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A BIO-INSPIRED OPTIMIZATION ALGORITHM FOR FEATURE SELECTION IN MEDICAL IMAGE CLASSIFICATION

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ABSTRACT

Computer-aided diagnostic systems are now considered to include automated medical image classification, which can be viewed as an essential part of the system; nevertheless, deep learning-based methods tend to produce high-dimensional feature representations that are redundant and computationally expensive. This present study describes a bio-inspired framework of feature selection that combines deep feature extraction with Lyrebird Optimization Algorithm to overcome dimensionality issues in the multi-class chest X-ray classification. Deep features are obtained with a pretrained convolutional neural network and then are represented as a binary optimization problem, in which classification performance and feature sparsity are both optimized together in a single fitness function. The optimization procedure determines a small set of informative features, and the results are analyzed with the help of Logistic Regression as a comprehensible classification model. The experimental findings indicate that the proposed framework is able to achieve high dimensionality reduction without significant changes in classification performance in training, validation and test sets. Class-wise analysis shows that there is a high level of discriminative ability to clinically relevant categories and the generalization behavior is consistent across independent data splits. The results indicate that bio-inspired optimization is effective in addressing feature redundancy present in deep representations, and that optimization-based feature selection is useful in creating effective, interpretable, and reproducible medical image classification pipelines.

KEYWORDS: Medical image classification, Feature selection, Bio-inspired optimization, Lyrebird Optimization Algorithm, Chest X-ray analysis

1. INTRODUCTION

Medical imaging takes the centre stage in modern clinical decision support, as it facilitates non-invasive diagnosis, disease screening and monitoring of a broad spectrum of conditions. Chest X-ray imaging is one of the most common types of imaging modalities because it is available, affordable, and can be used to diagnose pulmonary diseases. The increasing amount of radiographic data produced in clinical settings has increased the focus on automated image classification systems that can assist clinicians with better efficiency, consistency, and scalability, especially in large-scale screening and resource-limited environments (Sabri et al., 2025).

The recent developments in deep learning have significantly improved the ability of automated image analysis systems to derive informative representations of medical images (Alnaggar et al., 2024). Convolutional neural networks are often used as feature extractors, producing high-dimensional embeddings that represent complex spatial and semantic features. Although these representations are highly descriptive, they also present the difficulty of redundancy, collinearity, and complexity of computation (Bohmrah and Kaur, 2025; Adablanu et al., 2025). The high dimensionality of feature space can negatively impact the stability and interpretability of classification, which contributes to the motivation of the effective feature selection strategies.

The nature-inspired optimization algorithms offer versatile mathematical frameworks to solve complex optimization problems with large, nonlinear and discrete search space. These adaptive and evolutionary based algorithms have proven useful in combinatorial solution space where exhaustive search is not possible (Jamali et al., 2025; Kumar et al., 2021). One such issue is featuring selection where it is necessary to find informative subsets of high-dimensional representations by balancing predictive performance with sparsity and computational efficiency (Şahin and Anka, 2025). Although deep learning architectures have been widely used in medical image classification, relatively little effort has been put on systematic elimination of redundancy in features before classification. Most of the existing methods focus on the complexity of end-to-end models, usually neglecting the opportunities of optimization-based feature selection acting on the pretrained deep representations (Khan et al., 2025). Moreover, interpretable classification models are not fully used together with optimized feature subsets, although they are also relevant to transparency, reproducibility, and clinical trust.

Logistic Regression is a statistically based and computationally efficient model of multi-class classification that gives probabilistic results and clear decision boundaries (Ashwini et al., 2025). Logistic Regression can be used to produce stable predictive accuracy when used with heavily structured feature representations without the use of very complex nonlinear models. This property renders it appropriate in assessing the discriminative power of feature subsets detected with the help of optimization-based selection procedures (Premalatha et al., 2024).

