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Deep Q-Network (DQN) Model for Disease Prediction Using Electronic Health Records (EHRs)

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Abstract: Many efforts have proved that deep learning models are effective for disease prediction using electronic health records (EHRs). However, these models are not yet precise enough to predict diseases. Additionally, ethical concerns and the use of clustering and classification algorithms on small datasets limit their effectiveness. The complexity of data processing further complicates the interpretation of patient representation learning models, even though data augmentation strategies may help. Incomplete patient data also hinder model accuracy. This study aims to develop and evaluate a deep learning model that addresses these challenges. Our proposed approach is to design a disease prediction model based on deep Q-learning (DQL), which replaces the traditional Q-learning reinforcement learning algorithm with a neural network deep learning model, and the mapping capabilities of the Q-network are utilized. We conclude that the proposed model achieves the best accuracy (98%) compared with other models.

Keywords: Electronic Health Records (EHRs); Deep Q-Network (DQN); disease prediction; machine learning; Deep Reinforcement Learning (DRL)



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1. Introduction

Real-world data (RWD) necessitate the routine collection of health information about patients and the supply of healthcare from several sources. Among the different types of RWD, the utilization of electronic health record (EHR) data for medical revisions is experiencing rapid growth. This growth is dependent on several factors, such as the growing implementation of EHRs and the use of digital technologies that record the healthcare methods found in EHRs [1]. Fortunately, alongside advancements in the measurement and collection of health-related data, there have been significant developments in computing power, storage, processing capabilities, and analytical methods, particularly in the field of artificial intelligence (AI). As a result, the integration between the comprehensive clinical data found in EHRs and the ability to analyze these data using AI has expanded the chances to gain a deeper understanding of diseases and the individuals we treat [2]. Deep learning methods are used in the artificial intelligence (AI) discipline of machine learning (ML). For the purpose of predicting the future, an analytical model uses a training set. Based on prior knowledge, the model pulls useful information from fresh input. AI and machine learning are two cutting-edge technologies that are revolutionizing personalized clinical support and healthcare. Clinical data in the healthcare industry are comprised of sensor data from internet of things (IoT) devices and electronic health records [3]. Previously, statistical techniques such as logistic regression, support vector machines, and random forests, as

well as standard machine learning techniques, have been implemented to analyze rich EHR data. However, the advent of deep learning techniques, which are the best at creating hierarchical features and identifying long-range correlations in data, has led to significant advancements in a number of domains. Publications using deep learning techniques for clinical informatics tasks have expanded along with deep learning's popularity and the availability of additional patient data. These techniques perform more effectively than conventional ones and need less time-consuming preprocessing and feature engineering [4]. Current research is motivated by the progress made in AI algorithms, which help improve individuals' quality of life. The data enable patients, healthcare providers, and medical personnel to evaluate medical conditions, provide comments on treatments and medicine therapies, assess patient results, etc. [5].

The remainder of this article is organized as follows.

Section 2 provides a review of related work on various AI and machine learning techniques for disease prediction. Section 3 introduces the proposed deep Q-learning framework and elaborates on how it is applied for disease prediction using EHRs. In Section 4, we present the dataset used in this study, covering its attributes and how the data were processed. Section 5 shows the experimental results in terms of a performance comparison between the proposed DQN model and other machine learning algorithms. Finally, Section 6 concludes the study with the findings and outlines a future research direction to further improve the accuracy and applicability of AI models in healthcare.

The objectives of our work are the following:

- Presenting previous related work using AI and machine learning algorithms to predict various diseases.
- Designing a novel integrated framework that exploits deep reinforcement learning for the best accuracy in prediction.
- Comparison of the performance of the proposed model for heart disease prediction with several machine learning algorithms using various evaluation metrics.
- Introduction of a comparison between other studies and our work.

2. Related Work

In the middle of the 20th century, expert systems and symbolic thinking became the main areas of research in artificial intelligence. Early computing models and algorithms mimicking human cognitive processes were developed by pioneers such as John McCarthy and Marvin Minsky, laying the foundations for artificial intelligence. AI did not start to be used in healthcare in an effective manner until the machine learning (ML) algorithms of the 1980s and 1990s [6].

In the following section, we highlight the most recent developments leveraging artificial intelligence (AI) for the prediction of disease risks.

Ref. [7] modified an RL framework to specifically show how DRL could provide explainable diagnoses through the creation of decision pathways and accurate diagnoses. Ref. [8] demonstrated that combining information from clinical notes with structured assessment data allowed for the identification of home healthcare (HHC) patients at risk of hospitalization or emergency department (ED) visits. A risk model that integrated both structured data and clinical notes showed a notable improvement in predicting the likelihood of hospitalization or ED visits among HHC patients, with an increase of up to 17.8%. Among the five machine learning algorithms evaluated, random forest displayed the strongest predictive performance. In another work [9], a deep learning model was developed to predict heart failure and categorize patients using tEHR data; this model was called tBNA-PR (temporal bidirectional neural network with an attention mechanism). The performance of tBNA-PR was compared with that of other advanced methods, and

it demonstrated superior predictive abilities, achieving an accuracy of 0.7800, an F1 score of 0.7671, and an AUC of 0.7198. Ref. [10] proposed various essential aspects, such as compiling physiological index data and electronic medical records, determining pertinent risk variables to glean insightful information, putting in place a self-learning mechanism for anomaly detection and building an ensemble deep learning model for the prediction of heart failure. The model used the backpropagation learning process and was based on the scalable conjugate gradient idea.

