Efficient lung disease classification through luminescent feature selection using firefly algorithm

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ABSTRACT

Over the past couple of decades, there has been a substantial increase in the prevalence of lung ailments, resulting in 3.5 million fatalities each year. This necessitates the adoption of a lung disease detection technology that is effective, trustworthy, and cost-effective. In this study, we propose an optimized convolutional neural network (CNN) model, used for multiclass categorization of lung ailments based on frontal chest X-rays. The classification includes four categories: COVID-19, viral pneumonia, lung opacity, and non-infectious normal group. We implemented the firefly algorithm to optimize the global efficiency of feature selection of the lung abnormality in the X-ray images of lung disease and COVID-19 to classify the input according to the target class. The proposed algorithm was tested for accuracy, precision, recall, and F1-score. The findings were validated using the transfer learning model VGG-16; the algorithm achieved a superior accuracy of 99.3% compared to that of other cutting-edge models such as Inceptionv3 and ResNet50.

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1. INTRODUCTION

The lung is a crucial organ in the human body, and lung diseases can cause serious health issues, including impaired lung function, difficulty breathing, and even death if not treated or diagnosed promptly. Consequently, respiratory ailments are the third-leading cause of mortality globally, resulting in around five million fatalities per year. This could be attributed to several variables including contaminants in the air, microbial infiltration, chemical consumption, and physical ailments. Furthermore, lung diseases, particularly pneumonia, COVID-19, tuberculosis, and pneumothorax are indicated as the major causes of death worldwide by the World Health Organization (WHO) [1].

Pneumonia is a lung infection caused by bacteria, viruses, or fungi. It results in inflammation and fluid buildup in the lung's air sacs, leading to breathing difficulties and symptoms like cough, chest pain, and fever [2]. Similarly, COVID-19, or the novel coronavirus disease, is caused by the virus SARS-CoV-2. It appeared in late 2019 and rapidly became a global pandemic. The disease mainly impacts the respiratory system, leading to symptoms like fever, cough, shortness of breath, and fatigue. In severe cases, it can cause pneumonia and acute respiratory distress syndrome (ARDS). As a result of delayed results reporting, limited testing capacity, and inadequate diagnosis, the COVID-19 pandemic has raised mortality rates. Therefore, improved testing infrastructure, universal access, and effective diagnostic techniques are essential for pandemic mitigation. A series of tests, including antigen testing, real-time polymerase chain reaction, the Mantoux tuberculin skin test, and a complete blood count (CBC) level are recommended for diagnosis. These methods are time-intensive and have limitations such as a 20% rate of inaccuracies and an 80% level of adaptability [3]. Early identification of these diseases greatly enhances the chances of survival and reduces fatalities [4]. Accurate diagnosis and classification of chest diseases are essential for effective treatment and management. Recently, technological advancements, including deep learning and artificial intelligence algorithms, have proven beneficial in diagnosing and classifying chest diseases through radiographic imaging like chest X-rays or computed tomography (CT) scans. These technologies help healthcare professionals quickly and accurately identify various chest conditions, resulting in timely interventions and better patient outcomes.

Moreover, feature selection is an essential task in feeding knowledge; it is usually carried out during the data preparation stage [5]. The objective is to identify the most suitable collection of features that encompass important features of the dataset while eliminating unnecessary or redundant features that may have negative impacts on the accuracy of the classification and the efficacy of a classifier. This is crucial for validating the accuracy of the proposed algorithms [6]. The suggested technique utilizes fireflies filtering to optimize feature selection in machine learning. This filtering strategy facilitates the detection of appropriate features while minimizing the probability of false positives [7]. Numerous metaheuristic algorithms, particularly those inspired by nature, such as intelligence from swarms and evolutionary algorithms, have shown impressive effectiveness in addressing the difficulties in feature selection [8]. However, there is potential for further advancements in classifying the disease, ensuring precision, improving training duration, and increasing the number of parameters. Several established metaheuristic methods encounter stagnation within sub-optimal domains [9], [10]. Additionally, it is challenging to screen for systemic pulmonary ailments owing to a lack of test procedures and limited hospital resources. Consequently, automation in the field of medical imaging in lung disease classification can enhance early diagnosis.

