Mayfly Algorithm Based Convolutional Neural Network for Human Diseases Recognition System

James Olujoba Adegboye[1]; Wasiu Oladimeji Ismaila[2]; Adeleye Samuel Falohun[3]; Folasade Muibat Ismaila[4]; Abiodun Adebayo Owolabi[5]

[1]Department of Computer Science, Federal Polytechnic, Ilaro, Nigeria.
[2]Department of Computer Science, Ladoke Akintola University of Technology, Ogbomoso, Nigeria.
[3]Department of Computer Engineering, Ladoke Akintola University of Technology, Ogbomoso, Nigeria.
[4]Department of Computer Science, Osun State University, Osogbo, Osun State, Nigeria.
[5]Department of Mathematics and Computing Science, Thomas Adewumi University, Oko-Irese, Nigeria.

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Abstract: Convolutional Neural Network (CNN) is a machine learning method which mainly focused on the automatic feature selection and matching of images and has been used for detection and recognition. CNN suffers from hyperparameter selection and overfitting problem and can be solved using an optimization technique. Existing optimization technique such as Mayfly Algorithm (MA) still suffers from initial parameter tuning and had slow convergence behaviour. This research developed a Mayfly Algorithm based on Convolutional Neural Network for pulmonary diseases recognition. The X-ray images which include normal and pulmonary diseases cases were obtained from a repository via www.kaggle.com. The images were pre-processed using cropping, contrast adjustment, histogram equalizer and normalization to obtain good images quality. A Mayfly Algorithm was used to optimize CNN hyperparameters. The developed technique was implemented in MATLAB (R2020a) Software. The results obtained were evaluated using standard metric. The CNN technique average results are 96.0%, 94.6%, 3.7%, 95.4% and 82.4µs while MA-CNN average results are 97.1%, 95.9, 3.0%, 96.7% and 60.7µs for Specificity, sensitivity, false positive rate, Accuracy and Computation time respectively at 0.75 threshold. This shows the effectiveness of optimizing CNN hyperparameters for image recognition.

Keywords: *Mayfly Algorithm, Convolutional Neural Network, Pulmonary Diseases, Hyperparameters, Optimization Technique.*

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I. INTRODUCTION

Machine learning (ML) is a facet of Artificial Intelligence, which enables researchers, physicians, and patients to solve some issues like biometric analysis [18, 19, 25], identification of numerous diseases [4]. Thus, in medical domains, ML primarily focuses on developing algorithms and techniques to determine whether a system's behavior is correct in disease diagnosis. Alzheimer's disease, heart failure, breast cancer, and pneumonia are just a few of the diseases that may be identified with ML. The emergence of ML techniques, like Support Vector machine, K-nearest neighbor, Artificial Neural Network, Deep learning, autoencoder algorithm, CNN, in disease diagnosis domains illustrates the technology's utility in medical fields. [1]. Pulmonary diseases have become apparently a fatal Severe Acute Respiratory Syndrome (SARS) infection over the last six years [2, 3]. 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 [5, 6].

However, CNN is a machine learning method focusing on the automatic feature selection and matching from images as well as being used for recognition and detections. It has proven its effectiveness in the tasks of computer vision, computer-aided diagnosis, natural language processing, and pattern recognition [13,22,23]. Unlike traditional neural networks, CNN can reduce the number of parameters remarkably during feature extraction phase. CNN hyperparameter optimization performs the parameter selection for CNN model which provides the better accuracy for any classification task. However, this selection process is challenging since a huge amount of parameters need to be adjusted which is time consuming and requires a substantial amount of computational resources [8]. CNN suffers from hyperparameter selection problems, which can be solved using optimization techniques such as genetic algorithm and mayfly algorithms [7].

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The Mayfly Algorithm is a nature-inspired optimization algorithm that imitates the life cycle of mayflies to solve optimization problems. Mayfly algorithm is an optimization technique that has shown promising results in some optimization problems. However, it is important to consider its strengths and weaknesses and to compare its performance with other optimization techniques in specific problem domains before deciding to use it. Mayfly algorithm is relatively easy to implement. It has shown promising results in terms of convergence speed in some optimization problems. balances exploration and exploitation by using two separate types of search operators, namely the search operator that explores the search space and the mating operator that exploits the search space. Hence, this work employed Mayfly Algorithm to select appropriate CNN hyperparameters such as number of layers, number of filters, filter size and batch size, to solve CNN hyperparameters selection problem and reduced computational time for Pulmonary disease recognition system from Chest X-ray images [24].

II. RELATED WORK

In 2020, the authors in [6] developed a COVID-19 prediction system using chest X-ray images with smote and machine learning classifiers. Random Forest (RF) and XGboost model were used on deep features for classification. The results of the experiment showed that the RF and XGBoost algorithms produced prediction accuracy of 97.3% and 97.7% respectively. The [9] researchers in 2020 employed five traditional deep learning models, in which the Xception model produced identification accuracy of 96.75%. The model was subjected to 1102 chest x-ray dataset images. The simulation of Xception-SVM gave 99.33%, 99.27%, 99.38% and 99.32%, for accuracy, sensitivity, specificity and AUC respectively.

