handcrafted features and machine learning algorithms such as Support Vector Machines (SVM), Decision Trees, and Artificial Neural Networks (ANNs). However, these methods often suffered from low generalization capability and limited feature representation (Albahli et al., 2024).

Recent studies have adopted CNN-based architectures for lung disease classification because of their superior feature extraction capabilities. Apostolopoulos and Mpesiana (2023) utilized transfer learning-based CNN models for COVID-19 detection and achieved high classification accuracy. Similarly, Deep CNN models have been applied for pneumonia and tuberculosis classification with promising results.

The Mayfly Algorithm (MA) is a nature-inspired optimization technique developed by Zervoudakis and Tsafarakis (2020). The algorithm mimics the swarming, mating, and flight behaviors of mayflies to solve optimization problems effectively. MA combines the exploration capability of swarm intelligence algorithms with exploitation strategies for achieving global optimal solutions.

The MA has demonstrated excellent performance in feature selection, parameter tuning, and optimization problems due to its balanced exploration and exploitation mechanisms (Mansouri et al., 2019). In deep learning applications, MA has been employed to optimize hyper-parameters such as learning rate, batch size, filter size, and feature weights, thereby improving model convergence and predictive accuracy.

CNN architectures have become highly effective tools for automated lung disease classification using Chest X-ray images. VGG-19, ResNet, DenseNet, and EfficientNet architectures have been widely used because of their deep feature extraction capabilities and classification efficiency (He et al., 2016).

Studies have integrated optimization algorithms with CNN architectures to enhance classification performance. Optimization techniques improve hyper-parameter tuning, feature selection, and network convergence, thereby reducing overfitting and improving model generalization (Sharma & Kumar, 2023). The integration of MA with CNN architectures has shown potential for improving classification accuracy and reducing false positive rates in medical image analysis.

Rajpurkar et al. (2022) developed the CheXNet model for pneumonia detection using Chest X-ray images and achieved radiologist-level classification performance. Apostolopoulos and Mpesiana (2023) applied transfer learning-based CNN models for COVID-19 detection and reported improved sensitivity and specificity.

Similarly, Albahli et al. (2024) proposed a deep learning framework for lung disease classification and achieved high diagnostic accuracy using CNN architectures. Sharma and Kumar (2023) reviewed optimization techniques in deep learning and observed that nature-inspired optimization algorithms significantly improved CNN performance in medical image classification tasks.

Zervoudakis and Tsafarakis (2020) introduced the Mayfly Optimization Algorithm and demonstrated its effectiveness in solving complex optimization problems with improved convergence speed and solution quality.

Despite the significant achievements of CNN-based lung disease classification systems, several studies have reported challenges such as overfitting, computational complexity, poor hyper-parameter selection, and high false positive rates. Most existing studies focused primarily on conventional CNN architectures without integrating efficient optimization algorithms for parameter tuning and feature optimization.

Furthermore, limited studies have explored the integration of the Mayfly Optimization Algorithm with CNN architectures for automated lung disease classification using Chest X-ray images. Therefore, this study seeks to bridge this gap by developing an optimized MA-CNN framework for improved lung disease classification accuracy, reduced false positive rates, and enhanced diagnostic efficiency.

3.0 Methodology

This study adopted deep learning techniques for lung disease classification using Chest X-ray images. The methodology integrated Convolutional Neural Network (CNN) architectures with the Mayfly Algorithm (MA) to enhance classification accuracy and model performance.

The dataset used for this study was obtained from publicly Chest X-ray image repositories available https://github.com/ieee8023/covid-chestxray-dataset. A total of 2,820 Chest X-ray images were utilized, comprising 1,414 COVID-19 positive cases and 1,406 non-COVID cases. The dataset was divided into training and testing sets, where 60% (1,692 images) were used for training and 40% (1,128 images) for testing. All images were validated and annotated by expert radiologists based on major radiographic findings relevant to lung disease classification. The dataset comprised normal and abnormal lung images including pneumonia, tuberculosis, COVID-19, and other lung-related infections. Data pre-processing techniques were employed to enhance image quality and improve the performance of the classification model. The processes involved image resizing for dimensional uniformity, histogram equalization for contrast enhancement, and data augmentation techniques to increase dataset diversity and reduce overfitting.

