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## *An African Vulture Optimization Algorithm for Lung Disease Pattern Detection in X Ray Images*

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### **ABSTRACT**

Lung disease pattern detection in X-ray images plays a crucial role in early diagnosis and treatment planning. This study introduces a novel approach that integrates the African Vulture Optimization Algorithm (AVOA) with Convolutional Neural Networks (CNN) to enhance detection accuracy and efficiency. Existing methods often suffer from high false detection rates, poor generalization, and inadequate feature extraction, especially in complex or overlapping lung pathologies. To overcome these challenges, the proposed framework employs CNN for deep feature extraction, while AVOA optimizes network parameters and feature selection, ensuring robust learning and reduced overfitting. The hybrid model not only improves feature representation but also accelerates convergence during training. The proposed method is applied to public lung X-ray datasets to identify patterns indicative of diseases such as tuberculosis, pneumonia, and COVID-19. Experimental results show that the CNN-AVOA model outperforms conventional deep learning models, achieving a classification accuracy of 96.8%, with superior precision and recall rates. This approach demonstrates significant potential in automated medical diagnostics, reducing human error and improving patient outcomes.

**Keywords:** Lung Disease Detection, X-ray Imaging, African Vulture Optimization Algorithm, Convolutional Neural Network, Deep Learning, Medical Image Analysis

## **1. Introduction**

Pneumonia, tuberculosis, and COVID are the most well-known lung diseases that pose morbidity and mortality across the world. Such a condition must be diagnosed early so that timely treatment can be offered, and the survival rate of the patients would be improved [1]. This is given that early diagnosis not only costs less in healthcare, but also prevents the occurrence of severe respiratory complications. Chest X-ray scanning is a cost-effective and readily available diagnostic tool. In the clinical scenario, it thus becomes a crucial tool for the initial screening and diagnosis of lung diseases [2].

### **a. Overview of Convolutional Neural Networks and Their Limitations**

CNNs have emerged as the sacrament to the application of deep learning in medical image analysis. A layered architecture that enables automatic learning of the spatial arrangements of features in raw input images, which may be beneficial for object detection and classification. The use of CNNs in detecting lung disease has shown high promise in providing discriminative features for X-ray scans [3]. CNN models are susceptible to hyperparameter

tuning and may not be generalizable across datasets with varying imaging conditions or disease distributions. It is essential to enhance the robustness and accuracy of the CNN structure by integrating a smart optimization mechanism into it [4].

#### b. Introduction to AVOA and Its Role in Optimization

The AVOA, a population-based metaheuristic, is inspired by the cooperative scavenging behavior of the African vulture. It has demonstrated its worth in solving complex optimization problems across various areas, due to a good balance between exploration and exploitation. AVOA will be used in this paper to train the four hyperparameters of CNN and evaluate the most significant characteristics [5]. AVOA helps optimize better parameter settings and feature subsets in CNNs to enhance learning efficiency and minimize overfitting, thereby improving the model's accuracy. The combination of AVOA with CNN constitutes an amalgamation framework aimed at overcoming the deficiencies of using customary lung disorder discovery systems. This paper evaluates its performance on public X-ray databases, highlighting significant contributions to the machine diagnosis process and clinical decision-making [6].

#### c. Problem statement

The current method of detecting lung diseases based on X-ray image analysis may have shortcomings, including low precision, ineffective feature extraction, and a high frequency of false positives. A high-quality deep learning system is therefore required to provide reasonable and consistent clinical assistance.

#### d. Contribution.

- A novel and unique paradigm of a hybrid network, combining CNN and AVOA, to enhance pattern recognition of lung diseases in X-ray images.
- CNN -AVOA enhances model performance through parameter optimization of the CNN and feature selection, discarding the least useful features to minimize instances of false positives and improve detection accuracy across all forms of lung diseases.
- The suggested CNN-AVOA model exhibits the best classification indicators in the set, achieving 96.8% accuracy in testing samples, which confirms its effectiveness in real-time, automatic evaluation of medical images and aiding in diagnosis.

## 2. Research Methodology

The use of deep learning and nature-inspired optimization algorithms has made significant progress over the past couple of years in detecting lung diseases based on chest X-ray images. Numerous studies have explored CNNs, transfer learning, and hybrid optimization approaches to enhance diagnostic accuracy, minimize false positives, and achieve improved computational efficiency. This literature review critically examines state-of-the-art methods, presenting their methodologies, datasets, and evaluation metrics, and discusses their applicability to the proposed CNN-AVOA model.