In 2021, researchers in [10] developed a diseases detection system that classified selected pulmonary disease viz; pneumonia, covid-19 and normal. Thus, there was a proposal on optimization of Convolutional Neural network (OptCoNet). The proposed OptCoNet architecture composed of accumulation of dataset, preprocessing stage, optimized CNN for feature extraction and classification components with Grey Wolf Optimizer (GWO) algorithm. The developed model was tested and compared with some selected classifiers with the dataset. The developed optimized CNN model gave 97.78%, 97.75%, 96.25%, 92.88%, and 95.25% for accuracy, sensitivity, specificity, precision, and F1-score respectively., which are better than the results of some selected classifiers.

In 2022, the researchers in [14] hybridized quantum with Convolutional neural network (HQ-CNN) employing random quantum circuits as a base to detect COVID-19 patient. A total of five thousand four hundred and forty-five chest x-ray dataset, including COVID-19, normal, viral and bacterial pneumonia images were acquired to evaluate the proposed model. The proposed model produced accuracy and recall of 98.6% and 99% respectively on using COVID-19 and normal cases. Also, it produced accuracy and recall of 98.2% and 99.5% on COVID-19 and viral pneumonia cases; while it gave 98% and 98.8% for accuracy and recall, respectively, on COVID-19 and bacterial pneumonia cases. And lastly, it gave accuracy and recall of 88.2% and 88.6%, respectively, on the multiclass dataset cases.

[16] researchers in 2023 examine radiographic images for chest X-ray images (CXI) which involve COVID-19. A standout CNN based model termed (PulDi-COVID) for detecting nine selected pulmonary diseases was proposed. Several transfer-learning models were trained on CXI of chronic lung diseases and COVID-19 instances. The results showed that PulDi-COVID gave accuracy, precision, recall and F1 score of 99.70%, 98.68%, 98.67%, 98.67% respectively. [17] researchers in 2024 developed a model using a deep-based Convolutional neural network to identify pulmonary diseases like pneumonia (lungs) in chest X-rays images. The strengths of EfficientNetB0 and DenseNet121 were combined to analyze X-ray images pictures and pinpoint signs of pneumonia. The results showed accuracy, precision, recall, F1-Score, specificity and Area under curve of 95.19%, 98.38%, 93.84%, 96.06%, 97.43% and 0.9564. Further related works can be found in [11], [12] and [15].

III. MATERIALS

- *Mayfly Algorithm*

The MA is a nature-inspired optimization algorithm that imitates the life cycle of mayflies to solve optimization problems. The MA is a modification of Particle Swarm Optimization (PSO) and combines major advantages of PSO, Genetic Algorithm (GA) Firefly Algorithm (FA) [20]. It offers a powerful hybrid algorithmic structure, based on the behavior of mayflies. It is inspired by the social behavior of mayflies, and particularly from their mating process. There are some assumptions that after hatching from the egg, mayflies are already adults and fittest mayflies survive, regardless of how long they live. The position of each mayfly in the search space represents a potential solution to the problem [21].

Despite the fact that mayfly algorithm is relatively new optimization algorithm that is inspired by the mating behavior of mayflies. It has been used in various optimization problems, including feature selection and parameter optimization in machine learning. Its strengths include its simplicity, produced good results in terms of convergence speed, ability to balance exploration and exploitation. [21]. MA algorithm can be found in [12].

- *CNNs*

CNNs are a type of deep learning model that can learn features directly from the raw image data. They consist of multiple layers of Convolutional and pooling operations followed by fully connected layers for classification. CNNs have been used in pulmonary disease detection systems by [26]. Convolutional Neural Networks (CNNs), depicted in Figure 1, are a specific type of models conceived to accept 2-dimensional input data, such as images or time series data. These models take their name from the mathematical linear operation of Convolutional which is always present in at least

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one of the layers of the network. The most typical Convolutional operation used in deep learning is 2D Convolutional of a 2-dimensional image I with a 2-dimensional kernel K, given by the following equation:

$$c(i,j) = (I * K)(i,j) = \sum_m \sum_n I(m,n)K(i-m, j-n) \tag{1}$$

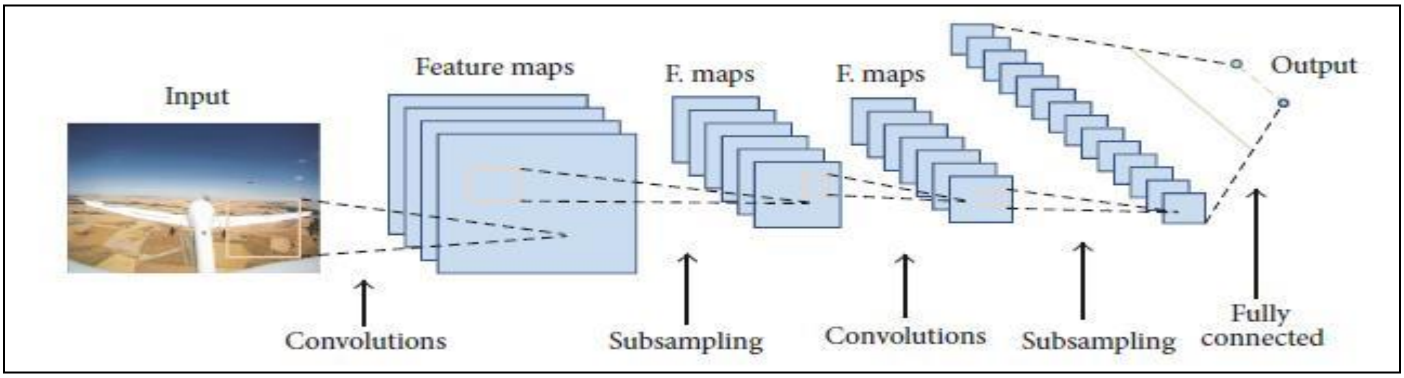

Fig 1 A CNN Model. [13]