The segmentation stage was carried out to isolate the lung region and eliminate irrelevant structures such as bones from the Chest X-ray images. Sobel Edge Detection was employed to identify the Regions of Interest (ROIs) for effective lung disease detection.

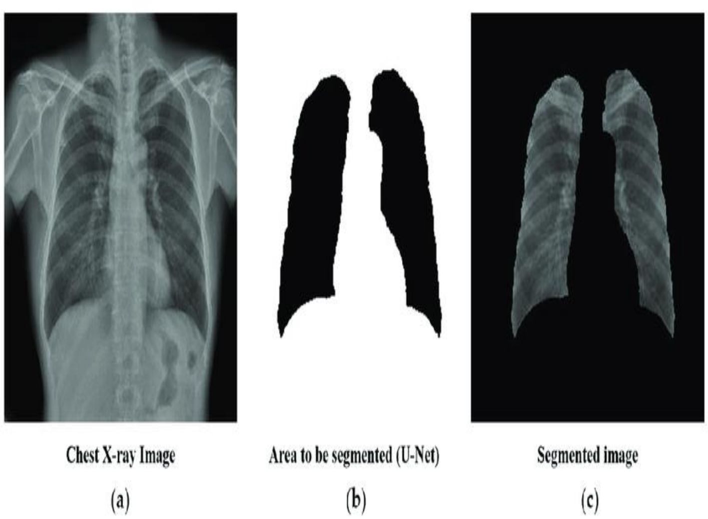

Figure 1 Image segmentation

Both cleaned non-augmented and augmented datasets were utilized during the process. Threshold-based segmentation was adopted to partition the image into meaningful regions based on pixel intensity values. The technique converted the images into binary representations by applying a predefined threshold, thereby separating the lung area from the background for accurate feature extraction and classification.

Following image segmentation, feature extraction was performed to identify and isolate salient characteristics from the Chest X-ray images relevant to lung disease classification. The extracted features were subsequently subjected to max-pooling to generate a reduced feature map containing the most significant attributes. This process minimized data dimensionality, improved computational efficiency, and enhanced the learning capability of the CNN model while preventing overfitting and underfitting during classification.

