

Detecting Pneumonia Based On Chest X-Ray Images Using Reinforcement Learning

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Abstract—While early detection of diseases helps in managing and improving patient outcomes, most detection methods employed today are largely manual, costly, and time-consuming. Accordingly, computer-aided diagnosis is emerging as an innovative solution to improving the accuracy of detection by eliminating human errors and lowering the cost of diagnosis. One of the diseases that can benefit immensely from computer-aided diagnosis is pneumonia, which is an acute pulmonary infection accounting for thousands of hospitalizations and deaths globally. Current pneumonia detection approaches entail manually examining radiology images such as X-rays. Because of subjective variability, the outcomes of the examination are not always accurate. As a result, researchers have started to develop models based on machine learning to aid in detecting pneumonia based on chest X-ray images. Most of the models developed are based on deep learning, especially convolutional neural networks. However, these models require vast data sets for training and their accuracy values can be improved. For that reason, this paper developed a detection model based on Reinforcement Learning (RL) with convolutional neural network (CNN). The chest X-ray images of pneumonia is a data set that is used for the experiments. The obtained results confirm that applying the RL model is a good choice for detecting pneumonia. The efficacy of these model's performance was evaluated by measuring the precision, recall, F1-score, accuracy, and confusion matrix.

Index Terms—Pneumonia; Detection; Reinforcement learning; CNN; Deep learning

I. INTRODUCTION

Early disease detection is an essential goal in health care as it allows the implementation of appropriate interventions to improve patient outcomes. The management of pneumonia, which is an acute pulmonary infection due to fungi, bacteria, and viruses, is dependent largely on early detection. Pneumonia is a leading cause of hospitalization in the U.S., responsible for more than 400,000 emergency unit visits and 800,000 hospitalizations as in 2014 [1]. Worldwide, more than one hundred and fifty million people suffer from pneumonia annually [2]. The most affected demographic is children below the age of five. Additionally, people living in developing nations are disproportionately affected mainly due to environmental risk factors such as pollution and poor hygiene [3]. The challenge is compounded by the lack of adequate health care workers to diagnose the disease and treat it in a timely way.

Generally, radiological exams are utilized to diagnose pneumonia with X-rays being the commonly used since they

are inexpensive and non-invasive [4]. However, using X-rays to diagnose pneumonia can be inaccurate because of subjective variability [3]. Differences in the level of expertise, personal factors, and environmental conditions routinely affect the accuracy of radiologists to detect pneumonia precisely. Accordingly, the usage of automated tools to detect pneumonia accurately and in a timely manner is key.

Computer-aided disease diagnosis by leveraging machine learning has become popular in recent years. In addition to helping to increase the accuracy of detection, the use of computer-aided tools addresses the problem of inadequate health care workers. Specifically, deep learning techniques are the most preferred machine learning approaches in pneumonia detection. Deep learning uses multi-layered artificial neural networks to solve problems in the areas of natural language processing and image classification [5]. Deep learning differs from conventional machine learning approaches in that it can learn representations from data automatically without direct human intervention or manually coded rules. Its architecture is also highly flexible hence the possibility of learning from data instantly and improving the prediction accuracy with more experience [5].

The convolutional neural network (CNN), which is a type of deep learning technique, is the most commonly utilized method for image classification [6]. Likewise, CNN is applied to pneumonia detection problems due to its superiority in classifying images [7]. However, CNNs and other deep learning methods require large amounts of data to function optimally [3]. This aspect is challenging in biomedical settings as access to large volumes of data tends to be difficult. Moreover, collecting and labeling data is time-consuming and expensive.

In addition to deep learning, researchers have started experimenting with reinforcement learning. Whereas deep learning is based on training an algorithm using data and then applying it to a problem, reinforcement learning enables dynamic learning by altering actions according to continuous feedback to enhance rewards [8]. Based on this method of operation, it is postulated that reinforcement learning can perform better in computer-aided diagnostics than in neural networks. Indeed, various studies demonstrate the potential benefits of reinforcement learning in diagnostics [9], [10].

