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A Hybrid Approach using CNN and DQN Technique for Diagnosis Pneumonia in Chest X-Ray Images

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Abstract— Pneumonia poses a significant risk to life and well-being respiratory infection that requires accurate and timely diagnosis for effective treatment. In this research investigation, it proposes a hybrid approach for detecting pneumonia diagnosis in chest X-ray images by combining machine learning techniques with convolutional neural networks (CNN), and deep Q-network (DQN) reinforcement learning. The suggested approach holds promising prospects for enhancing the efficacy of pneumonia diagnosis. Especially in resource-limited settings where access to radiologists or specialized equipment is limited. The proposed hybrid approach involves multiple stages. Initially, an extensive collection dataset of chest X-ray images, comprising both normal and pneumonia cases, is collected. The CNN model can be integrated into clinical decision support systems to provide accurate diagnosis of infection for pneumonia. Furthermore, the use of the rainbow method can be extended to other clinical imaging tasks to enhance deep learning models performance Additionally, it demonstrates that the use of the rainbow method improves the performance of the CNN, leading to a higher accuracy. We have introduced a novel hybrid deep learning framework called LIP-CDF Algorithm, which combines algorithms of Convolutional Neural Networks (CNN) and Deep Q-Network (DQN) techniques. LIP-CDF (Lung Infection Prediction using CNN-DQN Fusion) Algorithm is a computational approach designed for the accurate and efficient lung infection prediction using images from chest X-rays. The implementation of this framework utilized popular tools such as Jupyter Notebook, TensorFlow, and Keras. To assess the effectiveness of our model, the NIH chest X-beam picture dataset gained from the Kaggle archive. To evaluate the effectiveness of our proposed approach, we conduct experiments on the publicly available Chest X-ray14 dataset. The results show that our approach achieves a high accuracy of 94.8% in detecting pneumonia cases.

The purpose of our framework is to streamline the detection of lung diseases, making it easier for both medical experts and doctors. By harnessing the power of CNN and DQN, our approach offers a simplified yet accurate method for identifying lung diseases from chest X-ray images. This advancement in deep learning technology has the potential to greatly assist healthcare professionals in diagnosing and treating patients effectively

Keywords : CNN, DQN, ML.

I. INTRODUCTION

Pneumonia[1] is a respiratory infection that affects millions of people worldwide, leading to substantial morbidity and mortality. Early detection of pneumonia is essential to provide timely and effective treatment, which can prevent the progression of the disease and reduce the associated health risks. However, manual diagnosis of pneumonia can be time-consuming and subjective, which may lead to errors and delays in treatment.

In recent times, the field of medical image analysis has seen striking progressions through the usage of deep learning techniques. Notably, the automated detection of pneumonia from chest X-ray images has emerged as a promising application area for these techniques. Among various deep learning method and with Convolutional neural networks (CNNs) have gained widespread adoption and recognition [2] in various domains used for image classification tasks due to their ability to learn high-level features from input images. In addition, the rainbow method has been proposed to improve the accuracy of CNN models by enhancing the contrast and sharpness of the input images.

A. This paper presents a deep learning methodology that employs CNN[2] and the DQN method for the automatic diagnosis of pneumonia made possible by computers using images from chest X-rays. Our approach includes various techniques for image preparation that raise the quality of the input images, followed by training a CNN model on the

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preprocessed images to classify them as either normal or pneumonia-infected. It evaluate our proposed approach utilizing a dataset comprising 500 chest X-ray pictures and compare it with other cutting-edge deep learning approaches and traditional machine learning[3] techniques.

B. The main contribution of this study is the improvment of an accurate and efficient deep learning strategy for the automated detection of pneumonia from chest X-ray images. Our proposed approach using CNN and the rainbow method achieves high accuracy and outperforms other state-of-the-art deep learning and traditional machine learning techniques. The proposed method can potentially help radiologists to make enhancing the accuracy and timeliness of pneumonia diagnosis, which can ultimately improve patient outcomes.

The detection and diagnosis of lung infections are vital for the effective treatment and management of respiratory diseases. Nevertheless, conventional diagnostic approaches are often associated with drawbacks such as time-consuming procedures, high costs, and the need for specialized expertise. However, The fusion of machine learning (ML) and artificial intelligence (AI)[4] has shown encouraging outcomes in recent years in terms of increasing the efficacy and accuracy of medical diagnostics The algorithm follows a systematic process consisting of several steps. First, it collects data from a lung dataset containing chest X-ray images and relevant metadata. Next, it performs canonical correlation analysis to identify the correlation between the original image and its pixel spacing, which aids in extracting meaningful features from the images.