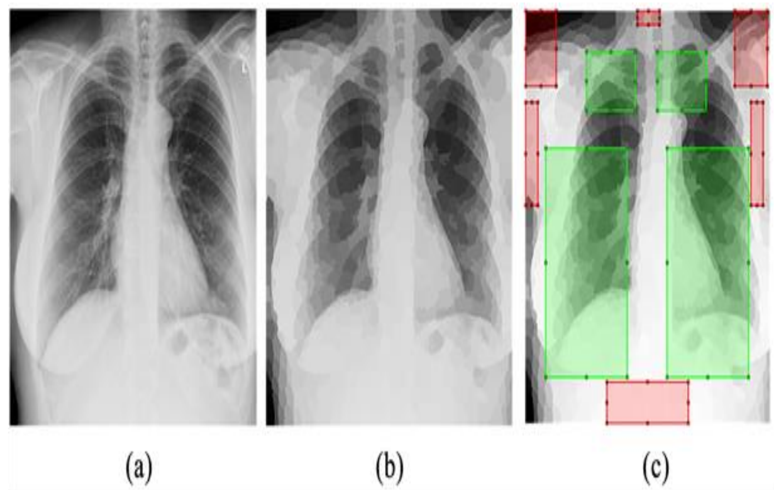

Figure 2 Feature extraction

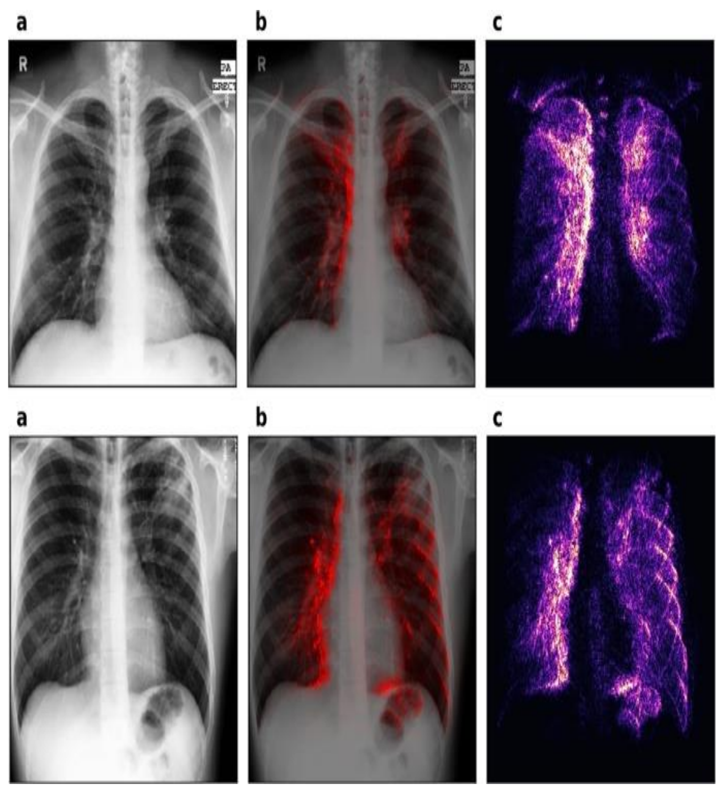

Figure 3 set max pooling

The developed CNN architecture was employed for automated feature extraction and classification of Chest X-ray images. The architecture consisted of convolutional layers, activation functions, pooling layers, and fully connected layers for deep feature learning. The extracted features were utilized to detect and classify lung diseases efficiently, thereby improving the accuracy and performance of the classification model.

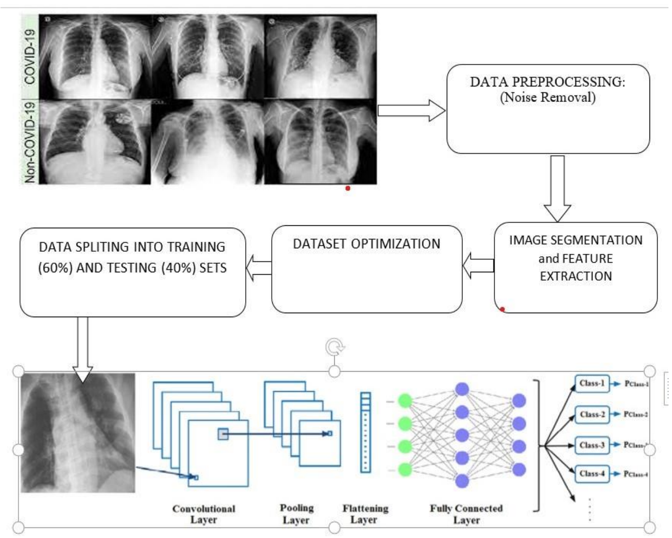

Figure 4: Feature Extraction Using CNN Architecture

The CNN architecture comprised convolutional, activation, pooling, and fully connected layers designed for effective deep feature extraction and learning. The model automatically learned discriminative lung patterns from Chest X-ray images and utilized the extracted features for accurate and efficient lung disease classification, thereby enhancing the overall performance of the system.

3.1 Integration of the Mayfly Algorithm (MA) and CNN

This study integrated the Mayfly Algorithm (MA) with a Convolutional Neural Network (CNN) to enhance lung disease classification from Chest X-ray images. The CNN architecture was utilized for automatic feature extraction and classification, while the Mayfly Algorithm was employed to optimize CNN parameters and feature selection.