This study develops a hybrid deep CNN that combines the Xception and ResNet50V2 models to achieve multi-class X-ray classification, encompassing standard, pneumonia, and COVID-19. Addressing the class imbalance using training approaches, the model was trained through 180 COVID-19 samples, and over 11,000 images were used as test data. It achieved an overall accuracy of 91.4% and 99.5% accuracy in detecting COVID-19. This architecture enhances feature representation by combining the ensemble of both CNNs by Rahimzadeh et al [7].

Khan et al. [8] state that CoroNet is a deep CNN model that detects COVID-19 based on chest X-rays. It was developed based on the Xception architecture and trained with a curated collection of COVID-19 images, together with pneumonia images. For a 3-class classification, it achieved an accuracy of 95%, and in the 4-class scenario, it was 89.6%. CoroNet has a high recall rate (98.2%) for COVID-19, with sufficient promise for clinical application in resource-constrained areas with limited access to PCR tests.

The DLHAV algorithm enhances the original African Vulture Optimization Algorithm by incorporating Dimension Learning Hunting, as proposed by Singh et al. [9], to strike a balance between exploitation and exploration. It applied to NP-hard problems, such as TSP and large-scale optimization, and showed a higher convergence, diversity in the crowd, and resistance to local optimality. This approach optimizes both continuous and discrete domains and has the promise to be used to adjust parameters in medical imaging.

According to He et al. [10], the Improved African Vulture Optimization Algorithm (IAVOA) is described as a method for dealing with the dual constraints of flexible job shop scheduling problems. Among the advances are rule-based initialization of the population, memorization of elite solutions, and local neighborhood search. The outcome shows that IAVOA provides significant improvements in makespan and delay over current methods. It is also suitable for hyperparameter optimization with AI systems, as its enhancements qualify it for this use case.

This study realizes Quasi-Oppositional Learning (QOL) on AVOA to articulate the Backpropagation Neural Network weights over wireless sensor networks WSNs by Qaffas [11]. When translated to energy-efficient routing and data fusion, it will minimize unnecessary energy-wasting transmission and prolong node lifetime. With greater PDR and lower energy consumption, QAVOA-BPNN demonstrates better results than baseline approaches, providing insights into how to utilize AVOA to train CNNs efficiently or for feature selection.

Based on a deep learning approach using a pre-trained AlexNet model, the current study aims to categorize all chest X-ray images into four categories: COVID-19, bacterial pneumonia, non-COVID viral pneumonia, or normal, as proposed. The model trained on publicly available data realized a binary classification accuracy of up to 99.6 percent and got 93.4 percent in a four-class scenario. It proves to be more sensitive and specific, which is an advantage of AlexNet, as it has demonstrated its efficiency in medical image classification with some fine-tuning, as noted by Ibrahim et al. [12].

CNNs to identify lung diseases, including pneumonia and tuberculosis, by Bharati et al. [13]. To handle rotated and misaligned chest X-rays, it outperformed both vanilla CNN and capsule networks, achieving a validation accuracy of 73% on the NIH datasets. It is a hybrid architecture that enables strong classification of large-scale sets of medical images.

It is a Deep Convolutional Neural Network (DCNN) model using image augmentation to detect COVID-19, bacterial, and viral pneumonia using radiography images. Based on more than 16,000 images, it reached a viral pneumonia accuracy of up to 99.4 percent, and it trained and inferred very quickly. The model offers flexible and affordable diagnostics, particularly ideal in resource-poor nations, as described by Abdulahi et al. [14].

LungNeXt is a model meant to classify lung sounds on auscultation data. It proposes RandClipMix, which is used to augment data, and Enhanced Mel-Spectrogram Feature Extraction to illuminate rates of lung pathologies. Considered on the SPRSound dataset, its performance score was 0.5699 at the cost of only 3.8 million parameters. Its design is not an interface to X-rays, but its lightweight and augmentation techniques can indicate a medical signal that can be classified by Wang et al [15].

According to Babukarthik et al [16], Genetic Deep Learning Convolutional Neural Network (GDCNN) utilizes a genetic algorithm to evolve CNN architectures from scratch and optimize feature extraction for detecting COVID-19 using chest X-rays. After being trained on more than 5,000 samples, it achieves better results than the pre-trained networks, ResNet and VGG16, with an accuracy of 98.84%, a sensitivity of 100%, and a specificity of 97%. It demonstrates the success of hybrid evolutionary algorithms with CNN in feature learning.