Likewise, this paper intends to develop a novel approach for

detecting pneumonia using images of chest X-rays by leveraging reinforcement learning. Reinforcement learning addresses sequential tasks through the recognition of the foundational dynamics of an environment and shaping it by choosing actions aimed at optimizing rewards over time, which are key elements in diagnosis. The novel approach will be evaluated using a data set obtained from Ayan et al. [11], and the accuracy of detection will be compared with the results of the same paper. The results will help in demonstrating the improved accuracy in using reinforcement learning over deep learning in pneumonia detection using chest X-ray images.

This paper is organized into five sections following the introduction. The related work is discussed in Section II. In Section III, the methodology is detailed including the background of reinforcement learning, AIGym and CNN as well as the proposed approach. The experiments and results are illustrated in Section IV, where the results are obtained from the RL model and the comparison with previous work [11] are provided. Section V summarizes the paper and presents the paper's findings.

II. RELATED WORK

The problem of detecting pneumonia using images of chest X-rays has been an area of interest in the recent past [12]. While the area is promising as it would enable the provision of quality health care services, the lack of accurate detection methods combined with the scarcity of data sets have been challenging elements. Nevertheless, significant advancements have been attained. To start with, conventional machine learning methods have been applied to pneumonia detection and positive outcomes have been achieved. For instance, Chandra and Verma segmented regions within the lung based on chest X-ray images and extracted various features, which were then utilized in the classification process [13]. After applying various traditional classifiers, the authors observed a 95.4% accuracy when the multi-layer perception (MLP) was used to detect pneumonia [13]. In another study, researchers obtained a 94.5% accuracy when a decision-tree classifier was implemented to detect pneumonia among schizophrenia patients [14]. Although these studies attained high accuracy levels, their generalizability is low as the data sets utilized were of a small sample size.

Traditional methods of machine learning are challenging as they require one to handcraft features and then select them for segmentation or classification [15], [16]. Consequently, there was a need to develop end-to-end classification algorithms. To do so, deep learning methods have emerged as they support the automatic extraction of informative and relevant features from the input to enable classification [17], [18]. CNNs, which are types of deep learning methods, have gained popularity in image classification and imaging. Sharma et al. [19] developed a CNN architecture for classifying chest X-ray images to detect pneumonia and leveraged data augmentation to compensate for data scarcity. Based on the findings, the CNN model attained around 90% accuracy [19] on the Kermany data set [20].

Rajpurkar et al. developed an algorithm called Chexnet based on CNN to detect pneumonia and obtained a classification score of 76.8% for f1 [21]. A key reason for this poor score was the unavailability of the adequate amount of data.

Some studies have focused on addressing the issue of data scarcity in medical classification problems. To do so, the practice of transfer learning has emerged, which encompasses using knowledge obtained from a big data set to tune a model [22]–[24]. Shah et al. also demonstrated an improvement in detection accuracy when transfer learning was combined with deep learning (CNN) [24]. The overarching finding is that transfer learning can help in improving accuracy by leveraging knowledge obtained from other data sets.

Most deep learning methods only rely on a single model. However, in the recent past, ensemble models have emerged, which combine two or more classifiers, to enhance performance. The method of operation of ensemble learning is that it enters the input into multiple classifiers and the various outputs are combined to support decision-making. In other words, they incorporate the salient features of the base model and capture supporting information from the other classifiers to improve the robustness of the decision [25], [26].

Jaiswal et al. utilized a mask region-based CNN for detecting pneumonia and incorporated other models, specifically, ResNet-101 and ResNet-50, into the algorithm [25]. Also, Gabruseva et al. developed a deep learning model based on an ensemble involving a number of checkpoints during the training process for a single-shot detector for pulmonary opacity and realized exemplary precision [26]. Kundu et al. developed an ensemble model and applied it to CT scans for diagnosing COVID-19 and achieved state-of-the-art performance [27]. Although this study did not focus on pneumonia, it demonstrated the potential associated with using ensemble models in classification problems.

