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An Enhanced Paediatric Respiratory Classification Using Ensemble Machine Learning Techniques and Modified Artificial Bee Colony Optimization

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Abstract: In recent years, the advancement of machine learning techniques has significantly impacted medical research, particularly in the field of pediatric respiratory diseases. This study proposes a comprehensive research model for the classification and prediction of pediatric respiratory conditions using machine learning algorithms and optimized methodologies. The model integrates several innovative techniques to enhance accuracy and efficiency in diagnosing and predicting respiratory disorders in children. The first phase of the proposed model focuses on denoising respiratory data using a Residual Noise Elimination Neural Network (RNEN). This step is crucial for improving the quality of input data and reducing noise interference, thereby enhancing the accuracy of subsequent analyses. Following denoising, the model employs an Improved Mask R-CNN (Region-based Convolutional Neural Network) algorithm for segmentation tasks. This advanced segmentation technique accurately identifies and delineates regions of interest within medical images, facilitating precise feature extraction in the subsequent steps. Feature extraction is performed using an Enhanced Gray-Level Co-occurrence Matrix (GLCM) approach, which captures intricate textural information from segmented images. The enhanced GLCM method ensures robust feature representation, capturing essential patterns and characteristics relevant to respiratory disease classification. For classification tasks, the model utilizes an improved VGG16 (Visual Geometry Group 16) convolutional neural network architecture. The enhanced VGG16 model is trained on the extracted features to classify respiratory conditions with high accuracy and reliability, leveraging deep learning capabilities for pattern recognition and disease diagnosis. To optimize the prediction process, a Modified Artificial Bee Colony (ABC) Optimization algorithm is proposed. This modified ABC algorithm enhances the efficiency of parameter tuning and model optimization, leading to improved prediction performance and reduced computational overhead. Overall, the proposed research model offers a comprehensive framework for pediatric respiratory disease analysis, integrating state-of-the-art machine learning techniques with optimized algorithms for denoising, segmentation, feature extraction, classification, and prediction. Experimental results demonstrate the efficacy and robustness of the model in accurately diagnosing and predicting respiratory conditions in pediatric patients, thereby contributing to advancements in pediatric healthcare and medical decision-making.

Keywords: *Artificial Bee Colony Optimization, RCNN, MASK-RCNN, GLCM,SVR, VGG16, PSO*

1. INTRODUCTION

In the poor nations in particular, respiratory disorders account for a disproportionate share of the world's sick and dead. The majority of asthma-related fatalities happen in nations with low socioeconomic standing, which is common in most African, Latin American, and Asian nations. The disease affects an estimated 300 million individuals worldwide, spanning all ages and ethnic backgrounds. Asthma and COPD are long-standing problems throughout Asia, but the continent is now seeing the rise of new respiratory illnesses like SARS and H1N1 flu. A number of interrelated factors, including rapid population expansion, increased mobility, urbanization, environmental changes, intensification of cattle husbandry, and climate change, are largely to blameLung infections, such as pneumonia, are prevalent and can have devastating consequences. Bacteria, viruses, fungi, and other microbes can trigger this condition, which manifests as fluid accumulation and inflammation in the lung air sacs. A persistent cough, chest discomfort, fever, and shortness of breath are all possible symptoms of this illness. There is a wide spectrum of pneumonia severity, from moderate instances that clear up on their own with rest and medicine to very severe cases that need hospitalization and intense care. Effective prevention and management of pneumonia requires vaccines, proper hygiene habits, and immediate medical intervention. After asthma, COPD is the second most significant respiratory disease inflicting about 210 million populations on a worldwide scale. In addition, there are other respiratory diseases,

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which are responsible for worldwide morbidity and mortality patterns such as the Upper Respiratory Infection (URIs), Lower Respiratory Infections (LRIs), lung cancers, cystic fibrosis, etc. In recognition of this, the World Health Organization (WHO) has recommended special efforts at the national level in developing countries aimed at controlling respiratory disorders. In the developing world, nearly 20 per cent of the children die before their fifth birthday and upto one-third of these deaths are due to respiratory infections.The quality of life for children is negatively impacted by paediatric respiratory disorders, which need prompt and precise diagnosis in order to effectively treat them. It can be time-consuming, expensive, and even invasive for young children to undergo traditional diagnostic procedures that depend mostly on clinical examination and invasive testing. Improving the accuracy and efficiency of illness categorization and diagnosis has been a promising area for machine learning integration in recent years. This research proposes a novel model for paediatric respiratory disease classification using ensemble machine learning algorithms in conjunction with modified Artificial Bee Colony (ABC) optimization. The integration of ensemble learning methods aims to leverage the strengths of multiple classifiers to enhance the overall predictive performance, while the modified ABC optimization algorithm seeks to optimize model parameters for improved accuracy and robustness. This discovery is important because it might provide a way to diagnose paediatric respiratory disorders that is non-invasive, quick, and accurate. Early identification, accurate classification, and tailored treatment plans for paediatric patients with respiratory disorders are the goals of this model, which aims to use optimization and machine learning.