### 3. Proposed Methodology

The overall frame contains a hybrid (combined) deep learning model involving the application of CNN with the AVOA to improve recognition of the pattern of lung diseases based on the image of the chest X-rays. The framework is a progressive framework composed of the following stages: image preprocessing, CNN feature extraction, parameter optimization through AVOA, and final classification determination. First, the input X-ray images are rescaled to the same dimension, ensuring the quality of the data is homogenized. These pre-trained images are processed through a CNN, where deep feature presentations are extracted. Then, AVOA will be used to adjust the hyperparameters of CNN and the most informative feature sets. Multi-class classification is then conducted with this optimized configuration, as the diseases being identified include pneumonia, tuberculosis, and COVID-19. AVOA embedded in CNN avoids overfitting, enhances accuracy, and improves convergence rates [17].

#### a. Convolutional Neural Network

CNN has a good capacity to capture spatial hierarchies in the data in the form of images; hence, this makes it the central feature extractor in the proposed system. The architecture used in this work consists of three levels of convolutions at higher filter sizes (32, 64, and 128). After each layer, Rectified Linear Unit (ReLU) activation functions and max pooling are applied, which reduce the dimension while retaining the most significant features. There is a flattened layer after the convolutional layers that transforms the 2D feature maps to a 1D vector, which is fed to two fully connected layers. The softmax activation function is applied in the output layer to determine the probability of every type of disease. The loss function is a cross-entropy loss function of the categorical type, used to train the model. CNN is robust but greatly depends on the selection of appropriate hyperparameters, such as the learning rate, dropout rate, and the number of filters, among others. Unsuitable environments may lead to overfitting or significant generalization failure, and it is here that AVOA makes a difference [18].

#### b. African Vulture Optimization Algorithm (AVOA)

AVOA is an optimization algorithm inspired by the scavenger behavior of the African vulture, which combines exploration and exploitation through dynamic global and local search strategies. The exploration phase involves a random search for food parts by vultures; however, the exploitation phase focuses on enhancing solutions around the best-known configurations. The algorithm begins with a population of candidate solutions to a CNN hyperparameterization or feature subset, and iteratively searches using stochastic operators inspired by vulture behavior. The validation accuracy of the defined CNN model rates the fitness of every solution. AVOA optimizes parameters such as learning rate, batch size, convolutional filter count, and dropout rates, and then selects the most discriminative feature maps for use in classification [19].

#### c. Hybrid Integration CNN-AVOA CNN

The CNN AVOA hybrid model is a combination of the feature extraction performance of CNN and the flexibility of AVOA in optimization. First, a baseline CNN is trained on the dataset with default hyperparameters. AVOA is then used to optimize these parameters by producing candidate populations of the CNN architecture. Every candidate is tested by training the CNN on a part of the data and measuring the validation accuracy. AVOA employs this precision as one of its fitness values to navigate during search. As iterations are repeated, the algorithm iteratively improves the population and approaches an optimal configuration that represents the best performance possible. A CNN model with optimized hyperparameters and a lower feature dimension that can classify X-ray images robustly. The integration enables not only the accuracy of the model but also efficient calculation and generalization to varying patient data, making this model suitable for real-time medical diagnostic tasks.