Ref. [11] applied deep learning to endoscopic ultrasonography (EUS) pictures to anticipate the malignancy potential of gastrointestinal stromal tumors. Twenty CNN kernels were used in total for the first layer, and fifty were used for the second layer in the deep learning component. Ref. [12] developed two digital twin systems, with each utilizing SEIRS models to simulate the spatial and temporal spread of COVID-19. These models were then compared with real data to assess their predictive capabilities. A detailed evaluation and comparison of the two digital twin models, which are sometimes referred to as non-invasive reduced-order models (NIROMs), were conducted.

Ref. [13] employed artificial neural networks (ANNs) to detect Alzheimer's disease (AD) and they compared them with other machine learning models. The findings revealed that ANNs demonstrated the best accuracy when appropriate data were available. After conducting a comprehensive data analysis, Ref. [14] inferred that blood profile data have the potential to serve as a non-invasive machine learning approach for the early detection of breast cancer metastasis. Out of the nine algorithms examined, with an accuracy rate of 83%, the decision tree (DT) classifier outperformed the ensemble and logistic regression models. While the obtained accuracy cannot be regarded as very good, it can be improved by adding other characteristics. Ref. [15] demonstrated the effectiveness of the DQN approach in enhancing diagnostic accuracy. Their comparative analysis revealed notable advantages of DQN over PG in terms of performance and adaptability in disease diagnosis. Table 1 shows the characteristics and outcomes from related work.

Table 1. Characteristics and results of related work.

Approaches	Objective	Technique	Results
[7]	Explainable clinical diagnosis using artificial health records	Modified RL framework with DRL to create decision pathways	Accurate diagnosis despite noisy/missing data; improved explainability
[8]	Predicting hospitalization risks for HHC patients	Combined structured data with clinical notes; used random forest	17.8% improvement in risk prediction accuracy
[9]	Predicting heart failure and stratifying patients using tEHRs	Developed tBNA-PR (temporal bidirectional neural network with attention)	Accuracy: 0.7800, F1 score: 0.7671, AUC: 0.7198
[10]	Detecting and predicting heart failure	Ensemble deep learning model with a scalable conjugate gradient and anomaly detection	Advanced physiological data analysis with backpropagation
[11]	Anticipating the malignancy potential of gastrointestinal stromal tumors	Applied deep learning to EUS images using a CNN with Lanczos interpolation	EUS images were downsized to $28 \times 28 \times 1$; utilized 20 kernels (1st layer) and 50 kernels (2nd layer)
[12]	Simulating COVID-19's spatial and temporal spread	Developed two SEIRS-based digital twins	Models were compared with real data; predictive capabilities were assessed
[13]	Detecting Alzheimer's disease	Compared ANNs with other ML models	ANNs showed the best accuracy with appropriate data

Table 1. *Cont.*

Approaches	Objective	Technique	Results
[14]	Early detection of breast cancer metastasis	Non-invasive ML approach using blood profile data; decision tree (DT) classifier	DT accuracy: 83%; suggested improvements using additional characteristics
[15]	Enhancing diagnostic accuracy using conversational data	Employed DQN (deep Q-network)	DQN outperformed PG in terms of adaptability and performance

3. Artificial Intelligence and Electronic Health Records

Organizations face several challenges in adopting AI, with data-related issues being key. These include the need for data digitization, data consolidation, and ensured availability [16]. In addition, they pose privacy and legal challenges that encompass matters related to individual privacy, lawful considerations, and governmental regulations [17]. The last group within this dimension comprises difficulties associated with the patient, encompassing mistakes in decision making, errors in treatment, inconsistencies in data, and human interventions [18].

3.1. Data Integration

While the availability of diverse data forms and sources holds promise for advancing AI applications in healthcare, significant challenges remain. Ethical concerns, data scarcity, the need for extensive preprocessing, and the complexity of integrating multi-modal data types must be addressed. Overcoming these obstacles is critical for developing reliable and effective AI-driven healthcare solutions that can enhance patient care and medical research [19].

3.2. Patient Security

While AI holds great potential for enhancing medical decision making, challenges such as data quality, accuracy, and the risk of erroneous diagnoses must be carefully addressed. Ensuring high-quality data and implementing rigorous validation processes are essential to minimize errors and build reliable AI systems that can safely and effectively support healthcare professionals [20].

Another difficulty faced is the occurrence of decision-making errors by machine learning algorithms which can arise due to unsuitable algorithms being chosen for the given data or the data being unreliable for use in classification algorithms [18]. The healthcare industry presently utilizes a substantial number of AI and IoT devices and pieces of software; however, not all of them operate automatically. The ultimate decision is made by doctors, and the collaboration between AI models in the healthcare industry might result in incorrect diagnosis and treatment outcomes [21].