To address these issues, the current paper presents a feature selection model that combines deep feature extraction with a nature-inspired optimization algorithm and assesses the acquired representations with the help of an interpretable classification model. By formulating feature selection as an optimization problem operating on pretrained deep representations, the study aims to reduce dimensional complexity while maintaining robust classification performance in multi-class chest X-ray analysis. The objectives of the study are as follows:

- To formulate medical image feature selection as a mathematical optimization problem inspired by adaptive search mechanisms
- To apply the Lyrebird Optimization Algorithm for binary feature subset selection from deep feature representations
- To evaluate the optimized feature subset using Logistic Regression for multi-class chest X-ray classification

The contributions of this work include the development of an optimization-driven feature selection framework for high-dimensional deep representations, the application of a nature-inspired search strategy to medical image feature selection, and the demonstration of stable classification performance using an interpretable statistical classifier despite substantial dimensionality reduction.

2. LITERATURE REVIEW

Deep learning has emerged as a new medical image classification paradigm owing to its capability to automatically learn hierarchical representations of complex imaging data. Convolutional neural networks have shown good performance in a broad variety of diagnostic tasks, such as disease detection and classification in radiographic images. Deep learning-based methods have become popular in the chest X-ray analysis to detect pulmonary diseases, including pneumonia, tuberculosis, and viral infections (Bose and Garg, 2024). Pretrained models are often used in transfer learning to balance limited labelled medical data and successfully extract features without training models themselves (Bilal et al., 2024; Dahou et al., 2025). Although successful, these architectures usually produce high-dimensional representations of features, which pose the challenge of redundancy, computational cost and interpretability of the model.

Selection of features has been known to be a significant aspect of medical image analysis especially when dealing with high-dimensional data. The traditional feature selection methods can be broadly categorized into filter-based, wrapper-based and embedded methods. Filter-based approaches are based on statistical metrics to rank features without considering classification models, and they are computationally efficient but have a low ability to model feature interactions (Prajapati et al., 2023). Wrapper-based techniques test subsets of features based on the performance of the classifier, and can therefore be more selective at the expense of higher computational complexity. Embedded approaches incorporate feature selection as a part of the learning process (Thaher et al., 2022). Although these methods have been demonstrated to be useful in other medical imaging tasks, they tend to perform poorly when using very correlated and nonlinear deep feature representations.

In order to overcome the drawbacks of traditional feature selection methods, nature-inspired optimization algorithms have been considered more and more as versatile mathematical search methods. Adaptive and evolutionary algorithms are based on these algorithms, which are aimed at exploring large and complex search spaces that cannot be explored exhaustively (Nadimi-Shahraki et al., 2022). They are stochastic and therefore can be used to efficiently explore the solution space of a combinatorial problem, and are especially well-suited to feature selection problems where optimal subsets need to be found in exponentially large sets (Hussien et al., 2020). Nature-inspired optimization algorithms can overcome local optima and find small, informative feature subsets in high-dimensional environments by balancing exploration and exploitation.

Nature-inspired optimization has been applied to feature selection, which has become popular in biomedical studies, such as medical image analysis and disease prediction. In these models, subsets of candidate features are normally represented as binary vectors and measured in terms of classification performance measures. Trade-offs between predictive accuracy and feature sparsity are often included in optimization objectives in order to promote compact representations (Sallam et al., 2022). A number of studies have also noted better performance with optimization-based feature selection than with conventional methods especially with high-dimensional data (Oyelade and Ezugwu, 2022). Much of the current literature, however, is on handcrafted, or shallow feature representations, and relatively little has been done on optimization-based selection of deep feature representations of pretrained neural networks.

The use of Logistic Regression in medical and clinical prediction studies remains popular because of its statistical interpretability, computational efficiency and strength. The model offers probabilistic results and clear decision boundaries, which is why it can be used in situations where explainability and reproducibility are valued (Zafar et al., 2023). Logistic Regression can be used to perform competitively when combined with informative feature representations, without using complex nonlinear classifiers (Alsaeedi et al., 2024). Its sensitivity to feature redundancy also contributes to it being a suitable evaluation model to determine the effectiveness of feature selection strategies, especially in optimization-based frameworks.