Besides deep learning, reinforcement learning is also emerging as an important tool in medical diagnosis. Reinforcement learning is a goal-oriented approach in which an agent examines data within a given setting, derives rules for making decisions, and maximizes long-term rewards [28]. It entails having an agent that receives feedback about performance and then utilizing it to improve subsequent performance through trial and error [28]. Within the radiology realm, the application of reinforcement learning has not become a reality despite its immense potential [29]. This gap in literature requires further examination and hence this is the reason for this study. In addition to developing a model to detect pneumonia using reinforcement learning on chest X-ray images, the paper intends to examine the performance of this model with a deep learning model.

III. METHODOLOGY

This section provides the background on reinforcement learning, Open AIGym, CNN, and the proposed approach used.

A. Background of Reinforcement Learning (RL)

Reinforcement learning (RL) denotes a general approach to solving reward-based problems [30], [31]. This system attempts to mimic how humans learn novel things from interacting with the environment, as exemplified by cases, such as driving a car, managing an investment portfolio, flying stunt maneuvers in a helicopter, controlling a power station, and making a humanoid robot walk [30]. While RL represents how machines learn to realize the goal by interacting with the environment, it serves as a mathematical tool for sequential decision-making and control problems [32]. Moreover, it is among the types of machine learning widely used in economics, mathematics, psychology, neuroscience, and engineering. RL is critical in classification in machine learning since, through its algorithms, an agent can learn an optimal behavior when allowing it to interact with some unidentified environment and learn from its obtained rewards [33].

Mathematical foundations form the basis for constructing RL, where the Markov Decision Process (MDP) marks the critical component by providing a formulation of the environment, whereas value iteration and policy iteration aid in the identification of the optimal policy [30].

A sequence of states is only considered a Markov process if the probability of moving to the subsequent state S_{t+1} depends on the current state S_t and not on the previous states, such as S_{t-1} [32]. Thus, a Markov Process denotes a tuple (S, P) , where S and P represent a finite set of states and a state transition probability, respectively as in Equation (1) [30].

$$P_{ss'=P[S_{t+1}=s'|S_t=s]}(1)$$

The Markov Process advances to MDP, a tuple (S, A, P, Y, R) denoting a finite set of states, a finite set of actions, the state transition probability matrix ($P_{ss'=P[S_{t+1}=s'|S_t, A_t = a]}$), the discount factor ($[0, 1]$), and a reward function ($S * A$), respectively.

The MDP dynamic could be represented as: $(s_0 \xrightarrow{a_0} s_1 \xrightarrow{a_1} s_2 \xrightarrow{a_2} s_3 \xrightarrow{a_3} \dots)$ [30]. It begins in a state s_0 , and upon the selection of some actions, A , to be taken in the MDP, a random transition of the MDP to some successor state s_1 , obtained from $P_{s_0s_1}^{a_0}$ becomes evident. The process is continuous; hence, representing sequential decision making.

Another equation, return and policy, entails choosing actions over time to maximize the expected return value, where the return G_t exhibits the sum discounted reward from time step t as in Equation (2) [30].

$$G_t = R_{t+1} + \gamma R_{t+2} + \dots + \sum_{n=0}^{\infty} \gamma^n R_{t+n+1} \quad (2)$$

Further to the return function, the action-value and the state-value functions are introduced to facilitate the identification of the optimal policy. The state value function is denoted as $V_{\pi}(s) = E_{\pi}[G_t | S_t = s]$, whereas the latter is defined as $q_{\pi}(s, a) = E_{\pi}[R_{t+1} + \gamma q + \pi(S_{t+1}, A_{t+1}) | S_t = s, A_t = a]$ [30].