3.3. Interpretability of AI Models

Many AI algorithms function as “black boxes”, making it challenging for medical specialists to comprehend the decision-making process. This lack of openness may cause people to become distrustful and reluctant to embrace insights produced by AI [22].

3.4. Resource Limitations

Not all healthcare providers have access to the substantial financial and technical resources needed to implement AI technologies. Educating employees on how to utilize AI products efficiently is another resource-intensive problem [23].

In summary, challenges in data integration, security, model interpretability, and resource constraints must be carefully addressed to ensure successful and ethical implementation.

4. The Proposed Deep Q-Learning Framework (EHR-DQN)

The present section discusses the deep Q-learning (DQN) model, where RL is combined with neural networks in order to overcome challenges in disease prediction, enhance stability in learning, and significantly raise the accuracy level in the medical field.

4.1. Reinforcement Learning

This work specifically focuses on predicting disease occurrence by using electronic health records (EHRs) as a regression issue while utilizing supervised learning. The EHR data and related factors are inputs of the supervised learning algorithm, which uses them to predict the disease [24]. However, in reinforcement-learning-based techniques, the effectiveness of the learning of the agents that predict disease is determined by the total rewards, leading to unstable feedback for the agents; therefore, agents can modify their performance in conjunction with supervised learning. As a result, the agents are unable to identify which samples were not effectively learned in the process of learning and implement them when predicting diseases, thus incentivizing the agents to be more successful. In order to understand the deep reinforcement learning (DRL)-based disease forecasting approach, one first needs to build a disease prediction environment based on the input parameters. This procedure translates the supervised learning process into a reinforcement learning process. The environment is called a “disease prediction game” and each game includes limits and mixtures of parametric features that help predict diseases; each combination has a set of samples and labels that go along with it. As soon as an agent starts to play, it performs certain activities to obtain rewards, which help identify the disease parameter values. Positive rewards are given to the agent for each target value that is nearly predicted, while negative rewards are given for values that are not. Following this procedure, the agent is given a total score based on the actions that it performed [25].

4.2. Q-Learning

The Q-learning algorithm is a form of reinforcement learning [26] that assesses the different states of an environment in order to determine the best actions to take. Throughout its iterations, the algorithm continually strives to enhance the overall expected rewards associated with each state. Imagine an agent who is situated at a specific state (S) and performs an action (represented by a) in order to receive a reward (denoted as R); γ represents the discount factor. The optimal policy can be ascertained through the Bellman optimal policy equation, which is defined as follows:

$$V(S) = \text{MAX}_a R(s,a) + \gamma V(S'). \quad (1)$$

By utilizing the action–value function outlined in Equation (1), the learning agent is able to make informed decisions regarding the actions to be taken in different states. The q-function, which takes the current state of the environment and the chosen action as input, provides an output representing the expected reward (q values) associated with that action. Through a series of iterative steps, the agent effectively identifies the highest possible reward values for all states in the environment. The limited capacity of actual reinforcement learning methods, such as Q-learning, to characterize states makes it difficult to distinguish between them and to analyze disease prediction. The suggested approach uses a neural network to forecast heart diseases using a variety of parameters such as blood pressure, blood sugar, and heart rate. It is inspired by the notion of using a DQN to analyze massive amounts of data. We call this model deep Q-learning. A description of deep Q-learning is presented in Figures 1 and 2.

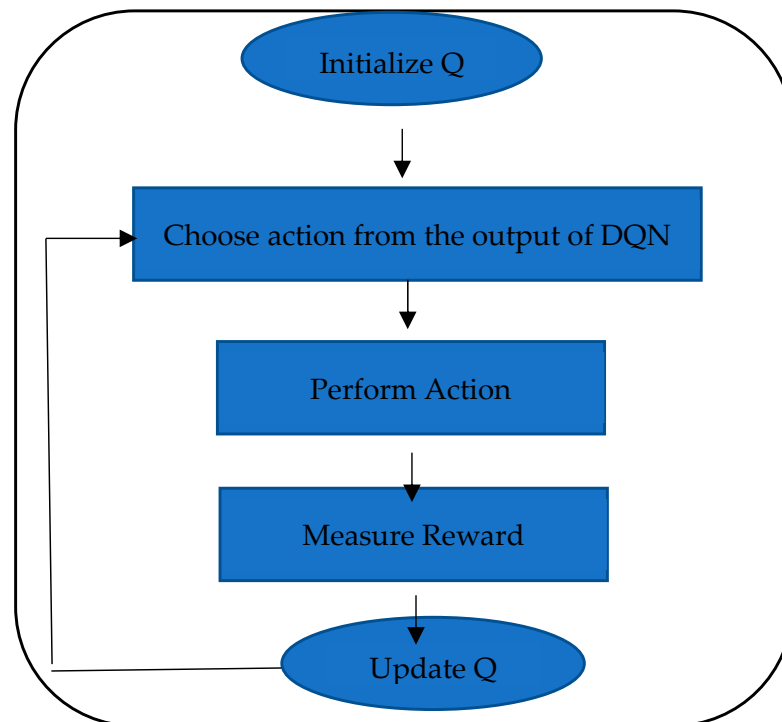


Figure 1. Flow diagram of deep Q-learning. Source: authors' creation.