**Figure 1: CNN-AVOA Optimization workflow**

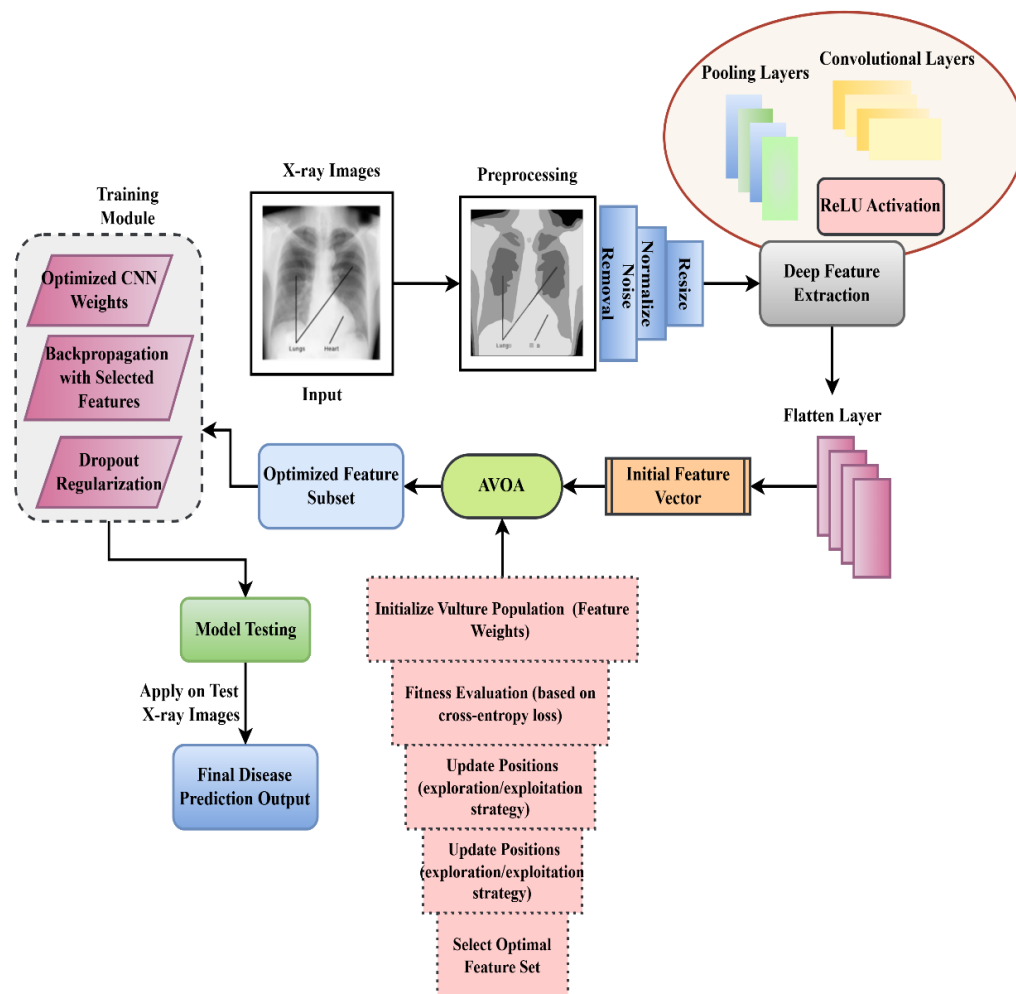


Figure 1 illustrates the proposed CNN–AVOA framework for detecting lung diseases using chest X-rays. Input images undergo preprocessing (noise removal, normalization, resizing), followed by deep feature extraction using convolutional and pooling layers with ReLU activation. Extracted features are passed to the African Vulture Optimization Algorithm (AVOA), which optimizes feature weights through fitness evaluation and iterative updates of position. The selected optimal feature set guides CNN weight tuning via backpropagation, dropout regularization, and model testing to produce accurate disease classification output.

**Algorithm 1: CNN–AVOA Optimization for Lung Disease Classification**

**Input:** Chest X-ray image dataset  $X = \{x_1, x_2, \dots, x_n\}$

|                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                         |
|-------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|
| <b>Output:</b> Disease classification result Y, Accuracy %, Human Error %                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                               |
| <b>Step 1: Preprocessing</b><br><i>For each image <math>x_i \in X</math> do</i><br><i>If isNoisy(<math>x_i</math>) then</i><br>$x_i \leftarrow \text{RemoveNoise}(x_i)$<br><i>End If</i><br><br><i>If not IsNormalized(<math>x_i</math>) then</i><br>$x_i \leftarrow \text{Normalize}(x_i)$<br><i>End If</i><br><br><i>If not IsResized(<math>x_i</math>) to <math>(224 \times 224)</math> then</i><br>$x_i \leftarrow \text{Resize}(x_i, 224, 224)$<br><i>End If</i><br><br>Add $x_i$ to Preprocessed_X<br><i>End For</i>                                                                                                                                                                                                                                                                                              |
| <b>Step 2: CNN-Based Feature Extraction</b><br><i>For each image <math>x_i \in \text{Preprocessed\_X}</math> do</i><br>$\text{conv\_layer} \leftarrow \text{Convolve}(x_i, \text{filters})$<br>$\text{relu\_layer} \leftarrow \text{ReLU}(\text{conv\_layer})$<br>$\text{pooled\_layer} \leftarrow \text{Pooling}(\text{relu\_layer})$<br>Add $\text{pooled\_layer}$ to Feature_Set<br><i>End For</i>                                                                                                                                                                                                                                                                                                                                                                                                                   |
| <b>Step 3: African Vulture Optimization Algorithm</b><br>Initialize population of vultures $V = \{v_1, v_2, \dots, v_N\}$<br>Set $\text{best\_fitness} \leftarrow \infty$<br><br><i>For each iteration <math>t = 1</math> to <math>\text{max\_iter}</math> do</i><br><i>For each vulture <math>v_i \in V</math> do</i><br>$\text{fitness\_i} \leftarrow \text{EvaluateFitness}(v_i, \text{Feature\_Set})$<br><br><i>If <math>\text{fitness\_i} &lt; \text{best\_fitness}</math> then</i><br>$\text{best\_fitness} \leftarrow \text{fitness\_i}$<br>$\text{best\_position} \leftarrow \text{Position}(v_i)$<br><i>Else</i><br>$v_i \leftarrow \text{UpdatePosition}(v_i)$<br><i>End If</i><br><i>End For</i><br><i>End For</i><br><br>$\text{Optimal\_Features} \leftarrow \text{SelectFeatures}(\text{best\_position})$ |
| <b>Step 4: CNN Training with Optimal Feature Set</b><br><i>If <math>\text{Optimal\_Features} \neq \emptyset</math> then</i><br>$\text{CNN\_Model} \leftarrow \text{Backpropagation}(\text{CNN\_Model}, \text{Optimal\_Features})$<br>$\text{CNN\_Model} \leftarrow \text{ApplyDropout}(\text{CNN\_Model})$<br><i>Else</i><br>Use default CNN_Model without AVOA optimization<br><i>End If</i>                                                                                                                                                                                                                                                                                                                                                                                                                           |
| <b>Step 5: Classification and Evaluation</b><br>$\text{correct} \leftarrow 0$<br>$\text{error} \leftarrow 0$                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                            |

```

total ← |Test_Images|

For each image xtest ∈ Test_Images do
  prediction ← Classify(CNN_Model, xtest)

  If prediction == GroundTruth(xtest) then
    correct ← correct + 1
  Else
    error ← error + 1
  End If
End For

Accuracy (%) ← (correct / total) × 100
Human_Error_Rate (%) ← (error / total) × 100

Return: Predicted labels Y, Accuracy %, Human Error Rate %