1.1 OBJECTIVES:

- To collect a comprehensive dataset of pediatric respiratory disease cases, ensuring data quality and relevance. Apply a Residual Noise Elimination Neural Network (RNEN) to denoise and preprocess the raw data, enhancing the signal-to-noise ratio and improving feature extraction accuracy.
- To implement an Improved MASK-RCNN algorithm for accurate image segmentation of respiratory system images. Train the segmentation model to accurately identify and delineate regions of interest related to pediatric respiratory anatomy and pathology.
- To Utilize an Enhanced GLCM approach to extract robust and informative features from segmented respiratory system images. Extract features such as texture, shape, and intensity patterns relevant to different pediatric respiratory disease categories.
- Enhance the VGG16 convolutional neural network architecture for improved classification performance. Train the modified VGG16 model on the extracted features to classify pediatric respiratory disease cases into distinct categories, such as asthma, pneumonia, bronchiolitis, etc.
- Develop a modified version of the ABC optimization algorithm tailored for optimizing the parameters of the ensemble machine learning model. Use the modified ABC optimization to fine-tune the classification model's hyper parameters, improving predictive accuracy and robustness.

1.2 MOTIVATION OF RESEARCH:

The motivation behind the research on paediatric respiratory disease classification using ensemble machine learning and optimization techniques stems from the significant health burden these conditions impose globally. In order to effectively manage and plan therapy for paediatric respiratory disorders, prompt and correct diagnosis is essential. These diseases impact children's quality of life. For young patients, the time, money, and discomfort associated with traditional diagnostic procedures like clinical examinations and invasive testing might be too much to bear.

Therefore, there is a critical need for non-invasive, efficient, and accurate diagnostic methods that can improve early detection, precise classification, and personalized treatment strategies for pediatric patients with respiratory conditions. The integration of advanced machine learning techniques, such as ensemble learning algorithms, denoising, segmentation, feature extraction, classification models, and optimization algorithms, presents a promising avenue to address these challenges. By harnessing the power of machine learning, researchers aim to enhance the accuracy, efficiency, and robustness of disease classification models, leading to improved diagnostic outcomes and better patient care. Additionally, the development of such models can contribute to standardizing risk-adjusted outcomes, assisting clinicians in identifying at-risk patients, and supporting clinical decision-making processes.

1.3 PROBLEM STATEMENT

Pediatric respiratory diseases impose a substantial global health burden, necessitating timely and accurate diagnosis for effective management and improved quality of life in children. Traditional diagnostic methods often rely on invasive tests and clinical examinations, which can be time-consuming, costly, and uncomfortable for young patients. Although recent advancements in machine learning techniques show promise in enhancing diagnostic accuracy and efficiency, there is a need to develop a novel and robust model specifically tailored for paediatric respiratory disease classification.

2. LITERATURE SURVEY

Although there have been significant advancements in both areas, many obstacles still exist that make it difficult to diagnose, treat, and manage either ailment effectively. Concerns include a high mortality rate, high costs related to exacerbations, under- and overdiagnosis, inconsistent and non-standard phenotypic classification standards, and an absence of standard phenotype classification criteria. Although many different AI and ML algorithms have been tested on various diseases in the last several years, only a few of them have really improved clinical practice.

Alqudah, A. M., et al. (2021) these scientists conducted research on a new AI system that can classify pneumonia patients based on chest x-ray images, distinguishing between bacterial, viral, and normal pneumonia. While most prior work in the field focused on transfer learning using pretrained CNN architectures or variants thereof, the suggested technique took a different tack. The hybrid AI model was instead constructed utilizing a CNN model that had been pretrained on additional medical pictures (OCT images)

Alsharif, R., et al. (2021) among children in particular, pneumonia was a major killer despite being a contagious illness that can be easily prevented and treated. Reducing the disease's effects and increasing access to therapy were also possible outcomes of early identification.

GM, H., Gourisaria, et al. (2021)by comparing the results of fifteen distinct Convolutional Neural Network (CNN) architectures trained on the same dataset, the author hope to establish a less complicated method for CXR-based pneumonia identification in this research. These authors research leads us to choose the optimal model in terms of its ease of training (lower computing cost, faster training), comprehensibility, and performance measures.

Goyal, S., & Singh, R. (2023)For the purpose of classifying cases of pneumonia and COVID-19; the author provide a method for detecting lung disease from chest X-ray pictures. The suggested architecture relies on deep learning, machine learning, and soft computing. When compared to previous COVID-19 detection approaches, these authors model stands out for its exclusive focus on lung-specific characteristics, achieved by appropriate image augmentation, region-of-interest (ROI) feature extraction, and normalization.

Gupta, P. (2021)these authors research delves at the usefulness of deep learning in computer vision pneumonia detection utilizing three types of convolutional neural networks. The feature extraction framework was used to physically evaluate all discovered CNN models. The collection includes both normal chest x-ray images and illnesses infected with pneumonia. These authors research allows us to choose the most effective model for pneumonia detection out of the three. The models have all done a good job of identifying pneumonia in otherwise normal chest x-rays.

