Systems and Soft Computing 6 (2024) 200129

Contents lists available at ScienceDirect

Systems and Soft Computing

journal homepage: www.journals.elsevier.com/soft-computing-letters

Enhancing heart disease prediction with reinforcement learning and data augmentation

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A R T I C L E I N F O

Keywords:
Cardiac disease
Data augmentation
Heart disease
Machine learning in cardiology prediction
Reinforcement learning

A B S T R A C T

The study presents a novel method to improve the prediction accuracy of cardiac disease by combining data augmentation techniques with reinforcement learning. The complex nature of cardiac data frequently presents challenges for traditional machine learning models, which results in subpar performance. In response, our fusion methodology improves predictive capabilities by augmenting data and utilizing reinforcement learning's skill at sequential decision-making. Our method predicts cardiac disease with an astounding 94 % accuracy rate, which is an outstanding result. This significant improvement outperforms existing techniques and shows a deeper comprehension of intricate data relationships. The amalgamation of reinforcement learning and data augmentation not only yields superior predictive accuracy but also bears noteworthy consequences for patient care and accurate cardiac diagnosis. Through the efficient combination of these approaches, our method provides a powerful response to the difficulties presented by complicated cardiac data. The potential to transform illness prediction and prevention techniques and ultimately improve patient outcomes is demonstrated by this integration's success.

1. Introduction

Heart disease continues to be a major global health concern, causing a significant number of fatalities annually. For cardiac disease to be effectively treated and prevented, early and accurate identification is essential. The availability of big healthcare datasets and the development of machine learning techniques present a chance to improve the forecast accuracy of cardiac disease. In this study, to enhance the prediction accuracy of heart disease data augmentation with reinforcement learning are combined. Heart disease, which is another name for cardiovascular illness, includes a variety of disorders that affect the heart and blood arteries, such as arrhythmias, heart failure, and coronary artery disease. The World Health Organization (WHO) estimates that heart disease killed 18.6 million people worldwide in 2019. Heart disease is the world's top cause of death. Reducing mortality and improving patient outcomes are contingent upon early detection and precise prognosis of heart disease.

Risk factors for heart disease, including age, sex, family history, and lifestyle choices, are assessed in traditional techniques of heart disease prediction. Even while these elements are important, they might not give a complete picture of a patient's risk. In order to evaluate complicated medical data and spot trends that traditional methods can miss, machine learning has shown to be a very useful tool. The prediction of heart disease is one of the many medical tasks for which machine learning approaches have proven effective. These methods can examine a wide range of data sources, including lab results, patient histories,

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https://doi.org/10.1016/j.sasc.2024.200129
Received 8 January 2024; Received in revised form 24 April 2024; Accepted 7 August 2024
Available online 17 August 2024

Table 1
Comparison analysis.

Paper/Study Title	Focus	Key Methodologies/ Techniques	Application Domain
Majhi et al. (2019)	Precision in medical diagnoses	AI, ML efficacy in examining medical data	Healthcare, medical diagnoses
Alizadehsani et al. (2017)	Identifying high-risk cardiac conditions	Various algorithm performance analysis	Cardiac disease prediction
Akter et al. (2019), Jain et al. (2018)	Predictive power for heart disease	Different ML approaches in heart disease prediction	Cardiology, disease diagnosis
Kora et al. (2014), Hossain et al. (2012)	Enhancing precision in heart disease prediction models	Application of ML approaches	Cardiac health, predictive analytics
Goyal et al. (2013), Singh et al. (2015), Ponselvi et al. (2017)	Data mining for early prediction of heart-related issues	Identifying patterns in medical data	Heart-related problems, early prediction
Rajkomar et al. (2018)	Hospital readmission predictive modeling	Data-driven strategies for improved patient care	Patient care, hospital readmission
Gayathri et al. (2022)	Using hybrid Dc-Lg algorithm for heart disease prediction	Algorithmic approaches for accuracy improvement	Cardiac disease prediction
Yair Movshovitz -Attias et al. (2012)	Data augmentation techniques	Various augmentation methods for model performance	Computer vision, image recognition
Lorraine Dautriche et al. (2021)	Data augmentation in NLP	Role of augmentation in NLP models	Natural Language Processing
Ali Dabouei et al. (2021)	Data augmentation in deep learning applications	Diverse applications for model enhancement	Audio classification, COVID-19 diagnosis, medical imaging
Jirayus Jiarpakdee et al. (2019)	Data augmentation in specific domains	Domain-specific augmentation methods	Brain tumor detection, autonomous vehicles, sensor data
Esteva et al. (2016)	Reinforcement Learning applications	RL in healthcare, finance, medical imaging	Medical analysis, financial portfolios
Murphy et al. (2017)	Deep RL in personalized medicine	RL for dynamic treatment regimens, cancer treatment	Personalized medicine, cancer treatment
Liao et al. (2019)	Advantages and difficulties of Deep RL in healthcare	Analysis of DRL in medical settings	Medical applications, operational efficiency
Mao et al. (2019)	RL in critical care scenarios	DRL for hemodynamic management, sepsis treatment	Intensive care, critical care interventions