Furthermore, the use of deep learning techniques like convolutional neural networks (CNNs) has proven successful in extracting features from chest X-ray images, aiding in the quick and accurate detection of lung diseases. However, there is a research gap in exploring more advanced feature selection methods to further improve classification accuracy and optimize the performance of deep learning models in diagnosing lung diseases using chest X-ray images. This study investigated the effects of using metaheuristic algorithms to optimize feature selection in deep learning models, specifically focusing on the firefly nature-inspired optimization algorithm. While earlier studies have explored the impact of traditional feature selection methods, they have not explicitly addressed their influence on the performance and efficiency of deep learning models when optimized using metaheuristic algorithms. The firefly algorithm, known for its simplicity and ability to avoid local optima, offers advantages such as enhanced exploration of the search space, efficient handling of high-dimensional data, and robust performance in noisy environments. This study introduces an optimized CNN model for classifying lung diseases from chest X-rays into four categories: COVID-19, viral pneumonia, lung opacity, and non-infectious normal. Furthermore, the firefly algorithm was used to improve feature selection efficiency for lung abnormalities.

2. LITERATURE REVIEW

The research presents a method for diagnosing pneumonia using X-ray images. This method combines CNN and transfer learning techniques. Specifically, it adopts a previously trained MobileNet model and incorporates additional layers for fine-tuning. Notably, the proposed strategy exhibited superior performance in comparison to other CNN models utilizing conventional machine learning techniques, thereby demonstrating its effectiveness in diagnosing pneumonia [11]. Additionally, deep learning can create models that can effectively forecast and detect certain diseases, including COVID-19, using images [12]. This technology is particularly effective in achieving precise results in medical diagnosis. For instance, a categorization system for COVID-19, different forms of pneumonia, tuberculosis, and normal X-ray images has been suggested [13]. Moreover, Khasawneh *et al.* [14] proposed the use of automation for identifying COVID-19 disease from chest X-rays using deep learning algorithms.

This study examines applying deep learning approaches to detect pneumonia in chest X-ray images. The author discussed the challenges and limitations of annotated datasets, inequalities in classes, comprehension of model predictions, generalization, and insertion into clinical procedures. Furthermore, the literature review examines CNN-based frameworks, transfer learning, dataset development, and data preprocessing methods, such as image scaling, and normalization, to improve model performance [15]. For example, Ozyurt *et al.* [16] implemented VGG-16, DenseNet-169, and DenseNet-201 to diagnose the chest X-ray images. During the feature extraction stage, they identified the important characteristics using the scale-invariant method, and the results were enhanced by using the binary-robust invariant scalable key points. They developed a dynamic-sized pyramid fused with the base model for feature selection and classification of chest X-ray images according to the target disease, achieving an accuracy of 95.84% using this feature generation network [17].

Machine learning encounters notable difficulties in feature selection; this includes choosing a subset of complimentary attributes from collection of characteristics to enhance classification accuracy. The trait 'complementary' is essential due to the potential for several interactions between features, which becomes more challenging as number of features increases. Furthermore, the difficulty in implementation could be attributed to the need for achieving a balanced classification accuracy and minimizing false positives, to avoid incorrect treatment recommendations. Feature selection minimizes dimensionality of the input data by eliminating extraneous qualities and noise, thus obtaining an optimal subset of features. There are three primary types of feature selection approaches: wrapper-based technique, filter-based method, and embedding methods [18].