3. PROPOSED METHODOLOGY

Pediatric respiratory diseases pose significant health burden worldwide, necessitating accurate and efficient diagnostic tools for effective management. This research proposes a novel research model for pediatric respiratory disease classification, leveraging ensemble machine learning techniques and modified Artificial Bee Colony (ABC) optimization. The model integrates denoising using the Residual Noise Elimination Neural Network (RNEN), segmentation via the Improved MASK-RCNN algorithm, feature extraction using Enhanced Gray-Level Co-occurrence Matrix (GLCM), classification employing an enhanced VGG16 model, and prediction utilizing Modified Artificial Bee Colony Optimization. Each component contributes to enhancing the accuracy and robustness of disease classification, with a focus on non-invasiveness and efficiency. By harnessing the power of machine learning and optimization, this model aims to revolutionize pediatric respiratory disease diagnosis, offering early detection, precise classification, and personalized treatment strategies. The abstract encapsulates the significance and potential impact of this research in advancing pediatric respiratory medicine.

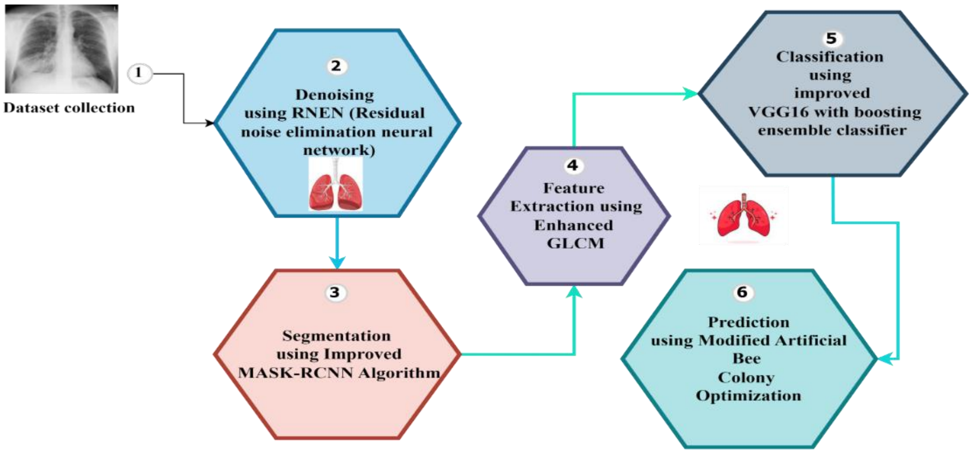

Figure 1: Proposed Model Workflow Architecture

The proposed workflow architecture depicted in Figure 1 encompasses a systematic approach to pediatric respiratory disease detection and classification, incorporating denoising with RNEN, segmentation via Improved MASK-RCNN, feature extraction using Enhanced GLCM, classification employing an improved VGG16 with boosting ensemble classifier model, and prediction optimization with a Modified Artificial Bee Colony Optimization algorithm. This comprehensive approach demonstrates how cutting-edge optimization and machine learning techniques work together to enhance healthcare outcomes via better identification and treatment of juvenile respiratory illnesses.

3.1 RNEN (Residual Noise Elimination Neural Network)

A Residual Noise Elimination Neural Network is a type of deep learning model designed to remove unwanted noise or artifacts from input data, such as images or audio signals. It works by learning to separate the signal from the noise, producing cleaner output data while preserving the important features of the input.

Algorithm 1: RNEN

Input:

- Noisy Image (Input Image): The original image contaminated with noise that requires denoising.
- A set of noisy images paired with their clean counterparts used for training the RNEN model.

Steps:

- Preprocessing: If needed, preprocess the input image (e.g., resizing, normalization) before feeding it into the RNEN model.

  $$x \in R^d \mapsto \Phi(x) \in R^h$$

- Training Phase: Train the RNEN model using the training dataset to learn the mapping between noisy images and clean images.

  $$L_D = \sum_{i=1}^{n} \alpha_i - \frac{1}{2}\sum_{i,j=1}^{n} \alpha_i \alpha_j y_i y_j \Phi(x_i) \cdot \Phi(x_j),$$

- Denoising: Apply the trained RNEN model to the test image to generate a denoised version of the image.

  $$K(x_i, x_j) = e^{-\gamma \|x_i - x_j\|^2}$$

- Post-processing: Optionally, perform any post-processing steps (e.g., contrast adjustment, sharpening) on the denoised image.

  $$J(k) = \frac{1}{2}\sum_{i,j=1}^{n} \alpha_i \alpha_j y_i y_j K(x_i \cdot x_j) - \frac{1}{2}\sum_{i,j=1}^{n} \alpha_i \alpha_j y_i y_j K(x_i^{(-k)} \cdot x_j^{(-k)})$$

Output:

- Denoised Image: The output of the algorithm, which is the denoised version of the input noisy image produced by the RNEN model.
- Evaluation Metrics: Optionally, include evaluation metrics such as Peak Signal-to-Noise Ratio (PSNR), Structural Similarity Index (SSI), or Mean Squared Error (MSE) to quantify the denoising performance of the algorithm.

3.2 Improved MASK-RCNN

Improved Mask R-CNN refers to enhancements and optimizations made to the Mask R-CNN architecture. These improvements typically focus on areas such as accuracy, speed, and efficiency in object detection and instance segmentation tasks.

