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An Enhanced Whale Optimization Algorithm With Reinforcement Learning For Accurate Covid-19 Prediction From Chest X-Ray Images

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Recent technological advancements have enabled the widespread use of Reinforcement Learning techniques across various domains, particularly in the healthcare sector. These techniques offer high accuracy and efficiency in the detection and classification of different diseases. COVID-19, being a highly contagious respiratory disease, requires rapid and reliable diagnostic methods to support effective monitoring and treatment. Chest X-ray imaging has emerged as a safe, fast, and accessible diagnostic tool for identifying lung abnormalities associated with COVID-19 infection. In this study, a Q-Learning based Reinforcement Learning model is employed to classify COVID-19 and non-COVID-19 cases using chest X-ray images. To further enhance the learning capability and classification performance, an Optimized Whale Optimization Algorithm is integrated into the framework for optimal feature selection and improved model optimization. The chest X-ray dataset undergoes preprocessing and data augmentation techniques to enhance image quality and increase dataset diversity. The processed data is then divided into training and testing sets for model development and validation. The performance of the proposed model is evaluated using various metrics such as accuracy, sensitivity, specificity, F-Measure, AUC and Error Rate. The proposed framework, which integrates Optimized Whale Optimization Algorithm (OWOA) for feature selection with Q-Learning for classification, achieved the highest accuracy of 90.89%.

Keywords: Reinforcement Learning, Q-Learning, Whale Optimization Algorithm (WOA)

1. INTRODUCTION

Coronavirus Disease 2019 (COVID-19) is a highly infectious respiratory illness caused by the novel coronavirus SARS-CoV-2. The disease was first identified in late 2019 and rapidly spread across the globe, leading the World Health Organization (WHO) to declare it a global pandemic. COVID-19 primarily affects the respiratory system and may lead to symptoms such as fever, cough, fatigue, breathing difficulties, and in severe cases, pneumonia and respiratory failure. Due to its rapid transmission rate and global impact on public health systems, early detection and accurate diagnosis of COVID-19 have become essential for effective treatment and disease management. Medical imaging techniques such as chest X-ray and computed tomography (CT) scans have been widely used to identify lung abnormalities associated with COVID-19 infection. However, manual analysis of these images can be time-consuming and highly dependent on the expertise of medical professionals.

In recent years, Artificial Intelligence (AI) techniques, particularly Machine Learning (ML) and Deep Learning (DL), have demonstrated significant potential in medical image analysis. These techniques can automatically extract meaningful patterns from large datasets and assist healthcare professionals in disease diagnosis and prediction. However, medical datasets often contain a large number of features, some of which may be irrelevant or redundant. The presence of such features can reduce the efficiency and accuracy of predictive models. Therefore, feature selection plays a crucial role in improving model performance by identifying the most relevant features and eliminating unnecessary information. Feature selection not only enhances classification accuracy but also reduces computational complexity and training time. Optimization algorithms, such as the Whale Optimization Algorithm (WOA), are commonly used to identify optimal feature subsets by searching the feature space efficiently.

Another promising approach in artificial intelligence is Reinforcement Learning (RL), which is a learning paradigm where an agent learns to make decisions by interacting with an environment and receiving rewards or penalties based on its actions. Unlike supervised learning, reinforcement learning focuses on learning optimal strategies through trial and error. One of the widely used reinforcement learning techniques is Q-Learning, which enables the system to learn optimal actions for different states by updating a Q-value function. Reinforcement learning models have been successfully applied in various domains; including robotics, control systems, and healthcare decision support systems. In the context of COVID-19 diagnosis, reinforcement learning can be used to improve classification models by learning optimal decision strategies based on medical imaging data.

In this study, a hybrid framework combining Q-Learning based Reinforcement Learning and an Optimized Whale Optimization Algorithm is developed for COVID-19 classification using chest X-ray images. The proposed approach utilizes preprocessing and data augmentation techniques to improve dataset quality, followed by optimal feature selection using PWOA. The selected features are then used by a reinforcement learning-based classifier to accurately distinguish between normal and COVID-19 cases. The integration of optimization techniques with reinforcement learning aims to enhance prediction accuracy and provide a reliable automated system for COVID-19 detection.

2. REVIEW OF LITERATURE

Several studies have explored the application of artificial intelligence techniques for the detection and classification of COVID-19 using medical imaging data such as chest X-ray and CT scans. These approaches aim to improve the speed and accuracy of diagnosis and assist healthcare professionals in clinical decision-making.