The MA mimics the swarming and mating behavior of mayflies, where male and female mayflies update their positions and velocities based on personal best and global best solutions. The optimization process improved the exploration and exploitation capabilities of the CNN model, thereby enhancing classification accuracy and reducing convergence errors.

The hybrid MA-CNN model consisted of convolutional, activation, pooling, and fully connected layers for deep feature learning, while the MA optimized important parameters such as feature weights, learning rates, and classification performance. The integrated framework improved feature representation, minimized overfitting, and enhanced the overall efficiency of the lung disease classification system.

Algorithm : MayFly Algorithm

Step 1: Initialize the male mayfly population $\boldsymbol{x_{ij}^{0}}$(i=1,2, …, N) and velocities $\boldsymbol{v_{ij}^{0}}$,

initialize the female mayfly population $\boldsymbol{y_{ij}^{0}}$ (i=1,2, …, M),

$\boldsymbol{Max_{iter}}$ =max.

no of iteration

Step 2: Set iteration t = 1

Step 3: Evaluate the objective function values of male and female mayfly as $\boldsymbol{f(x) = f(x_i^t)}$.

(1)

where $\boldsymbol{f}: \boldsymbol{R^n} \rightarrow \boldsymbol{R}$ is the objective function which evaluates the quality of a solution

$$\boldsymbol{f(x) = \sum_{k=2}^{m}\left[\sum_{i=1}^{n}\left(x_{i,k-1} - x_{i,k}\right)^2\right]} \quad \textbf{(2)}$$

Where $\boldsymbol{x_i^t}$ represent the CNN paramtersfeatures at *i=1,2, …, n* and *k=2,3, …, m*

Step 4: Find the personal best for each male and female as $\boldsymbol{P_{best,iD}^{t} = x_i^t}$ and global best as $\boldsymbol{G_{best,iD} = min\{P_{best,iD}^{t}\}}$(3)

Step 5: Calculate gravity coefficient:

The gravity coefficient *g* can be a fixed number in the range of [-1, 1], or it

can be gradually reduced over the iterations, allowing the algorithm to

exploit some worst and best specific areas as demonstrated in equation

$$\boldsymbol{g = g_{std} - \frac{(g_{std} - g_{mean})*(iter_{max} - iter + 1)}{iter_{max}} - iter}(4)$$

where $\boldsymbol{g_{std}}$and $\boldsymbol{g_{mean}}$ are the standard deviation and mean values that the gravity

coefficient can take, $\boldsymbol{iter}$ is the current iteration of the algorithm and $\boldsymbol{iter_{max}}$ is the maximum number of iterations.

Step 6: Update velocities and solution of males and females

Using roulette wheel selection ($\boldsymbol{p_i}$)

$$\boldsymbol{p_i = rand \le \frac{f(x_i^t)}{\sum_{i=1}^{N} f(x_i^t)}}(3.42$$

$$V_{std} = p_i * (x_{std} - x_{mean}) \text{where } rand\ \epsilon\ (0,1) \quad (5)$$

where x_{std} and x_{mean} are the search space limits for the fitness function,

$$v_{ij}^{t+1} = \begin{cases} v_{std}, & if\ v_{ij}^{t+1} > v_{std} \\ -v_{std}, & if\ v_{ij}^{t+1} < -v_{std} \end{cases} \quad (6)$$

$$v_{ij}^{t+1} = g * v_{ij}^{t} + \alpha_1 \quad e^{-\beta r_p^2}\left[pbest_{ij} - x_{ij}^{t}\right] + \alpha_2 \quad e^{-\beta r_g^2}\left[gbest_j \ - x_{ij}^{t}\right] \quad (7)$$