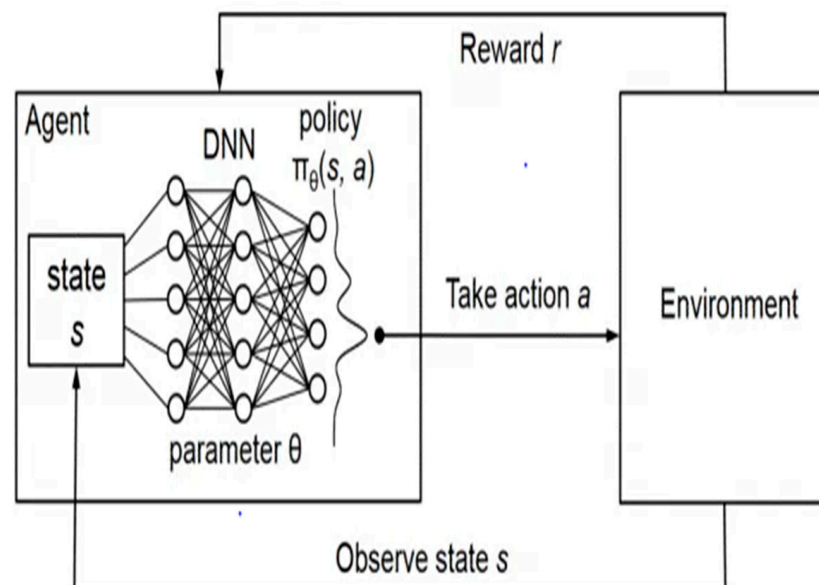


Figure 2. Deep Q-learning. Source: reproduced from [27].

4.3. Proposed Deep Q-Learning Model

A DQN merges deep-learning-based neural networks with the Q-learning algorithm to enhance and accelerate predictive capabilities. The deep neural network (DQN) algorithm [28] is capable of delivering more accurate predictions with enhanced stability, and it requires a significant number of training samples to achieve higher precision. When equipped with a million training samples, the predictive system can exhibit optimal performance. However, the dataset that is currently available consists of only thousands of samples, and the goal is to attain the utmost accuracy in prediction while reducing computational and time complexities. Similarly, Q-learning encounters instability issues due to the interdependencies among states, as each present state relies on the previous one.

To address these challenges, a fusion of Q-learning and neural network technologies was implemented to yield optimized results. In the context of disease prediction, after receiving the state as input, a neural network was trained to identify suitable action values for the next states. By associating states with appropriate actions, the Q-learning algorithm makes use of a q table to update the state and action values, making it easier to calculate the total rewards. The deep Q-network (DQN) agent is an enhanced version of a reinforcement learning (RL) agent that uses neural network training to map states to actions, unlike the more conventional q table technique. The network iteratively modifies the q values in order to reduce correlations between the q values and the target values. To ensure accurate q value predictions, the DQN serves as the DQN agent in the suggested method and is trained using input parameters.

The core equation used in deep Q-learning is derived from the Bellman equation.

Q-Learning Update Rule

The update rule for the Q value function $Q(s,a)$ is given by the following:

$$Q(s,a) \leftarrow Q(s,a) + \alpha(r + \gamma a' \max_{a'} Q(s',a') - Q(s,a)) \quad (2)$$

where:

- s = the current state;
- a = the action taken;
- r = the reward received after taking action a ;
- s' = the next state after taking action a ;
- α = the learning rate (controls how much the Q-values are updated);
- γ = the discount factor (determines the importance of future rewards).

Deep Q-Network (DQN)

In the deep Q-learning, we replaced the Q table with a neural network $Q(s,a;\theta)$, where θ represents the weights of the neural network. The update becomes the following:

$$\Theta \leftarrow \theta + \alpha(r + \gamma a' \max_{a'} Q(s',a';\Theta) - Q(s,a;\theta)) \quad (3)$$

where Θ represents the weights of a target network which are periodically updated from θ to stabilize training. This framework enables the agent to acquire optimal policies in intricate environments through deep learning methods. Figure 3 shows the structure of the DQN agent that was used for training.