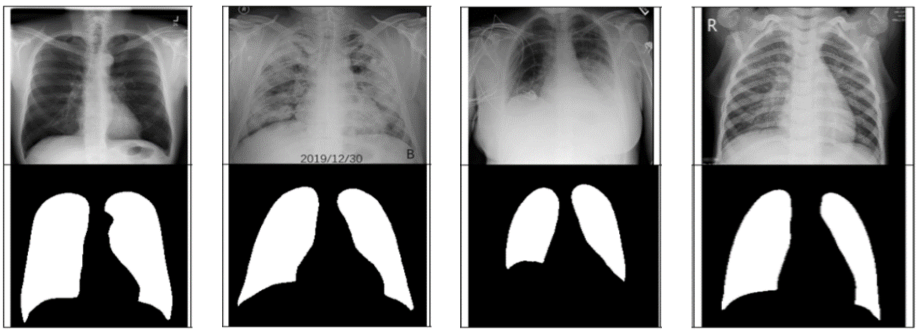
Metaheuristics algorithms, particularly nature-inspired techniques such as evolutionary generated algorithms and swarm optimization, are very efficient for feature selection because they can effectively explore the vast search area. For example, the genetic algorithm (GA) is frequently employed as a wrapper technique in these methodologies [19]. Swarm intelligence is a robust optimization method that is effective for solving actual problems that are difficult to solve using traditional algorithms [20]. This is achieved by imitating natural systems and using operations that include both exploiting and exploring the issue space. Popular intelligent systems have been developed based on ant colony-inspired optimization techniques, inheritance of working patterns of bee colonies, bat algorithm, and the fireflies algorithm (FA) [17], [18], [21]–[24].

Gupta *et al.* [25] proposed the FA metaheuristics, inspired by the gregarious and flashing characteristics of fireflies. FA employs several approximation rules to accurately represent the intricate and advanced nature of the practical applications of natural systems. The fitness value is obtained based on the luminosity of the bright fly and the attraction of fireflies with the brighter fly; the attraction in most common FA implementations is contingent upon the luminosity, whose value is determined by the objective function. The approach in this study is suitable for minimization scenarios. Additionally, applying pre-trained neural networks like VGG-16, CapsNet, MobileNet, InceptionV3, and DenseNet for analyzing lung images, especially in cases such as lung infections and COVID-19, is promising [26]. Pneumonia is one of the key symptoms of COVID-19 disease. Transfer learning facilitates the identification of a shared causative agent for both pneumonia and COVID-19 disease and its variants. This study presents essential knowledge obtained using a trained model in distinguishing between viral pneumonia, tuberculosis, and COVID-19.

3. PROPOSED METHODOLOGY

3.1. Dataset description

The COVID-19 radiography database is a comprehensive repository of chest X-ray images that capture instances of COVID-19, normal conditions, lung opacity, and viral pneumonia. The database expanded significantly starting with an initial set of 219 images. A major update added 1,200 COVID-19 X-ray images. The second edition, released in 2021, includes images of 3,616 COVID-19 cases, 10,192 normal cases, 6,012 lung opacity cases, and 1, 345 viral pneumonia cases. The database is expected to be continuously updated with new X-ray images, particularly those of COVID-19 patients with new variants and pneumonia [27], [28]. The X-ray images and masks used in this study are shown in Figures 1(a) to 1(d).



(a) (b) (c) (d)

Figure 1. Lung disease types of (a) normal, (b) COVID-19, (c) pneumonia, and (d) lung opacity with their relevant mask

The methodology section outlines the deep learning approach employed for efficiently categorizing chest X-ray images using pre-trained CNNs. Pre-trained models trained on substantial datasets are available for related tasks and have already learned diverse features and patterns. This study implemented a VGG-16 pre-trained model. The expanded dataset includes lung images and their corresponding masks to enhance the performance of the model. The FA was utilized to select a limited set of features, followed by the deployment of a transfer learning model. This methodology ensures a higher accuracy in classifying lung diseases, particularly in the context of COVID-19 diagnosis.