Yang et al. (2021) investigated the use of deep learning techniques for detecting COVID-19 from medical images. In their study, several pre-trained convolutional neural network models, including VGG16, DenseNet121, and ResNet architectures, were used to classify CT-scan images. The results showed that deep learning models can effectively identify

COVID-19 infection patterns and assist radiologists in early disease detection. However, the performance of these models depends heavily on the availability of high-quality and balanced datasets.

Khan et al. (2022) proposed a deep learning-based framework for classifying COVID-19 from chest X-ray images. Their study highlighted that deep learning models can automatically extract relevant features from medical images and achieve high classification accuracy in distinguishing COVID-19 cases from other lung diseases. The authors demonstrated that artificial intelligence techniques can significantly improve the efficiency of medical image analysis compared with traditional diagnostic approaches.

AbdElhamid et al. (2022) developed a deep learning-based multi-classification system for diagnosing COVID-19 using chest X-ray images. Their research applied several deep learning algorithms to categorize images into multiple classes, including COVID-19, pneumonia, and normal cases. The experimental results indicated that deep learning models can provide accurate diagnostic support and help reduce the burden on healthcare professionals during pandemic situations.

Le Dinh et al. (2022) investigated the use of convolutional neural networks and transformer-based models for COVID-19 detection and severity assessment using chest X-ray images. Their approach demonstrated that deep neural networks could effectively identify disease patterns and evaluate the severity levels of COVID-19 infection. The study also highlighted the importance of data preprocessing and balanced datasets for improving model performance.

Albahli and Albattah (2022) introduced a deep transfer learning model using architectures such as VGG-16 and Inception networks to classify chest X-ray images into COVID-19, normal, bacterial pneumonia, and viral pneumonia categories. Their approach achieved high classification accuracy and demonstrated that transfer learning can effectively address the challenge of limited medical imaging datasets.

In addition, Teimoor and Mohammed (2022) conducted research on machine learning-based COVID-19 detection using chest X-ray images. Their study emphasized the importance of preprocessing, feature extraction, and classification algorithms in improving disease prediction performance. The findings suggested that combining machine learning techniques with optimized feature selection methods can significantly enhance diagnostic accuracy

3. CONTRIBUTIONS OF THE RESEARCH WORK

The main contribution of this research work is the development of an efficient and automated framework for the detection and classification of COVID-19 using chest X-ray images. The proposed system integrates advanced artificial intelligence techniques to improve the accuracy and reliability of disease prediction. In this study, a Q-Learning based Reinforcement Learning approach is employed to classify COVID-19 and non-COVID-19 cases by learning optimal decision strategies from the dataset. To further enhance the performance of the classification model, an optimized Whale Optimization Algorithm is introduced for effective feature selection and optimization. The optimization process helps in identifying the most relevant features while eliminating redundant or irrelevant information, thereby improving the overall efficiency of the model. Additionally, preprocessing and data augmentation techniques are applied to enhance the quality and diversity of the chest X-ray dataset. The integration of reinforcement learning with the proposed optimization technique leads to improved classification accuracy and reduced computational complexity. The proposed hybrid framework provides a reliable decision-support system that can assist healthcare professionals in the early detection and diagnosis of COVID-19, ultimately contributing to better disease monitoring and management.

4. METHODOLOGY

4.1 Dataset Description

The dataset used to train and evaluate the proposed model is publicly available on Kaggle. The dataset consists of chest X-ray images collected from multiple publicly accessible medical imaging repositories. These datasets were combined to form a unified dataset suitable for COVID-19 classification. The collected dataset includes two primary categories: COVID-19 and Normal cases. Since the dataset was compiled by merging several smaller datasets, it is important to describe its composition in detail. Each category contains images obtained from different sources, ensuring diversity in the dataset.

In total, the dataset contains 5,863 chest X-ray images in JPEG format, collected from four different sources. These images represent both COVID-19 infected patients and normal healthy individuals. The dataset is divided into training and testing sets to evaluate the performance of the proposed classification model. The availability of this dataset enables the development and validation of machine learning and deep learning approaches for automated COVID-19 detection.

4.2 Data Augmentation

Deep learning models generally require a large amount of training data in order to achieve high accuracy and generalization capability. However, since COVID-19 is a relatively new disease, publicly available datasets are limited in size. To overcome this limitation and improve model performance, data augmentation techniques are applied to artificially increase the size and diversity of the dataset.

In this study, several augmentation strategies are implemented, including random rotation, random noise addition, and horizontal flipping. Random rotation is applied with angles ranging from $-10°$ to $+10°$ to introduce variation in the orientation of the images. Horizontal flipping is used to reverse the pixel columns of the image, which helps the model learn invariant features. Additionally, random noise is introduced to simulate variations that may occur in real-world medical images. Image noising allows the model to learn how to distinguish meaningful patterns from noise, thereby improving its robustness and adaptability to different image conditions.