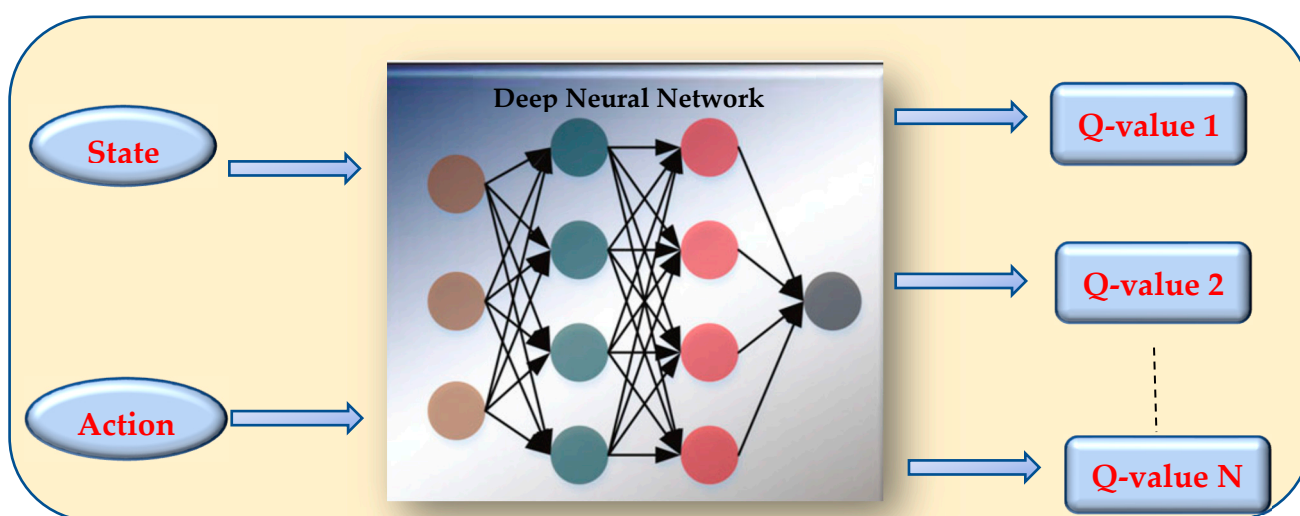


Figure 3. Structure of the proposed DQN. Source: author's creation.

In our proposed method, the dataset was split into training and test sets in proportions of 0.8 and 0.2, respectively, using a stratified approach to preserve the distribution of classes. A robust scalar was used for feature scaling. It was assumed that each feature had three different sets of actions, which were increasing, decreasing, and holding. The environment was defined as sets of states and actions: the states were the samples, and the actions were triple the number of features. The deep Q learning model was built using stacked dense layers, which acted as a state–action mapping function. The agent starts at a random state or sample, and the target of the agent is to reach a state where its class is 1. The training procedure of the model was as follows: the model makes the agent take an action based on its current state. The resultant state is then compared with all training samples using cosine similarity, and the largest similar sample is picked up. Examining the label of this sample, if the label is 1, then the training is stopped, and the “done” flag is raised to show that this episode has ended; otherwise, the reward is decreased by 1, and the next state is assigned to be that sample. The model’s parameters were learned using the state and action, next state, and reward. The model was trained on 100 episodes. A flow diagram of the DQN used in the proposed model’s training is displayed in Figure 4.

Cross-Validation Process and Steps to Mitigate Overfitting

1. Training–Testing Split:

- Using stratified splitting, the dataset was divided into training (80%) and testing (20%) subsets, and the class distribution was maintained in both sets to avoid bias and overfitting issues.

2. Feature Scaling:

- A robust scaler that manages outliers, standardizes the data for consistency during training, and enhances generalization was used to scale the features.

3. Deep Q-Learning with Episodes:

- The model was trained on 100 episodes to iteratively improve its performance.
- In every episode, the agent learned to search states and actions, while rewards were updated depending on the outcomes.
- This iterative learning reduces overfitting because it makes the model generalize over a number of states and actions rather than memorizing certain outcomes.

4. Cosine Similarity:

- The resultant states were then compared with the training samples based on the cosine similarity to select the most relevant state. This avoids overreliance on less representative samples which may lead to overfitting.

These strategies help the model generalize well to unseen data while minimizing overfitting issues.

The proposed Deep Q-Learning Framework (EHR-DQN) combines reinforcement learning and neural networks to enhance accuracy, stability, and scalability in disease prediction using EHRs. Advanced techniques such as episodic learning, cosine similarity, and cross-validation ensure robust model performance and generalization across datasets. The use of stratified dataset splitting and feature scaling minimizes overfitting. The provided algorithm and flowchart offer a clear implementation guide, promoting future progress in data-driven disease prediction. Algorithm provided in (Table 2) offer a clear implementation guide, promoting future progress in data-driven disease prediction.