Although the state of the art in deep learning and optimization methods has improved, there are still a number of gaps in the literature. Most medical image classification works focus on the complexity of end-to-end models and little on feature redundancy in deep representations (Rostami et al., 2020). Combining nature-inspired optimization methods with deep feature extraction to select systematic features has not been well studied, especially in multi-class diagnostics (Nagaraja Kumar et al., 2023). Moreover, there has been little focus on using interpretable classifiers with optimized deep feature subsets. It is necessary to fill these gaps in order to create effective, transparent, and reproducible medical image classification models.

3. MATHEMATICAL FORMULATION

This section formalizes the feature selection problem addressed in the study and describes the optimization objective guiding the selection of informative deep features. The formulation explicitly integrates classification performance and feature sparsity within a constrained optimization framework suitable for high-dimensional medical image representations.

3.1 Problem Definition and Feature Space Representation

Consider a labeled dataset

$$\mathcal{D} = \{(x_i, y_i)\}_{i=1}^{N},$$

where x_i denotes the i-th chest X-ray image and $y_i \in \{1,2,\dots,C\}$ represents its associated label of the class, where C denotes the number of diagnostic categories.

Each image is processed by a pretrained convolutional neural network operating as a fixed feature extractor, producing a high-dimensional representation that encodes salient visual characteristics. This procedure yields a feature matrix

$$\mathrm{X} \in \mathbb{R}^{N \times D},$$

where N is the number of samples and $D = 2048$ is the dimensionality of the extracted deep feature space.

The objective of feature selection is to identify a subset of features that retains discriminative capability while reducing dimensionality. To this end, a binary selection vector

$$\mathrm{z} = [z_1, z_2, \dots, z_D], z_j \in \{0,1\},$$

is introduced, where $z_j = 1$ indicates that the j-th feature is retained and $z_j = 0$ indicates exclusion. Applying this selection vector yields a reduced feature matrix

$$\mathrm{X_z} = \mathrm{X}[:, \mathrm{z} = 1],$$

which serves as the input for subsequent classification and evaluation.

3.2 *Objective Function Integrating Accuracy and Sparsity*

Feature selection is formulated as an optimization problem that simultaneously considers predictive performance and model compactness. Let

$$\mathcal{A}(\mathrm{X_z}, \mathrm{y})$$

denote the classification accuracy obtained by training a Logistic Regression model on the selected feature subset $\mathrm{X_z}$.

To discourage excessive feature retention, a sparsity measure is defined as the normalized count of selected features:

$$\mathcal{S}(\mathrm{z}) = \frac{1}{D}\sum_{j=1}^{D} z_j.$$

The optimization objective is defined as a weighted combination of classification error and feature sparsity:

$$\min_{\mathrm{z}} \ \mathcal{J}(\mathrm{z}) = \alpha(1 - \mathcal{A}(\mathrm{X_z}, \mathrm{y})) + (1-\alpha)\,\mathcal{S}(\mathrm{z}),$$

where $\alpha \in (0,1)$ controls the relative importance of predictive accuracy versus dimensionality reduction. This formulation ensures that the optimization process favors feature subsets that achieve high classification performance while remaining compact.

3.3 *Fitness Function Design*

The objective function $\mathcal{J}(\mathrm{z})$ serves as the fitness function guiding the optimization process. For each candidate solution z, classification accuracy is estimated using a stratified cross-validation scheme to ensure balanced evaluation across classes.

Lower values of $\mathcal{J}(\mathrm{z})$ correspond to higher-quality solutions, reflecting improved classification accuracy and reduced feature dimensionality. The formulation, by incorporating both of these criteria in one fitness function, eliminates the problem of degenerate solutions, where minimizing dimensionality is at the price of high accuracy, or low dimensionality is at the price of high predictive accuracy.

