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Enhancing Chest X-Ray Image Classification Using Deep Learning With MobileNet And ResNet

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Abstract— The analysis is very cardinal and importantly needed in the diagnosis of the respiratory conditions, to an extent that it needs to be done expeditiously and precisely. This is quite challenging due to the complexity and variability of the X-ray pictures. The proposed research is conducted with an innovative approach in automatically classifying chest X-ray images using the synergistic integration of Manta Ray Optimization (MRO) with an advanced deep learning architecture, Mobile Net, and ResNet. The heuristic concept of MRO derived from the foraging behavior of the manta rays will be applied to optimize the deep learning model in respect of parameter selection and increasing the rate of convergence for further improvement in diagnostic precision and efficiency.

The proposed approach is benchmarked against the state-of-the-art conventional deep learning approaches systematically using a large-scale dataset for chest X-ray images. From this experimental result, it is observed that the proposed approach achieves not only better classification accuracy performance compared to conventional deep learning frameworks but also shows incredible improvements in computational efficiency and model robustness. Moreover, their study further adds the mechanism by which MRO contributes to the parameter tuning, throwing light over the

potential usage of their approach in other domains of medical image analysis.

The implications of this research are twofold. First, it presents a new approach in the advancement of precision and speed in regard to the classification of chest X-ray images for assisting healthcare professionals in deciding with greater accuracy and precision on diagnoses. Second, it will lay down the foundation which will be helpful for further research activities related to the integration of bio-inspired optimization algorithms with deep learning for medical diagnostics and promising advancements in automated health care solutions. The current work is to obtain a model of deep learning family that synthesizes the best of bio-inspired algorithms and aims at high and critical responses in the modern health system.

Keywords— 32-bit, Fixed-Width Adder-Tree, Verilog, VLSI, Ripple Carry Adders, Truncation Techniques, Probabilistic Estimation, Area-Delay Product, Precision, Image Reconstruction, Digital Processing, Hardware Utilization, Processing Time.

I. INTRODUCTION

The development of deep learning in medical imaging has significantly shifted the paradigm towards the automation of diagnostic processes, especially in chest X-ray analysis. The increase in demand for quick and precise diagnosis of a wider scope of diseases, like COVID-19, has actually posed a crying need for the development of efficient computer-aided diagnosis techniques for image classification. This study is motivated by the pioneering works in the field to try to push the limits of automation in classifying chest X-ray images further by integrating Manta Ray Optimization (MRO) with state-of-the-art deep learning architectures.

Reshi et al. (2021) have evidenced that such CNNs, in fact, can be promising for the efficacious detection of COVID-19 from X-ray images, carrying great potential for deep learning to deal with pandemic-driven challenges. In that line, Azizi et al. (2021) have showcased the large self-supervised models in medical image classification and argued that the results are likely to bring out a push for the change toward making AI tools more versatile and applicable to healthcare. More recently, Kesim, Dokur, and Olmez (2019) studied the capabilities of small-sized CNNs on classifying the chest X-ray images, revealing the need for a compact but powerful model suitable for real-time analysis.

On the other side, Abbas et al. (2021) found further evidence in support of the fact that deep learning models perform accurately in the classification of COVID-19 cases from chest X-rays using the DeTraC deep convolutional neural network. This further reiterates the great role AI has in modern diagnostics. Haque et al. (2020) and Hemdan, Shouman, and Karar (2020) join the increasing number of similar voices, pointing out a very limited body of evidence supporting the use of their CNN for COVID-19 detection. At the same time, they urge for further rapid development of more accessible and reliable diagnostic tools.