3.2. Fireflies algorithm

The firefly algorithm is a fly-inspired nature algorithm that replicates the behavior of fireflies at night, specifically their flashing pattern, to determine the attractiveness of the brighter firefly. The three rules are derived from the behavioral patterns exhibited by fireflies [29]–[31]. The ruleset for the feature selection with FA is represented in Figure 2. The implemented results are shown in Figure 3 has an iteration of 50 for value n=4 and Figure 4 represents the recursive stride to capture the feature for one iteration. The logical steps of the FA are as follows:

– Rule 1 states that ∀ fireflies, regardless of gender, are attracted to each other based on their brightness, which is tied to an objective function B=f(O).
– When two fireflies (F1 and F2) are present, the movement of F1 towards F2 is determined by their brightness difference, movement F1→F2=$\alpha(B_{F2}-B_{F1})$, where α is a constant factor.
– Fireflies with lower luminosity move towards fireflies with higher luminosity, Movement low→high=$\beta\cdot(B_{high}-B_{low})$, where β is another constant factor.
– The level of attractiveness (A) is directly correlated to the brightness of the firefly (B): A=B.
– Observationally, if firefly F1 is less bright than F2 ($B_{F1}<B_{F2}$), both fireflies become less bright as their distance (D) increases from the observer, $B_{F1}=B_{F1}\cdot e-\alpha\cdot D$, $B_{F2}=B_{F2}\cdot e-\alpha\cdot D$.
– If no fireflies emit stronger light, a firefly moves randomly, Movement=γ·random(), where γ is a constant factor.
– Rule 2 states that the firefly brightness is influenced by the encoded objective function, guiding their interactions.
– Rule 3 states that attractiveness is directly linked to the brightness. For instance, as shown in Figure 2, firefly F1 is less bright than F2, and both decrease in brightness with distance from the observer. If no brighter fireflies are nearby, random movement ensues.
– The algorithm proposes a method for feature selection based on the intensity of light I (r) adheres to the inverse square rule. I_0 denotes the intensity of light at the source as shown in (1).

$$I(r) = \frac{I_0}{r^2} \tag{1}$$

– The inverse square law can be transformed into Gaussian form for estimating absorption:

$$I(r) = I_0 e^{-\gamma r^2} \tag{2}$$

where γ is a constant.
– The variation in the force of attraction may be characterized as the inverse square relationship between the intensity of light I and the distance r (random motion).

$$\beta(r) = \beta_0 e^{-\gamma r^2} \tag{3}$$

– In (4) updates the attractiveness position X_i based on the attractiveness of neighboring fireflies and random movement,

$$X_i^{t+1} = X_i^t + \beta_0 e^{-\gamma r^2 ij} \left(X_j^t - X_i^t\right) + \alpha_t + \in_i^t \tag{4}$$

The algorithm was implemented stepwise in the dataset after pre-processing the number of classes for classification, with the selection of flies initiated at n=4. The number of fireflies was fixed at 50 and the maximum iteration was fixed at 100. The graphs represent the maximum features of 50 iterations, and frequency is a positive feature of the model that produces accuracy. The feature subset array was passed into the CNN to classify the diseases. The FA algorithm, proposed in [32], is inspired by the luminous and gregarious behavior of fireflies. FA employs many approximation principles to simulate complex and sophisticated real-world biological systems. Firefly brightness and attractiveness are used to represent fitness functions in a way that, in most common FA implementations, attractiveness is dependent on brightness, which is determined by the value of the function with the objective. For minimization issues, the formula is expressed as described by [32].