3.4 *Optimization Constraints and Search Space*

The feature selection problem is defined over a discrete binary search space of dimension D, subject to the constraint

$$z_j \in \{0,1\}, j = 1,2,\dots,D.$$

To facilitate efficient exploration of this combinatorial space, candidate solutions are internally represented as continuous-valued vectors

$$\mathrm{u} \in \mathbb{R}^{D},$$

which are transformed into binary selection vectors using a sigmoid-based stochastic mapping:

$$z_j = \begin{cases} 1, & \text{if } \sigma(u_j) > r_j, \\ 0, & \text{otherwise,} \end{cases}$$

where $\sigma(\cdot)$ denotes the sigmoid function and r_j is a random variable drawn from a uniform distribution over [0, 1].

This transformation enables the optimization algorithm to operate in a continuous space while producing valid binary feature selection masks. The Lyrebird Optimization Algorithm iteratively updates candidate solutions and guides the search toward an optimal selection vector z^* that minimizes the fitness function under the defined constraints.

4. MATERIALS AND METHODS

4.1 *Dataset Description and Class Distribution*

The experimental assessment used a publicly available, multi-class chest X-ray image dataset, which was divided into a training, validation and test partition. The data set included radiographic images, which were based on six clinically relevant categories Covid-19, Emphysema, Normal, Pneumonia-Bacterial, Pneumonia-Viral, and Tuberculosis (Adel, 2025). The training subset had 14,551 images whereas the validation and test subsets had 1,748 and 1,737 images, respectively. There was a fair distribution of classes across splits, which made strong assessment in multi-class conditions. All images were given in grayscale with a spatial resolution of 224 × 224 pixels, which is compatible with a standard convolutional neural network architecture.

4.2 Image Preprocessing

All the chest X-ray images were first subjected to a standardized preprocessing pipeline before feature extraction. All grayscale images were scaled to 224 x 224 pixels and brought to the range of continuous intensities [0, 1]. In order to allow processing by a pretrained convolutional neural network that assumes three-channel input, grayscale images were replicated in three channels, producing tensors of shape 224 x 224 x 3. This preprocessing provided numerical stability, homogenous input dimensionality, and compatibility with transfer learning-based feature extraction.

4.3 Deep Feature Extraction Using ResNet50

A ResNet50 architecture that was trained on ImageNet was used as a fixed feature extractor to extract deep feature representations. The classification layers were eliminated and the network output was taken out of the last global pooling layer. The network generated a 2048-dimensional feature vector, which contained high-level spatial and semantic features that were important to the disease classification of each input image. The training, validation, and test subsets were independently extracted with the features. The resultant feature matrices were saved to be optimized and classified later, thus separating feature learning and feature selection and evaluation.

4.4 Lyrebird Optimization Algorithm (LOA)

4.4.1 Biological Inspiration

Lyrebird Optimization Algorithm (LOA) is a bio-inspired metaheuristic that is based on the adaptive foraging and mimicry behavior of lyrebirds that dynamically change their exploratory behavior based on environmental signals. These actions are mathematically represented to trade off between exploration of the search space and exploitation of promising candidate solutions.

4.4.2 Algorithmic Framework

LOA was used in the proposed framework to tackle the binary feature selection problem on the high-dimensional deep feature space. The population was represented by each candidate solution as a continuous-valued vector, which was subsequently converted to a binary selection mask. Initialization of the population was performed randomly within predetermined limits and the iterative updates were directed by the most successful solution at each iteration. The optimization algorithm was run with a given number of iterations and a small population size, which represents the computational constraints of high-dimensional medical data.

4.4.3 Binary Feature Selection Strategy

A sigmoid based stochastic thresholding mechanism was used to map continuous solution vectors to binary masks to allow binary feature selection. The solution vector was represented by each dimension of a solution, with a binary value of 1 representing feature selection and 0 representing feature exclusion. The optimization problem aimed at finding a small set of features that retained discriminative ability and minimized redundancy and dimensionality.

4.5 Logistic Regression Classifier

The evaluation of the features was done with the help of the Logistic Regression (LR) because of its statistical interpretability, computational efficiency, and its ability to be used in multi-class medical classification. The optimized feature subsets were used to train the classifier and assess it under a stratified cross-validation strategy to estimate the performance of the classifier in a balanced way. LR accuracy was used as the main performance element in the optimization fitness function thus directly relating feature selection and classification effectiveness.