Where β is a fixed visibility coefficient which is used to limit a mayfly's visibility to others, r_p is the Cartesian distance between x_i and $pbest_{ij}$ and r_g is the Cartesian distance between x_i and $gbest$. The distances are calculated as:

$$\|x_i - X_i\| = \sqrt{\sum_{j=1}^{n}(x_{ij} - X_{ij})^2} \quad (8)$$

Where x_{ij} is the j^{th} element of mayfly i and X_{ij} corresponds to $pbest_{ij}$ or $gbest$..

$$x_i^{t+1} = x_i^{t} + v_{ij}^{t+1} \quad (9)$$

With $x_i^{0} \sim U(x_{mean} \ \ , x_{std} \ \ )$ male mayfly

$$y_i^{t+1} = y_i^{t} + v_{ij}^{t+1} \quad (10)$$

With $y_i^{0} \sim U(y_{mean} \ \ , y_{std} \ \ )$ female mayfly

Using roulette wheel selection p_i

$$p_i = r \leq \frac{f(x_i^t)}{\sum_{i=1}^{N} f(x_i^t)} \quad (11)$$

$$v_{ij}^{t+1} = \begin{cases} v_{ij}^{t} + \alpha_2 \quad e^{-\beta r_{mf}^2 (x_{ij}^{t} - y_{ij}^{t})} & if\ f(y_i\ ) > f(x_i\ ) \\ v_{ij}^{t} + fl * p_i & if\ f(y_i\ ) \leq\ f(x_i\ ) \end{cases} \quad (12)$$

Where v_{ij}^{t} is the velocity of female mayfly i in dimension j = 1, …, at time step t, y_{ij}^{t} the position of female mayfly i in dimension j at time step t , α_2 is a positive attraction constant and β is a fixed visibility coefficient, while r_{mf} is the Cartesian distancebetween male and female mayflies, calculated using equation (12). Finally, fl is a random walk coefficient, used when a female is not attracted by a male, so it flies deterministicallyby roulette wheel selection and r is a random value in the range of [-1, 1].

Step 7: Evaluate Solutions

$$f(x) = f(x_i^{t+1}) \quad (3.50)$$

where $f: R^n \rightarrow R$ is the objective function which evaluates the quality of a solution

Step 8: Mate the mayflies and Evaluate offspring

$$offsprint1 = L * male + (1 - L) * female$$

$$offsprint2 = L * male + (1 - L) * male$$

where $male$ is the male parent, $female$ is the female parent and L is a random value within a specific range. Offspring's initial velocities are set to be zero

Step 9: Update $Pbest$ of population

$$pbest_i \ = \begin{cases} x_i^{t+1}, & if\ f(x_i^{t+1}) > f(pbest_i\ ) \\ is\ kept\ the\ same, & otherwise \end{cases}$$

Step 10: Update $Gbest$ of population

The global best position $gbest$ at time step t, is defined as

$$gbest \in \{pbest_1, pbest_2, \ldots, pbest_N | \ f(cbest)\} = \min\ \{\{f(pbest_1), f(pbest_2), \ldots, f(pbest_N)|\}$$

Where N is the total number of male mayflies is the swarm,

Step 11: If t< Max_{iter} then t= $t + 1$ and GOTO step 1 else GOTO step l2

Step 12: Output optimum feature selected solution as $Gbest_{bD}$.

$$Gbest_{bD} = x_b$$

The technique was developed for the classification of Chest X-ray images using deep learning-based Convolutional Neural Networks (CNN). The Chest X-ray images were categorized into two classes: normal and COVID-19 infected patients. The input images were processed through the CNN framework to produce accurate classification outputs.

To improve the performance of the CNN model, the Mayfly Algorithm (MA) was employed for hyper-parameter optimization and fine-tuning of the pre-trained VGG-19 architecture. The optimization of hyper-parameters was carried out to improve the performance of the pre-trained CNN architecture. Although pre-trained CNN models provide efficient feature extraction capabilities, some critical hyper-parameters such as mini-batch size, dropout rate, and dense layer configurations require fine-tuning for optimal classification performance. In this study, the Mayfly Algorithm (MA) was integrated with the CNN model to optimize hyper-parameters, particularly the mini-batch size and dropout layer rate, thereby enhancing model generalization and reducing overfitting.