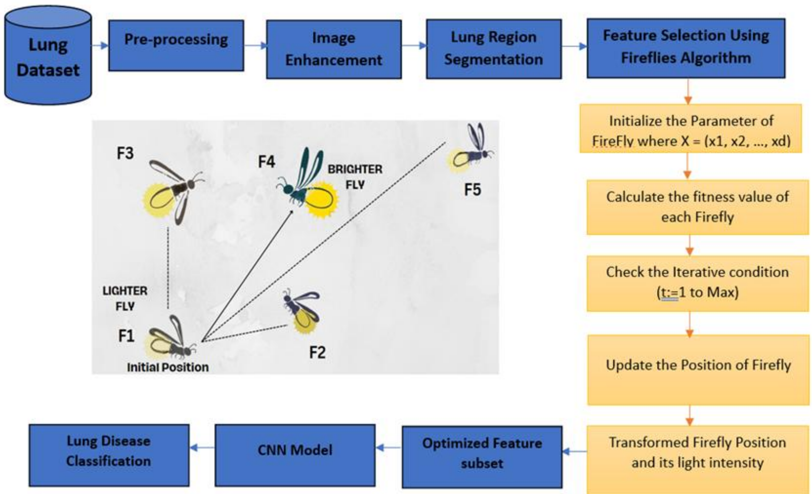


Figure 2. Diagram illustrating workflow of the FA

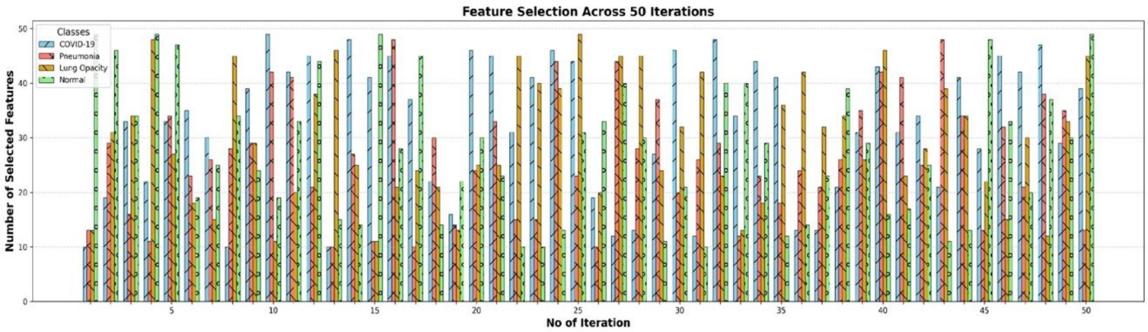


Figure 3. The proposed firefly algorithm and its selected features with 50 iterations

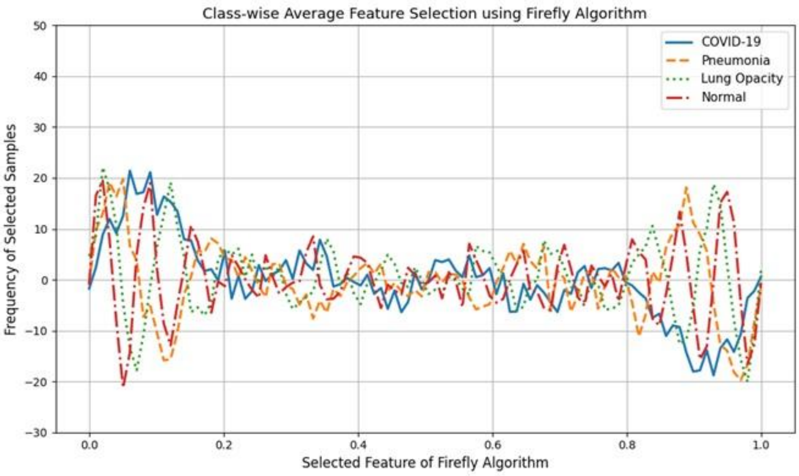


Figure 4. The frequency density graph of the firefly algorithm shows positive feature attainment

3.3. Proposed classification model

For classification, the proposed model employed a combination of a pre-trained VGG-16 model and a CNN with fully interconnected layers. The X-ray images used to determine the presence of specific types of chest diseases were analyzed using the VGG-16 model [20], followed by the CNN model. Figure 5 provides a comprehensive depiction of the model architecture and Table 1 details the implementation of the proposed system. During the feature extraction stage, dimensionality reduction was achieved using the firefly algorithm, after which the VGG-16 model was integrated with additional CNN blocks. The VGG-16 model, renowned for its exceptional precision in image-related tasks, served as the backbone of the architecture. It consisted of 16 convolutional layers, each configured with 3×3 convolution filters and a stride of 1.