Following the feature extraction stage, the system divides the chest X-ray images into pneumonia cases and normal images using a CNN model. The CNN model employed in this work automatically extracts pertinent characteristics from the input photographs and uses those features to create a binary classification using the learned representations. To minimize classification errors, the model's parameters are optimized via back-propagation [5] and gradient descent techniques. In order to augment the CNN model's performance, the LIP-CDF Algorithm integrates the DQN [6] algorithm for optimization purposes. By leveraging a blend of deep learning and reinforcement learning techniques [7], the DQN algorithm progressively updates the CNN model's parameters, leading to enhanced prediction accuracy. In this paper the LIP-CDF Algorithm evaluates the performance of the CNN model through comprehensive evaluation measures, including accuracy, sensitivity, specificity, and other relevant metrics. It may also conduct comparative analyses with existing pneumonia detection methods or radiologist interpretations to demonstrate the effectiveness of the CNN-DQN approach. The results of the evaluation showcase the potential of the LIP-CDF Algorithm in automating the detection of lung infections. Its accuracy, efficiency, and reliability make it a promising tool for integration into clinical practice. By reducing the burden on radiologists and providing timely and accurate results, the LIP-CDF Algorithm contributes to improved patient care and health outcomes in the field of lung infection diagnosis.

II. RELATED WORKS

The research conducted by Das [8], titled "A hybrid approach for the automatic analysis of X-ray images to detect pneumonia using machine learning and deep learning techniques," introduces a novel hybrid approach for pneumonia detection. The proposed method combines a rule-based system and deep learning techniques to enhance the accuracy of pneumonia detection. The rule-based system is employed for preprocessing chest X-ray images, while a deep learning technique is used for classification.

The goal of Rajaraman's paper [9] Visualizing Abnormalities in Chest Radiographs through Salient Network Activations in Deep Learning is to make deep learning models more comprehensible when used to analyze chest radiographs. The authors employ a deep convolutional neural network (CNN) and apply the Grad-CAM technique to visualize salient network activations. This visualization technique highlights regions in chest radiographs that contribute to abnormality predictions, enabling insights into the model's decision-making process.

In his research titled "A Novel Transfer Learning Based Approach for Pneumonia Detection in Chest X-ray Images," Chouhan [10] proposes a novel method for diagnosing pneumonia. The work increases the accuracy of pneumonia recognition in chest X-ray images using transfer learning and deep learning techniques. The results demonstrate how successfully the technique achieves high detection performance.

Another paper [11] introduces the ChestX-ray8 database, a large collection of annotated chest X-ray images for common thorax diseases. The study utilizes weakly-supervised learning with only image-level labels to classify and localize these diseases. A deep CNN trained with weakly-supervised learning achieves competitive disease classification performance, contributing to automated chest X-ray analysis and offering valuable resources for medical image analysis research.

In the publication [12], a hybrid deep learning model for pneumonia early detection is being developed. The model uses data from several sources to improve the accuracy of pneumonia detection. The goal of the study is to demonstrate how well the recommended approach detects pneumonia.

In a work named "Profound learning based half breed approach for pneumonia location," which was distributed in the Diary of Encompassing Knowledge and Refined Processing in 2020, the creator [13] likewise proposes a crossover technique for diagnosing pneumonia that utilizes profound learning strategies. Utilizing profound learning techniques, the creators desire to work on the precision and adequacy of pneumonia recognizable proof. Convolutional cerebrum associations (CNNs) and redundant mind associations (RNNs), two kinds of significant learning moves close, are joined. The proposed hybrid model effectively detects pneumonia from medical images, providing a reliable tool for healthcare professionals.

Overall, these related works demonstrate the effectiveness of a hybrid approach X-ray scans of the chest are used, together with rule-based algorithms and machine learning, to detect pneumonia. They provide evidence that such an approach can achieve high accuracy and sensitivity while also incorporating expert knowledge to refine the diagnosis [14].