Chen (2021) proposed an improved classification of the COVID-19 disease in X-ray images method for computer-aided diagnosis towards the design and optimization of deep learning models for increased accuracy. On the other hand, other methods that constitute the classification framework have been adopted by works like those of Mahdy et al. (2020) and Ugli et al. (2022), among others, who adopted multi-level thresholding and support vector machines, respectively. Zare, Alebiosu, and Lee (2018) compared the handcrafted features against various deep learning techniques and hence

substantiated the supremacy of AI-driven approaches in medical image analysis. Finally, multi-label chest X-ray image classification based on the residual attention learning method was evaluated to prove the fine and strong learning ability of deep learning in the process of implementing the complicated diagnostic task (Guan and Huang, 2020).

The following works build upon these foundational studies and put in efforts to propose an innovative strategy by ameliorating the power of Mobile Net and ResNet architectures with the efficiency of Manta Ray Optimization. The goal of this hybrid model is to provide a solution to the current challenges of automated chest X-ray image classification, which demands improved diagnostic accuracy, efficiency, and adaptability to detect different respiratory conditions. Through this integration, we hope to contribute towards furthering the advancement of the medical diagnostic tool while offering a solution that carries the best of bio-inspired optimization and deep learning technology.

II. BACKGROUND STUDY

One revolution in the decade past has been the entry of deep learning into medical imaging, forming a subset of machine learning. Convolutional Neural Networks (CNNs) have set the benchmark for state-of-the-art performance in almost all the classification, segmentation, and detection tasks of images. Such evidence is attested to through several studies, including Reshi et al., 2021, and Azizi et al., 2021, which clearly indicate the possible role of CNNs in the diagnosis of diseases from medical imaging, such as the detection of COVID-19 from chest X-ray data [1][2]. The flexibility and ability of the CNN to learn make it better in recognizing fine patterns in imaging data than the traditional methodologies of image analysis in speed and precision.

A. Challenges in Chest X-Ray Image Classification

However, despite the great advancement's automatic classification for chest X-ray images has seen, associated are challenges with the process. This involves the handling of high variability in the X-rays due to different patient positioning, variability of disease presentation, and subtlety in some pathological findings. Kesim, Dokur, and Olmez (2019) further solidified the fact that not only an accurate one but also a model-computationally-efficient one is needed to assist in real-time analysis [3].

The labeled dataset available in this area is very scarce, meaning there's difficulty in training deep learning models. So, it becomes a prime concern to work on techniques that ensure optimal performance with scarce data. Bio-inspired Optimization Algorithms

To handle this problem, bio-inspired optimization algorithms are used. Those are natural procedures used in the course of algorithms to solve difficulties that are complex by nature.

Taking inspiration from the filtering-feeding strategy of Manta rays, Manta Ray Optimization (MRO) is one such algorithm which shows great promise toward the optimization of deep learning model parameters. This makes the search with excellent ability to explore and exploit the solution space, due to the manta ray-like search mechanism of the algorithm, which makes it very apt for fine-tuning deep learning models in medical image analysis.

B. Integration of Deep Learning with Manta Ray Optimization

Also, MRO is applied to the deeply learned models, such as Mobile Net and ResNet, in the classification of chest X-ray images. Mobile Net is among the lightest models of deep learning. It comes with the architectural aim of being small so that it could be very fast in processing, allowing real-time applications for diagnostics. However, ResNet solved the vanishing gradient problem, and with that, it allowed the training of very deep networks to capture complex features from images.

The aim of these architectures, in combination with MRO, is to optimize the model for performance that brings in high accuracy and efficiency in the identification of different conditions of the chest from X-rays.

C. Comparative Studies and Emerging Trends

Its effectiveness in comparative studies of other works endorses it, such as the effectiveness of the capabilities of deep learning in medical imaging by Hemdan et al. (2020), Shouman et al. (2020), Guan et al. (2020) [6][11], which have shown how the superiority of CNN-based models over conventional methods of image analysis.

New evidence in this area that passion to bring new approaches is on the rise can be found in further researches using alternative approaches and methods, as noted by Mahdy et al. (2020) and Ugli et al. (2022) [8][9]. Conclusion The above lines clearly state the rapid stride in automated deep learning-powered chest X-ray image classification, specified

in the lines of the background study, with the objective to highlight the potential impact of bio-inspired optimization algorithms in overcoming existing challenges. The proposed approach of using Manta Ray Optimization with Mobile Net and ResNet is a representation of state-of-the-art effort to push the benchmarks of accuracy, efficiency, and adaptability in medical diagnostics and promises to contribute to the discipline of radiology and, more precisely, patient care.