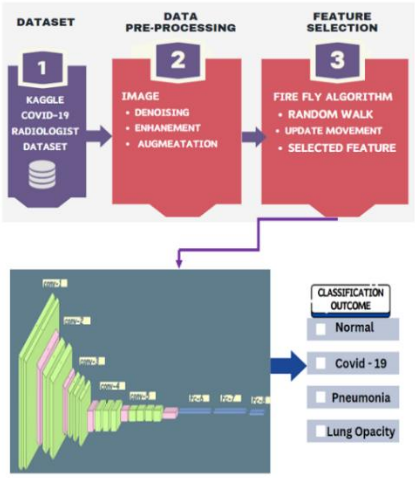


Figure 5. A proposed approach for four-class classification methodology

Table 1. Detailed overview of the proposed system implementation

Stage	Description	Languages/Frameworks
Data acquisition	X-ray images resized to 128×128×3, standardized, and normalized	Python, OpenCV
Feature extraction	Firefly algorithm for dimensionality reduction	Python, SciPy
Pre-trained model	VGG-16 with 16 convolutional layers (3×3 filters, stride of 1)	TensorFlow, Keras
CNN architecture	Additional CNN layers with ReLU, batch normalization, max-pooling, dropout	TensorFlow, Keras
Classification	Fully connected layers with SoftMax for four-class categorization	TensorFlow, Keras
Training and Evaluation	Cross-entropy loss, Adam optimizer, accuracy, precision, recall, F1-score	Python, TensorFlow
Dataset splitting	Train (70%), validation (15%), test (15%)	Python, Pandas
Hardware	NVIDIA GPUs for accelerated training	-
Software	TensorFlow, Keras, NumPy, OpenCV, Matplotlib	Python

3.4. Layer configuration

A deep learning framework was employed for the multi-classification of lung disorders. The design implemented a flattening layer in the initial phase of classification, followed by subsequent thick layers to achieve further abstraction. The VGG-16 model incorporates a flattening layer as a pivotal component in the initial stage of its classification process. This layer is essential for converting the multi-dimensional output from the preceding convolutional layers into a one-dimensional array. This transformation is critical as it prepares the extracted features for subsequent processing in the dense layers. In the VGG-16 architecture, the flattening layer connects the convolutional layers responsible for feature extraction to the fully connected layers dedicated to classification. Flattening the output, the hierarchical features learned by the convolutional layers are effectively fed into the dense layers, ensuring a smooth transition for accurate classification. Following the flattening layer, the model employs three dense layers with varying neuron counts of 512, 256, and 128 neurons, respectively. These densely interconnected layers are designed to learn intricate patterns and relationships in the extracted features. The high concentration of neurons in each dense layer enhances the model's ability to capture both low-level and high-level features, thereby contributing to its capacity to discern complex patterns and make precise classifications. The final output layer consists of four neurons, each representing a different class: COVID-19, pneumonia, lung opacity and normal. The SoftMax activation function is applied to this layer to generate a probability distribution across these classes, facilitating accurate outcome categorization.

4. RESULTS AND DISCUSSION

A chest disease classification model was developed using the 3.11.0 release of Python and the Keras framework. The simulation of the model was performed on a Google Colab Premium version, which provided 2 TB of storage, 25 GB of RAM, and a CPU-P100. The pre-processing stage involved utilizing the ImageDataGenerator class in Keras for tasks such as image expansion, normalization, and data conversion.