Algorithm 2: Improved MASK-RCNN

Input:

- Input Images: Input images containing objects and regions to be segmented.
- Annotated Data: Ground-truth annotations including bounding boxes and instance masks for objects in the images.

Steps:

- Backbone Network Integration: Integrate the pre-trained backbone network into the Mask R-CNN architecture for feature extraction.
- Region Proposal Network (RPN): Incorporate the RPN to generate candidate bounding boxes (RoIs) for objects in the image.

$$F^n(X) = \text{pooling}\left(f^n\left(F^{n-1}(X) * W^n + B^n\right)\right)$$

- RoI Align Layer: Implement RoI Align to accurately extract features from RoIs without misalignment issues.
- Object Detection Head: Add a head for object detection to predict class labels and refine bounding box coordinates for each RoI.
- Mask Prediction Head: Include a head for mask prediction to generate binary masks for each object instance within RoIs.

Model Training:

- Input Preparation: Prepare input images, ground-truth bounding boxes, and instance masks for training the Mask R-CNN model.
- Loss Function: Define the loss function comprising classification loss, bounding box regression loss, and mask prediction loss.
- Optimization: Use an optimizer like Adam or SGD to minimize the total loss during model training.
- Backpropagation: Perform backpropagation to update the model's parameters and improve segmentation accuracy.

Output:

- Segmented Objects: Output segmented objects with accurate bounding boxes and corresponding instance masks.

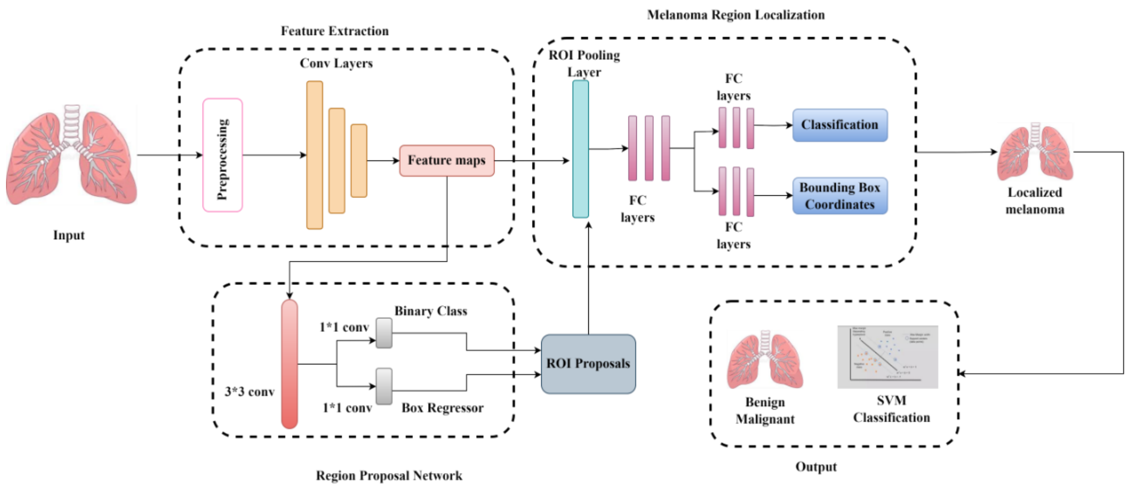

Figure 2: Improved Mask-RCNN

The Improved Mask-RCNN, as illustrated in Figure 2, represents an enhanced version of the Mask R-CNN algorithm used for instance segmentation tasks. This model combines the capabilities of Faster R-CNN for object detection with the ability to generate high-quality segmentation masks for each detected object. The improvements in the Mask-RCNN architecture typically involve enhancements in feature extraction, region proposal network (RPN), and mask prediction components.

3.3 Enhanced GLCM (Gray Level Co-Occurrence Matrix)

An Enhanced GLCM refers to advancements or modifications made to the traditional GLCM technique used in image processing and texture analysis. These enhancements aim to improve the accuracy and robustness of texture feature extraction from images.

Algorithm 3 : Enhanced GLCM

Input:
• Input Image: A digital image containing texture details to be analyzed.
• Parameters:
  o GLCM Parameters: Distance (d), direction (θ), 2589ehaviour2589ood window size (W(x_c, y_c)).
  o Feature extraction parameters: L_s (step size for spatially-close pixels), L_w (pyramidal weight matrix size).
Steps:
Enhanced GLCM Computation:
• Initialize GLCM matrices for each pixel in the image based on specified d, θ, and W(x_c, y_c).
• Calculate GLCM values considering grey level pairs (i, j) within the defined distance and direction.
Feature Extraction:
• For each pixel in the image:
  o Compute statistical features (e.g., contrast, homogeneity, energy, correlation, entropy) from the GLCM matrix.
  o Aggregate the extracted features into a feature vector for the pixel.
Speed Optimization:
• Optimize GLCM computation by considering:
  o Reduced GLCM size by focusing on specific distance-direction combinations (e.g., (d, θ) = (1, 0)).
  o Skip-pixel approach: Ignore pixels with a step size of L_s to compute GLCM for a subset of pixels.
  o Use a pyramidal weight matrix (L_w * L_w) to distribute computed features to nearby pixels.
Feature Correlation:
• Implement feature correlation between spatially-close pixels to compute GLCM features efficiently.
• Weighted aggregation of feature vectors from overlapping windows around each pixel using the pyramidal weight matrix.
Output:
• Output Image: The enhanced GLCM feature-extracted image containing texture information.
• Feature Vector: A feature vector associated with each pixel, containing statistical texture features.