A non-linear activation function in CNN is used to run the output of convolutional operation and further modified by means of a pooling function. This is then replaced by the output in a certain location with a value obtained from nearby outputs. This pooling function (e.g max pooling) helps make the representation learned invariant to small translations of the input and performs sub-sampling of the input data. Convolutional and pooling layers are stacked together to achieve feature learning in a hierarchical way. For example, when learning from images, layers closer to the input learn low-level feature representations (that is., edges and corners) and those closer to the output learn higher level representations (that is., contours and parts of objects) [13].

The CNNs activations are used at the final stage with fully connected neurons once the relevant features have been learned for classification or perform regression tasks. The CNN pseudocode is shown in Algorithm I.

- *Algorithm I: Pseudocode of CNN*

Parameters: input x (512,1), output y_t (512,5)
For each epoch **do:**
CNN Feature Extraction
For each convolutional layer **do:**
for each sample in X **do:**
Calculate a_{ij}^{m} from X by the convolution layer process
End for
#Dimension of a is (512 – *KernelSize* + 1, *FilterSize*)
If a_{ij}^{m} *length* < 512 **do:**
Apply zero padding to a_{ij}^{m}
#Dimension of a is (512, *FilterSize*)
End if
End for
For each sample in a **do:**
Calculate Forward Pass of a
Calculate Backward Pass of a
Dimension of the output a is (512,2**NeuronSize*)
Calculate y_t
End for
End for

IV. METHODS

This section discusses the methodology employed in this research. The architectural design of the developed system, as shown in figure 2, comprises of data acquisition, data pre-processing, feature selection and classification phases. The feature selection phase entails the optimization of CNN with MA technique. The output of developed system was evaluated with confusion matrix parameters from which performance metrics were estimated.

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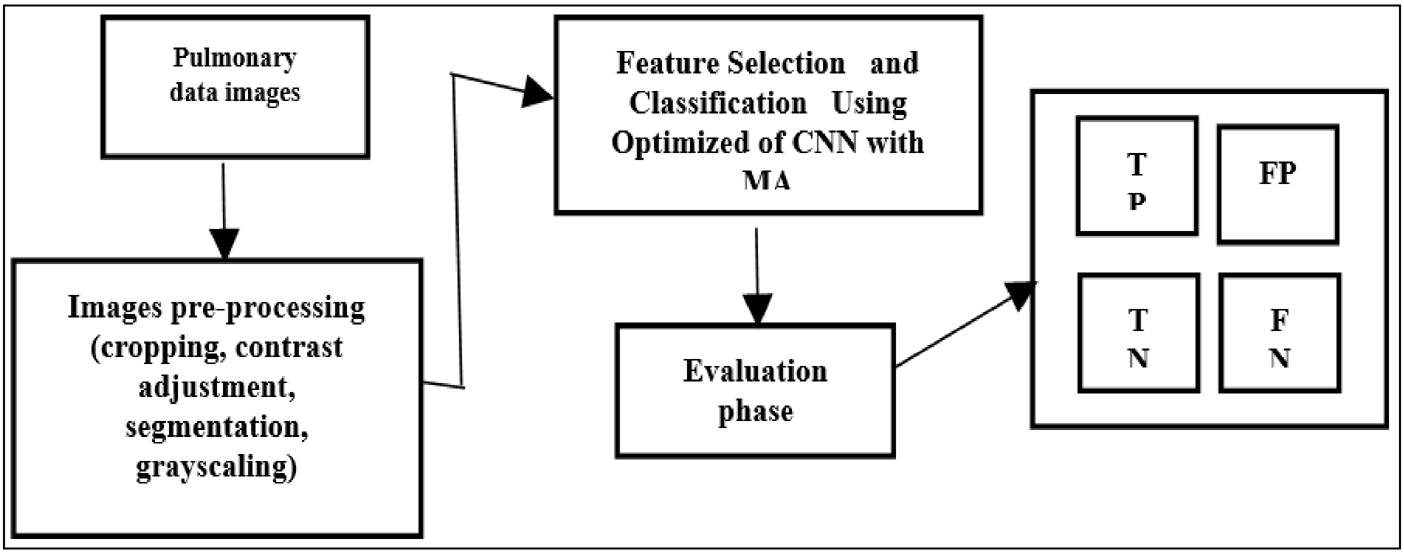

Fig 2 The Architecture of CNN-MA Diseases Recognition System

➢ *Image Acquisition*

The dataset was collected from a Comprehensive Dataset for AI-driven Analysis of Chest X-ray Images consisting of COVID-19, pneumonia and normal via www.kaggle.com. Dataset consisting of 1,980 pulmonary diseases comprises of 990 COVID-19 cases, and 990 pneumonia cases.