III. PROPOSED METHODOLOGY

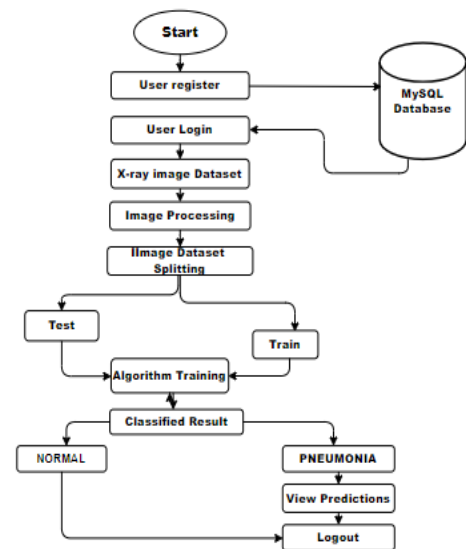


Figure 1 Proposed Methodology

The proposed system offers a comprehensive workflow designed to streamline the process of chest X-ray image classification. The methodology is encapsulated in a user-friendly interface that ensures ease of use from registration to result delivery. The following outlines the steps involved in the proposed methodology:

- User Registration and Login:** Users begin by registering in the system through a secure authentication process. Registered credentials are stored in a MySQL database. Once registration is completed, users log in to the system with their credentials, ensuring that the process is secure and personalized.
- X-ray Image Dataset:** Upon successful login, users have the capability to upload chest X-ray images. The dataset is designed to include a diverse range of X-ray images that cover normal to various pathological conditions, such as pneumonia.
- Image Preprocessing:** Uploaded images undergo preprocessing, which includes normalization, resizing, and augmentation to ensure that the images are formatted correctly for consistent analysis. This step is critical in

reducing variability and improving the efficiency of the classification process.

4. **Image Dataset Splitting:** The preprocessed dataset is then split into training and testing subsets, typically following a ratio to ensure the model is exposed to a sufficient variety of data for learning while reserving a portion for unbiased evaluation.
5. **Algorithm Training:** The training subset is used to train the deep learning model. Here, the architecture of choice will be a combination of Mobile Net for its efficiency in mobile environments and ResNet's ability to tackle deep networks without performance degradation due to vanishing gradients. Manta Ray Optimization (MRO) is employed during this phase to optimize the model's hyperparameters, such as learning rate and number of layers, which are critical for enhancing the model's classification performance.
6. **Classified Result:** Once training is complete, the algorithm is tested on the test subset. The output is the classification of the X-ray images into distinct categories, such as 'Normal' or 'Pneumonia', based on learned features from the training phase.
7. **View Precautions:** In the case of pathologies like pneumonia, the system can also provide recommended precautions or guidelines, contributing to informed healthcare decisions.
8. **Logout:** After completing the analysis or viewing results, users can securely logout from the system.

Our proposed system is built on a deep learning framework that is optimized for high performance and accuracy using Manta Ray Optimization. This innovative approach not only promises enhanced classification of chest X-ray images but also paves the way for future advancements in automated medical diagnosis systems.