medical imaging, and electrocardiograms (ECGs). Machine learning models can make predictions that are more accurate and help healthcare professionals make well-informed decisions by utilizing the wealth of information present in these data sets [43].

Using supervised learning algorithms is a popular method for predicting heart disease. In this method, models are trained on labeled datasets to determine the relationship between input features and the desired outcome, such as the existence or absence of heart disease. Although supervised learning models have demonstrated potential, their capacity to discern intricate and ever-changing patterns in medical data is restricted. A branch of machine learning called Reinforcement Learning (RL) is devoted to sequential decision-making. RL agents are trained to maximize a cumulative reward signal by making a series of decisions. Numerous industries, including robotics, gaming, and recommendation systems, have effectively used this paradigm.

Table 2
Dataset description.

Feature	Description
Age	The age of the patient.
Sex	The gender of the patient (0 for female, 1 for male).
Chest Pain Type	The type of chest pain experienced (0–3, e.g., typical angina).
Resting Blood Pressure	The patient's resting blood pressure in mm Hg.
Cholesterol	The patient's serum cholesterol level in mg/dL.
Fasting Blood Sugar	Fasting blood sugar level (0 for ⟨= 120 mg/dL, 1 for ⟩ 120 mg/dL).
Resting Electrocardiographic Results	Results of resting electrocardiogram (0–2, e.g., normal, abnormal).
Maximum Heart Rate Achieved	The maximum heart rate achieved during exercise.
Exercise-Induced Angina	Whether the patient experienced exercise-induced angina (0 for no, 1 for yes).
ST Depression	ST segment depression induced by exercise relative to rest.
Number of Major Vessels (Fluoroscopy)	The number of major vessels colored by fluoroscopy (0–3).
Thallium Stress Test	Results of the thallium stress test (0–3, e.g., normal, fixed defect).
Old Peak	The ST depression in response to exercise relative to rest.
Slope of the Peak Exercise ST Segment	The slope of the ST segment during peak exercise (0–2, e.g., upsloping).
Thallium Scintigraphy	Results of thallium scintigraphy (0–3, e.g., normal, fixed defect).
Diagnosis	The presence or absence of heart disease (0 for no disease, 1 for disease).

Table 3
Feature description.

S.NO	Features	Score
1	CHOL	2854.089406
2	THALACH	604.436447
3	AGE	121.687344
4	EXANG	108.744459
5	CP	53.996025
6	TRESTBPS	25.516333
7	SEX	18.450545
8	FBS	9.752496

RL has drawn interest in the medical field due to its potential to improve treatment regimens and medical interventions. RL models are appropriate for individualized patient care because they can adjust and make decisions in dynamic environments. A combined approach that takes into account the sequential nature of patient responses and healthcare decisions in order to leverage RL is used to improve heart disease prediction. Data augmentation is a widely used technique in natural language processing and computer vision to increase the diversity of training data and hence improve model performance. Data augmentation in the healthcare industry refers to the process of creating artificial data points that bear similarities to actual patient data. Concerns about privacy, data scarcity, and imbalanced datasets can all be addressed with this strategy [44,45].