The expression of the $q_{\pi}(s, a)$ in terms of $v_{\pi}(s, a)$ yields the Bellman equation, which is instrumental in computing the value function for a given policy [30], [34].

Recently, there has been a lot of research on the intersection of reinforcement learning and deep learning. For example, methods using CNN to approximate Q-Learning functionality in game agents and automated control have proven successful. These methods rely on phases of exploration, where the agent tries to learn about its environment through sampling, and exploitation, where the agent uses what it learned about the environment to find better paths [35].

B. Background of Open AI Gym

Gym is a unique environment that is specifically designed to facilitate the implementation of Reinforcement Learning (RL) models. Due to its vast open interfaces, it permits the development and testing of different RL classification models. Using the environment, developers can train their agents to do a variety of tasks [36]. In this study, the modified gym environment is used to train an agent for the classification of images.

C. Background of Convolutional Neural Network (CNN)

The CNN is used in image classification, consists of two principal types of hidden layer: the convolutional layer and the pooling layer [37]. The convolutional layer carries out a set of weighted convolution operations on small subsets of the layer's inputs using the same weights for each subset. The pooling layer, on the other hand, takes the outputs from the convolution layer and aggregates them across larger subsets of the data. This has the effect of making the results insensitive to particular aspects of the image such as the exact location or orientation of an item within the image. In this study, CNN is used as the agent to determine the actions.

D. Proposed Approach

In this paper, an approach of RL with CNN is proposed. RL is an efficient to handle medical data when final interpretation has been made since it is a dynamic and mathematically powerful technique [38]. A CNN is designed as the agent to process observations (dimensional inputs) coming from the modified environment, typically extracted from image data to obtain actions geared towards the classification and prediction of the medical data.

Fig. 1 shows the RL model with the CNN structure. Thus, based on the principle of RL, a part of the model known as the CNN-Agent takes actions on the environment modified from which it receives observations and reward signals that are used to influence the next action towards the classification model.

Firstly, initializing the input data set by resizing all images to size $150 \times 150 \times 1$ for the target network RL model and normalizing the range of all image pixels to $[0,1]$. Then, the input data set (x_{train}, y_{train}) is given to the environment. Afterwards, the observations (x_{train}) are passed to the agent to take action based on the CNN policy and return this action to the environment to compare with the actual action (y_{train}) , which is relied on to get the reward or loss.

The agent’s actions are determined by a CNN policy, which must balance the benefits of exploitation, in other words taking action with the current highest expected future reward, against exploration, which means taking another action with a lower currently expected future reward in order to seek even higher rewards in the future. Thus, the value function is used to calculate the total expected future reward of taking an action from a given system state where the goal is to achieve a stable result, the agent’s interaction with the environment can be represented by a finite sequence called episodes.



Figure 1. RL model structure with CNN

IV. EXPERIMENTS AND RESULTS

In this section, the pneumonia data set from the chest X-Ray images is used and described followed by the explanation of the outputs of the RL model used. Furthermore, the accuracy and other measurements of the resulting model are analyzed as well as comparisons with previous work is conducted.

A. Data Set Description

The data set that was utilized are the ones used by Ayan et al. [11]. It has 5,856 chest X-ray images provided by Kermany et al. [20]. The data set contains 1,583 normal cases and 4,273 pneumonia case images. 1,349 normal images and 3,883 pneumonia images are used during the training while 234 normal images and 390 pneumonia images are used for testing the model. Table I represents the distribution of the data during the training and testing phase, where 0 represents pneumonia cases and 1 represents normal cases. Some X-ray image samples from the data set are showed in Fig. 2.

Table I
DISTRIBUTION OF DATA SET

Class	Train	Test	Total
Pneumonia	3883	390	4273
Normal	1349	234	1583
Total	5232	624	5856

B. Results Obtained

The results obtained using the RL model were presented. Evaluating the model’s performances was done by using metrics such as Precision, Recall, F1-Score as well as accuracy and confusion matrices. Furthermore, the outcomes are compared with a deep learning model developed by Ayan et al. [11].