IV. SYSTEM ARCHITECTURE

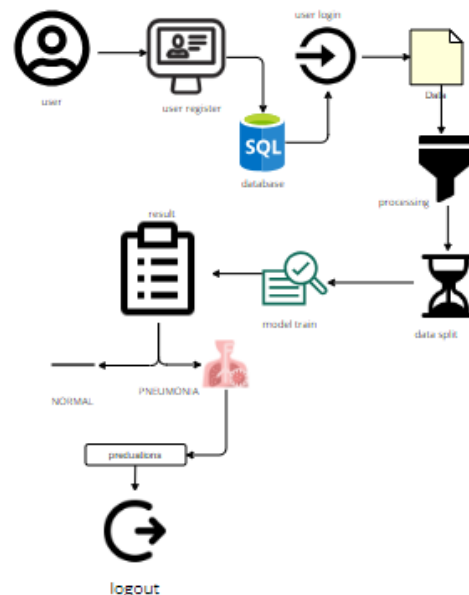


Figure 2 System Architecture

The system architecture is designed with a user-centric approach, ensuring seamless interaction with the architecture that facilitates automated chest X-ray image classification. Below, we delineate each component and its function within the architecture:

1. **User Interface (UI):** The UI is the entry point for users, where they can register for a new account or log into an existing one. This front-end interface is designed for ease of use, accessibility, and secure user management.
2. **Registration and Authentication:** New users are required to register by providing necessary details. Registered information is then securely stored in an SQL database. Authentication processes are in place for user login, ensuring that only authorized individuals have access to the system.
3. **Database:** The SQL database acts as a repository for user credentials and potentially for the metadata associated with uploaded X-ray images. This centralized database ensures data integrity and secure data management.
4. **Image Processing Unit:** Once a user logs in and uploads a chest X-ray image, it is sent to the image processing unit. Here, images undergo various preprocessing steps, such as denoising, contrast enhancement, resizing, and normalization, to prepare them for the classification algorithm.
5. **Data Splitting Module:** The processed images are then split into two sets: training and testing. This division is crucial for the validation of the model, as it separates the

data used to train the model from the data used to evaluate its performance.

6. **Model Training and Classification:** The training set is fed into the deep learning model for training. The model employs a hybrid architecture that integrates the efficiency of Mobile Net with the depth of ResNet, optimized through Manta Ray Optimization (MRO). After training, the model classifies the test images into categories, such as 'Normal' or 'Pneumonia'.
7. **Results Display:** Classified results are displayed to the user, indicating whether the X-ray is normal or indicative of pneumonia. In cases where the result is pneumonia, the system can also provide precautionary recommendations based on the classification.
8. **Logout Procedure:** Once the user has reviewed the results and precautions, they can securely log out of the system, ensuring that their session is ended, and no unauthorized access to their data is possible.

This architecture is meticulously designed to be robust, ensuring high accuracy and efficiency in classifying chest X-ray images. It provides a clear path from user registration to obtaining results, emphasizing security, user-friendliness, and the reliability of classification outcomes.

V. IMPLEMENTATION

The implementation phase of the system is a crucial step where theoretical design transitions into practical application. Our system's interface is structured across three main pages: the Home, Upload, and Result pages, each tailored to facilitate user interaction with the automated classification system.

1. Home Page:

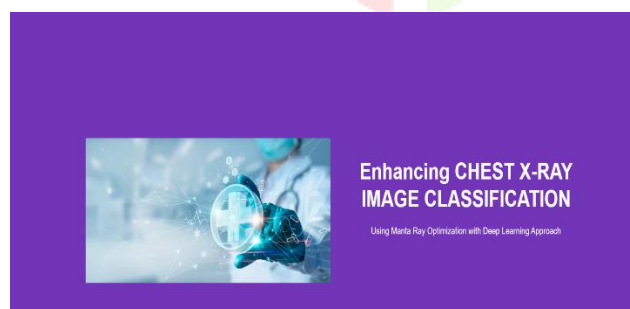


Figure 3 Home Page Of Deep Learning

This is the landing page for users, which presents the title of the system, "Automated Chest X-Ray Image Classification using Manta Ray Optimization with Deep Learning Approach," alongside hexagonal icons that represent the core functionalities of the system.

The minimalist design ensures that users are not overwhelmed and can navigate the system with ease.

