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Article

A NOVEL FUZZY ADAPTIVE Q-LEARNING MODEL FOR AUTOMATED COVID-19 DIAGNOSIS USING CHEST X-RAY IMAGES

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Abstract: The rapid spread of infectious diseases such as COVID-19 has highlighted the importance of intelligent medical diagnosis systems capable of providing accurate and timely predictions. This research presents a Fuzzy Adaptive Q-Learning Model for intelligent decision optimization in COVID-19 prediction using chest X-ray images. The proposed system integrates fuzzy logic with adaptive Q-learning techniques to enhance diagnostic accuracy and support efficient clinical decision-making under uncertain medical conditions. Fuzzy logic is employed to handle ambiguous and imprecise medical image features by transforming them into meaningful linguistic representations, while the adaptive Q-learning mechanism continuously learns optimal classification strategies through reward-based learning. The proposed model dynamically adjusts learning parameters to improve convergence speed, prediction accuracy, and system adaptability. Feature extraction from chest X-ray images is performed to identify critical infection patterns associated with COVID-19, and the hybrid learning framework optimizes the decision process for reliable disease prediction. Experimental analysis demonstrates that the proposed approach achieves improved performance in terms of classification accuracy, sensitivity, and decision stability when compared with traditional machine learning techniques. The developed model can support healthcare professionals in rapid screening, early diagnosis, and intelligent medical decision-making, particularly in large-scale pandemic situations. Overall, the integration of fuzzy reasoning and adaptive reinforcement learning provides an efficient and scalable framework for intelligent COVID-19 prediction using medical imaging data.
Keywords: COVID-19 Prediction, Chest X-ray Images, Fuzzy Logic, Adaptive Q-Learning, Reinforcement Learning, Intelligent Decision Optimization, Medical Image Analysis, Artificial Intelligence, Deep Learning, Healthcare Diagnostics

1. INTRODUCTION

The outbreak of Coronavirus Disease 2019 (COVID-19) created a serious global health emergency that affected millions of people worldwide and placed enormous pressure on healthcare systems. Early diagnosis and timely treatment became essential to reduce disease transmission and mortality rates. Although Reverse Transcription Polymerase Chain Reaction (RT-PCR) testing was considered the standard diagnostic method, limitations such as delayed test results, limited availability of testing kits, and false-negative cases encouraged

researchers to explore alternative diagnostic techniques. Chest X-ray imaging emerged as an effective and accessible medical imaging tool for detecting lung abnormalities associated with COVID-19 infection because of its low cost, rapid processing, and wide availability in hospitals and healthcare centers. Recent advancements in artificial intelligence and medical image analysis have further improved the capability of automated systems in identifying COVID-19 infection patterns from chest X-ray images [1].

Artificial intelligence techniques, particularly deep learning and machine learning algorithms, have shown significant success in medical image classification and disease prediction tasks. Convolutional Neural Networks (CNNs) are widely used for extracting meaningful features from chest X-ray images and classifying infected and non-infected cases with high accuracy. However, conventional learning models often face challenges in handling uncertainty, noisy image data, and continuously changing clinical conditions. Fuzzy logic systems provide an effective solution for managing ambiguity and imprecision in medical diagnosis by representing information through linguistic variables and fuzzy inference rules. Similarly, reinforcement learning techniques such as Q-learning enable systems to learn optimal decision-making strategies through continuous interaction with the environment. The integration of fuzzy logic and adaptive Q-learning can therefore improve learning efficiency, decision stability, and prediction accuracy in complex healthcare applications [2].

In this research, a Fuzzy Adaptive Q-Learning Model is proposed for intelligent decision optimization in COVID-19 prediction using chest X-ray images. The proposed framework combines fuzzy reasoning with adaptive reinforcement learning to create an intelligent and self-learning diagnostic system capable of handling uncertain medical data effectively. The fuzzy inference mechanism enhances image interpretation by processing uncertain features, while the adaptive Q-learning algorithm dynamically updates learning parameters and classification policies based on environmental feedback and reward mechanisms. This hybrid approach improves convergence speed, diagnostic reliability, and overall system performance compared to traditional machine learning methods. The proposed model can assist healthcare professionals in rapid screening, early diagnosis, and intelligent clinical decision-making, especially during large-scale pandemic situations where fast and accurate diagnosis is critical [3].