When dealing with limited patient data or sensitive medical records that are subject to privacy regulations, data augmentation can be especially helpful for heart disease prediction. The training dataset can be made larger and more diverse by creating synthetic data, which will help the machine learning model identify stronger patterns and features. Accurately predicting heart disease is still a difficult task in the field of medicine, with significant effects on both public health and patient care.

Table 4
Classification description.

ID	Age	Gender	BMI	Smoking	Family History	Exercise	Diet	Stress Level	Heart Disease
1	45	Male	25.6	No	Yes	Regular	Balanced	Moderate	Yes
2	61	Female	28.3	Yes	No	Rarely	High-Fat	Low	No
3	52	Male	30.1	No	Yes	Regular	Vegetarian	High	Yes
4	35	Female	22.8	No	No	Regular	Balanced	Low	No
5	48	Male	27.5	Yes	Yes	Rarely	Low-Fat	High	Yes

Table 5
Classification parameters.

ID	Blood Pressure	Cholesterol (HDL)	Cholesterol (LDL)	Fasting Blood Sugar	ECG Result	Heart Disease
1	130/85	55	120	130	Normal	Yes
2	140/90	45	150	160	Abnormal	No
3	125/80	60	130	110	Normal	Yes
4	120/75	65	140	95	Normal	No
5	135/88	50	125	140	Abnormal	Yes

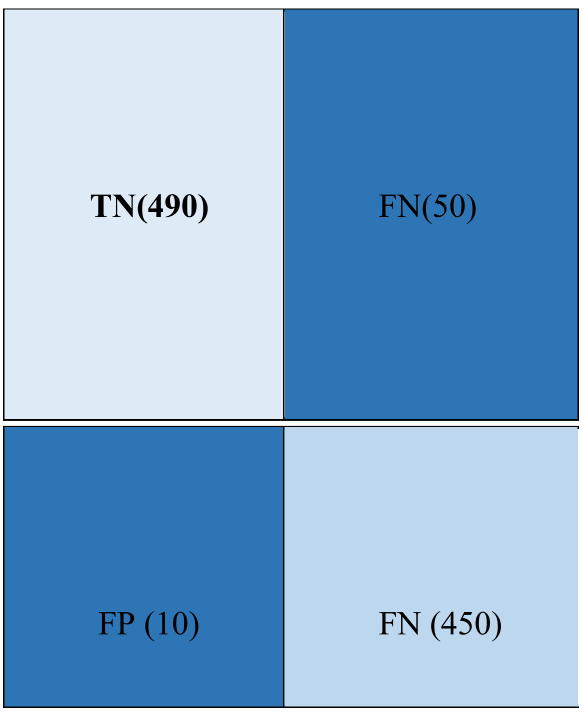

Fig. 1. Confusion matrix.
Accuracy = (TN+TP) / (TN+TP+FN+FP)= 490+450/490+450+50+10=0.94
Recall = (TP/TP+FN) =450/450+50 = 0.90
Specificity = (TN/TN+FP) =490/490+10 = 0.98
Precision = TP /TP+FP = 450/450+10=0.98
F-Measure=2TP/ 2TP+FP+FN=2*450/2*450+10+50=0.93.

Table 6
Comparison analysis.

S. No	Algorithm	Accuracy	Precision	Recall	F1 Score	AUC-ROC
1	Logistic Regression	0.85	0.81	0.90	0.85	0.89
2	Decision tree	0.80	0.76	0.85	0.80	0.83
3	Random Forest	0.88	0.87	0.91	0.89	0.92
4	Support Vector Machine	0.84	0.79	0.89	0.84	0.87
5	Neural Network	0.87	0.85	0.92	0.88	0.90
6	Ensemble Reinforcement Learning	0.94	0.98	0.90	0.93	0.93

This study improves prediction accuracy by utilizing state-of-the-art technologies in order to address this pressing issue. The aim is to reshape the field of heart disease prediction by merging reinforcement learning with data augmentation methods.