During the learning phase, the MA-CNN architecture was employed for the classification of Lung Chest X-ray images. Transfer learning and fine-tuning techniques were utilized by adapting the pre-trained VGG-19 network to the current dataset. The convolutional layers were retained for deep feature extraction, while the classifier section was modified to suit the classification task.

The modified classifier architecture consisted of a flatten layer, batch normalization layer, dropout layer, and two fully connected dense layers. The first dense layer employed the Rectified Linear

Unit (ReLU) activation function for nonlinear feature learning, while the final dense layer utilized the SoftMax activation function for multi-class classification.

Fine-tuning was achieved by retraining the last convolutional layers together with the modified classifier over several iterations. Upon completion of the training process, the optimized MA-CNN framework generated the final prediction for lung disease classification based on the posterior probabilities produced by the SoftMax classifier.

3.2 Results and Discussions

The developed Mayfly-based Convolutional Neural Network (CNN-MA) classifier was evaluated for lung COVID-19 disease recognition using Chest X-ray images. The experiments were conducted using pre-processed and segmented images, while 60% of the dataset was used for training and 40% for testing through random sampling cross-validation.

The performance of the CNN-MA classifier was evaluated using False Positive Rate (FPR), Accuracy, Sensitivity, Precision, Specificity, and Recognition Time. Different threshold ranges were examined, and the system maintained stable recognition performance across varying threshold values.

The optimization process of the CNN-MA model was carried out over 30 iterations by varying the number of convolutional layers, number of filters, filter sizes, and batch sizes. The results revealed that the best recognition accuracy of 99.27% was achieved using: 3 convolutional layers, 128 filters per layer, filter size of 6 × 6, and batch size of 155.

The experimental results demonstrated that the integration of the Mayfly Algorithm with CNN significantly enhanced feature optimization and classification performance, leading to improved accuracy and efficient lung disease detection from Chest X-ray images.

Table 1: Optimization result obtained by the CNN-MA

S/N	No. Layers	No. Filters	Filter Size	Batch Size	Recognition Rate (%)
1	3	104	3x3	236	97.31
2	3	109	3x3	136	98.47
3	3	112	5x3	150	96.51
4	1	83	6x6	149	98.15
5	1	57	7x7	238	95.55
6	**3**	**128**	**6x6**	**155**	**99.27**
7	3	128	6x6	203	97.81
8	2	128	5x5	228	95.62
9	3	128	5x5	256	95.98
10	1	128	6x6	256	95.38
11	3	128	6x6	156	96.78
12	2	128	5x5	256	98.87
13	2	128	3x3	256	99.15
14	1	128	5x5	256	98.60
15	2	128	3x3	256	97.96
16	1	128	6x6	256	96.42
17	2	128	3x3	256	98.76
18	3	128	5x5	256	96.02
19	2	128	6x6	256	96.74
20	3	128	4x4	156	98.57
21	3	128	4x4	155	98.70
22	2	128	7x7	256	96.95
23	2	128	3x3	256	98.19
24	3	128	4x4	155	98.33
25	3	128	3x3	155	96.09
26	1	128	6x6	256	95.28
27	2	128	6x6	256	96.44
28	1	128	5x5	256	95.69
29	3	128	4x4	155	98.73
30	2	128	3x3	256	97.08

3.3 Results of the CNN Classifier

The Convolutional Neural Network (CNN) classifier was evaluated using a dataset of 2,820 Chest X-ray images comprising 1,692 training images, 568 positive test images, and 560 negative test images. The performance of the model was assessed at different threshold values using metrics such as False Positive Rate (FPR), Sensitivity, Specificity, Accuracy, and Recognition Time.