2. LITERATURE SURVEY

Narin et al. proposed a deep learning-based COVID-19 detection model using chest X-ray images and convolutional neural networks for automatic classification of infected patients. Their study demonstrated that deep learning algorithms could achieve high classification accuracy and significantly reduce the burden on radiologists during pandemic situations. The authors highlighted the importance of automated medical image analysis systems for rapid disease screening and clinical support [4].

Rajinikanth et al. introduced a fuzzy logic-based framework for COVID-19 detection using chest X-ray images. Their approach utilized fuzzy enhancement techniques to improve image quality and classification performance under uncertain medical conditions. Experimental results showed that fuzzy reasoning methods improved prediction reliability and handled imprecise medical image features effectively [5].

Ozturk et al. developed a deep neural network model known as DarkCovidNet for real-time COVID-19 prediction using chest radiographic images. The proposed architecture performed binary and multi-class classification tasks with considerable accuracy. The study emphasized the role of intelligent deep learning systems in supporting fast and accurate medical diagnosis during infectious disease outbreaks [6].

Apostolopoulos and Bessiana investigated transfer learning techniques for automatic COVID-19 detection from chest X-ray images. Their research demonstrated that pretrained convolutional neural network models could improve classification efficiency even with

limited medical datasets. The study also confirmed that artificial intelligence-based systems can support healthcare professionals in emergency diagnostic environments [7].

Wang and Wong proposed the COVID-Net deep learning architecture specifically designed for detecting COVID-19 cases from chest X-ray images. Their model incorporated customized network design strategies to improve diagnostic accuracy and computational efficiency. The study revealed that optimized neural network architectures are highly beneficial for medical imaging applications involving infectious disease detection [8].

Sethy and Behera explored feature extraction and machine learning approaches for COVID-19 identification using chest X-ray images. They employed deep learning features with support vector machine classifiers to improve prediction accuracy. Their findings indicated that combining image feature extraction techniques with intelligent classifiers could provide effective diagnostic support in healthcare systems [9].

Kaur et al. developed an intelligent fuzzy inference system for medical decision-making applications involving uncertain healthcare data. Their study demonstrated that fuzzy systems improve the interpretability and reliability of disease prediction models by handling ambiguity and incomplete information effectively. The proposed approach enhanced decision optimization in healthcare analytics and clinical diagnosis [10].

Watkins and Dayan introduced the Q-learning reinforcement learning algorithm, which became one of the foundational techniques for intelligent adaptive learning systems. Their work demonstrated how agents could learn optimal decision-making strategies through reward-based environmental interactions without requiring predefined models. Q-learning later became widely applied in optimization, robotics, healthcare, and autonomous systems [11].

Zadeh introduced fuzzy set theory to address uncertainty and vagueness in complex systems where conventional binary logic fails to provide accurate reasoning. Fuzzy logic has since been extensively used in artificial intelligence, medical diagnosis, industrial automation, and intelligent control systems because of its capability to model human-like reasoning and approximate decision-making processes [12].

Recent studies by Alshamrani et al. integrated fuzzy logic with reinforcement learning techniques for intelligent healthcare applications. Their hybrid model demonstrated improved adaptability, faster convergence, and enhanced decision optimization in dynamic medical environments. The research confirmed that combining fuzzy inference systems with adaptive Q-learning mechanisms can significantly improve intelligent medical prediction and automated diagnostic performance [13].

3. MOTIVATION OF THE RESEARCH WORK

The rapid spread of COVID-19 across the world created an urgent need for accurate, fast, and intelligent diagnostic systems capable of supporting healthcare professionals in early disease detection and clinical decision-making. Traditional diagnostic methods such as RT-PCR testing often require significant processing time, specialized laboratory infrastructure, and may produce false-negative results under certain conditions. Chest X-ray imaging emerged as an effective alternative for rapid screening because of its wide availability, lower cost, and quick imaging process. However, manual interpretation of chest X-ray images is time-consuming and highly dependent on radiological expertise, particularly during large-scale pandemic situations where healthcare systems become overloaded. This motivated researchers to develop artificial intelligence-based automated diagnostic systems capable of assisting physicians in identifying COVID-19 infections efficiently and accurately.