Heart disease continues to be a major global health concern, taking a significant toll on lives each year. For cardiac diseases to be effectively treated and prevented, early detection and accurate diagnosis are essential. With the introduction of large-scale healthcare datasets and the development of machine learning methods, there is a chance to improve the prediction of heart diseases. Even with conventional techniques that evaluate risk factors such as age, sex, family history, and lifestyle choices, a patient's risk may not be fully captured by these factors. Because medical data is complex, identifying patterns that traditional methods miss is essential to making an accurate prognosis. A potent tool for analysing complicated medical data and identifying patterns necessary for precise illness prediction is machine learning.

The goal of the research is to improve the accuracy of heart disease prediction by combining reinforcement learning and data augmentation. This includes heart failure, arrhythmias, and coronary artery disease. The intention is to use these technologies' advanced capabilities to transform the prediction of heart disease. Since there are many factors that can influence heart disease, it is difficult to predict with precision. The dynamic capabilities of reinforcement learning algorithms in our quest for increased accuracy. With the help of these algorithms, prediction models are improved and modified to account for changing patient data. Furthermore, the idea of data augmentation is presented, which offers a wealth of extra data to train and improve these models. Our work aims to improve the accuracy of heart disease predictions by means of this novel combination of reinforcement learning and data augmentation. The research results show significant improvements in prediction accuracy, highlighting the unrealized potential of this combined strategy. Our findings have implications that go beyond heart disease and highlight the importance of advanced machine learning techniques in the field of medical diagnosis. Our research adds a valuable and transformative dimension to the ongoing search for more accurate heart disease predictions, as part of ongoing efforts to improve the precision of healthcare practices [46].

The main objectives are

1. To improve the accuracy of predicting cardiac diseases by integrating reinforcement learning and data augmentation techniques.
2. To facilitate early and accurate diagnosis of cardiac diseases to enable timely intervention and prevention strategies, crucial for better patient outcomes.

With this detailed introduction, the related works are discussed in

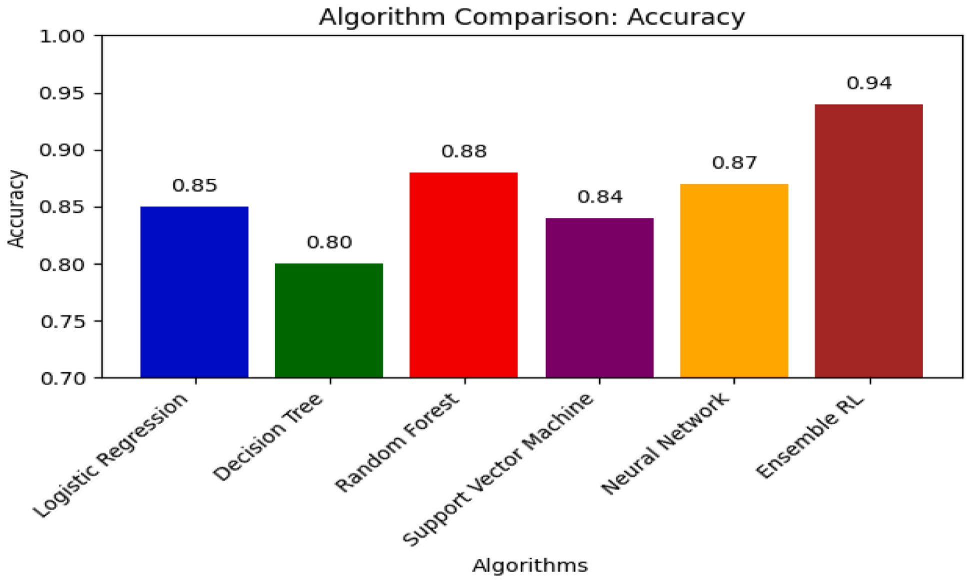

Fig. 2. Accuracy comparison.