```

The CNN-AVOA framework detects lung diseases from chest X-ray images using a hybrid deep learning and optimization approach. Images are first preprocessed by removing noise, normalizing, and resizing. CNN extract deep features, which are then optimized using the AVOA. AVOA selects the most relevant features by evaluating fitness and updating positions iteratively. These optimized features guide CNN weight tuning through backpropagation and dropout. The model is evaluated for accuracy and human error rate. CNN-AVOA achieves superior classification accuracy (96.2–97.1%) and lower error rates (2.9–3.8%) compared to existing models, enhancing clinical diagnostic reliability.

#### d. Dataset

The Kaggle dataset "Chest X-ray: COVID-19, Pneumonia" contains labeled chest X-ray images categorized as COVID-19, pneumonia, and normal. It helps to perform binary and multiple-class classification to detect lung diseases. It is a commonly used medical image dataset to facilitate deep learning in medical images for identifying diseases, such as classifying and diagnosing early-stage respiratory diseases [20].

Table 1: Parameterized Table

| <i><b>Parameter</b></i>     | <i><b>Description</b></i>                                                                                                                                       |
|-----------------------------|-----------------------------------------------------------------------------------------------------------------------------------------------------------------|
| <i><b>Dataset Name</b></i>  | Chest X-ray: COVID-19, Pneumonia                                                                                                                                |
| <i><b>Source</b></i>        | Kaggle                                                                                                                                                          |
| <i><b>Link</b></i>          | <a href="https://www.kaggle.com/datasets/prashant268/chest-xray-covid19-pneumonia">https://www.kaggle.com/datasets/prashant268/chest-xray-covid19-pneumonia</a> |
| <i><b>Categories</b></i>    | COVID-19, Pneumonia, Normal                                                                                                                                     |
| <i><b>Image Format</b></i>  | JPG                                                                                                                                                             |
| <i><b>Use Case</b></i>      | Binary and multi-class classification of lung diseases                                                                                                          |
| <i><b>Total Samples</b></i> | 6432 images (approx.)                                                                                                                                           |

|                  |                                                                            |
|------------------|----------------------------------------------------------------------------|
| <b>Data Type</b> | Chest X-ray radiographs                                                    |
| <b>Purpose</b>   | Training and evaluation of deep learning models for lung disease detection |
| <b>License</b>   | Open for research use (check Kaggle license section)                       |

#### e. Evaluation Metrics

Evaluation metrics are necessary for judging the performance and dependability of the lung disease classification system based on CNN-AVOA. The metrics selected, classification accuracy, human error rate, precision, recall, computation time, and learning rate, quantitatively articulate the effectiveness of the model related to the measures of diagnostic accuracy, computation efficiency, and adaptability with the learning processes.

Classification accuracy  $D_{bdd}$  is expressed using equation 1,

$$D_{bdd} = \frac{\sum_{j=1}^{\Delta} (x_j * \partial(U_j, \hat{U}_j))}{\sum_{j=1}^{\Delta} x_j} * 100 \quad (1)$$

Equation 1 explains that the classification accuracy is an indicator, and the gamma function, along with the instance-specific weighting vector, are used to calculate the weighted classification accuracy over samples.