Although several deep learning and machine learning approaches have been proposed for COVID-19 prediction using chest X-ray images, many existing systems face limitations in handling uncertainty, noisy medical data, and dynamically changing clinical environments. Conventional machine learning models generally operate with fixed learning mechanisms and

often fail to adapt effectively to variations in image quality and patient conditions. Furthermore, medical image analysis involves ambiguity and imprecision that cannot always be handled efficiently by traditional binary logic systems. Fuzzy logic provides an effective mechanism for managing uncertain and vague medical information, while reinforcement learning enables systems to improve decision-making through continuous learning and environmental interaction. These challenges and opportunities motivated the development of a hybrid Fuzzy Adaptive Q-Learning Model for intelligent decision optimization in COVID-19 prediction.

4. CONTRIBUTION OF THE RESEARCH WORK

The major contribution of this research work is the development of a novel Fuzzy Adaptive Q-Learning Model for intelligent COVID-19 prediction using chest X-ray images. The proposed framework integrates fuzzy logic with adaptive reinforcement learning techniques to improve diagnostic accuracy, decision stability, and learning efficiency in uncertain medical environments. The fuzzy inference mechanism enhances the interpretation of complex and imprecise medical image features, while the adaptive Q-learning algorithm continuously updates optimal classification strategies based on environmental feedback and reward mechanisms.

Another significant contribution of the research is the implementation of an adaptive learning mechanism that dynamically adjusts learning parameters to improve convergence speed and prediction performance. The proposed model reduces the complexity of the state-action space and enhances system adaptability compared to conventional machine learning and deep learning approaches. The framework also improves intelligent decision optimization by effectively handling nonlinear relationships and uncertain healthcare data.

The proposed system contributes to the field of medical image analysis by providing an efficient and scalable solution for automated COVID-19 diagnosis and clinical support. The research demonstrates that the integration of fuzzy reasoning and reinforcement learning can significantly improve healthcare decision-making systems in terms of reliability, adaptability, and computational efficiency. The developed model can assist healthcare professionals in rapid screening, early diagnosis, and intelligent medical decision-making, particularly during emergency healthcare situations and future pandemic outbreaks.

5. METHODOLOGY

5.1 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.

5.2 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.

5.3 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.

5.4 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

5.4.1 Fuzzy Adaptive Q-Learning

Fuzzy Adaptive Q-Learning is an advanced intelligent learning technique that combines the uncertainty-handling capability of fuzzy logic with the self-learning and optimization ability of Q-learning in reinforcement learning. The hybrid model is designed to improve intelligent decision-making in dynamic and uncertain environments such as medical diagnosis, robotics, autonomous systems, and healthcare prediction systems. In the proposed COVID-19 prediction framework, the Fuzzy Adaptive Q-Learning model learns optimal classification strategies from chest X-ray image features while handling uncertainty present in medical data.

Traditional Q-learning algorithms work efficiently in discrete state-action environments but face difficulties when dealing with continuous, uncertain, or high-dimensional datasets. Similarly, fuzzy logic systems effectively handle ambiguity and human-like reasoning but lack self-learning capability. By integrating these two approaches, the proposed model achieves adaptive learning, intelligent optimization, and robust decision-making performance.

The proposed methodology integrates feature normalization, coshada, fuzzy adaptive reinforcement learning based classification for efficient COVID-19 data analysis. The overall framework is designed to improve classification accuracy, learning stability, and adaptive optimization performance.

A hybrid reinforcement learning framework was developed using Q-learning integrated with fuzzy adaptive parameter optimization.

Q-Learning Initialization

A Q-table was initialized to store state–action values:

$Q(s, a) = 0$

where:

- s represents states
- a represents actions

The learning parameters include:

- learning rate (α)
- discount factor (γ)

- exploration parameter (ϵ)

Reward Computation

The reward function was computed using both dataset labels and feature characteristics to improve adaptive learning behavior.