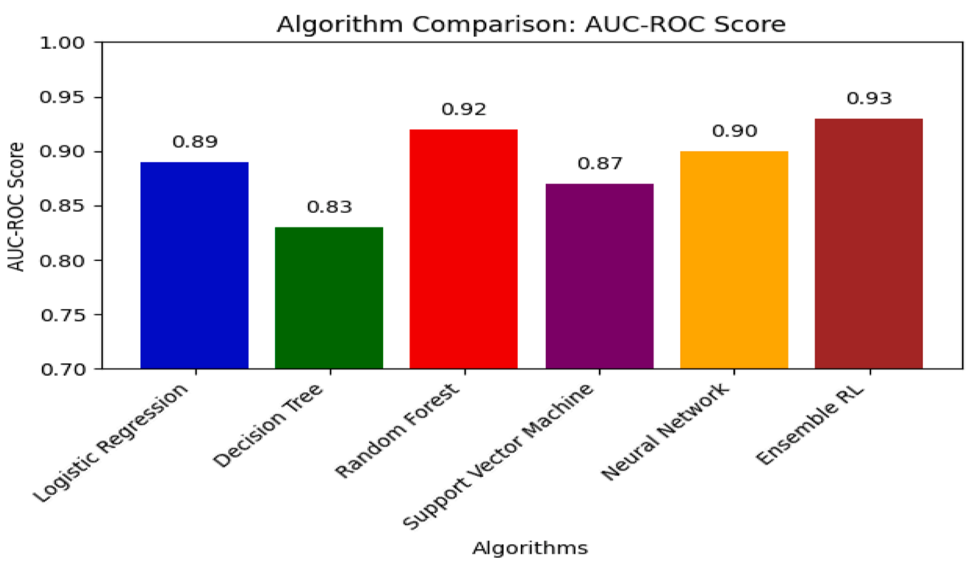

Fig. 3. AUC-ROC Score comparison.

Section 2. The proposed augmented ensemble reinforcement learning is explained in Section 3. The experimental environment is shown in Section 4. The conclusion is covered in Section 5.

2. Related works

Artificial intelligence and machine learning have become potent instruments in the healthcare industry in recent years, with the potential to improve the precision of medical diagnoses. examines the efficacy of these techniques in examining medical data, emphasizing the possibility of precise and prompt diagnosis [1]. It assesses various algorithms' performance and offers information about how well they identify cardiac conditions at high risk [2]. It assesses the performance of different models and offers a thorough analysis of their predictive power for diagnosing heart disease [3,4]. Examine how different machine learning approaches can be applied to improve the precision of heart disease prediction models [5,6]. The study assesses how well these algorithms handle medical data to enable accurate diagnosis. Examine how data mining might be used to identify important patterns in medical data that could help predict heart-related problems early [7–9]. The study provides information on hospital readmission predictive modeling and uses data-driven strategies to improve patient care [10]. Suggests using a hybrid Dc-Lg algorithm to improve heart disease prediction accuracy [41,42]. Enhancing a dataset with every possible combination of input features becomes crucial when it comes to small datasets.

Data augmentation techniques were investigated to improve object recognition performance, particularly when dealing with limited training data [11]. AlexNet, a deep neural network architecture, was introduced, and it significantly improved image classification on the ImageNet dataset, paving the way for deep learning in computer vision [12]. Cutout regularization, which involves randomly masking regions of input images during training, has been proposed to improve the generalization of convolutional neural networks [13]. The Random Erasing technique was introduced, which is a data augmentation method that randomly masks rectangular regions of input images to improve model robustness [14]. The Mix-up augmentation strategy was proposed, which involves linearly interpolating pairs of input samples and their labels to create synthetic training examples, thereby improving