4.3 Data Pre-processing

Data preprocessing is an essential step in preparing the dataset for machine learning and deep learning models. Since chest X-ray images may have different sizes and resolutions, it is necessary to standardize them before feeding them into the model. During the preprocessing stage, all images are resized and normalized according to the requirements of the classification model. In this study, the original images have varying dimensions; therefore, they are resized to a uniform resolution of 224×224 pixels**.** This standardization ensures compatibility with deep learning architectures and improves computational efficiency during training. Furthermore, normalization is applied to scale the pixel values to a consistent range, which helps improve model convergence and stability during the learning process.

4.4 FEATURE SELECTION
4.4.1 Dragonfly Optimization
The goal of Dragonfly Optimization (DFO), a nature-inspired optimization algorithm, is to solve optimization problems by efficiently and effectively searching the solution space by imitating the foraging behavior of dragonflies, which are nimble predators with effective hunting strategies that combine both exploration (finding new prey locations) and exploitation (concentrating on areas with abundant prey).

Algorithm Steps:
1. **Initialize Dragonflies:** To begin, start by randomly allocating a population of dragonflies, each of which stands for a possible solution**.**
2. **Assess Fitness:** Determine the fitness of each dragonfly's present location in the solution space.
3. **Update Global and Personal Bests:** Update the personal best if a dragonfly's current level of fitness surpasses its prior peak. The global best should be updated if it is superior.
4. **Position Update:** The exploitation-exploration balance determines how each dragonfly modifies its position. The previously mentioned movement equation determines the new position.
5. **Repeat:** Until the halting requirements are satisfied (for example, when the improvement in the global best is negligible), the algorithm iterates for a predetermined number of iterations.
6. **Terminate:** The algorithm comes to an end when the halting condition is met and the optimal answer is given back.

4.4.2 Particle Swarm Optimization
The optimization technique known as Particle Swarm Optimization (PSO) was motivated by the social behavior of fish schools and flocks of birds. Russ Eberhart and James Kennedy created it in 1995. PSO is frequently used to identify the best answers to optimization issues by simulating how animal groups exchange information and communicate while looking for resources or food.

1. **Initialize:** Assign locations and velocities to particles in the solution space at random.
2. **Assess Fitness:** Using the objective function, determine each particle's fitness.
3. **Update Personal Best:** A particle's personal best position should be updated if its current location surpasses it.
4. **Update Global Best:** Adjust the global best position if a particle has a higher fitness than the global best.
5. **Update Velocity:** Adjust each particle's velocity according to its own best position as well as the world's best position.
6. **Update Position:** Add each particle's updated velocity to its existing position to move it.
7. **Termination:** Continue until a stopping condition (convergence or maximum iterations)

is satisfied.

8. **Return Best Solution:** Provide the best position in the world as the ideal answer.

4.4.3 Whale Optimization Algorithm

Based on humpback whales' social interactions and foraging habits, the Whale Optimization Algorithm (WOA) is an optimization algorithm inspired by nature. Like Particle Swarm Optimization (PSO) and Ant Colony Optimization (ACO), it belongs to the family of bio-inspired algorithms and was first presented by Seyedali Mirjalili in 2016. Optimization problems in continuous, discrete, and multi-objective optimization spaces are resolved using the WOA.

Steps:

1. **Initialize Population:** Determine the population size, maximum iterations, and coefficients by randomly generating the locations of whales (solutions).
2. **Assess Fitness:** Using the objective function, determine each whale's position's fitness.
3. **For every iteration, the main loop:**

- ✓ **Update Parameters:** Modify parameters such as aa, AA, and CC to modify the exploration-exploitation balance.
- ✓ **Encircling Prey (Exploitation):** Use a position update algorithm to guide the whale in the direction of the most well-known solution.
- ✓ **Bubble-Net Attacking (Exploration):** To investigate additional regions of the search space, employ a spiral motion.
- ✓ **Update Best Solutions:** If necessary, update the global best solution while keeping track of your own best.

4. **Termination:** Come to an end after the maximum number of iterations or convergence requirements have been met.
5. **Return Solution:** Provide the best position in the world as the ideal answer.