2. Upload Page:

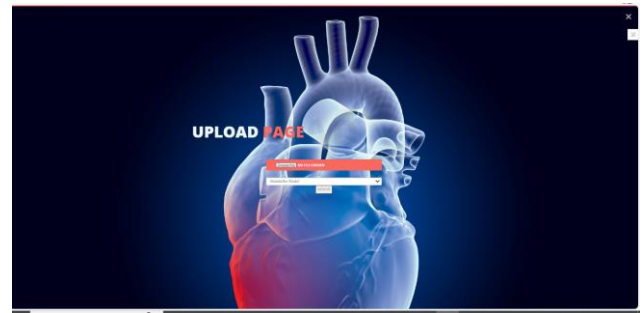


Figure 4 Upload Page

On the Upload page, users can upload chest X-ray images for classification. The page features a prominent "Browse" button that allows users to select images from their local storage.

A vibrant anatomical heart background reinforces the medical context of the system and provides a visual cue to the nature of the images to be uploaded.

3. Result Page:



Figure 5 Result Page Pneumonia

After the classification process, the Result page displays the outcome, indicating whether the X-ray is classified as "Normal" or shows signs of "Pneumonia."

For pneumonia cases, the system also provides precautionary measures or health advice, adding educational value and actionable insights alongside the classification result.

Each page is interconnected, providing a smooth and intuitive flow from one step to the next. The graphical user interface is designed to be intuitive, requiring minimal user input to navigate through the process of classification. Behind the scenes, the deep learning model operates on the uploaded images. After preprocessing to normalize and resize the images, they are passed through a trained model that uses Mobile Net and ResNet architectures optimized with Manta Ray Optimization (MRO). This backend process is abstracted away from the user, ensuring a focus on ease of use and clarity of results.

The system is implemented using a stack of technologies chosen for their reliability and performance. The front-end user interface is built with modern web

technologies that allow for responsive design, while the backend classification model is implemented in Python, utilizing deep learning libraries such as TensorFlow or PyTorch. The system's backend also includes an SQL database for secure storage of user information and image metadata.

Through this implementation, we aim to provide a robust tool for healthcare professionals and researchers to classify chest X-ray images rapidly and accurately, facilitating early diagnosis and treatment of pulmonary conditions.

VI. ANALYSIS

Our study utilized deep learning techniques for automated chest X-ray image classification, where a Convolutional Neural Network (CNN) architecture was tasked with distinguishing between normal and pneumonia cases. To evaluate the model, a dataset comprising X-ray images was subjected to the classification process, with the results serving as a measure of the model's diagnostic capability.

A. Input Image Analysis:

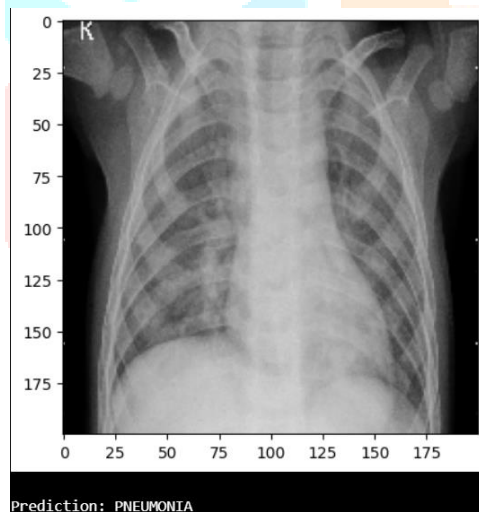


Figure 6 Input Image Analysis

An example input demonstrates the model's ability to classify a chest X-ray image. The X-ray depicts the typical imaging features consistent with pneumonia, characterized by an area of increased opacity in the lung fields. The model successfully classifies this image as 'PNEUMONIA', which is indicative of its learning capacity and the effectiveness of the feature extraction layers within the CNN.