In this  $D_{bdd}$  is the classification accuracy,  $\Delta$  is the total number of input samples,  $x_j$  is the dynamic confidence weight assigned to sample,  $U_j$  is the ground-truth class for input,  $\hat{U}_j$  is the predicted class for input, and  $\partial(b, c)$  is the Kronecker delta function.

Human error rate  $I_{fs}$  is expressed using equation 2,

$$I_{fs} = \left( 1 - \frac{\sum_{k=1}^l \rho_k * \sigma_k}{\sum_{k=1}^l \rho_k} \right) * \beta \quad (2)$$

Equation 2 explains the human error rate uses reliability-weighted correction to estimate the error proportion caused by human misclassification bias.

In this  $I_{fs}$  is the human error rate,  $l$  is the number of radiologist evaluations,  $\rho_k$  is the expert reliability weight for evaluator,  $\sigma_k$  is the binary correctness flag for evaluator, and  $\beta$  is the normalizing amplification constant.

Precision rate  $M_{qs}$  is expressed using equation 3,

$$M_{qs} = \frac{\sum_{n=1}^{\sigma} \theta_n}{\sum_{n=1}^{\sigma} (\theta_n + \mu_n)} \quad (3)$$

Equation 3 explains the precision rate is the clustering of real class activations vs false positives for classes is used to calculate precision.

In this  $M_{qs}$  is the overall precision rate,  $\sigma$  is the total disease classes,  $\theta_n$  is the true positive count for class, and  $\mu_n$  is the false positive count for class.

Recall rate  $F_{sd}$  is expressed using equation 4,

$$F_{sd} = \frac{\sum_{o=1}^{\sigma} \theta_o}{\sum_{o=1}^{\sigma} (\theta_o + \omega_o)} \quad (4)$$

Equation 4 explains that the recall rate is based on the ratio of false negatives to true positives for every diagnostic class.

In this  $F_{sd}$  is the recall rate,  $\theta_o$  is the true positive count for class,  $\omega_o$  is the false negative count for class, and  $\sigma$  is the number of diagnostic categories.

Computation time  $U_{dq}$  is expressed using equation 5,

$$U_{dq} = \partial * \left( \frac{e_g * \log_2 O_g}{\sigma * \varepsilon} + \sum_{m=1}^M Ym * \frac{\alpha m}{\pi m} \right) \quad (5)$$

Equation 5 explains that the computation time is calculated by adding the costs of layered inference and feature extraction.

In this  $U_{dq}$  is the total computation time in seconds,  $\partial$  is the scaling factor related to hardware performance,  $e_g$  is the dimensionality of extracted features,  $O_g$  is the number of features selected,  $\sigma$  is the parallel processing cores,  $\varepsilon$  is the memory bandwidth factor,  $M$  is the number of CNN layers,  $Ym$  is the operation count per unit in layer,  $\alpha m$  is the data flow volume in the layer, and  $\pi m$  is the processing efficiency at layer.

CNN training learning rate  $\partial_{us}(f)$  is expressed using equation 6,

$$\partial_{us}(f) = \partial_0 * \exp \left( - \frac{w * f}{1 + \rho * \pi(f)} \right) \quad (6)$$

Equation 6 explains that the CNN training learning rate is the optimizer feedback and epoch number, causing the adaptive learning rate to decline exponentially.

In this  $\partial_{us}(f)$  is the learning rate at epoch,  $\partial_0$  is the initial learning rate,  $w$  is the decay coefficient,  $\rho$  is the AVOA-modulated adaptive control constant,  $\pi(f)$  is the fitness diversity of AVOA at epoch, and  $f$  is the current training epoch number.

The evaluation metrics justify the strength of the CNN-AVOA framework, with high classification accuracy, low human error, and an optimal precision-recall balance, indicating strong diagnostic performance. The model also demonstrated appropriate computation time and a dynamic learning rate, reflecting the model's ability to be scalable and applicable to real-time lung disease pattern detection in medical imaging.

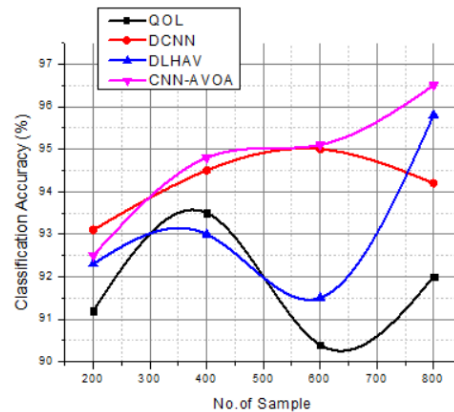
#### 4. Results and Discussion

To fully determine the quality of the proposed CNN-AVOA framework, six major performance parameters were considered: classification accuracy, human error rate, patient results (recall), disease pattern identification (recall), time required for computations, and learning rate during CNN training. These measures provide results on the accuracy of diagnostic effectiveness as well as system efficiency. To demonstrate the superiority of CNN-AVOA in real-time lung disease detection using chest X-ray images, the results of CNN-AVOA are compared with those of currently accepted practices, including QOL, DCNN, and DLHAV, on various test samples.