4.4.4 Optimized Whale Optimization Algorithm

The Whale Optimization Algorithm is a nature-inspired metaheuristic optimization technique introduced by Mirjalili in 2016. It is based on the bubble-net hunting strategy of humpback whales, where whales surround and capture their prey through spiral movements. In optimization problems, WOA simulates this hunting behavior to search for the optimal solution within a defined search space. However, the traditional WOA may suffer from limitations such as slow convergence and the possibility of getting trapped in local optima. To overcome these limitations, this research proposes an Optimized Whale Optimization Algorithm (OWOA) to enhance feature selection performance in the COVID-19 classification framework.

The Optimized Whale Optimization Algorithm (OWOA) improves the exploration and exploitation capabilities of the original WOA by refining the search mechanism used to update whale positions. In this method, candidate solutions represent feature subsets extracted from chest X-ray images. The algorithm iteratively evaluates these subsets using a fitness function based on classification performance. During the optimization process, whales update their positions by encircling the best solution, performing spiral movements, and exploring new regions of the search space to identify the optimal feature combination.

The optimized algorithm helps eliminate redundant or irrelevant features while selecting the most informative features that contribute significantly to the classification process. By integrating the Optimized Whale Optimization Algorithm with the Q-Learning based reinforcement learning classifier, the proposed model achieves improved accuracy, faster convergence, and better generalization capability. As a result, the optimized algorithm plays a crucial role in enhancing the efficiency of the COVID-19 detection system using chest X-ray images.

- Initialize a population of whales randomly in the search space. Each whale represents a possible solution (feature subset).
- Evaluate the fitness of each whale using a fitness function based on classification performance.
- Identify the best whale (optimal solution) with the highest fitness value.
- Update the control parameters and adjust the positions of whales based on encircling prey, spiral movement, and random search.
- Recalculate the fitness of the updated whale positions and update the best solution if a better result is found.
- Repeat the updating process until the maximum number of iterations is reached.
- Output the best solution, which represents the optimal set of selected features for classification.

4.5 CLASSIFICATION

Reinforcement learning (RL) isn't typically used for classification, but it can be applied in certain scenarios, such as sequential decision-making tasks. In RL, an agent interacts with an environment and learns to take actions that maximize cumulative rewards. In a classification context, class labels can be treated as actions, and the agent learns to select the correct class based on input features. The reward signal could reflect whether the classification is correct or not. RL may also be useful in adaptive settings, like when dealing with changing data distributions or feature selection, though it’s less common compared to traditional supervised learning.

4.5.1 Q-Learning

Q-learning is a model-free reinforcement learning algorithm used to find the optimal action-selection policy for a given environment. It enables an agent to learn how to behave by interacting with its environment and receiving rewards or penalties for its actions. The key idea behind Q-learning is to estimate the Q-value (quality) for each action in each state, which represents the expected future rewards an agent can get by taking that action in that state and following the optimal policy thereafter.

Here's a simplified explanation of how Q-learning works:

- **Initialize Q-values**: Initialize a Q-table with arbitrary values (usually zeros), where each entry represents a state-action pair (Q(s, a)).
- **Interact with the Environment**: The agent chooses an action based on the current Q-values, often using an epsilon-greedy strategy (selecting the action with the highest Q-value most of the time but occasionally choosing a random action to explore new possibilities).

- **Update Q-values**: After taking an action and receiving a reward, the agent updates the Q-value for that state-action pair using the Bellman equation:

$$Q(s,a) \leftarrow Q(s,a) + \alpha \left[r + \gamma \max_{a'} Q(s',a') - Q(s,a) \right]$$

Where:

- Q(s,a) is the current Q-value of the state-action pair.
- α is the learning rate (controls how much new information is considered).
- r is the immediate reward received after taking action an in states.
- γ is the discount factor (how much future rewards are considered).
- Max a′Q(s′,a′) is the maximum Q-value of the next state's′.
- Repeat: The process continues as the agent explores and exploits its environment, gradually improving its Q-values until they converge to the optimal policy.

5. PERFORMANCE METRICS

(i) Accuracy

It is most common performance metric for classification algorithms. It may be defined as the number of correct predictions made as a ratio of all predictions made. We can easily calculate it by confusion matrix with the help of following formula:

$$Accuracy = \frac{TP + TN}{TP + FP + FN + TN}$$

(ii) Sensitivity

Recall may be defined as the number of positives returned by our ML model. We can easily calculate it by confusion matrix with the help of following formula –

$$\text{Sensitivity} = \frac{\text{True Positives}}{\text{True Positives} + \text{False Negatives}}$$

(iii) Specificity

Specificity, in contrast to recall, may be defined as the number of negatives returned by our ML model. We can easily calculate it by confusion matrix with the help of following formula –

$$\text{Specificity} = \frac{\text{True Negatives}}{\text{True Negatives} + \text{False Positives}}$$

(iv) F Measure

The F-measure is calculated as the harmonic mean of precision and recall, giving each the same weighting. It allows a model to be evaluated taking both the precision and recall into account using a single score, which is helpful when describing the performance of the model and in comparing models

$$F\text{ - }measure = \frac{2 * \text{Recall} * \text{Precision}}{\text{Recall} + \text{Precision}}$$

(v) AUC

AUC (Area Under the Curve) is a performance evaluation metric used to measure the effectiveness of a classification model. It represents the area under the Receiver Operating Characteristic (ROC) curve, which plots the True Positive Rate (TPR) against the False Positive Rate (FPR) at different threshold values.