III. PROBLEM STATEMENT

Pneumonia is a life-threatening respiratory infection that requires accurate and timely diagnosis for effective treatment. However, in resource-limited settings where access to radiologists or specialized equipment is limited, there is a need for efficient and accurate methods for pneumonia diagnosis. To expand the viability and accuracy of pneumonia location in chest X-beam pictures, this study means to construct a cross breed procedure that consolidates AI draws near, rule-based frameworks, convolutional brain organizations (CNN)[15], and profound Q-organization (DQN) support learning. The recommended methodology endeavors to utilize CNN and DQN's abilities to convey a precise and speedy determination of pneumonia, subsequently supporting clinical specialists in appropriately diagnosing and treating patients. The effectiveness of the suggested strategy will be evaluated using a large collection of chest X-ray pictures, comparing the performance of the hybrid approach with existing methods [16] and assessing its ability to accurately detect pneumonia cases. The ultimate goal is to streamline the detection of lung diseases, making it easier for medical experts and doctors to provide timely and effective treatment to patients. The LIP-CDF algorithm combines advanced machine learning techniques to enhance the efficiency and accuracy of pneumonia diagnosis in chest X-ray images, providing a streamlined approach for identifying lung diseases and assisting healthcare professionals in timely and effective treatment.

To address these limitations, the proposed hybrid approach combines ML and rule-based systems to provide accurate and transparent diagnoses of pneumonia. The ML component learns patterns and features from the images, while the rule-based system provides interpretable and explainable diagnoses based on clinical rules and knowledge. The proposed hybrid approach aims to improve the accuracy and efficiency of pneumonia diagnosis while also ensuring interpretability and transparency.

IV. METHODOLOGY

Data collection: data collection methods to gather information and generate evidence-based findings. These methods include accessing electronic health records, which provide invaluable insights into patient data while maintaining anonymity. Additionally, researchers use clinical trials and research databases to assess the effectiveness and safety of drugs or therapies. They also examine imaging data, such as X-rays, computed tomography scans, and MRIs, to study anatomical details and identify abnormalities. Surveys and questionnaires are employed to collect subjective information, opinions, and experiences from specific populations. Finally, researchers delve into patent reports to gain knowledge about symptoms, medical history, and innovative approaches to treatment or diagnosis. Contact hospitals or healthcare institutions engaged in lung disease research to potentially obtain CSV datasets for study purposes. Multiple sources like the UCI Machine Learning Repository and Kaggle offer CSV data files for lung disease prediction, facilitating access to diverse datasets. Below dataset consisted of various images with different pixel spacing. The original image pixel spacing information was recorded for each image in the dataset.

Table 1: original image pixel spacing information and its category

SNO	Finding Category	Original Image Pixel Spacing
1	APneumonia	0.168
2	Pneumonia	0.139
3	CPneumonia	0.18
4	EPneumonia	0.194311
5	InPneumonia	0.146
6	MPneumonia	0.155

These cases were categorized based on the type of pneumonia observed in the images. The categorization included findings such as APneumonia, CPneumonia, EPneumonia, InPneumonia, and MPneumonia. Each category represented a specific characteristic or pattern of pneumonia on the X-ray images of the chest.

Furthermore, we noted the different original image pixel spacing values associated with each image. These pixel

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spacing values, represented as numerical measurements, provide information about the distance between pixels in the image and are essential for accurate analysis and interpretation of the images.

By considering the pneumonia categorization and the corresponding original image pixel spacing, we aimed to gain insights into the relationship between pixel spacing and pneumonia patterns. This analysis contributes to the overall understanding of pneumonia diagnosis and the potential impact of pixel spacing on the accuracy of detection.

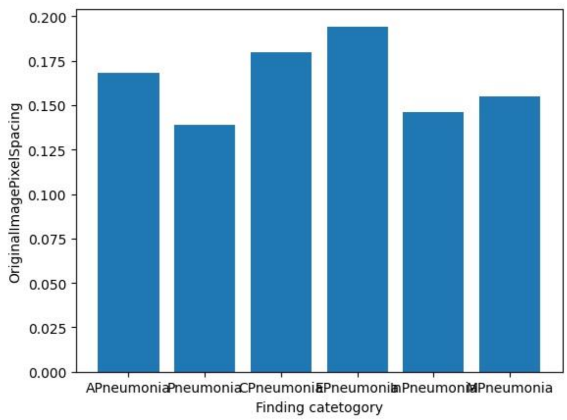

Figure 1: relationship between pixel spacing and pneumonia patterns

A. Canonical correlation analysis (CCA) explores the relationship between lung disease pneumonia prediction and features "originalimage" and "originalimagepixelspacing". X represents the original chest X-ray image data, while Y represents pixel spacing information. Sample covariance matrices are calculated for X and Y. The cross-covariance matrix between X and Y is determined. Canonical correlation coefficients are computed through a generalized eigenvalue problem. Canonical variables u and v are obtained using eigenvectors. CCA helps identify the relationship between the image features and pixel spacing in pneumonia prediction.