➢ *Image Pre-Processing*

The acquired images were pre-processed. The preprocessing techniques were applied which are image cropping, gray conversion, image enhancement (removal of noise, sharpen, or brighten an image) and segmentation. The image enhancement was done using histogram equalization. Segmentation also was done using the Sobel-edge detection algorithm. The original and pre-processed images are shown in figure 3.

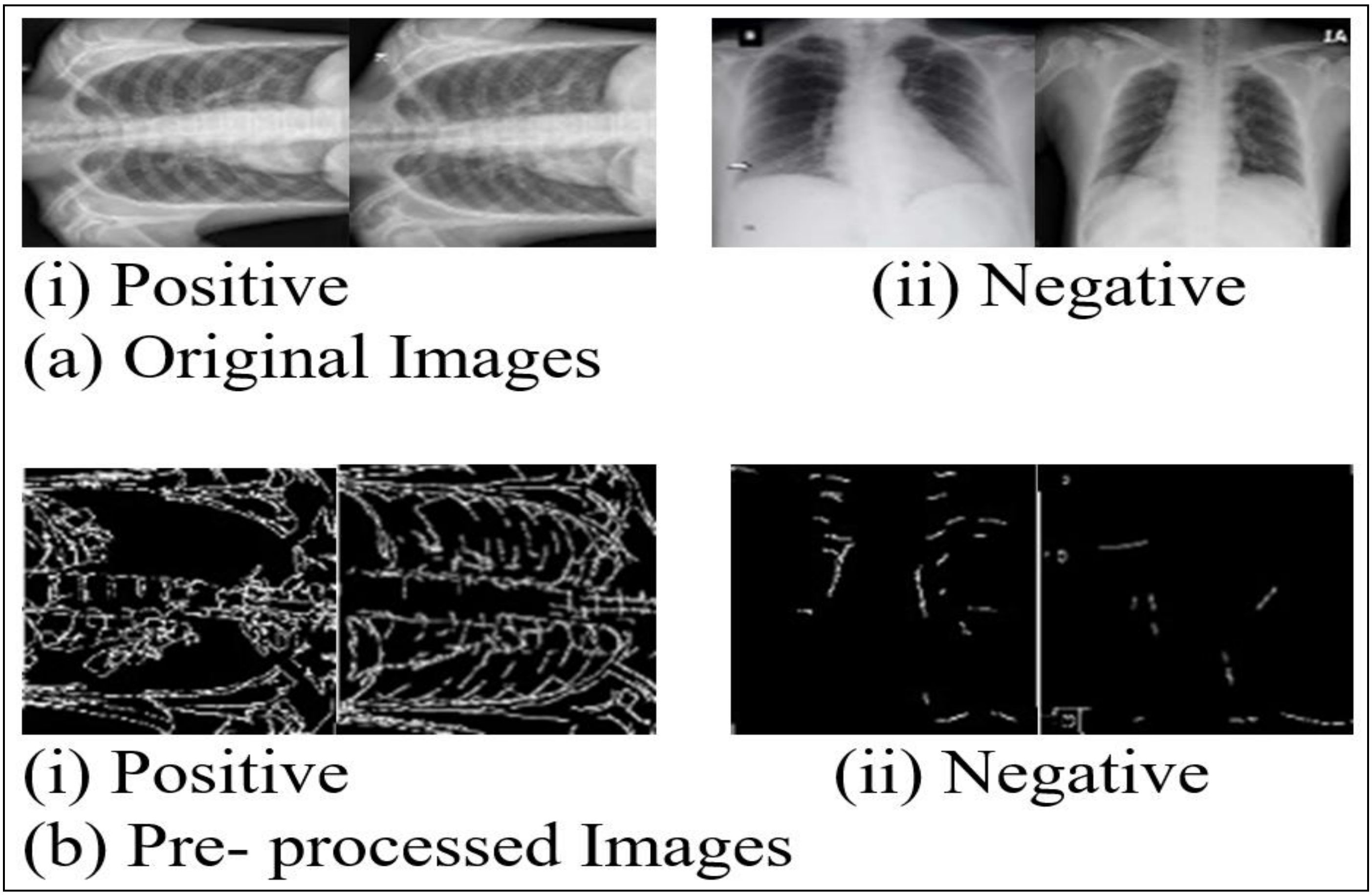

Fig 3 (a) Original and (ii) Pre-Processed Images

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➢ *Feature Selection and Classification*

The main aspect of this scheme is to create the method for feature selection and matching of Chest X-ray images using CNN. The Chest X-ray images were classified into pneumonia and Covid-19. These Chest X-ray images were given as the input to this scheme and the output was the classified images. CNN was fine-tuned by using the Mayfly Algorithm. By using this optimization approach, CNN was retrained with Chest X-ray images to achieve improved classification output. To achieve the best performance of the proposed approach, the hyper-parameters such as number of layers, filters and batch size of the CNN was optimized using MA.

After the Convolutional and pooling layers, fully connected layers were located to merge the features obtained and in the last, the SoftMax layer which is the output was computed. The strategy was used to combine fully connected layers blocks with studying a nonlinear mixture of the extracted features and executed the resultant classification.