(vi) Error Rate

The error rate measures the proportion of incorrect predictions made by the model.

$$\text{Error Rate} = \frac{\text{Number of Incorrect Predictions}}{\text{Total Number of Predictions}} = 1 - \text{Accuracy}$$

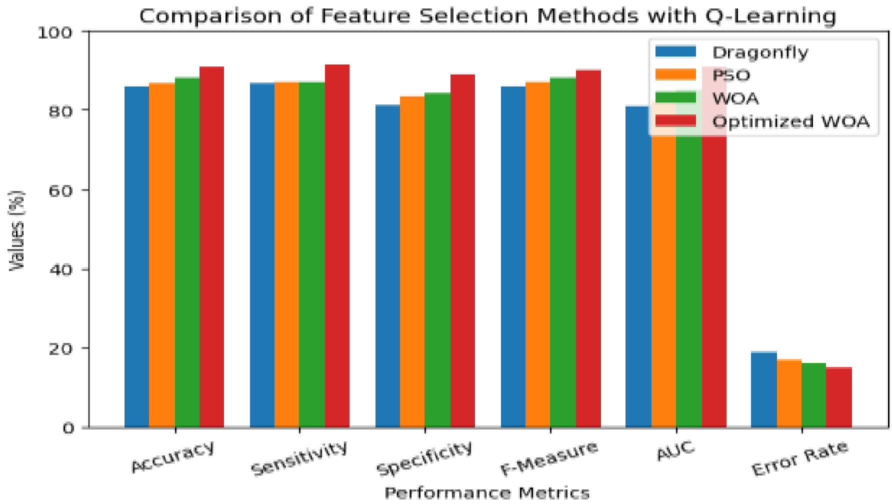
6. RESULTS AND DISCUSSION

In this research applied Optimized Whale Optimization algorithm using Q-Learning to classify COVID-19 from COVID-19 and normal.

Table.1 - Performance metrics for Q-Learning using various Feature Selection Methods

Feature Selection Method	Classification Method	Accuracy	Sensitivity	Specificity	F Measure	AUC	Error Rate
Dragonfly Optimization	Q-Learning	85.81	86.81	81.28	86.05	81	18.82
Particle Swarm Optimization	Q-Learning	86.72	86.92	83.38	87.15	82	16.81
Whales Optimization	Q-Learning	88.10	87.12	84.18	88.25	85	16.11
Optimized Whales Optimization	Q-Learning	90.89	91.59	89.08	90.05	91	14.81

Fig.1 – Graphical representation for Comparison of Feature Selection with Q-Learning



7. CONCLUSION

Based on the experimental analysis and detailed investigation, several important issues related to COVID-19 detection using chest X-ray images were examined in this study. One of the major challenges identified is the limited availability of publicly accessible COVID-19 X-ray datasets. Most available datasets contain a relatively small number of images, which makes the training and feature extraction process more difficult for machine learning models. The small sample size may also affect the generalization capability of the classification models. To address this challenge, appropriate preprocessing and feature selection techniques were applied to improve the effectiveness of the learning process.

Furthermore, a comparative analysis of three reinforcement learning-based classification models was conducted to determine the most effective approach for COVID-19 detection. Among the evaluated models, the Q-Learning based reinforcement learning model demonstrated superior performance compared with the other models. The evaluation of these models was carried out using several performance metrics, including Accuracy, Sensitivity, Specificity, F-Measure, AUC, and Error Rate. The experimental results indicate that all models achieved satisfactory performance in classifying COVID-19 and normal cases.

The proposed framework, which integrates Optimized Whale Optimization Algorithm (OWOA) for feature selection with Q-Learning for classification, achieved the highest accuracy of 90.89%. This demonstrates the effectiveness of the optimized feature selection method in improving the performance of the classification model. In future work, the research can be extended by developing a hybrid multimodal reinforcement learning framework that incorporates multiple medical data sources, such as CT scans, clinical data, and laboratory results, to further enhance the accuracy and reliability of COVID-19 classification systems.

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