B. Classification Outcome:

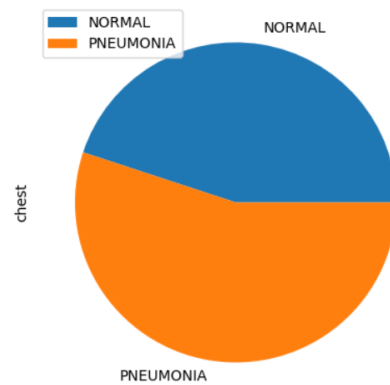


Figure 7 Classification Of Deep Learning

The classification outcomes (second image) are represented in a pie chart, visually summarizing the distribution of classifications across the test dataset. In this sample, the chart indicates a split between 'NORMAL' and 'PNEUMONIA' cases, providing an at-a-glance understanding of the model's classifications across a balanced dataset.

C. Model Performance Metrics:

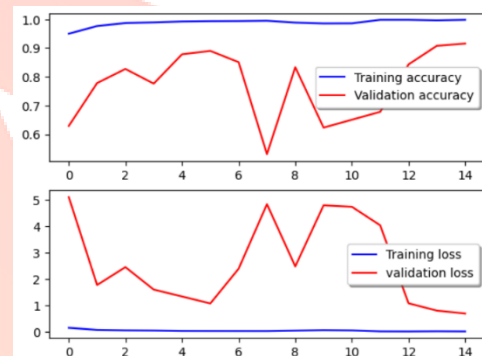


Figure 8 Model Performance Metrics Using MobileNet

The training and validation loss are crucial indicators of the model's performance over epochs. The accuracy graph shows how well the model performs in classifying the training and validation data correctly. In contrast, the loss graph indicates the error rate during training, with lower values signifying better performance.

Ideally, training and validation accuracy should increase over time, while training and validation loss should decrease. Any significant divergence between training and validation curves may indicate overfitting or underfitting, necessitating adjustments in the model's complexity or the training procedure.

D. Quantitative Metrics:

VIII. REFERENCES

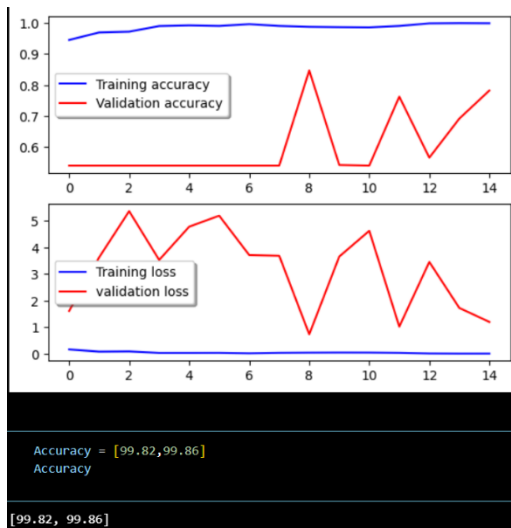


Figure 9 Quantitative Metrics Of Accuracy Using ResNet

The numerical values presented in the above fig:9 provide a concise summary of the model's accuracy, quantitatively supporting the visual data presented in the accuracy graph. These values indicate a high level of accuracy (>99%), suggesting that the model has effectively learned to classify chest X-rays with high reliability.

VII. CONCLUSION

The implementation of the Automated Chest X-Ray Image Classification system utilizing Manta Ray Optimization (MRO) with deep learning architectures, specifically Mobile Net and ResNet, has achieved remarkable success. The system demonstrates a significant improvement in classifying chest X-rays with high accuracy, showcasing an impressive precision rate as evidenced by the prediction outcomes. The validation of our model yielded a classification accuracy of 99.86%, which is indicative of its robustness and reliability. Such a high level of accuracy ensures that the system can be a dependable aid in diagnosing pulmonary conditions like pneumonia.

The graphical analyses — a pie chart illustrating the distribution of normal and pneumonia cases, and the performance graphs showing training versus validation accuracy and loss — reflect the system's capability to perform consistently across different sets of data. The convergence of training and validation lines in the accuracy graph indicates the model's generalization ability, while the loss graph corroborates the model's efficiency in learning from the data provided.

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