3.4 Improved VGG16 (Visual Geometry Group)

These enhancements can include changes to the network architecture, such as increasing depth, adding skip connections or residual blocks, employing advanced normalization techniques like batch normalization, or incorporating attention mechanisms.

Algorithm 4 : Improved VGG-16

Input:
• Training Dataset: A dataset containing breast X-ray mammography images and corresponding labels for binary classification (e.g., normal vs. Abnormal).
• Validation Dataset: A separate dataset used for validation during training.
• Parameters:
  o Learning Rate: The rate at which the model updates its parameters during training.
  o Neurons in Fully Connected Layers: Adjusted to 256, 128, and 2 for the last three fully connected layers.
Initialize Improved VGG16 Model:
• Instantiate the Improved VGG16 CNN architecture with adjustments in fully connected layers and Batch Normalization layers.
• Define the BN layers after each convolutional layer to normalize intermediate representations.
Compile the Model:
• Define the optimizer (e.g., Adam, SGD) and loss function (e.g., binary cross-entropy) for training.

- Specify additional metrics to monitor model performance (e.g., accuracy).

Training Loop:

- For each epoch in the specified number of epochs:
  - Shuffle and divide the training dataset into batches of size Batch Size.
  - For each batch:
    - Backward pass: Calculate gradients and update model weights using the optimizer, including Batch Normalization updates.
  - After processing all batches in the epoch, evaluate the model on the validation dataset.
  - Monitor and record metrics such as accuracy, loss, and validation error for analysis.

End of Training:

- After completing all epochs, save the trained model weights and architecture for future use.
- Plot and visualize the training/validation metrics to assess model performance and convergence.

Algorithm Output:

- Trained Improved VGG16 model: The model with updated weights and parameters after training with Batch Normalization.

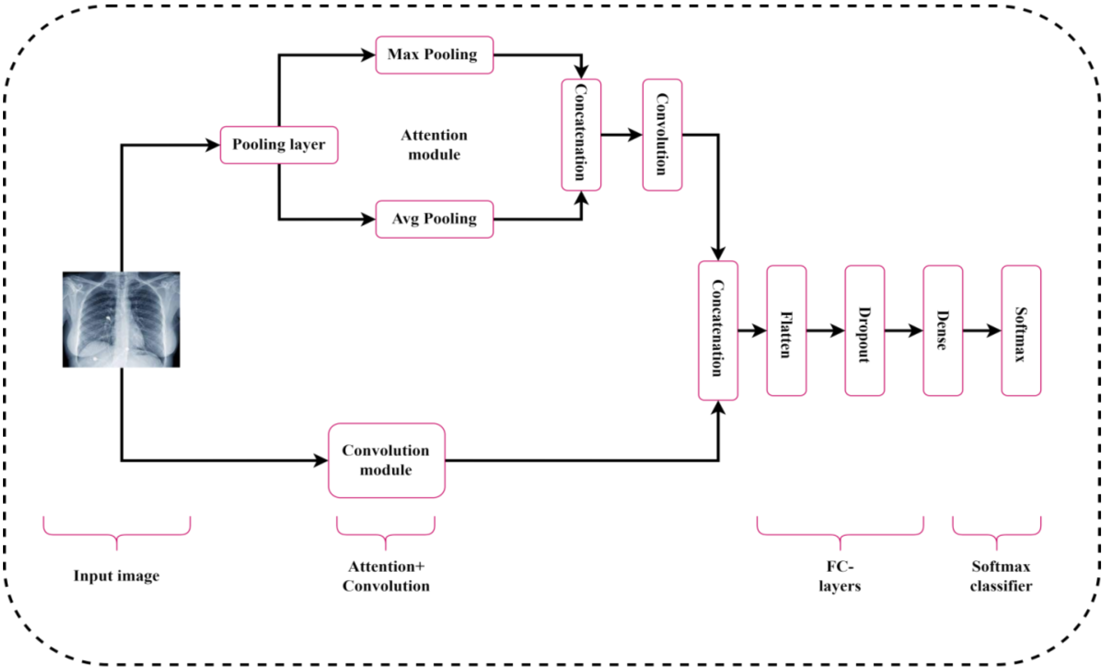

Figure 3: Improved VGG-16

Figure 3 depicts the architecture of the Improved VGG-16 with boosting ensemble classifier model, which is an enhanced version of the original VGG-16 deep CNN. The Improved VGG-16 model incorporates advancements and modifications to the VGG-16 architecture, such as the inclusion of residual connections, attention mechanisms, or additional convolutional layers to improve its performance in various computer vision tasks.