4.6 Experimental Setup and Evaluation Metrics

The feature selection process using LOA was set up with a set population size and number of iterations. A fitness function was formulated to trade off the classification accuracy and the cardinality of feature subsets, where predictive performance was given more weight and dimensionality reduction was promoted. The standard measures of model performance were evaluated based on accuracy, precision, recall, and F1-score, calculated on a validation and test set. Confusion matrices were created to enable the analysis of the errors by classes and to investigate the inter-class misclassification.

5. RESULTS

5.1. Feature Dimensionality Reduction Analysis

The pretrained ResNet50 architecture with deep feature extraction generated a 2048-dimensional feature vector of each chest X-ray image in the training, validation and test datasets. Even though these high-dimensional representations can encode rich spatial and semantic information, they often have redundant or weakly informative features that can negatively impact computational efficiency and downstream classification stability. After the

Lyrebird Optimization Algorithm (LOA) binary feature selection, the feature space was narrowed down to 1015 features which is a 50.44 percent decrease compared to the original representation. This degree of compression suggests that almost half of the extracted deep features were not found to be necessary to the classification task, which supports the existence of redundancy in the original deep feature embeddings.

Notably, the optimized feature mask was used throughout the training, validation, and test data, making the methodology correct and removing any bias due to feature discrepancy between evaluation splits. Table 1 and Figure 1 show a summary of feature dimensionality before and after optimization, and it can be observed that the magnitude of dimensionality reduction by means of LOA-based selection is significant.

Table 1: Feature dimensionality before and after LOA-based optimization.

Feature Representation	Number of Features
Original ResNet50 features	2048
LOA-selected features	1015
Features removed	1033
Reduction (%)	50.44

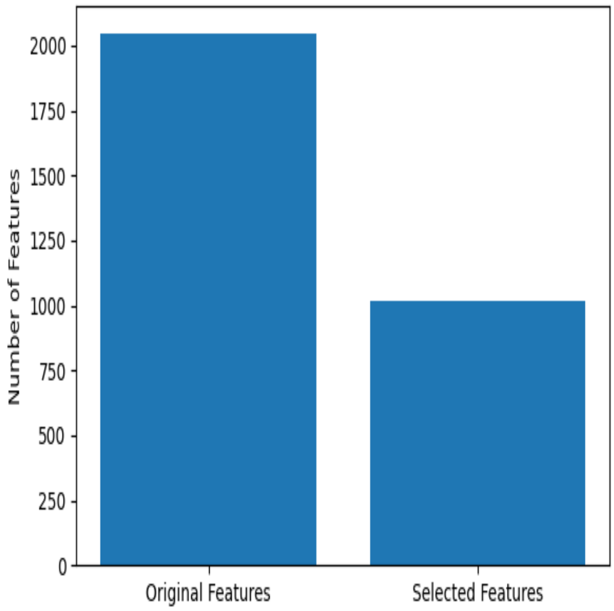

Figure 1: LOA-based feature space reduction.

5.2. Convergence Characteristics of LOA

The convergence behaviour of the feature selection process of LOA was assessed with eight optimization cycles. The highest value of fitness that was reached in the optimization process was 0.172954, and this did not change at any point of the iterations. Such convergence pattern shows that the optimization process was able to quickly find a stable and competitive subset of features at an early stage. The fact that there was no oscillatory behavior or deterioration of performance with increasing iterations indicates that the optimization landscape was successfully traversed with the chosen population size and iteration budget. This early stabilization is an indication of the strength of the fitness formulation and the capability of LOA to optimally trade off classification performance and feature sparsity. Figure 2 shows the convergence dynamics of the optimization process, and it can be seen that the fitness stabilizes quickly and converges in a steady manner.