➢ *Optimization of CNN with MA*

It has been highlighted that CNN models have several limitations which can be in its hyper-parameters of any such pre-trained CNN cannot be modified and has some of the hyper-parameters which require adjustment namely, the batch size and the unit numbers in every dense layer as well as the dropout layer. In this paper, the MA was employed in the CNN architecture (classifier model section) to optimize the batch size and dropout layer rate.

The dynamic parameters optimized by MA were the number of Convolutional layers, the size of the filters used in each Convolutional layer, the number of Convolutional filters, and the batch size. The general methodology of the proposal is shown in figure 4, which expresses the flowchart of the Mayfly Algorithm with Convolutional Neural Network (MA-CNN), as the "training and optimization" block is the most important part of the whole process, where the CNN is initialized to integrate the parameter optimization by applying the MA algorithm. In this process, the MA is initialized according to the parameter given for the execution in Algorithm 3 and this generates the male and female mayflies. Each mayfly is a possible solution and its position has the parameter to be optimized, so each solution represents a complete CNN training.

The training process is an iterative cycle that ends when all the mayflies generated by the MA were evaluated for each generation. The computational cost is higher and it depends on the database size, the size of mayflies, the number of iterations of the MA, and the number of male and female mayflies in each iteration. That is, if the MA was executed with 10 male and female mayflies and 10 iterations, the CNN training process is executed 100 times. The steps to optimize the CNN by the MA were illustrated in Algorithm 3 and explained as follows.

➢ *Algorithm 3: Mayfly Algorithm Based CNN*

- Input Data (pneumonia, covid-19 and normal)
- Initialise MA parameters (number of iterations, the number of male and female mayflies)
- Initialize the CNN parameters, with the parameter obtained by MA (Convolutional layers number, filter size, number of Convolutional filters, and batch size)
- CNN reads and processes the input data using data for training, validation, and testing; this step produces a recognition rate.
- Return values to the MA as part of the objective function.
- Evaluate the objective function to determine the best value.
- Update MA parameters. At each iteration, each male and female mayfly updates its velocity depending on its own best-known position (pbest) in the search-space and the best-known position in the whole swarm (gbest).
- The process is repeated, evaluating all the mayflies until the stop criteria are found (in this case, it is the number of iterations).
- Finally, the optimal CNN parameters was selected. In this process, the mayfly represented by gbest is the optimal one for the CNN model

In the learning phase, the CNN architecture model that is VGG-19 was used to classify the Chest X-Ray images. The Convolutional layer was stuck within the feature extraction process, while the classifier segment was swapped by the corresponding one. There were several layers in the current classifier: the fully connected layers consist of a dropout layer, flatten layer, batch normalization layer, and two dense layers. The first fully connected layer consists of neuron groups with a rectified linear unit and the second fully connected layer consists of four function units of SoftMax. After training the classifier for the number of iterations, the fine-tuning was achieved by reactivating the Convolutional last two layers and retraining with the classifier as shown in Figure 3. Once the training process is completed all these were merged to create the final recognition of pneumonia, lung cancer and Covid-19 using Chest X-Ray images which averages their posteriors of SoftMax class.

➢ *Performance Evaluation*

The performance of the developed technique for the recognition of pneumonia, and Covid-19 was evaluated based on False Positive Rate (FPR), sensitivity (SEN), specificity (SPEC), precision (PREC), accuracy (ACC) and Computation time (C_time) (details are in [13]).

V. RESULTS AND DISCUSSION

An interactive Graphic User Interface (GUI), as shown in Figure 5, interface was developed with an online database in MATLAB 2020a. The MATLAB software package was implemented on a HP computer system with Windows 10Pro, Intel® Core i7 CPU @2.80GHz, 16.0GB, 64-bit O.S, 500GB configuration. A total of 1980 cases were collected. The dataset consisted of 990 COVID-19 cases and 990 pneumonia cases. Seventy percent of the dataset was used for training and thirty percent for testing.