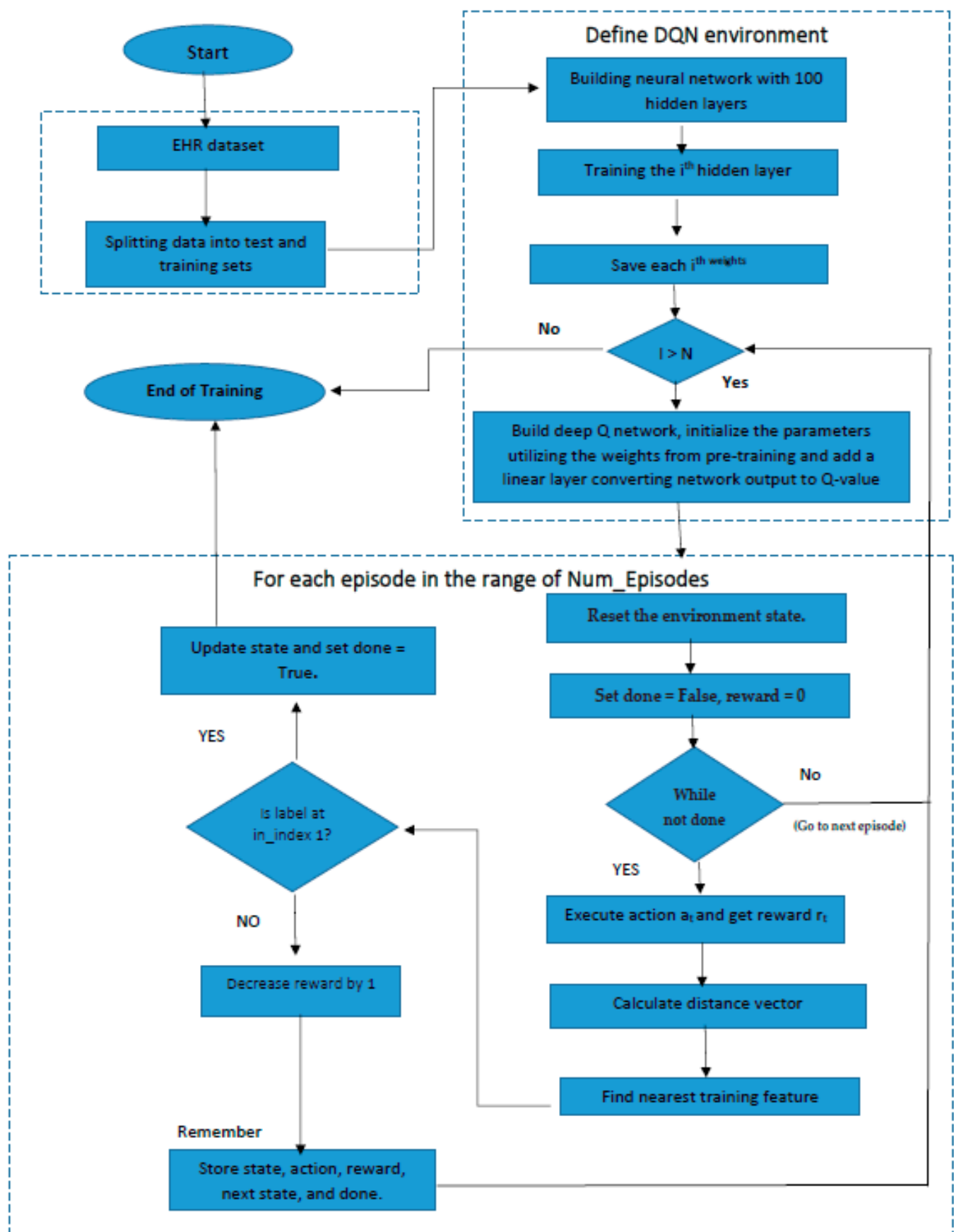


Figure 4. The proposed flowchart for disease prediction using the deep Q-learning model.

Table 2. Algorithm for training the deep Q-learning model.

Algorithm Training Model
<p>STEP 1: Split the dataset X into training_features, training_labels, test_features, and test_labels using the train_test_split function.</p> <p>STEP 2: Apply feature scaling to the training_features and test_features using the feature_scaling function.</p> <p>STEP 3: Define an environment with an observation space equal to the number of features and an action space that is three times the number of features.</p> <p>STEP 4: Define a deep Q-network (DQN) agent model using the define_DQNAGENT function.</p> <p>STEP 5: Set the number of training episodes num_episodes to 100.</p> <p>STEP 6: For each episode in the range of num_episodes:</p> <ol style="list-style-type: none"> Reset the environment state. Set “done” to “False” and “reward” to 0. While not done: <ol style="list-style-type: none"> Choose an action using the model.act(state) function. Take a step in the environment using the model.step(action) function to get the next_state. Calculate the distance vector between next_state and training_features. Find the index of the nearest training feature by getting the min_index from the distance vector. If the label at min_index in training_labels is not 1, decrease the reward by 1. Otherwise, set the next_state to the training_features at the min_index and set “done” to “True”. Remember the state, action, reward, next_state, and done values by calling model.remember(). <p>STEP 7: Repeat the training process for the specified number of episodes.</p>

5. Dataset Description

The Heart Disease Dataset was obtained from the UCI Data Repository via Kaggle (<https://www.kaggle.com/datasets/redwankarimsony/heart-disease-data/data>, accessed on 15 October 2024). The multivariate features of the dataset include multivariate numerical data and several independent mathematical or statistical variables. This dataset comprises 14 attributes (categorical, integer, and real data). The primary task associated with this dataset is classification. Although there are 76 characteristics in the database overall, only 14 attributes have been the subject of most research papers. This dataset can be analyzed with great assistance from the Cleveland database, which has only been used by machine learning researchers up until this point. Predicting if a particular patient has heart disease based on the qualities supplied is one of the dataset’s main goals. Table 3 presents the description of a representative dataset used in the current investigation.