At the optimal threshold value of 0.75, the CNN classifier correctly identified 511 positive lung disease images and 506 negative images. However, 57 positive images were misclassified as negative, while 54 negative images were misclassified as positive.

The results demonstrated that the CNN classifier effectively learned discriminative lung features from Chest X-ray images and achieved reliable performance in lung disease classification as shown in Table 2

Table 2: Performance of the CNN technique

Threshold	0.13	0.3	0.42	0.75
TP(positive)	514	513	512	511
FN(negative)	54	55	56	57
FP(positive)	61	59	57	54
TN(negative)	499	501	503	506
SPEC(%)	89.11	89.46	89.82	90.36
SEN(%)	90.49	90.32	90.14	89.96
FPR(%)	10.89	10.54	10.18	9.64
ACC(%)	89.80	89.89	89.98	90.16

Time(sec)	101.26	100.07	99.99	101.00

3.4 Results of the CNN-MA Classifier

The CNN-Mayfly Algorithm (CNN-MA) classifier was evaluated using a dataset of 2,820 Chest X-ray images comprising 1,692 training images, 568 positive test images, and 560 negative test images. The CNN-MA model utilized optimized parameters obtained through the Mayfly Algorithm, consisting of 3 convolutional layers, 128 filters per layer, a filter size of 6 × 6, and a batch size of 155.

At the optimal threshold value of 0.75, the CNN-MA classifier correctly identified 545 positive lung disease images and 540 negative images. However, 23 positive images were misclassified as negative, while 20 negative images were misclassified as positive.

The results demonstrated that the integration of the Mayfly Algorithm with CNN significantly improved classification accuracy, reduced false positive rates, and enhanced the overall efficiency of lung disease detection from Chest X-ray images as shown in Table 3.

Algorithm	**FPR (%)**	**Sensitivity (%)**	**Specificity (%)**	**Accuracy (%)**	**Time (sec)**
CNN-MA	3.57	95.95	96.43	96.19	89.54
CNN	9.64	89.96	90.36	90.16	101.00

Table 4: Performance of the CNN-MA technique

Threshold	**0.13**	**0.3**	**0.42**	**0.75**
TP(positive)	548	547	546	545
FN(negative)	20	21	22	23
FP(positive)	28	25	22	20
TN(negative)	532	535	538	540
SPEC(%)	95.00	95.54	96.07	96.43
SEN(%)	96.48	96.30	96.13	95.95
FPR(%)	5.00	4.46	3.93	3.57
ACC(%)	95.74	95.92	96.10	96.19
Time(sec)	89.21	88.99	88.25	89.54

3.5 Comparison Results between CNN-MA and CNN

The comparative analysis between the CNN-MA and conventional CNN classifiers revealed significant improvements in the performance of the CNN-MA model for lung COVID-19 classification using Chest X-ray images.

At the optimal threshold value of 0.75, the CNN-MA classifier outperformed the conventional CNN model across all evaluation metrics. The CNN-MA achieved: Accuracy: 96.19%, Sensitivity: 95.95%, Specificity: 96.43%, False Positive Rate (FPR): 3.57% and Recognition Time: 89.54 seconds

In comparison, the conventional CNN achieved Accuracy: 90.16%, Sensitivity: 89.96%, Specificity: 90.36%, False Positive Rate (FPR): 9.64% and Recognition Time: 101.00 seconds

The results indicated that the integration of the Mayfly Algorithm with CNN improved feature optimization and parameter selection, resulting in higher classification accuracy, lower false positive rate, improved sensitivity and specificity, and faster recognition time compared with the traditional CNN technique as shown in table 4.

4.0 Conclusion

This study developed an intelligent lung disease classification framework using Convolutional Neural Networks (CNN) integrated with the Mayfly Optimization Algorithm (MA) for the classification of Chest X-ray images. The developed CNN-MA model effectively enhanced feature extraction, hyper-parameter optimization, and classification performance for lung disease detection.