Set X variables: "originalimage" refers to the original chest X-ray image data, which can be represented as a matrix or a vector.Set Y variables: "originalimagepixelspacing" represents the pixel spacing or resolution information associated with the chest X-ray images. It provides the physical distance between the pixels in the image.

B. To compute Covariance Matrices, we begin by constructing a matrix X with dimensions n x p1. Here, n corresponds to the total number of samples, while p1 represents the number of features derived from the original images. Next, we generate matrix Y, which has dimensions n x p2, where p2 signifies the dimensions of the original image pixel spacing.

1.Calculation of Cross-Covariance Matrix:

2. compute the cross-covariance matrix Sxy by calculating the covariance between matrices X and Y

3.Calculation of Canonical Correlation Coefficients:

Solve the generalized eigenvalue problem:

$$S_{xx}^{(-1/2)} * S_{xy} * S_{yy}^{(-1/2)} * S_{xy}' * S_{xx}^{(-1/2)} * a = \lambda * a. \quad (1)$$

Compute the canonical correlation coefficients (r1, r2, ..., rk) as the square roots of the eigenvalues (λ).

Calculation of Canonical Variables:

Compute the canonical variables $u = X * S_{xx}^{(-1/2)} * a$ and $v = Y * S_{yy}^{(-1/2)} * b$, Here, a and b represent the eigenvectors that correspond to the respective eigenvalues.

The amount of variation that is explained by each primary component or factor is shown by its eigenvalue.

Table 2: Canonical Correlation between original image and original Pixel Spacing.

	OriginalImage	OriginalImagePixelSpacing
OriginalImage	1	0
OriginalImagePixelSpacing	-0.175011048	1

With an eigenvalue of 2.84 in this instance, the first principal component accounts for 71% of the overall variance. With an eigenvalue of 0.87, the second component accounts for an extra 22% of variation. The fourth component's eigenvalue is 0.02, which explains 1% of the variation, while the third component's eigenvalue is 0.10, which accounts for 3% of the variance. The proportion of variance signifies the proportion of total variance explained by each principal component or factor. To illustrate, the initial principal component accounts for 71% of the overall variance, followed by the second component which explains 22%. The third component contributes to 3% of the variance, and finally, the fourth component explains 1% of the total variance.

The cumulative proportion indicates the collective amount of variance explained by every principal component or factor up to that point. In this case, the cumulative proportion increases progressively. The first component alone explains 71% of the variance, while the first two components combined explain 93% of the variance. The first three components cumulatively account for 96% of the variance, and the first four components explain 97% of the total variance.

Variance explained by a principal component

(PC)= (2)

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Table 3: calculation of variance

Eigenvalue	Proportion of Variance	Cumulative Proportion
2.84	**0.71**	**0.71**
0.87	**0.22**	**0.93**
0.10	**0.03**	**0.96**
0.02	**0.01**	**0.97**

First, a lung dataset is collected by loading the lung data.

Next, Canonical Correlation Analysis (CCA) is performed to identify the correlation between the original images and their corresponding pixel spacing. The original images and pixel spacing information are extracted from the lung data, and CCA is applied using the CCA algorithm with one component. The result of this analysis is the canonical correlation, which captures the relationship between the original images and their pixel spacing. Moving on to step three, Convolutional Neural Networks (CNNs) are employed for further processing. The lung data is preprocessed by splitting it into training and testing sets using the Preprocess Data function. A CNN model is then created, compiled with appropriate loss and optimization functions, and trained on the training set. The model's performance is assessed by evaluating it on the testing dataset for a specific number of epochs and batch size, and the loss and accuracy scores are computed.