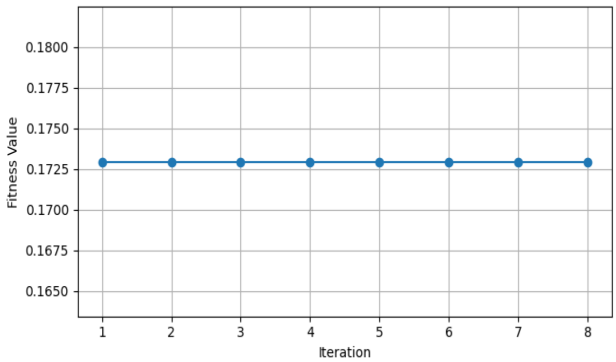

Figure 2: Convergence curve of the LOA-based feature selection algorithm.

5.3. Test Set Classification Performance

The Logistic Regression classifier was tested on the independent test dataset with the help of the LOA-optimized feature subset. The overall accuracy of the model was 87.45, which is a good result in terms of the discriminative ability despite the significant dimensionality reduction of features. Table 2 summarizes class-wise performance metrics, and it can be seen that there is variability in disease categories.

Table 2: Class-wise test set performance using optimized features.

Class	Precision	Recall	F1-score	Support
Covid-19	0.8842	0.9167	0.9002	300
Emphysema	0.8939	0.8760	0.8848	250
Normal	0.9346	0.9533	0.9439	300
Pneumonia-Bacterial	0.7651	0.7600	0.7625	300
Pneumonia-Viral	0.7820	0.7533	0.7674	300
Tuberculosis	0.9896	0.9930	0.9913	287

The Tuberculosis and Normal classes had especially high values of the precision, recall, and F1-score, which may be interpreted as the fact that the optimized feature subset was effective to identify the unique radiographic features of the specified conditions. Comparatively, lower performance was found in Pneumonia-Bacterial and Pneumonia-Viral classes, which is a reflection of the well-established visual similarity of these disease types in the chest X-ray images. Table 3 reports aggregate performance measures, such as macro-averaged and weighted performance measures, which indicate equal performance in classifying data without any particular category dominating the other. Figure 3 presents the corresponding confusion matrix of the test dataset, which gives a more detailed picture of the behavior of the predictions by the classes.

Table 3: Aggregate test set performance metrics.

Metric	Value
Accuracy	0.8745
Macro Precision	0.8749
Macro Recall	0.8754
Macro F1-score	0.8750
Weighted F1-score	0.8739

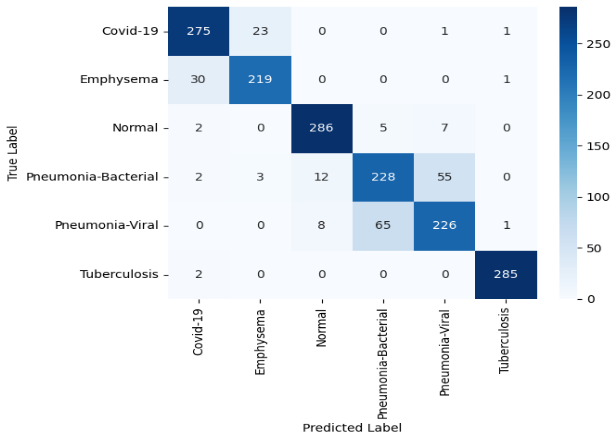

Figure 3: Confusion matrix for the test dataset.

5.4. Validation Set Performance

The optimized Logistic Regression model was further tested on a validation dataset to determine the level of generalization. The general accuracy of the classifier was 86.33, which is very similar to the results on the test set, so there is not much overfitting, and the generalization is stable. Trends by class on the test data were consistently replicated in the validation results as shown in Table 4.

Table 4: Class-wise validation set performance using optimized features

Class	Precision	Recall	F1-score	Support
Covid-19	0.8795	0.9000	0.8896	300
Emphysema	0.9050	0.8760	0.8902	250
Normal	0.9167	0.9533	0.9346	300
Pneumonia-Bacterial	0.7560	0.7333	0.7445	300
Pneumonia-Viral	0.7349	0.7300	0.7324	300
Tuberculosis	0.9899	0.9899	0.9899	298

Table 5: Aggregate validation set performance metrics.