The experimental results revealed that the CNN-MA classifier significantly outperformed the conventional CNN model across all evaluation metrics. The developed model achieved an accuracy of 96.19%, sensitivity of 95.95%, specificity of 96.43%, and a reduced false positive rate of 3.57%, compared to the conventional CNN accuracy of 90.16% and false positive rate of 9.64%. In addition, the CNN-MA model demonstrated faster recognition time and improved classification efficiency through optimal parameter selection.

The study therefore concluded that the integration of the Mayfly Optimization Algorithm with CNN provides a robust and efficient deep learning framework for automated lung disease classification using Chest X-ray images. The developed approach has significant potential for supporting intelligent medical diagnosis and improving clinical decision-making in healthcare systems.

Acknowledgements

The authors sincerely appreciate the contributions and support of all co-authors toward the successful completion of this research work.

Declaration of Conflict of Interest

The authors collectively contributed to the conceptualization, design, implementation, and review of this manuscript. This work has not been previously submitted or published elsewhere. The authors declare that there is no conflict of interest or financial affiliation that could influence the outcome of this study.

References

Albahli, S., Algarni, A., Alshahrani, S., & Alrashidi, A. (2024). Deep learning approaches for medical image classification and disease diagnosis. *Journal of Healthcare Engineering, 2024*(1), 1–15.

Apostolopoulos, I. D., & Mpesiana, T. A. (2023). COVID-19: Automatic detection from X-ray images utilizing transfer learning with convolutional neural networks. *Physical and Engineering Sciences in Medicine, 46*(2), 635–640.

World Health Organization. (2024). *Global tuberculosis report 2024*. World Health Organization

Zervoudakis, K., & Tsafarakis, S. (2020). A mayfly optimization algorithm. *Computers & Industrial Engineering, 145*, 106559.

Esteva, A., Robicquet, A., Ramsundar, B., Kuleshov, V., DePristo, M., Chou, K., Cui, C., Corrado, G., Thrun, S., & Dean, J. (2022). A guide to deep learning in healthcare. *Nature Medicine, 28*(1), 29–41.

Goodfellow, I., Bengio, Y., & Courville, A. (2016). *Deep learning*. MIT Press.

He, K., Zhang, X., Ren, S., & Sun, J. (2016). Deep residual learning for image recognition. *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*, 770–778.

Krizhevsky, A., Sutskever, I., & Hinton, G. E. (2017). ImageNet classification with deep convolutional neural networks. *Communications of the ACM, 60*(6), 84–90.

LeCun, Y., Bengio, Y., & Hinton, G. (2015). Deep learning. *Nature, 521*(7553), 436–444.

Litjens, G., Kooi, T., Bejnordi, B., Setio, A., Ciompi, F., Ghafoorian, M., Van der Laak, J., Van Ginneken, B., & Sánchez, C. (2021). A survey on deep learning in medical image analysis. *Medical Image Analysis, 42*, 60–88.

Mansouri, A., Babar, M., & Shah, M. (2019). Optimization algorithms for feature selection in machine learning. *International Journal of Advanced Computer Science and Applications, 10*(5), 120–129.

Rajpurkar, P., Irvin, J., Zhu, K., Yang, B., Mehta, H., Duan, T., Ding, D., Bagul, A., Langlotz, C., Shpanskaya, K., Lungren, M., & Ng, A. (2022). CheXNet: Radiologist-level pneumonia detection on chest X-rays with deep learning. *Nature Medicine, 28*(5), 890–896.

Sharma, R., & Kumar, P. (2023). Optimization techniques for deep learning-based medical image classification: A review. *Artificial Intelligence Review, 56*(4), 3121–3145.

World Health Organization. (2024). *Global tuberculosis report 2024*. World Health Organization

Zervoudakis, K., & Tsafarakis, S. (2020). A mayfly optimization algorithm. *Computers & Industrial Engineering, 145*, 106559.