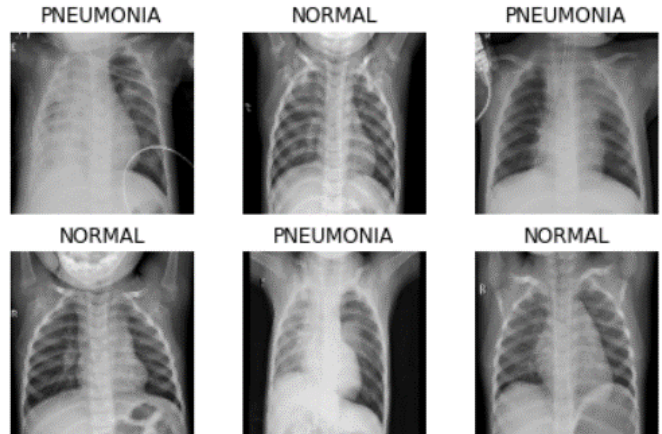


Figure 2. Data set samples shows normal and pneumonia cases

We evaluated our model with the test set, which uses 624 chest X-ray images. The test set contains 234 normal and 390 pneumonia cases.

1) **Precision Results:** Precision in our experiments measures the fraction of pneumonia’s instances among the retrieved image instances that are used. The formula of the precision metric is:

- $Precision = TP / (TP + FP)$

Table II summarizes the results of the RL model’s experiment. It can be seen that the performance of the RL is very reasonable as well as better than previous work whereby our model achieved 98% detecting pneumonia and 97% detecting normal cases while previous work obtained lower values for both pneumonia and normal cases.

Table II
PRECISION RESULTS

Class	Our RL-model	Vgg16 [11]	Xception [11]
Pneumonia	98%	91%	82%
Normal	97%	83%	86%

2) **Recall Results:** Recall is the fraction of pneumonia’s instances that have been identified and the total number of image instances present, which are used. The formula of the recall metric is:

- $Recall = TP / (TP + FN)$

The recall results of the RL model’s experiment is summarized in Table III. The table also shows that RL performs better compared to previous work whereby our model achieved 98% for pneumonia and 96% for normal cases, while previous work obtained lower values for both cases.

Table III
RECALL RESULTS

Class	Our RL-model	Vgg16 [11]	Xception [11]
Pneumonia	98%	89%	94%
Normal	96%	86%	65%

3) **F1-Score Results:** The F1-Score is the harmonic mean of precision and recall. The formula of the F1-Score metric is:

$$F1score = 2 \times (\text{precision} \times \text{recall}) / (\text{precision} + \text{recall})$$

Table IV summarizes the F1-score results of the RL model's experiment. The table shows that our model scores best while results of previous work models were lower for both pneumonia and normal.

Table IV
F1-SCORE RESULTS

Class	Our RL-model	Vgg16 [11]	Xception [11]
Pneumonia	98%	90%	87%
Normal	97%	84%	74%

4) **Accuracy, Sensitivity and Specificity Results:** The formulas of accuracy, sensitivity and specificity are:

- $Accuracy = (TP + TN) / (TP + FN + TN + FP)$
- $Sensitivity = TP / (TP + FN)$
- $Specificity = TN / (TN + FP)$

Accuracy, sensitivity and specificity results are summarized in Table V. Our RL model achieved the best results compared to previous work.

Table V
ACCURACY, SENSITIVITY, AND SPECIFICITY RESULTS

	Our RL-model	Vgg16 [11]	Xception [11]
Accuracy	97%	87%	82%
Sensitivity	96%	82%	85%
Specificity	98%	91%	76%

5) **Confusion Matrix Results:** Fig. 3 shows the confusion matrices of the classes Pneumonia and Normal of the chest X-ray image data set for the RL model.