Metric	Value
Accuracy	0.8633
Macro Precision	0.8637
Macro Recall	0.8638
Macro F1-score	0.8636

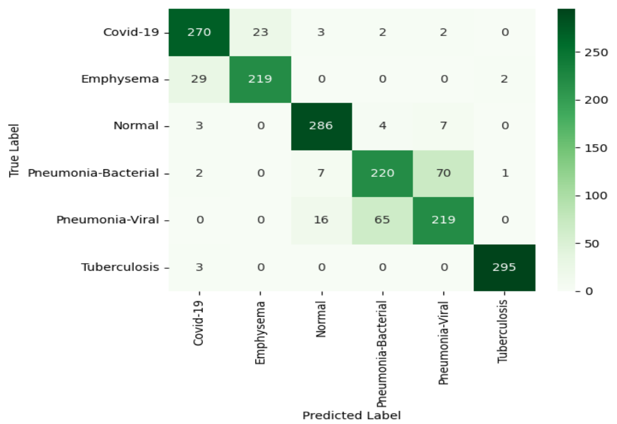

Figure 4: Confusion matrix for the validation dataset.

Tuberculosis, Normal, and Covid-19 classes had high predictive performance, whereas the pneumonia subclasses had moderate confusion. The aggregate validation measures are presented in Table 5, which once again indicates balanced performance in disease categories. Figure 4, the validation confusion matrix, has structural similarity to the test confusion matrix, which supports the consistency of the behavior in classification across datasets.

5.5. Confusion Matrix and Class-Wise Analysis

The analysis of confusion matrix on both test and validation datasets shows similarity in the classification behavior. Both confusion matrices show high diagonal dominance in the Tuberculosis and Normal classes, and this implies that there is little misclassification and distinct separability in the optimized feature space. Most misclassification errors are between Pneumonia-Bacterial and Pneumonia-Viral classes, which are similar radiographic appearances and visual similarities. Notably, the fact that this confusion pattern is repeated in both data sets indicates that such errors are due to inherent similarities in the data level and not unsteadiness in the optimization or classification process. The trends of class-wise F1-score in different disease categories are summarized in Figure 5, which gives a comparative visualization of predictive performance and further proves the consistency of the feature subset chosen by LOA.

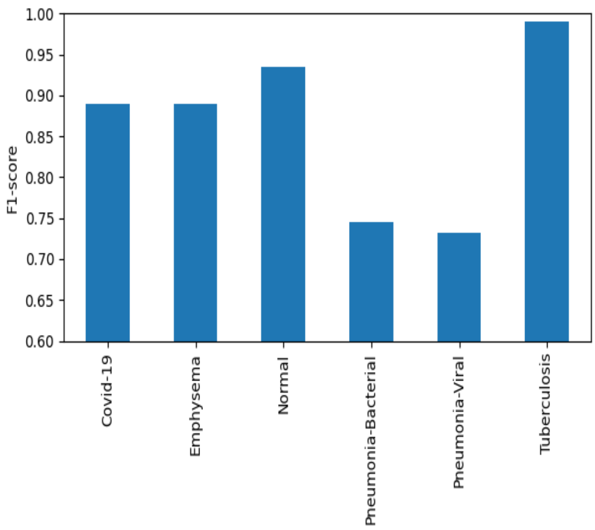

Figure 5: Class-wise F1-score visualization across disease categories.

6. DISCUSSION

Bio-inspired optimization has received growing interest as a principled methodology in the dimensional complexity of deep feature representations of medical imaging data. The findings presented in this paper suggest that biologically inspired search methods can be successfully combined with deep feature extraction and statistical classification to provide significant dimensionality reduction with a stable predictive accuracy in multi-class chest X-ray classification. The Lyrebird Optimization Algorithm was applied, and a smaller set of features was selected, which included about half of the original deep representation. The fact that the accuracy of classification was preserved after this decrease would indicate that a significant percentage of features generated by pretrained convolutional architectures add little discriminatory information in the studied diagnostic scenario (Raj et al., 2020). These results show that feature optimization is a crucial component of removing redundancy in high dimensional embeddings especially when the final task is classification based on linear decision boundaries.