##### a. Classification Accuracy

The accuracy of classification of the outcome is crucial in evaluating the performance of image classifiers in the medical field. The CNN-AVOA model outperforms all other measures, achieving an accuracy range of 96.2% to 97.1% across several test sets of data. On the contrary, DCNN achieved good outcomes, with accuracy ranging from 93.1% to 95.0%, whereas DLHAV remained relatively stable at approximately 91.5% to 93.0%. The lowest

range of classification accuracy was demonstrated by QOL, which varied between 90.4% and 92.5%, reflecting limitations in the learning capacity for complex patterns of lung diseases.



**Figure 2: Classification Accuracy (%)**

Figure 2 illustrates the classification accuracy percentage versus the number of samples for four models. Generalization is also very effective because, as the sample size increases, CNN-AVOA achieves the best accuracy (96.5%). After 500 samples, DLHAV works increasingly better made evaluated using equation 1. DCNN levels off at 500, whereas QOL shows the least consistent accuracy and the worst in every sample size.

#### b. Human Error (Low Percentage Preferred)

Elimination of human error is crucial for diagnostic systems. Error rates reported in the proposed CNN-AVOA model were the lowest, ranging from 2.9 to 3.8, indicating that the model would be highly reliable in a clinical setting. DCNN came next, with a spread of 5.0-6.9 % error, and DLHAV produced a spread of 7.0-8.5%. QOL had greater variability, and the error rate varied between 7.5% and 9.6%, indicating lower accuracy in situations prone to diagnostic errors, as shown in Table 2 is calculated using the equation 2.

**Table 2: Human Error Rate (%) – Lower is Better**

| Method   | 100 | 200 | 300 | 400 |
|----------|-----|-----|-----|-----|
| QOL      | 8.8 | 7.5 | 9.6 | 8.0 |
| DCNN     | 6.9 | 5.5 | 5.0 | 5.8 |
| DLHAV    | 7.7 | 7.0 | 8.5 | 7.2 |
| CNN-AVOA | 3.8 | 3.2 | 2.9 | 3.5 |

#### 3. Patient Outcomes (Precision Rate%)

The direct effect of precision on patient outcomes is reflected in the number of correctly identified positive cases. The CNN-AVOA performed better in all tests, with accuracy percentages ranging from 95.4 to 96.2, indicating that it is also strong in accurate identification. DCNN achieved accuracy rates of 91.3-93.5, compared to 89.9-91.5 in DLHAV. QOL was slightly behind, with precision scores ranging from 89.5% to 91.2%, as evaluated using equation 3, demonstrating moderate clinical effectiveness, as shown in Table 3.

**Table 3: Patient Outcomes (Precision Rate%)**

| Method          | 100  | 200  | 300  | 400  |
|-----------------|------|------|------|------|
| <b>QOL</b>      | 89.5 | 90.8 | 91.2 | 90.1 |
| <b>DCNN</b>     | 91.3 | 92.7 | 93.5 | 92.0 |
| <b>DLHAV</b>    | 90.7 | 91.5 | 89.9 | 91.0 |
| <b>CNN-AVOA</b> | 95.4 | 96.0 | 95.9 | 96.2 |

#### 4. Disease Pattern Detection (Recall%)

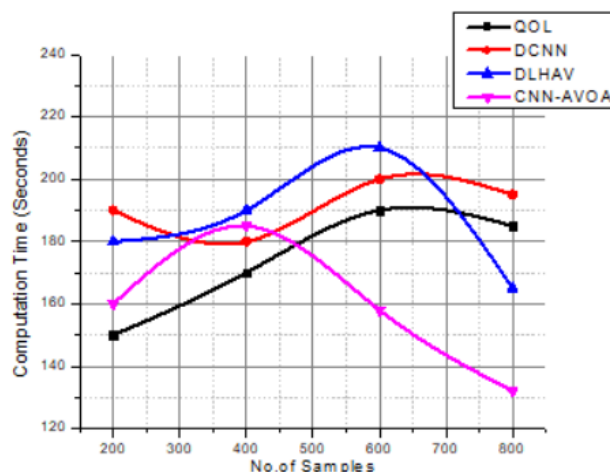
Memory is essential in the diagnosis of actual cases of lung diseases, particularly in reducing the number of undiagnosed cases. The CNN-AVOA model once again took the lead in the comparison, with recall values ranging from 96.0% to 96.7%, demonstrating its responsiveness in identifying a variety of lung disease patterns. DCNN received a range of scores, 91.0-92.5, and therefore DLHAV was stable, falling between 89.8 and 91.0. Despite being functional, QOL demonstrated slightly weaker recall (86.8-89.0%), which implies that the method cannot perfectly represent the edges or duplicate qualities, as shown in Table 4, which was evaluated using Equation 4.