The proposed deep learning architecture for classifying multiple lung diseases was developed using the FA. The model was trained and validated using an optimization algorithm and fit methods limited to 100 epochs. Each epoch consisted of four iterations and was used at a batch size of 128. The optimizer Adam was used with a learning rate of 0.001. The performance evaluation was carried out with precision, accuracy, recall, and F1-score. The performance measures are shown in Table 2. In comparison, to current state-of-the-art approaches, which often serve as the "ground truth," our model demonstrates superior performance. This is evidenced by the results presented in Table 3, where our model outperforms several highly robust pre-trained models. We assessed the categorization and identification of lung disorders, including the diagnosis of lung diseases and COVID-19 using the pre-trained network followed by the proposed CNN models.

Table 2. Evaluation of the VGG-16 performance with lung disease

	Accuracy	Precision	Recall	F1-score
COVID-19	0.9916	0.97	0.98	0.97
Lung opacity	0.9982	0.94	0.91	0.92
Normal	0.9964	0.90	0.96	0.95
Viral pneumonia	0.9889	1.00	0.93	0.97

Table 3. Performance comparison with state-of-the-art approaches

Models	Accuracy (%)	Precision (%)	Recall (%)	F1-score (%)
DenseNet-121	98.67	97.91	98.10	98.0
CapsNet	96.44	96.74	96.82	96.75
InceptionV3	97.0	96.73	96.56	96.66
MobileNet	97.58	97.21	97.42	97.39
EfficientNet	96.84	97.64	97.36	97.41
Proposed model (average)	99.38	95.25	94.50	95.25

The proposed model was introduced based on a refined VGG-16 model. To identify the optimal model, several training/validation ratios were employed. The performance metrics for lung disease detection are shown in Figure 6. These metrics were considered for a comprehensive analysis of the prediction, accuracy and robustness of the models. This model achieved an accuracy of 99.3%, the highest specificity, F1-score, and recall on the implemented X-ray dataset. Our findings show a significant improvement as provided by the model. Figure 7 show 11 features are selected at initial iteration 1 and features are reduced to 4 features at the 10^{th} iteration total feature result for 10 iterations is 1,920. Figure 8 shows the significant differences in the selected features of fireflies' optimization of data and storage of the subset for the proposed CNN. Over the 100^{th} iteration, the feature number drops to only 13 features are passed to the classification model. In summary, the proposed model stands out as the best-performing model among those compared, offering the highest accuracy and balanced precision and recall metrics. This indicates that the proposed model is not only more reliable in classifying lung diseases but also minimizes the chances of false positives and false negatives. Consequently, the implementation of this model in clinical settings could lead to better diagnostic outcomes, reduce unnecessary procedures, and improve patient care.