The optimization process convergence behavior that was observed can give more information about how feature selection problem is structured. It seems as though the fitness function stabilized at an early point in the optimization procedure, indicating that the search process was soon decreased to a level section of the binary solution space. This action is a sign of a well-trained objective formulation whereby predictive performance and feature sparsity are self-limiting in the search dynamics in the best possible way (Dey et al., 2023). This stability finds application in medical imaging where the ability to compute and reproducibility are desirable qualities. The comparison of the disease categories showed that the predictive performance changed with the classes. Tuberculosis, Normal and Covid-19 have a high accuracy and this means that the optimized feature subset is sensitive to radiographic patterns that are distinguishable at a level of linear model. On the contrary, poorer PneumoniaBacterial and PneumoniaViral classes performance is consistent with the fact that radiographic presentations are similar in the two conditions (Alwan et al., 2021). This pattern continues in independent evaluation datasets, indicating that the misclassification is the result of data nature, and not the result of model instability and optimization bias.

The Logistic Regression evaluation model employed gives a convenient understanding of the quality of the structure of the selected features. Logistic Regression is a linear and probabilistic classifier, which is susceptible to redundant and collinear features. The similarity of the results in the validation and test sets therefore indicates that the selected set of features are a consistent and generalizable representation (Houssein and Sayed, 2023). This finding highlights the significance of feature selection as a means to reduce the use of increasingly complex classifiers, particularly in clinical environments where interpretability and transparency continue to be highly regarded. The framework conceptually shows how the combination of feature selection by deep features extraction and the use of bio-inspired optimization has been successful. In comparison to the filter-based algorithms, which are not dependent on the objectives of the classification, the policy of optimization used in this case makes a direct use of predictive performance as a part of the feature selection process. The feature space can be studied in an informed manner using this kind of integration and allow a balanced classification of various types of diseases (Singh et al., 2025).

A number of limitations can be taken into consideration. The optimization was done in constrained population and iteration conditions that might restrict the search of alternative feature settings. In addition, a single pretrained architecture was applied to extract features and the classification performance was tested on a single linear model. Even though these design choices are helpful in attaining methodological clarity and reproducibility, future studies can generalize the framework to other deep representations, other classification models, or multi-objective optimization formulations that explicitly trade-off accuracy, sparsity, and computational cost. Taken together, the findings indicate that bio-inspired optimization provides a mathematically-driven feature selection algorithm in high-dimensional medical image classification. The technique enables the development of effective, interpretable and reproducible classification pipelines that may be applied in the analysis of medical imaging in large-scale environments by lowering the representational complexity without deteriorating diagnostic accuracy.

7. CONCLUSION

Bio-inspired optimization is an applicable mathematical approach to dimensional complexity of deep feature representations in medical image classification. The results presented here suggest that a combination of biologically inspired search algorithms with deep feature extraction and statistical classification can be used to obtain a significant dimensionality reduction without affecting the predictive accuracy when using a multi-class diagnostic task. The dimensionality reduction of deep features without a similar drop in classification accuracy implies that pretrained convolutional architectures represent a significant amount of redundancy to the task under consideration. The feature selection through optimization provides a principled way to isolate discriminative elements of such representations and thus enhances computational efficiency and facilitates strong model generalization. The structural stability of the optimized feature subset under linear classification is further suggested by the consistency in performance of the optimized feature subset with both validation and test datasets. The observation demonstrates the importance of the quality of the features compared to the complexity of the classifier and justifies the application of interpretable models with the use of well-chosen representations, especially in medical imaging systems where transparency and reproducibility are crucial. All these results suggest that bio-inspired optimization is a potent and mathematically inspired feature selection method of high-dimensional medical images. The framework enables the development of efficient and high-quality classification pipelines that can be used in the large-scale medical imaging setting through balancing the dimensionality reduction and diagnostic accuracy.

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