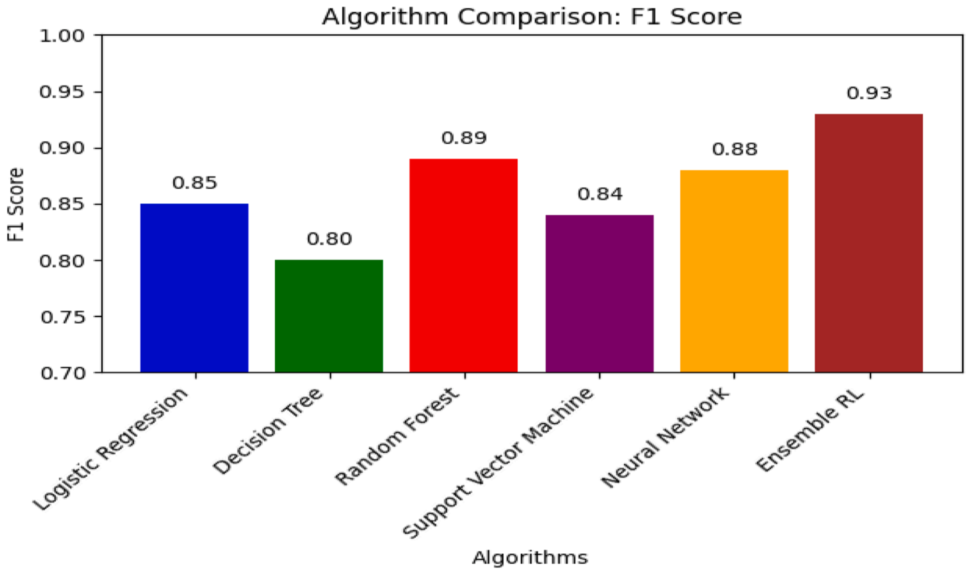

Fig. 4. F1 Score comparison.

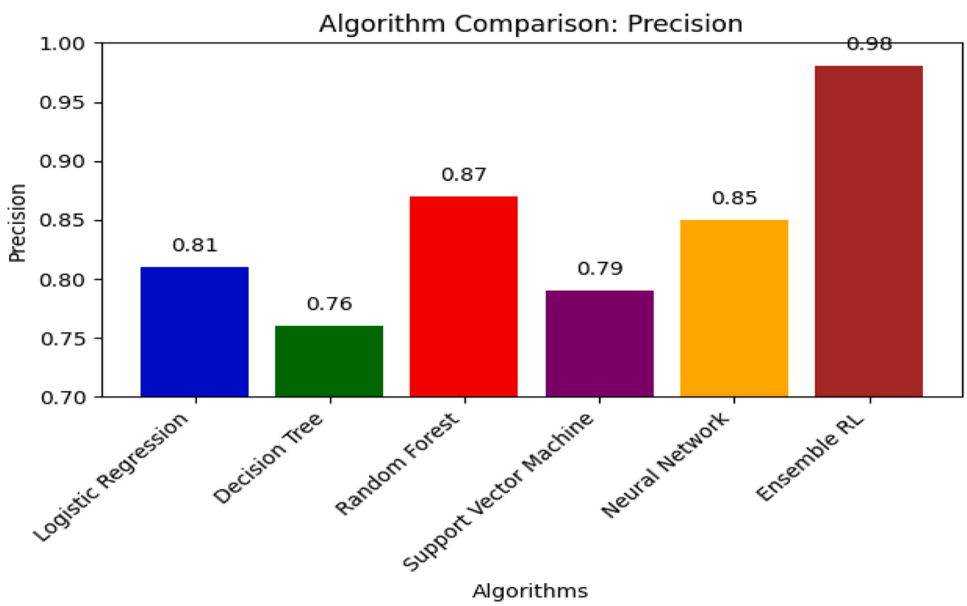

Fig. 5. Precision comparison.

model generalization [15].

By blending patches from different images, the Cutout approach was extended, encouraging models to learn from mixed samples and improving localization and classification capabilities [16]. Auto Augment, an algorithm that searches for effective data augmentation policies automatically, reducing the need for manual tuning [17], was introduced. A comprehensive review of various data augmentation techniques in convolutional neural networks (CNNs) was provided, along with a discussion of their impact on model performance [18]. Investigated data augmentation strategies for image super-resolution, proposing a new approach to improving image quality [19]. AugMix is a proposed data augmentation method that combines various augmentations to improve model robustness and uncertainty estimation [20].

Investigates several deep learning image data augmentation strategies, offering insights into approaches that improve model robustness and generalization [21]. Explains the function of data augmentation in Natural Language Processing (NLP) and how it enhances the generalization and robustness of NLP models [22]. Presents advances in the field, solves problems, and offers deep learning techniques for classifying data that is unbalanced [23]. Investigates small object detection-specific data augmentation methods with the goal of enhancing object detection models' performance, especially in situations involving small objects [24]. Summarizes the applications and effects of data augmentation techniques used in deep learning-based audio classification and offers a thorough analysis of them [25]. Focuses on effective data augmentation methods to enhance the deep learning-based COVID-19 chest X-ray image classification [26].