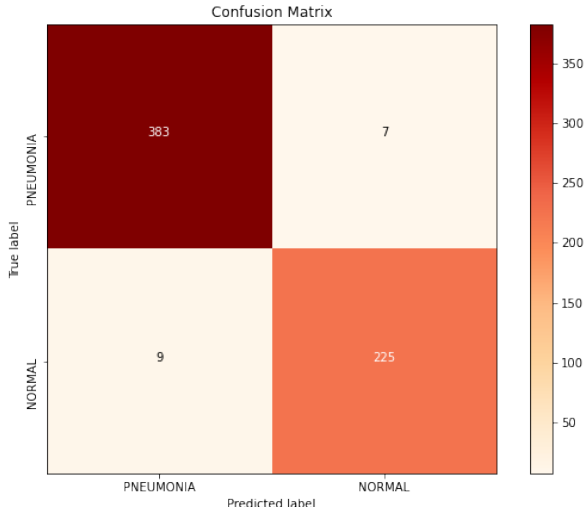


Figure 3. Confusion Matrix

Table VI shows that our model correctly classified 608 samples of images for both classes Pneumonia and Normal

of the test set (X-ray chest images) and it achieved the best results compared to the previous approaches by [11].

Table VI
CONFUSION MATRIX FOR CLASSES CORRECTLY CLASSIFIED

Class	Our RL-model	Vgg16 [11]	Xception [11]
Pneumonia	383	348	365
Normal	225	201	152
Total	608	549	517

6) **Rewards and Loss-rewards:** Fig. 4 and Fig. 5 show the rewards and loss to rewards of the agent that were obtained by training over 400 episodes. Fig. 5 shows that the RL-Agent achieved high rewards. Fig. 4 shows that the agent's reward-Loss also started decreasing during its training. This means that the RL model was able to classify the images very efficiently.

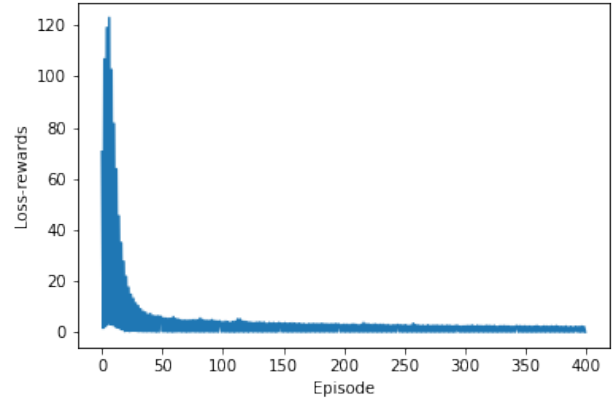


Figure 4. Loss-reward

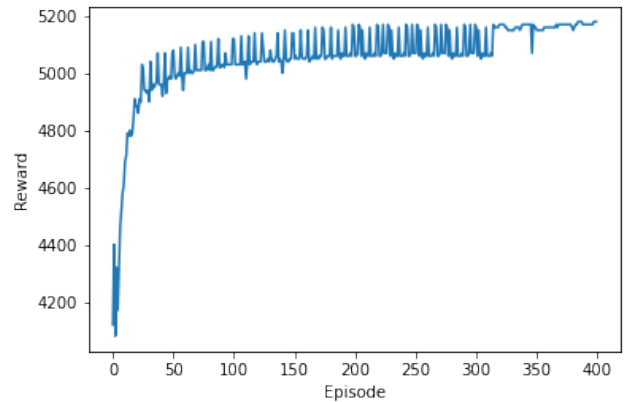


Figure 5. Reward

C. Predictions of RL Model

Fig. 6 shows the predictions of 12 images that were chosen randomly from the test set. As shown, the RL model succeeded