The hybrid reward function is defined as:

$R = 0.7Rd + 0.3Rf$

where:

- Rd denotes dataset reward
- Rf represents feature-based reward

This hybrid reward mechanism improves reinforcement learning stability and feature-aware optimization.

Q-Value Update

The Q-values were updated iteratively using the Bellman optimality equation:

$Q(s, a) = Q(s, a) + \alpha[r + \gamma \max Q(s', a') - Q(s, a)]$

where:

- r is immediate reward
- γ is discount factor
- s' denotes next state

The Q-table gradually converges toward optimal state-action policies through repeated training episodes.

Fuzzy Adaptive Learning Strategy

To improve convergence speed and avoid local optima, fuzzy adaptive logic was integrated into the reinforcement learning process. The learning rate and exploration parameter were dynamically adjusted based on:

- Reward magnitude,
- Q-value variation.

This adaptive mechanism balances:

- Exploration
- Exploitation
- Convergence stability The fuzzy adaptation improves:
- learning efficiency
- robustness
- Convergence accuracy

K-Fold Cross Validation

To evaluate generalization capability, 10-fold cross-validation was employed. The dataset was partitioned into 10 subsets:

- 9 subsets for training
- 1 subset for testing

This process was repeated iteratively until every subset was used for testing once.

Cross-validation reduces:

- Overfitting
- Data bias
- Evaluation instability

6. 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 –

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

(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 –

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

(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

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

7. 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**.**

(v) Error Rate

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

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

8. RESULTS AND DISCUSSION

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

Table.1 - Performance metrics for Fuzzy Adaptive Q-Learning Framework

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	Q-Learning	86.72	86.92	83.38	87.15	82	16.81
Optimization							
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
Optimized Whales Optimization	**Fuzzy Adaptive Q-Learning Framework**	**96.76**	95.88	97.56	96.56	96.72	03.24