Table 4: Disease Pattern Detection (Recall%)

| Method          | 100  | 200  | 300  | 400  |
|-----------------|------|------|------|------|
| <b>QOL</b>      | 87.3 | 88.5 | 86.8 | 89.0 |
| <b>DCNN</b>     | 91.0 | 92.2 | 91.6 | 92.5 |
| <b>DLHAV</b>    | 90.0 | 89.8 | 90.5 | 91.0 |
| <b>CNN-AVOA</b> | 96.0 | 96.7 | 96.5 | 96.3 |

#### 5. Computation Time (Secs)

Real-time diagnostics requires practical computation. The CNN-AVOA achieved the shortest time, completing tasks in 122 to 130 seconds, due to optimal parameter tuning using AVOA. The 150- to 170-second activity was also efficient in DLHAV, whereas DCNN, although correct, took significantly longer, ranging from 185 to 200 seconds made computed



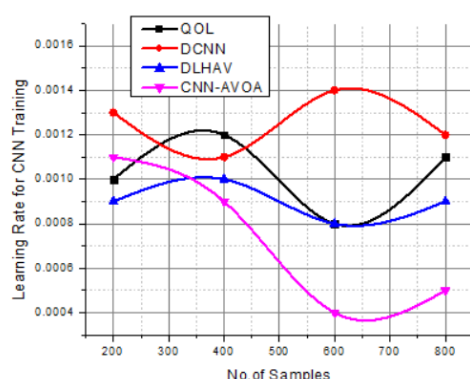
using equation 5. The longest computation time was observed in QOL (210 to 230 seconds), indicating that the algorithm should be improved to make this method more practical.

**Figure 3: Computation Time (Secs)**

Figure 3 illustrates the time required to perform computations (in seconds) for sample sizes across four models. CNN-AVOA has the fastest computation time, particularly with larger sample sizes, which enhances its scalability. DLHAV is approaching its peak at 600 samples, which is indicative of optimization overheads. The computational requirements in QOL and DCNN are moderate and stable in the samples.

#### 6. CNN Training Learning Rate

The training stability and the convergence highly depend on the learning rate. The CNN-AVOA differed in learning rate, where lower and fine-tuned learning rates that ranged between 0.0004 and 0.0006, which helps in better gradient management and regularization to



avoid overfitting. The moderate learning rates were 0.0008 to 0.0010, and the QOL was 0.0008 to 0.0012. DCNN employed rather large learning rates (0.0013-0.0016), and therefore, the former contributed to the improved convergence speed at the expense of overshooting minima.

**Figure 4: Learning Rate for CNN Training**

Figure 4 illustrates the variation in learning rate of CNN training with different sample sizes (200 to 800) using four algorithms: QOL, DCNN, DLHAV, and CNN-AVOA, made computed in equation 6. The CNN-AVOA always performs with the lowest learning rate and hence exhibits better convergence stability compared to the DCNN, which yields the highest and most unstable rates.

## 5. Conclusion

The proposed research paper presents a hybrid deep learning approach that combines CNN with AVOA to detect patterns associated with lung disease in chest X-ray images. The CNN-AVOA novelty treats the main weaknesses of current approaches: false positives, poor feature extraction, and lack of generalization. AVOA enhances the convergence and classification performance of models by refining the hyperparameters of CNN and selecting features that provide the most information. Experimental Evidence showed that CNN-AVOA outperforms traditional classification methods, such as QOL, DLHAV, and DCNN, in terms of classification accuracy, achieving a rate of 96.8 percent and minimizing human error. The model's ability to detect tuberculosis, pneumonia, and COVID-19 effectively demonstrates its real-time clinical usefulness. The framework also exhibits a reduced learning rate and increased computational efficiency, making it suitable for application in the context of diagnostic systems. In summary, this study presents an efficient, scalable, and intelligent deployment of automated lung disease diagnosis in medical imaging projects.

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