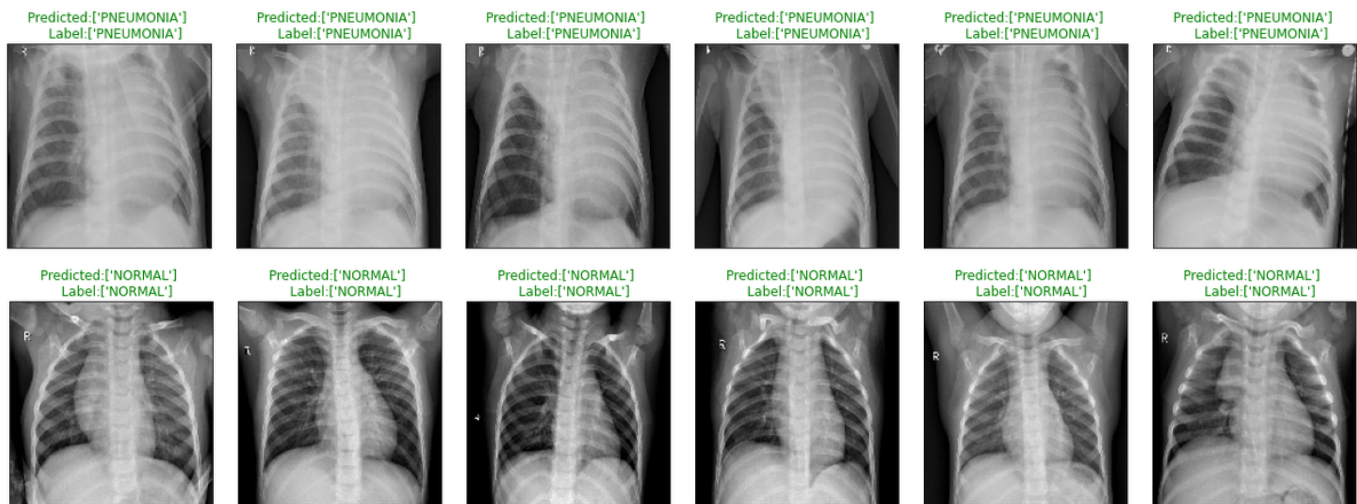


Figure 6. Predicted Pneumonia and Normal Images

in obtaining the correct prediction of all 12 images.

V. CONCLUSION

The research investigated the medical data set of Pneumonia from Chest X-ray images, which were used in a previous paper [11] consisting of two classes. Reinforcement Learning (RL) with convolutional neural networks were applied to diagnose and classify pneumonia and normal X-Ray images. In addition, the evaluation measures included accuracy, classification tables, and confusion matrices.

As seen from the results, the RL model achieved the best accuracy, sensitivity, specificity and F1-measure for the chest X-ray images of pneumonia. In terms of accuracy, the RL model achieved 97.4%. In terms of sensitivity, the RL model achieved 96% and for specificity 96%. Moreover, with regards to the confusion matrix results, the RL model correctly classified 608 samples of X-ray images, which is a larger number compared to the previous results [11]. Through the experiments, it can be seen that the agent of the RL model achieved the highest values for rewards and the lowest values of reward loss, which are significant results and shows that the agent performance is efficient for classification.

Although the purpose of this work was to classify pneumonia from chest X-ray images, the main limitation is the scarcity of publicly available data, and thus it is hard to get a large data set, i.e., many pneumonia X-ray images to work with. The larger the data set the more likely it will be to get a better accuracy model via training. In addition, data collection and labeling are time-consuming as well as costly. Therefore, it is necessary to collect all possible variations of chest X-ray images.

Finally, for future research we suggest reviewing all applications and domains using RL to categorize images based on the importance in different application areas such as robotic applications. RL could be specifically applied to image classification used in robots. In addition, using the proposed

approach is likely to improve the classification and analysis of other types of data sets as well.

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