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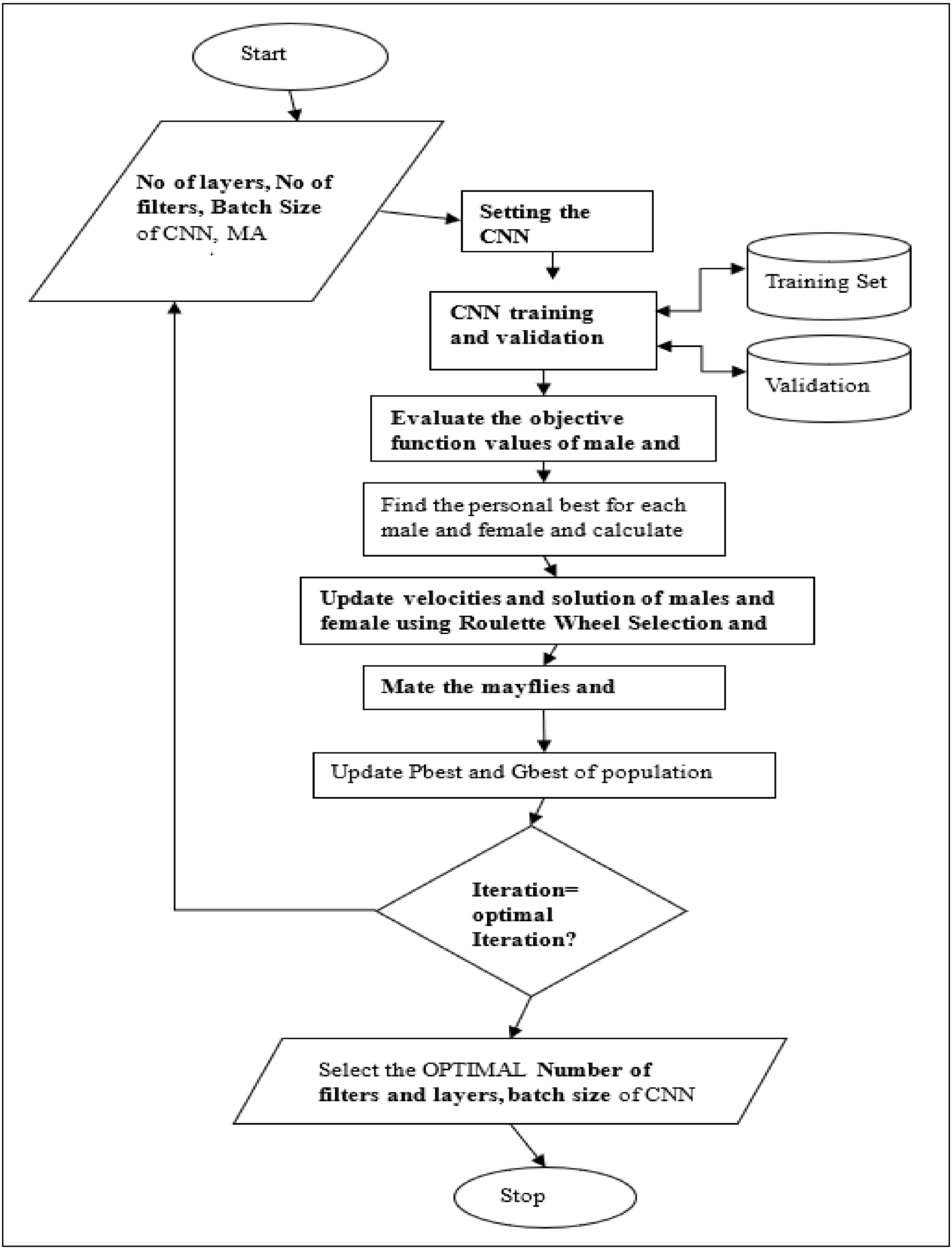

Fig 4 Flowchart of MA-CNN Model

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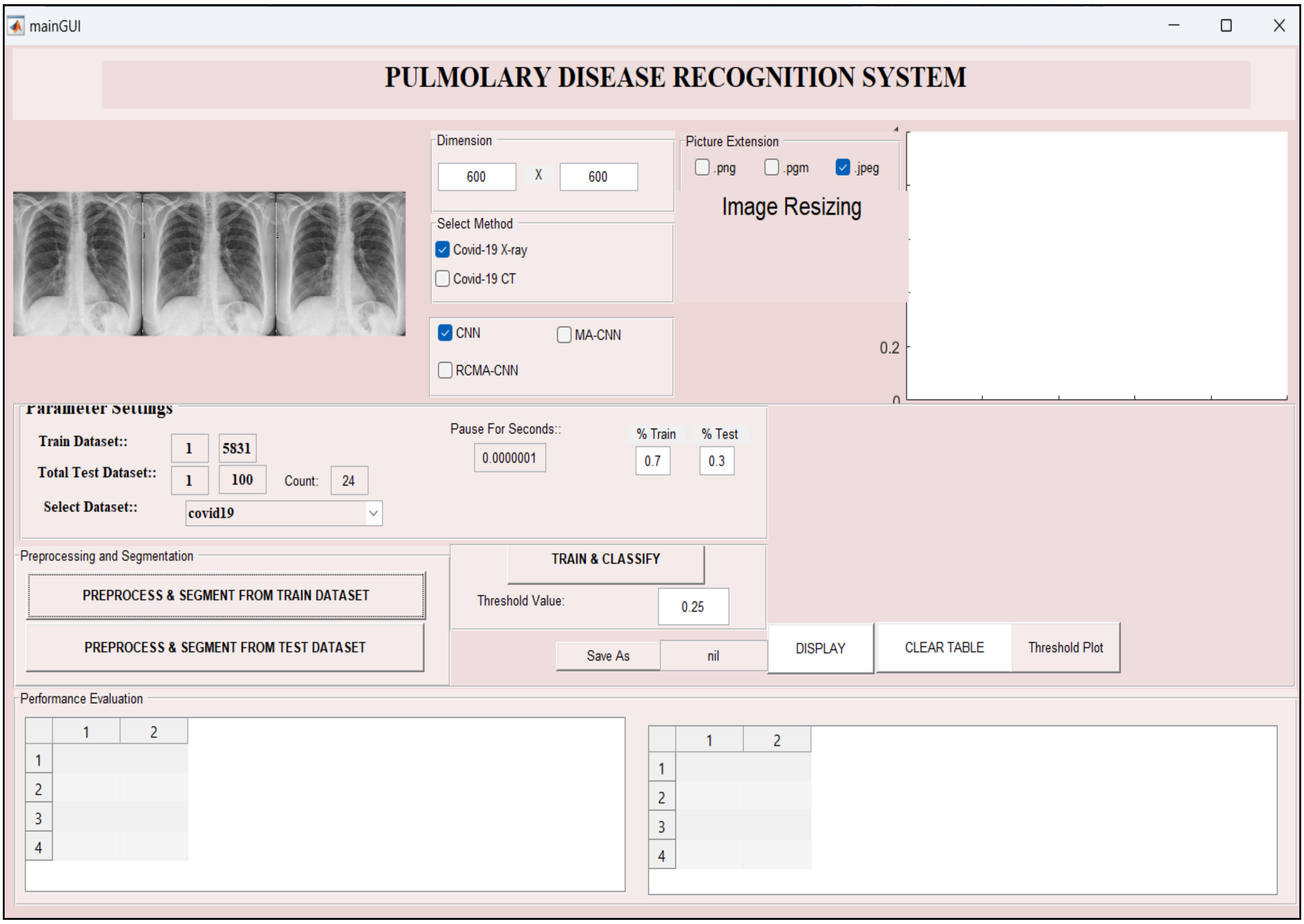