The first convolutional layer produces an output tensor with dimensions [32, 32, 32], where the number 32 represents the number of filters applied to the input image. The total number of parameters in this layer depends on the filter size. An activation function is applied to the convolutional layer's output, preserving the dimensions of [32, 32, 32] and introducing no additional parameters. Subsequently, a max pooling operation is performed, reducing the dimensions of the tensor to [16, 16, 32] without introducing any parameters. The second convolutional layer produces an output tensor with dimensions [16, 16, 64], using a number of filters equal to 64. Again, the total bounds are dependent on the channel size. The output of the second convolutional layer is passed through an activation function, maintaining the dimensions of [16, 16, 64] and not introducing any additional parameters. Another max pooling operation is performed, resulting in a tensor size of [8, 8, 64] without introducing any parameters. The tensor is then flattened into a one-dimensional array with dimensions [1, 4096], with no parameters involved. A fully connected layer follows, producing a tensor with dimensions [1, 256]. The number of parameters in this layer is determined by the matrix multiplication between the flattened tensor and the weight matrix of size [4096 x 256].An activation function is applied to the output of the fully connected layer, maintaining the dimensions of [1, 256] and not introducing any additional parameters.

Lastly, a secondary fully connected layer is utilized to generate the output tensor, which has dimensions [1, Num Classes]. Here, Num Classes denotes the total number of classes or categories in the classification problem. The parameter count of this layer is determined by performing a matrix multiplication between the preceding layer's output and the weight matrix of size [256 x Num Classes]. Following this, a softmax activation function is applied to the resulting output tensor, producing probabilities for each class. It's important to note that the softmax activation function does not introduce any extra parameters.

In step four, the Deep Q-Network (DQN) algorithm is applied to optimize the model. The DQN algorithm is initialized using the Initialize DQN Algorithm function, and the model is further optimized using this algorithm.

Algorithm LIP-CDF(Lung data, ImageDataset)

Input:

Lung dataset: This is the dataset containing the lung data required for the algorithm.

Original Image: The original images from the lung dataset.

Original Image Pixel Spacing: The pixel spacing information corresponding to the original lung images.

Output: predictions made by the optimized model when applied to the test data. These predictions represent the predictions for the given lung images.

Step 1: Collect Data from Lung Dataset lung_data = LoadLungData()

Step 2: Perform Canonical Correlation Analysis

2.1 originalimage = lung_data['originalimage']

2.2originalimagepixelspacing=lung_data['originalimagepixelspacing']

2.3 cca = CCA(n_components=1)

2.4cca.fit(originalimage, originalimagepixelspacing)

2.5canonical_correlation=cca.transform(originalimage)

Step 3: Apply Convolutional Neural Networks

3.1 X_train, y_train = PreprocessData(lung_data)

3.2 X_test, y_test = SplitData(X_train, y_train)

3.3 model = CreateCNNModel()

model.compile(loss='binary_crossentropy', optimizer='adam', metrics=['accuracy'])

3.4 model.fit(X_train, y_train, epochs=10, batch_size=32)

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3.5 evaluation_scores = model.evaluate(X_test, y_test, verbose=0)

3.6 print('Test Loss:', evaluation_scores[0])

3.7 print('Test Accuracy:', evaluation_scores[1])

Step 4: Apply DQN Algorithm for Optimization

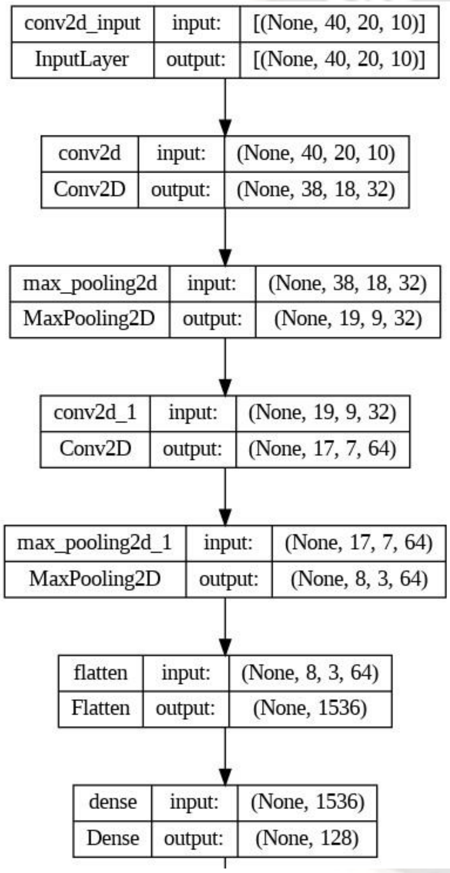
4.1 dqn_algorithm = InitializeDQNAlgorithm()