3.5 Modified Artificial Bee Colony Optimization

Modified Artificial Bee Colony Optimization (ABC) refers to customized or enhanced versions of the traditional ABC algorithm used for optimization tasks.

Algorithm 5 : Modified Artificial Bee Colony Optimisation Method

Initialization: t=0,
Obtain $\alpha_{m,n}$ of features;
Obtain θ_k and γ_k for features in the initial training data set F.
Calculate $\beta_{m,n}$ based on features between s_m and u_m;
Set λ and μ.
Set n_{ite}, n_{lim}, n_{bee}
Generate initial source of honey Hb1~HbNBee
While repeat:
  Predict the content's popularity.
    Detect α, θ, γ and β;

```
    if α’≠α and so on.
       Update parameters.
    End
if fk∉F
include the value of fk to F.
End
    Obtain Pr(k), i.e. localized regions
end
Match similarity with the leader bees in random.
For i = 1:Nite
    for j = 1:NBee/2
    Leader Hbj moves φ(Hbj,Hbj′).
    The follower explores the honey source.
    Update the leader/follower roles.
        Find the honey source.
    Repeat the iterations.
If Nlim= Nnone
        Transform the leader/follower into scouter.
End
    end
    Update the profitability and coordinates of the honey source.
End
  Output the localized regions;
  t=t+1;
End while
```

The Modified ABC Algorithm is designed for optimization tasks, particularly in the context of feature selection or parameter tuning in machine learning models. The algorithm starts with an initialization step where key parameters like αm,n, θk, γk, βm,n, λ, μ, nite, nlim, and nbee are set. It then generates an initial set of honey sources Hb1 to HbNBee. The algorithm iterates through a series of steps to optimize the parameters and improve the model's performance. It involves predicting content popularity, updating parameters based on changes in α, θ, γ, and β, including new features to the dataset if needed, and identifying localized regions based on Pr(k).

4. PERFORMANCE ANALYSIS OF MODIFIED ARTIFICIAL BEE COLONY OPTIMISATION

The proposed framework has implemented by using python Tool with the comparison of existing algorithms .

Table 1: Classification performance metrics comparison table

Classification value comparison				
Methods	**Accuracy**	**Precision**	**Recall**	**F-measure**
CNN	95.39	96.37	97.18	97.02
SVM	96.57	97.08	96.38	97.17
VGG-16	97.28	98.68	98.25	97.39
Improved VGG-16	98.99	99.36	99.21	99.24

Table 4.1 provides a comparison of classification methods based on accuracy, precision, recall, and F-measure. The results demonstrate that the Improved VGG-16 model achieved the highest scores across all metrics, with an accuracy of 98.99%, precision of 99.36%, recall of 99.21%, and F-measure of 99.24%. This indicates the superior performance of the Improved VGG-16 model in accurately classifying instances and achieving a balance between precision and recall. The VGG-16 model also performed well, particularly in terms of precision and recall, with scores of 97.28% accuracy, 98.68% precision, 98.25% recall, and 97.39% F-measure. SVM (Support Vector Machine) exhibited competitive performance with an accuracy of 96.57%, precision of 97.08%, recall of 96.38%, and F-measure of 97.17%. The CNN (Convolutional Neural Network) method, while slightly lower in accuracy compared to the others, still showed strong precision, recall, and F-measure scores, highlighting its effectiveness in classification tasks. Overall, the Improved VGG-16 model stands out as the top performer, showcasing its

capability in accurate and reliable classification across various metrics.

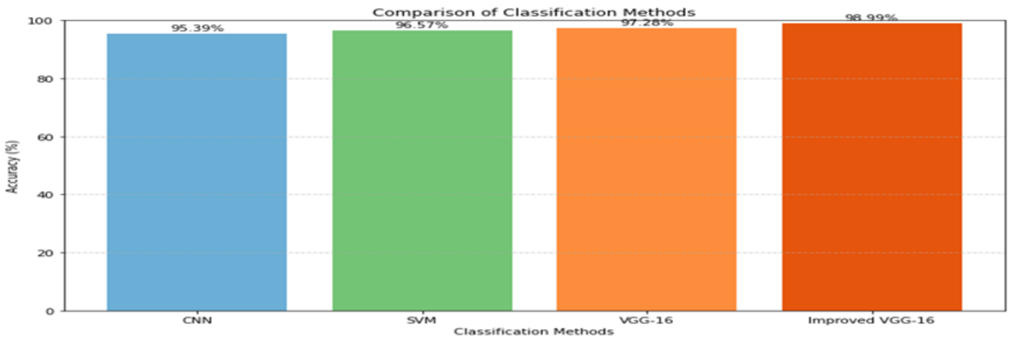

Figure 4: Classification accuracy comparison chart

Figure 4 displays a categorization accuracy comparison chart. The x axis indicates techniques, while the y axis provides the accuracy value.