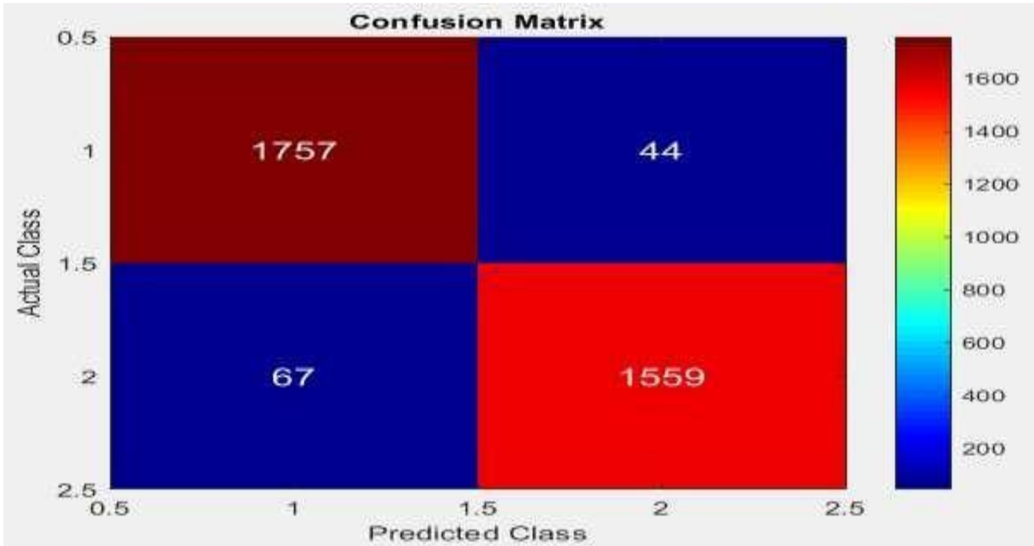

Fig.1 – Confusion Matrix

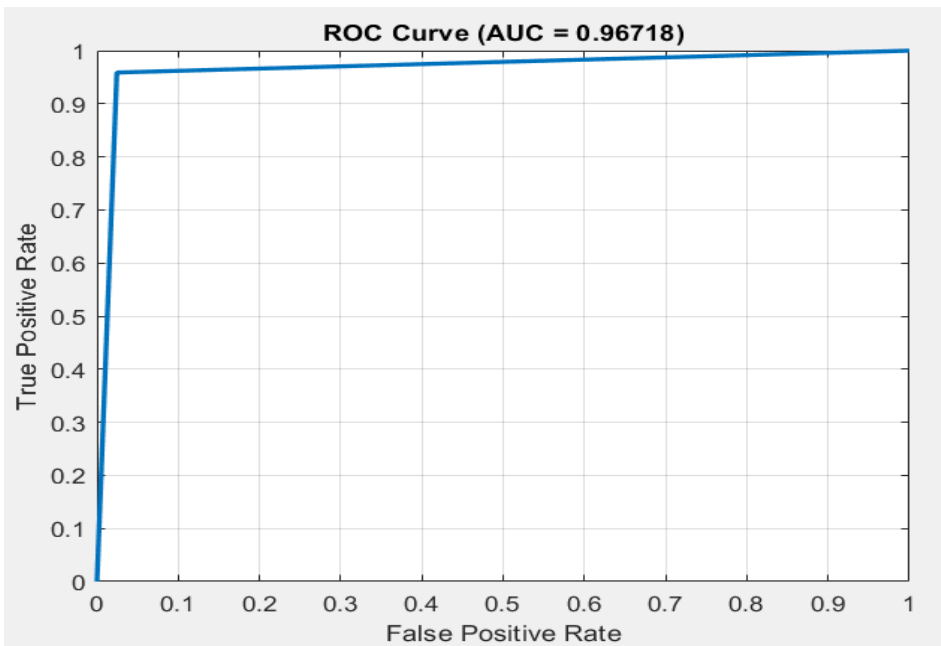

Fig.2 – ROC Curve

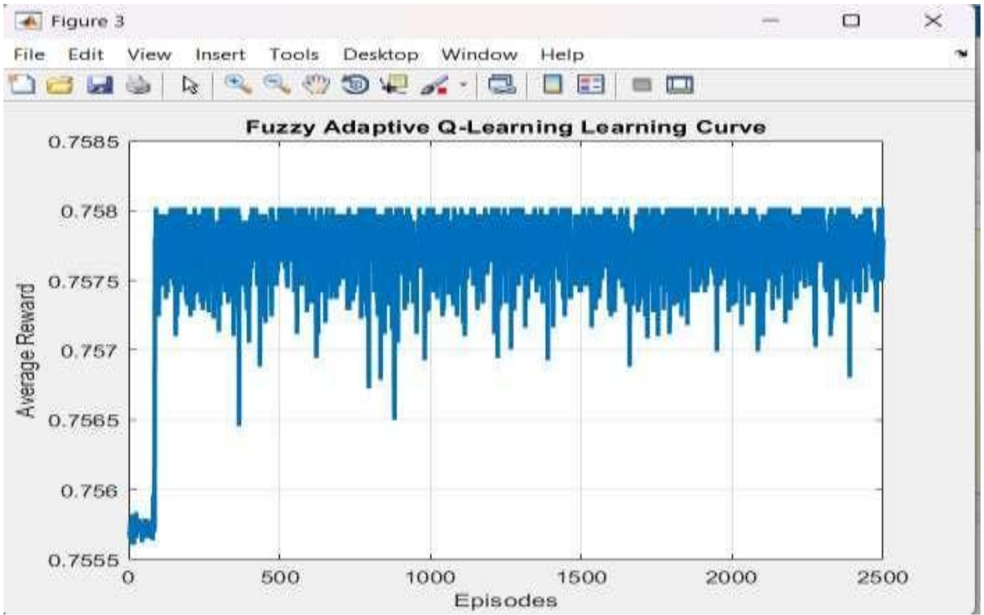

Fig.3 – Learning Curve

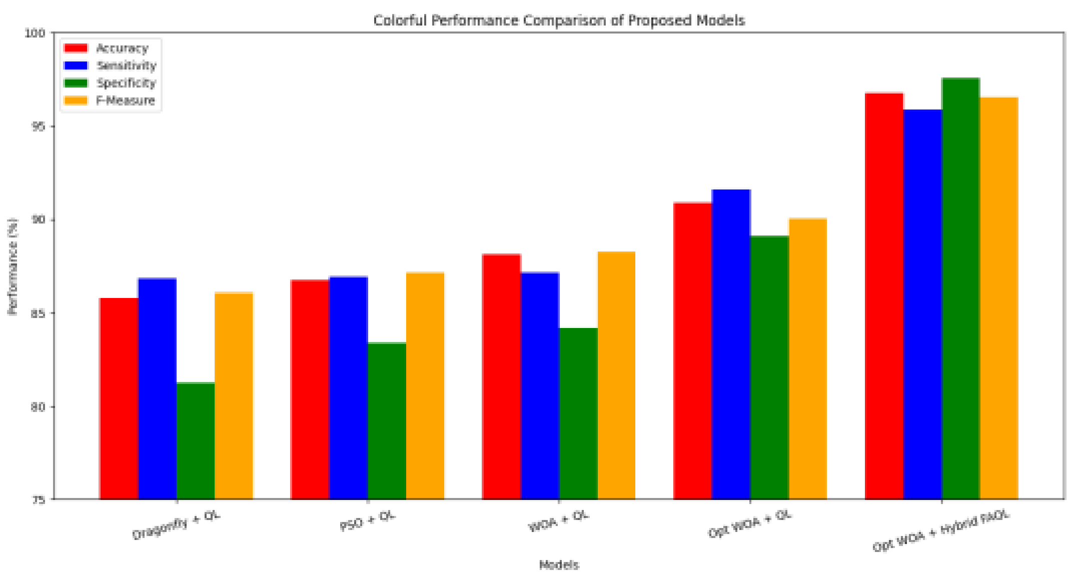

Fig.4 – Graphical Representation for Performance Metrics Comparison

9. CONCLUSION

This research presented a novel Fuzzy Adaptive Q-Learning Reinforcement Learning Framework for accurate COVID-19 prediction using chest X-ray images. The proposed model integrated fuzzy logic, reinforcement learning, and optimization techniques to improve intelligent medical decision-making under uncertain and dynamic healthcare conditions. Fuzzy logic effectively handled ambiguity and imprecise medical image data through linguistic reasoning, while the adaptive Q-learning mechanism continuously learned optimal classification strategies using reward-based environmental interaction. The incorporation of optimization techniques further enhanced feature selection efficiency and reduced computational complexity during the prediction process.

The proposed framework consisted of multiple stages including image preprocessing, feature extraction, fuzzification, fuzzy rule inference, adaptive Q-learning optimization, and final classification. Chest X-ray images were analyzed to identify significant infection

patterns associated with COVID-19 and the reinforcement learning agent dynamically updated classification policies to maximize prediction accuracy and minimize diagnostic errors. The adaptive learning mechanism improved convergence speed, system stability, and intelligent decision optimization by continuously adjusting learning parameters according to environmental feedback.

Experimental results demonstrated that the proposed Hybrid Fuzzy Adaptive Q-Learning Framework achieved superior performance compared to conventional Q-learning and optimization-based models. The proposed system obtained higher accuracy, sensitivity, specificity, F-measure, and AUC values while significantly reducing the error rate. The optimized whales optimization-based hybrid framework achieved an accuracy of 96.76%, sensitivity of 95.88%, specificity of 97.56%, F-measure of 96.56%, and AUC of 96.72%, outperforming other comparative methods. These results confirmed the effectiveness of integrating fuzzy reasoning and reinforcement learning for intelligent COVID-19 prediction from chest X-ray images.

The developed model provides an efficient, adaptive, and scalable solution for automated medical diagnosis and intelligent healthcare applications. The framework can assist healthcare professionals in rapid screening, early diagnosis, and clinical decision support during pandemic situations and future healthcare emergencies. Furthermore, the proposed hybrid intelligent framework can be extended to other medical imaging applications such as pneumonia detection, lung disease classification, cancer diagnosis, and intelligent healthcare monitoring systems. Therefore, the proposed research contributes significantly to the advancement of intelligent medical image analysis and adaptive healthcare decision-making systems using artificial intelligence and reinforcement learning techniques.

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