Table 3. Description of the dataset from the UCI data repository.

Attribute	Description
Age	Patient’s age in years
Gender	(0 = male, 1 = female)
Cp	Chest pain type—0: typical angina, 1: atypical angina, 2: non-angina pain, 3: asymptomatic
Trestbps	mm Hg for relaxing blood pressure
Chol	mg/dl of serum cholesterol
Fbs	Fasting blood sugar level, classified as above 120 mg/dL (1 = true, 0 = false)
Restecg	Resting electrocardiographic results—0: normal, 1: ST-T wave abnormality, 2: showing probable or definite left ventricular hypertrophy

Table 3. *Cont.*

Attribute	Description
Thalach	Maximum heart rate reached during a stress test
Exang	Exercise-induced angina (1 = yes, 0 = no)
Oldpeak	Exercise-induced ST depression compared with baseline resting levels
Slope	The peak workout segment's inclination is as follows: 0 is upsloping, 1 is flat, and 2 is downsloping
Ca	Count of major vessels (0–4) colored using fluoroscopy
Thal	Thallium stress test result—0: normal, 1: fixed defect, 2: reversible defect, 3: not described
Target	Condition of heart disease (0 = no disease, 1 = presence of disease)

Source: authors' creation.

In the previous section, we aimed to introduce an overview of the Heart Disease Dataset's structure and use in predictive modeling. This provides context for the dataset's importance in healthcare research, specifically in diagnosing heart disease.

6. Results and Discussion

6.1. Results

We examined and confirmed the suggested DQN model using a number of machine learning techniques, including logistic regression, decision tree classifiers, random forest classifiers, and gradient-boosting classifiers. The justification of the proposed model was evaluated using a comparative analysis of several execution metrics and assessment criteria. In this study, the accuracy, precision, recall, F1 score, mean square error (MSE), and average of the Gini coefficient are among the assessment metrics that are taken into consideration.

Using the Kaggle Heart Disease Dataset, experiments were carried out to train and test the machine learning algorithms. The results are displayed in Table 4. Figure 5 presents the results of the machine learning algorithms based on Table 4. The performance of several algorithms was compared across various metrics, such as accuracy, precision, recall, F1 score, mean squared error (MSE), and average Gini coefficient. The proposed EHR-DQN model demonstrated an excellent performance with metrics close to perfection, such as an accuracy of 0.9841 and an MSE of 0.0001. Similarly, the decision tree and gradient-boosting classifiers showed competitive results, with perfect precision, recall, and F1 scores. In contrast, logistic regression lagged, with an accuracy of 0.8424 and a higher MSE of 0.1576. The random forest model balanced high accuracy (0.9783) with a minimal MSE of 0, highlighting its reliability. Overall, the results favor the EHR-DQN, decision tree, and gradient-boosting models due to their superior predictive performance.

Table 4. Results of the proposed model and other machine learning algorithms.

Name of Algorithms	Accuracy	Precision	Recall	F1 Score	MSE	Avg. (Gini Coefficient)
EHR-DQN (Proposed model)	0.984137957	1	1	0.98198	0.0001	1.0
Logistic regression	0.8423913	0.73068	0.8424	0.77713	0.1576	0.94
Decision tree classifier	0.98563741	1	1	1	0.001	1.0
Random forest classifier	0.97826087	0.9594	0.9783	0.9682	0	0.99
Gradient-boosting classifier	0.98326977	1	1	1	0.0217	1.0

Source: authors' creation.

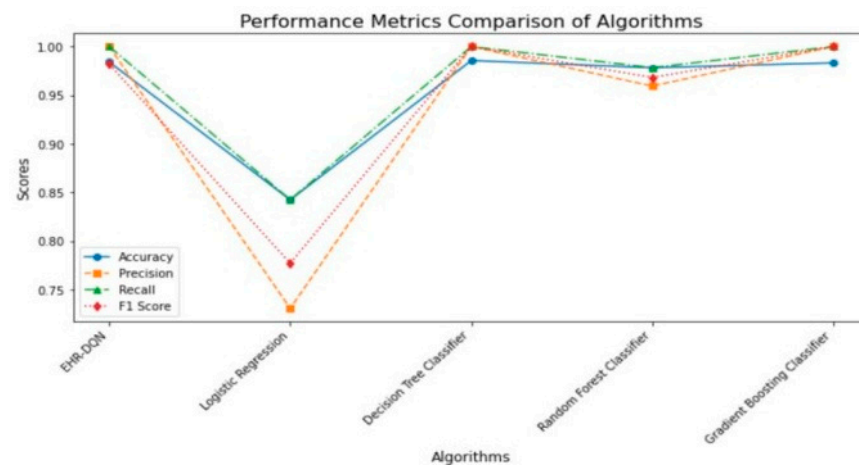


Figure 5. Evaluation metrics of the proposed (EHR-DQN) model’s performance in comparison with that of other machine learning models.