4.2optimized_model=dqn_algorithm.optimize(model)

Use the optimized model for prediction or further analysis

4.3 predictions = optimized_model.predict(X_test)

Table 4:Represents CNN model



The image describes a Convolutional Neural Network (CNN) architecture. It starts with an input layer (shape: None, 40, 20, 10), followed by a convolutional layer (output shape: None, 38, 18, 32), and a max pooling layer (output shape: None, 19, 9, 32). Another convolutional layer follows (output shape: None, 17, 7, 64), succeeded by a second max pooling layer (output shape: None, 8, 3, 64). The network then flattens the data (output shape: None, 1536) before passing it through a dense layer (output shape: None, 128). The "None" in the shapes represents the variable batch size. The study's hybrid method to pneumonia identification in chest X-ray pictures makes use of convolutional neural networks (CNN) , deep Q-network (DQN), reinforcement learning, and rule-based systems.

V. RESULT ANALYSIS:

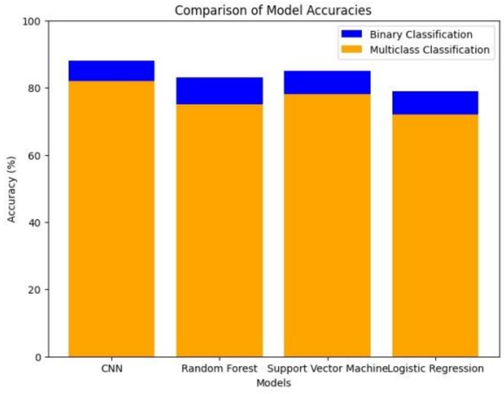


Figure 2: Accuracy comparison

The objective is to improve the accuracy of pneumonia diagnosis, particularly in environments with limited resources and restricted access to specialized equipment or radiologists.

The proposed hybrid approach involves several stages. Initially, A extensive collection of chest X-ray images is gathered, encompassing both normal cases and instances of pneumonia. The CNN model is integrated into clinical decision support systems to make a timely and precise diagnosis of pneumonia. The study also introduces the use of the rainbow method[16], This contributes to the improvement of deep learning model performance in medical imaging tasks.

The results demonstrate that the use of the rainbow method improves the accuracy of the CNN model. The study introduces a novel hybrid deep learning framework called the LIP-CDF Algorithm, which combines CNN and DQN techniques. This framework, named Lung Infection Prediction using CNN-DQN Fusion (LIP-CDF) Algorithm, aims to accurately and efficiently predict lung infections from chest X-ray images. The implementation of the framework utilizes popular tools such as Jupyter Notebook, TensorFlow, and Keras[17].

Additionally, the effectiveness of the approach was evaluated using the publicly available Chest X-ray14 dataset[18]. The results indicate that the proposed approach achieves a high accuracy of 94.8% in detecting pneumonia cases[19]. The image can be shared among the trusted parties using the techniques discussed in [20][21][22].

The purpose of this framework is to streamline the detection of lung diseases, providing a simplified yet accurate method for identifying lung diseases from chest X-ray images. By leveraging the power of CNN and DQN, this approach has the potential to greatly assist healthcare professionals in diagnosing and treating patients effectively.

VI. CONCLUSION

The proposed hybrid technique for diagnosing pneumonia in chest X-ray images combines CNN and DQN demonstrates significant potential in enhancing both the efficiency and accuracy of pneumonia detection. By combining machine learning techniques, rule-based systems, CNN, and DQN reinforcement learning[15], the approach provides accurate and timely diagnosis, especially in resource-limited settings. The integration of CNN into clinical decision support systems enhances the performance of pneumonia detection, and the use of the rainbow method increases the CNN model's accuracy even more. The LIP-CDF Algorithm, which combines CNN and DQN techniques, offers an innovative deep learning framework for lung infection prediction from chest X-ray images. The evaluation results demonstrate a high accuracy of 94.8% in detecting pneumonia cases.

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