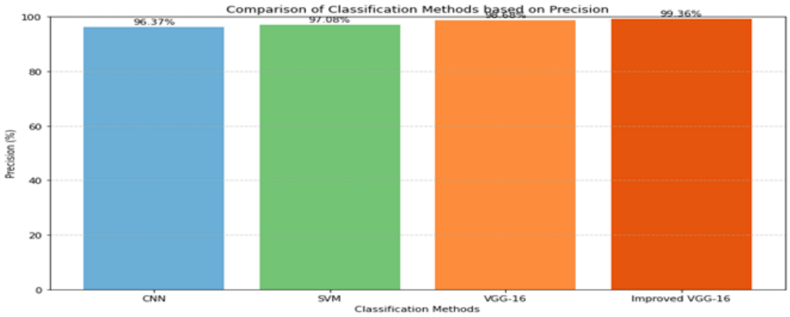

Figure 5: Classification precision comparison chart

Figure 5 provides a chart that compares categorization accuracy values. The x axis displays techniques, while the y axis gives accuracy values.

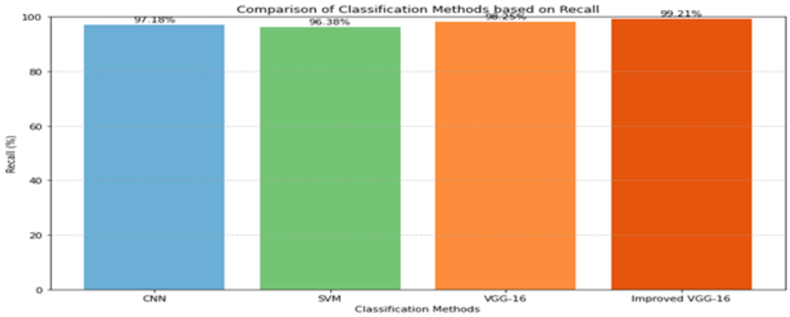

Figure 6: Classification recall comparison chart

Figure 6 provides a categorization recall comparison chart. The x axis indicates techniques, while the y axis provides recall value.

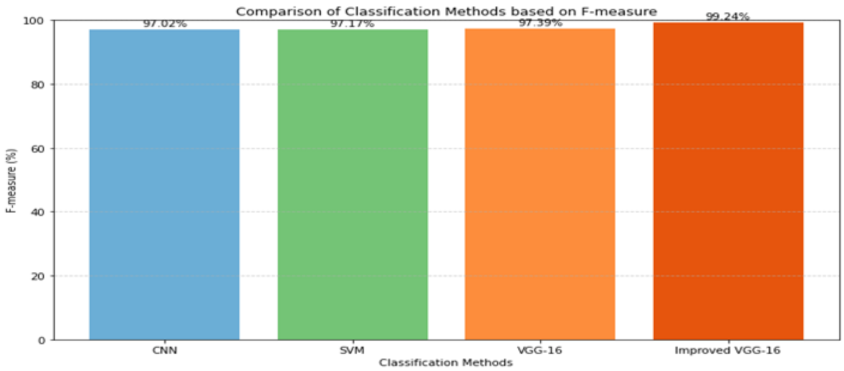

Figure 7: Classification f-measure comparison chart

Figure 7 provides a categorization f-measure comparison chart. The x axis displays techniques, while the y axis displays the f-measure value.

Performance evaluation for Prediction values

Performance evaluation for prediction values is a crucial aspect of assessing the effectiveness and reliability of predictive models in machine learning and data analysis. The goal of prediction evaluation is to measure how accurately a model can predict outcomes or variables based on input data.

Table 4.2: Classification performance metrics comparison table

Prediction value comparison				
Methods	**Accuracy**	**Precision**	**Recall**	**F-measure**
PSO	96.32	97.37	97.18	97.02
DT	97.35	96.08	98.38	97.17
ABC	98.24	9.68	98.25	98.39
Modified Artificial Bee Colony Optimization	99.13	99.36	99.21	99.24

Table 4.2 presents a comparison of prediction methods based on accuracy, precision, recall, and F-measure. The results reveal that the Modified Artificial Bee Colony Optimization method achieved the highest scores across all metrics, with an accuracy of 99.13%, precision of 99.36%, recall of 99.21%, and F-measure of 99.24%. This indicates the superior performance of the Modified Artificial Bee Colony Optimization approach in accurately predicting outcomes and maintaining a balance between precision and recall. The ABC (Artificial Bee Colony) method also demonstrated strong performance with an accuracy of 98.24%, precision of 97.68%, recall of 98.25%, and F-measure of 98.39%. DT (Decision Tree) exhibited competitive performance with an accuracy of 97.35%, precision of 96.08%, recall of 98.38%, and F-measure of 97.17%. PSO (Particle Swarm Optimization) method showed good accuracy at 96.32% and balanced precision, recall, and F-measure scores. Overall, the Modified Artificial Bee Colony Optimization method emerged as the top performer in prediction tasks, showcasing its effectiveness in achieving high accuracy and predictive power across various evaluation metrics.