Fig 5 GUI Showing Training Phase

The performance metrics were analyzed for different average threshold values (0.25, 0.35, 0.50, and 0.75). To optimize the MA on the CNN, experiment was carried out 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 is summarized in Table 1. Using 30 iterations the best recognition rates achieved by MA is 99.12% (Table 1). The optimal CNN architectures obtained using MA: 17 Convolutional layers, 256 filters per layer (5x5), batch size of 256.

Table 1 Optimization Result of MA-CNN

Threshold	**0.25**	**0.35**	**0.50**	**0.75**
TP	430	429	428	427
FN	20	21	22	23
FP	27	25	23	20
TN	513	515	517	520
SPEC (%)	95.0	95.4	95.7	96.3
SEN (%)	95.6	95.3	95.1	94.9
FPR (%)	5.0	4.6	4.3	3.1
ACC (%)	95.3	95.4	95.5	95.7
C_Time (µs)	82.7	82.3	80.0	84.1

Table 2 presents the results of the CNN technique applied to pneumonia dataset. The CNN technique produced 427, 23, 30, 510, 94.4%, 94.9%, 5.6%, 94.6% and 89.9µs for TP, FN, FP, TN, SPEC, SEN, FPR, ACC and Computation time respectively at 0.25 threshold; 426, 24, 28, 512, 94.8%, 94.7%, 5.2%, 94.8% and 88.6µs for TP, FN, FP, TN, SPEC, SEN, FPR, ACC and Computation time respectively at 0.35 threshold; 425, 25, 26, 514, 95.2%, 94.4%, 4.8%, 94.8% and 86.1µs for TP, FN, FP, TN, SPEC, SEN, FPR, ACC and Computation time respectively at 0.5 threshold; 424, 26, 23, 517, 95.7%, 94.2%, 4.3%, 95.1% and 80.6µs for TP, FN, FP, TN, SPEC, SEN, FPR, ACC and Computation time respectively at 0.75 threshold.

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Table 2 CNN Technique with Pneumonia

S/N	No. Layers	No. Filters	Filter Size	Batch Size	Recognition Rate (%)
1	17	512	5x5	256	95.77
5	17	512	7x7	256	95.44
6	18	512	7x7	256	97.31
10	18	512	3x3	256	95.58
15	18	512	3x3	256	95.55
20	19	512	5x5	256	94.80
21	19	512	5x5	128	95.62
26	19	512	7x7	128	98.74
29	17	**256**	**5x5**	**256**	**99.12**
30	19	512	7x7	128	95.72

- *Results for CNN*

Table 3 presents the results of the CNN technique applied to COVID dataset. The CNN technique produced 430, 20, 27, 513, 95.0%, 95.6%, 5.0%, 95.3% and 82.7µs for TP, FN, FP, TN, SPEC, SEN, FPR, ACC and Computation time respectively at 0.25 threshold; 429, 21, 25, 515, 95.4%, 95.3%, 4.6%, 95.4% and 82.3µs for TP, FN, FP, TN, SPEC, SEN, FPR, ACC and Computation time respectively at 0.35 threshold; 428, 22, 23, 517, 95.7%, 95.1%, 4.3%, 95.5% and 80.0µs for TP, FN, FP, TN, SPEC, SEN, FPR, ACC and Computation time respectively at 0.5 threshold; 427, 23, 20, 520, 96.3%, 94.9%, 3.1%, 95.7% and 84.1µs for TP, FN, FP, TN, SPEC, SEN, FPR, ACC and Computation time respectively at 0.75 threshold.