6.2. Discussion

Due to the conclusions of this study, it can be inferred that the proposed DQN model excels at disease prediction in comparison with other models. The DQN model effectively categorizes input data with remarkable accuracy. By incorporating artificial intelligence in the form of a neural network and by leveraging the reinforcement learning’s self-learning capacity, the model achieves an enhanced prediction performance. The neural network component resolves the uncertainty issue caused by correlations in the Q-learning model, while the integrated model establishes a clear connection between the input and target variables. The agent’s self-learning capability significantly decreases the computation time required for the prediction of disease class labels. Furthermore, the original dataset’s distribution is preserved by the model and is resilient to variations in input sample size and quality.

6.3. Comparison with Other Studies

Table 5 summarizes the qualitative and quantitative differences among various previously reported approaches for enhancing the detection and risk classification of heart diseases using the Kaggle Heart Disease Dataset that was used in our work. It highlights their respective strengths, weaknesses, and reported accuracy.

Table 5. Comparison between the proposed model and other studies on heart disease prediction using the Kaggle Heart Disease Dataset.

Work	Approach	Strengths	Weaknesses	Accuracy
[29]	Hard voting ensemble	Simple, interpretable	Limited by voting thresholds	90%
[30]	RF with linear model	Combines the strengths of ensemble and linear models	Static feature reliance	88.7%
[31]	LOFS-ANN	Reduces irrelevant features	Static feature reliance	90.5%
[32]	Random forest	High accuracy on structured data	Sensitive to feature imbalance	83%
[33]	Cluster-based BiLSTM	Effective for sequential data	Computationally expensive	94.78%
[34]	Naive Bayes	Evaluates multiple classifiers, dimensionality reduction (PCA/LDA)	Complexity in selecting the best classifier	83%
[3]	Naive Bayes, LR, SVM	Fair and interpretable results, robust metrics	Slightly lower accuracy than alternatives	89%
Proposed	DQN model	Self-learning, robust to variations	Needs hyper-parameter tuning	98%

Source: authors’ creation.

Ref. [29] studied an ensemble technique based on a majority voting strategy in order to develop a model for predicting Huntington's disease (HD) in medical decision support systems. Medical test data from both sick and healthy people at a nearby clinic were used to train the model. With their ensemble voting method, they were 90% accurate. Ref. [30] developed a machine-learning-based model by identifying the most significant features for predicting Huntington's disease (HD). The prediction system was created using a hybrid approach that combined a random forest and a linear model, and this approach achieved an accuracy of 88.7%. Ref. [31] proposed three Huntington's disease (HD) prediction methods that combined a lion-optimization-based feature selection (LOFS) technique with different machine learning algorithms: LOFS-ANN (LOFS with an artificial neural network), LOFS-SVM (LOFS with a support vector machine), and LOFS-DT (LOFS with a decision tree). Ref. [32] developed a healthcare application to assist in the detection of heart diseases among patients, including those presenting with relevant symptoms. By leveraging the random forest algorithm, their work achieved an improved accuracy in heart disease prediction. Additionally, the application was cost-effective to develop. Ref. [33] developed a cluster-based bidirectional long short-term memory (BiLSTM) algorithm that effectively classifies heart disease. The risk of cardiovascular disease and the risk factors related to it were determined using the proposed approach. The study's dataset came from real-time data sources and internet repositories. Based on major risk factors, Ref. [34] proposed a paradigm for predicting the development of heart disease. The framework used a variety of classifier configurations, such as the methods for lasso regression, ridge regression, support vector machine, naive Bayes, and K-nearest neighbors. Ref. [3] proposed a framework called the XAI-based classification model, and they discovered that the model was quite reasonable. Notably, an 89% accuracy was attained by the XAI-driven SVM, LR, and naive Bayes models.

7. Conclusions and Future Work

Artificial intelligence, machine learning, and the internet of things all play crucial roles in the healthcare sector, and they have emerged as powerful tools for constructing and deploying intelligent systems. Various models exist in the literature for disease prediction, but they lack sufficient accuracy to predict the correct disease. These models struggle to precisely match raw data with predicted values, and the quality of the input features has an important effect on their outputs. The accurate mapping of raw data to predicted values is made possible by the hybridization of Q-learning and deep learning which helps to overcome these restrictions. In order to predict heart disease, our proposed work replaces the Q-learning reinforcement learning algorithm with a deep learning algorithm in the form of a neural network, and the mapping capabilities of the Q-network are used. The overall accuracy of the proposed prediction model is 98%.

In future work, we aim to deploy our model on a serverless platform. Serverless computing provides a key solution for event-driven AI applications. Function-as-a-service (FaaS) involves high performance, low-cost deployment on the cloud, and ease of operational management. It eases the deployment of complex applications such as NLP and image processing which strongly depend on large deep learning models. The advantage of utilizing multiple servers in a serverless computing environment for running specific applications has enhanced the delivery of improved healthcare services. Serverless computing offers several benefits to healthcare systems, such as lower energy consumption and reduced delays and data traffic. In addition, in future work, we aim to validate the proposed model using real-world clinical datasets to enhance its applicability and reliability in disease prediction.

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