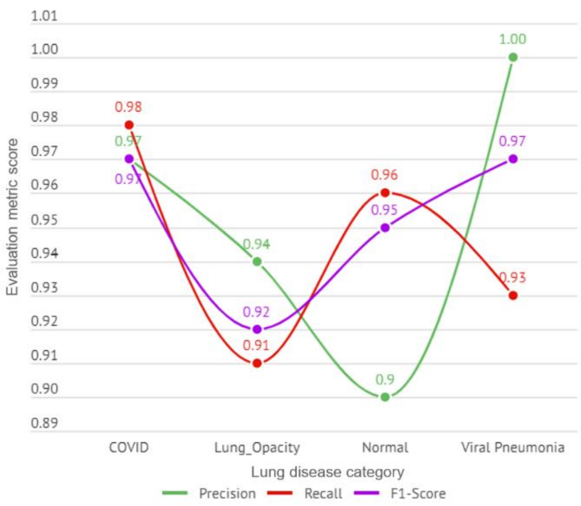


Figure 6. The lung disease outcome with VGG-16 evaluation results

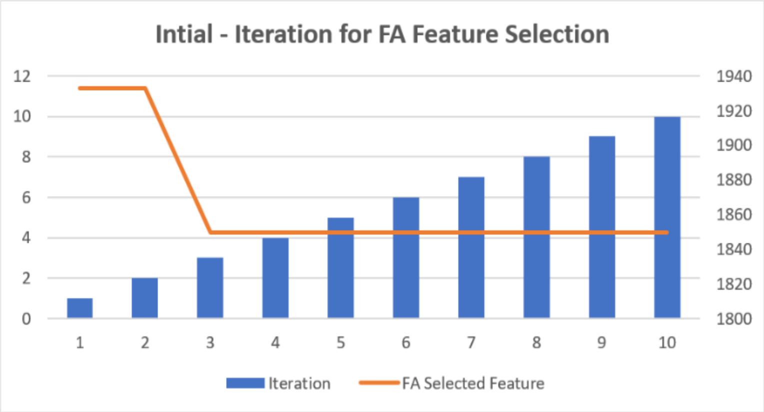


Figure 7. Feature selection of FA

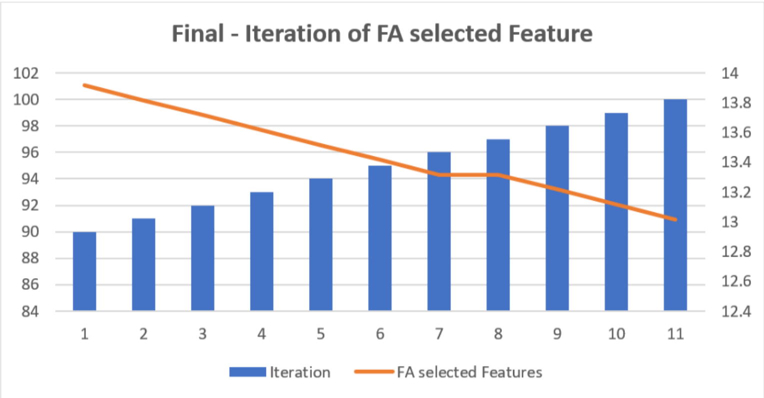


Figure 8. The reduced attraction value around 13 after 100 iterations of FA

5. CONCLUSION

This paper introduces an innovative approach using the firefly algorithm for optimal feature selection in the context of lung disease detection. By employing reciprocal cross-entropy, we effectively tackled challenges associated with undefined and zero values in the logarithmic functions. The algorithm leverages attractiveness and random walk mechanisms to identify and store abnormal data as a subset. This subset is then utilized for pattern matching in conjunction with CNN, contributing to enhanced efficacy in various lung diseases and COVID-19 detection. The application of the firefly algorithm extends to the calculation of optimal multi-thresholds, further refining precision. The current study focuses on achieving higher accuracy in the identification of COVID-19 and other lung disorders while reducing computational runtime. Furthermore, the paper specifically concentrates on the multiclass categorization of lung disorders based upon frontal X-ray images of chest, and thus, the scope is limited to this specific domain. This work lays a robust foundation for advancing the state-of-the-art methodologies in COVID-19 and lung disease detection, and it opens avenues for future research in developing innovative diagnostic techniques and treatment strategies for lung diseases using CT scans.

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Arul Leena Rose Peter Joseph	✓	✓		✓	✓	✓		✓	✓	✓		✓		

C : **C**onceptualization	I : **I**nvestigation	Vi : **Vi**sualization
M : **M**ethodology	R : **R**esources	Su : **Su**pervision
So : **So**ftware	D : **D**ata Curation	P : **P**roject administration
Va : **Va**lidation	O : Writing - **O**riginal Draft	Fu : **Fu**nding acquisition
Fo : **Fo**rmal analysis	E : Writing - Review & **E**diting	

CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest.

DATA AVAILABILITY

The data that support the findings of this study are openly available at https://www.kaggle.com/datasets/tawsifurrahman/covid19-radiography-database

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