Table 3 CNN Technique with COVID

Threshold	0.25	0.35	0.50	0.75
TP	427	426	425	424
FN	23	24	25	26
FP	30	28	26	23
TN	510	512	514	517
SPEC (%)	94.4	94.8	95.2	95.7
SEN (%)	94.9	94.7	94.4	94.2
FPR (%)	5.6	5.2	4.8	4.3
ACC (%)	94.6	94.8	94.8	95.1
C_Time (µs)	89.9	88.6	86.1	80.6

- *Results for MA-CNN*

Table 4 shows the results of the MA-CNN technique applied to pneumonia dataset. The MA-CNN technique produced 434, 16, 23, 517, 95.7%, 96.4%, 4.3%, 96.1% and 61.8µs for TP, FN, FP, TN, SPEC, SEN, FPR, ACC and Computation time respectively at 0.25 threshold; 433, 17, 21, 519, 96.1%, 96.2%, 3.9%, 96.2% and 59.8µs for TP, FN, FP, TN, SPEC, SEN, FPR, ACC and Computation time respectively at 0.35 threshold; 432, 18, 19, 521, 96.5%, 96.0%, 3.5%, 96.3% and 61.3µs for TP, FN, FP, TN, SPEC, SEN, FPR, ACC and Computation time respectively at 0.5 threshold; 431, 19, 16, 524, 97.0%, 95.8%, 3.0%, 96.5% and 61.7µs for TP, FN, FP, TN, SPEC, SEN, FPR, ACC and Computation time respectively at 0.75 threshold.

Table 4 MA-CNN Technique with Pneumonia

Threshold	0.25	0.35	0.5	0.75
TP	434	433	432	431
FN	16	17	18	19
FP	23	21	19	16
TN	517	519	521	524
SPEC (%)	95.7	96.1	96.5	97.0
SEN (%)	96.4	96.2	96.0	95.8
FPR (%)	4.3	3.9	3.5	3.0
ACC (%)	96.1	96.2	96.3	96.5
C_Time (µs)	61.8	59.8	61.3	61.7

The result in Table 5 portrays the result of the MA-CNN technique with COVID images dataset. The MA-CNN technique produced 435, 15, 22, 518, 95.9%, 96.7%, 4.1%, 96.3% and 60.3µs for TP, FN, FP, TN, SPEC, SEN, FPR, ACC and Computation time respectively at 0.25 threshold; 434, 16, 20, 520, 96.3%, 96.4%, 3.1%, 96.4% and 58.8µs for TP, FN, FP, TN, SPEC, SEN, FPR, ACC and Computation time respectively at 0.35 threshold; 433, 17, 18, 522, 96.7%, 96.2%, 3.3%, 96.6% and 60.1µs for TP, FN, FP, TN, SPEC, SEN, FPR, ACC and Computation time respectively at 0.5 threshold; 432, 18, 15, 525, 97.2%, 96.0%, 2.7%, 96.7% and 59.7µs for TP, FN, FP, TN, SPEC, SEN, FPR, ACC and Computation time respectively at 0.75 threshold.

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Table 5 MA-CNN Technique with COVID

Threshold	**0.25**	**0.35**	**0.45**	**0.75**
TP	435	434	433	432
FN	15	16	17	18
FP	22	20	18	15
TN	518	520	522	525
SPEC (%)	95.9	96.3	96.7	97.2
SEN (%)	96.7	96.4	96.2	96.0
FPR (%)	4.1	3.1	3.3	2.7
ACC (%)	96.3	96.4	96.5	96.7
C_Time (μs)	60.3	59.8	60.1	59.7

However, Table 6 shows the average results of CNN and MA-CNN techniques on pneumonia and COVID images dataset. The CNN technique average results are 96.0%, 94.6%, 3.7%, 95.4% and 82.4μs for SPEC, SEN, FPR, ACC and C_time respectively at 0.75 threshold while MA-CNN average results are 97.1%, 95.9, 3.0%, 96.7% and 60.7μs for SPEC, SEN, FPR, ACC and C_time respectively at 0.75 threshold.

Table 6 Average Results of CNN and MA-CNN

Algorithm	**FPR (%)**	**SEN (%)**	**SPEC (%)**	**ACC (%)**	**Time (sec)**
MA-CNN	3.0	95.9	97.1	96.7	60.7
CNN	3.7	94.6	96.0	95.4	82.4

The following depicts the performance of the Pulmonary diseases recognition system with CNN and MA-CNN techniques.

- For FPR: As contained in Table 6, MA-CNN yielded a lesser FPR than CNN which implies that MA-CNN is less prone to False positive error in image recognition than CNN.
- For Sensitivity: The results revealed that MA-CNN has higher Recall than CNN which implies that MA-CNN has the ability to identify the presence of images (True Positives) in the database than CNN.
- For Specificity: The results showed that MA-CNN has higher Specificity than CNN which implies that MA-CNN has the ability to identify the absence of images (True Negatives) in the database than CNN.
- For Recognition Accuracy: The results showed that MA-CNN is more accurate than CNN which implies MA-CNN has the ability to identify the presence and absence of images (True Negatives and True Positives) in the database than CNN.
- For Computation Time: The results revealed that MA-CNN has a faster recognition time than CNN which implies that CNN takes longer time to identify the presence and absence of images (True Negatives and True Positives) in the database than MA-CNN.

VI. CONCLUSION

The pulmonary disease recognition system, designed to identify COVID-19, pneumonia, and normal cases, demonstrated superior performance when a Convolutional Neural Network (CNN) optimized with Mayfly Algorithm (MA) was employed for selecting hyperparameters. The MA-CNN outperformed both the standard CNN in terms of achieving a lower false positive rate, as well as higher sensitivity, specificity, accuracy, and computation time. These enhancements suggest that the MA-CNN offers a more reliable and efficient diagnostic tool. Future work should focus on further refining the MA-CNN model by incorporating larger and more diverse datasets, exploring additional data augmentation techniques, and integrating other optimization algorithms to enhance the model's robustness and generalizability.

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