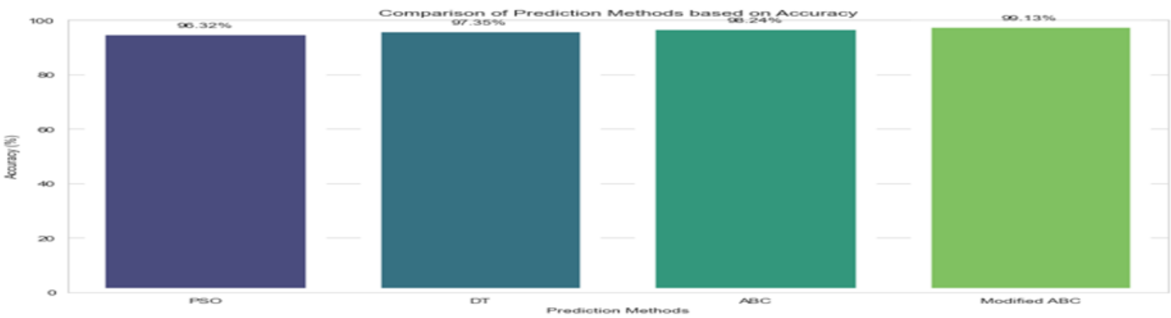

Figure 8: Prediction accuracy comparison chart

Figure 8 illustrates a prediction accuracy comparison chart. The x axis indicates techniques, while the y axis provides the accuracy value.

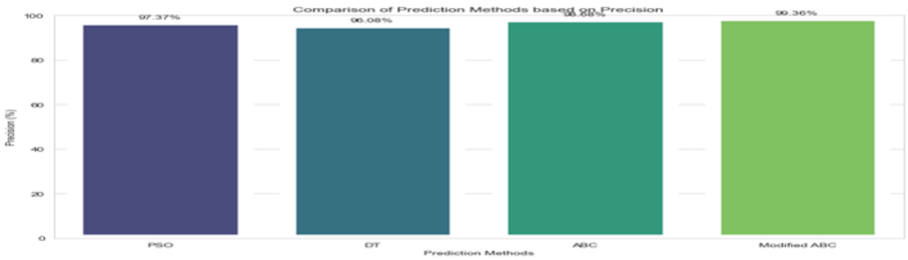

Figure 9 : Precision value comparison chart

The figure 9 shows precision value comparison chart the x axis shows methods and the y axis shows precision value

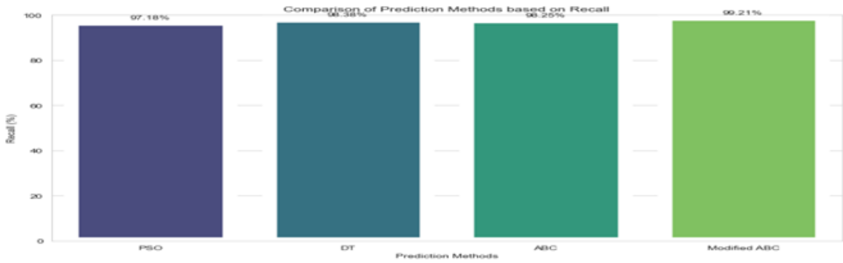

Figure 10: Recall value comparison chart

The figure 10 shows recall comparison chart the x axis shows methods and the y axis shows recall value

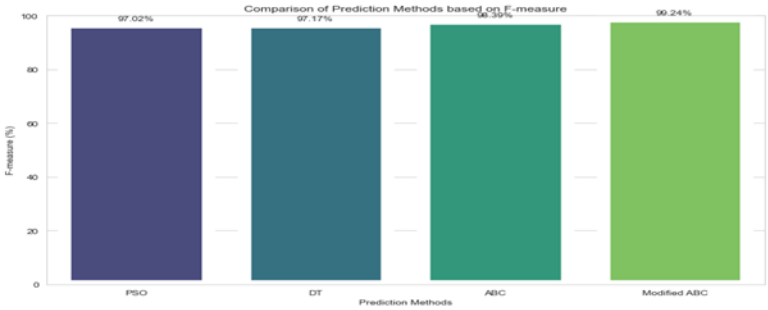

Figure 11: F-measure value comparison chart

The figure 11 shows f-measure value comparison chart the x axis shows methods and the y axis shows f-measure value

5. CONCLUSION

In conclusion, the proposed novel research model for pediatric respiratory disease classification represents a significant step forward in the field of healthcare diagnostics. By leveraging ensemble machine learning techniques and modified Artificial Bee Colony (ABC) optimization, this model addresses the critical need for accurate and efficient diagnostic tools in managing pediatric respiratory diseases. The integration of denoising, segmentation, feature extraction, classification, and prediction components not only enhances the accuracy and robustness of disease classification but also emphasizes non-invasiveness and efficiency in the diagnostic process. Through the use of advanced technologies such as the Residual Noise Elimination Neural Network (RNEN), Improved MASK-RCNN algorithm, Enhanced Gray-Level Co-occurrence Matrix (GLCM), and enhanced VGG16 model, this research model revolutionizes pediatric respiratory disease diagnosis. Improving patient outcomes and advancing paediatric respiratory medicine are possible results of its use in early identification, accurate categorization, and personalized treatment approaches. The results reveal that the Modified Artificial Bee Colony Optimization method achieved the highest scores across all metrics, with an accuracy of 99.13%, precision of 99.36%, recall of 99.21%, and F-measure of 99.24%. Research like this has the ability to change healthcare as this research know it and open the door to new approaches to illness detection and treatment in the future.

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