Investigates data augmentation techniques to improve convolutional neural networks' classification performance in the context of brain tumor detection [27]. Examines data augmentation methods designed specifically for speech recognition domain recurrent neural network training [28]. Analyses data augmentation methods to enhance the classification of endoscopic images, giving a summary of existing approaches and their effects [29]. Examines different methods of data

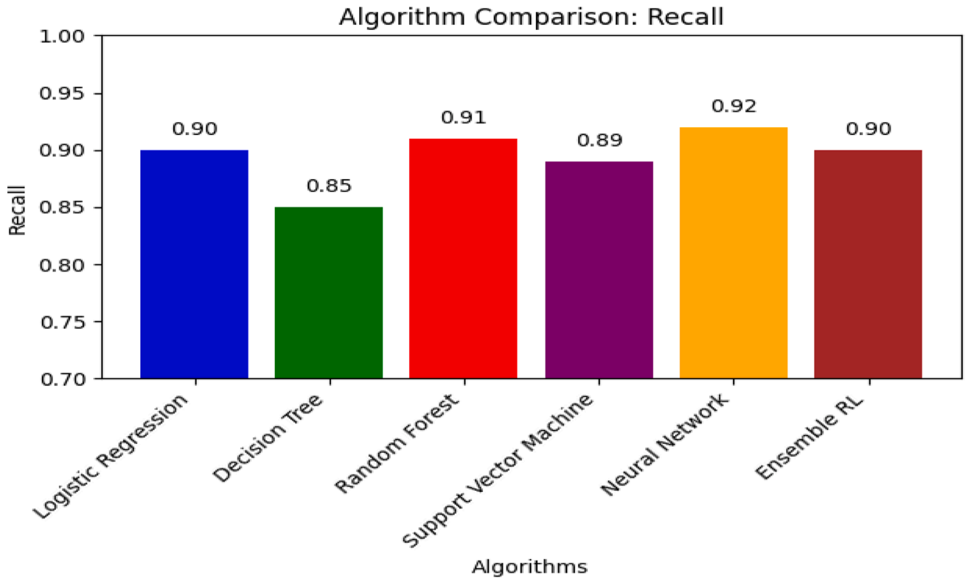

Fig. 6. Recall comparison.

augmentation and how they can be used to improve the reliability of sensor data for autonomous driving systems in the context of autonomous vehicles [30]. Presents a framework that uses reinforcement learning to improve the analysis of medical images and investigates the use of deep Q-learning in this field [31]. This paper, which focuses on managing financial portfolios, presents a deep reinforcement learning framework to optimize investment strategies and uses RL techniques to address financial domain challenges [32]. This paper offers a critical review of the applications of reinforcement learning in healthcare, analysing the potential advantages and difficulties in a range of medical settings [33].

The research, which focuses on dynamic treatment regimens, shows the potential of deep reinforcement learning in personalised medicine by optimising treatment decisions using data from medical registries [34]. This paper, which focuses on autonomous systems, presents a deep Q-learning method that improves autonomous agents' ability to make decisions by learning from examples [35]. This work uses deep reinforcement learning for automated radiation adaptation in the context of lung cancer treatment with the goal of optimising treatment regimens for better patient outcomes [36]. Gives a thorough rundown of the advantages and difficulties of using Deep Reinforcement Learning (DRL) in the medical field. The potential for bettering patient outcomes and operational efficiency is highlighted by the authors as they look at various DRL applications in medical settings. They offer guidance to researchers and practitioners in the field by talking about issues like interpretability, data privacy, and ethical considerations [37].

The paper, published in the Journal of the American Medical Informatics Association in 2019, focuses on using deep reinforcement learning for hemodynamic management in septic shock cases. The framework presented by Mao et al., the authors, optimises hemodynamic interventions by utilising DRL with the goal of improving patient outcomes in critical care scenarios. According to the study, DRL has the ability to offer patients in septic shock tailored and flexible interventions [38]. Examines how to use reinforcement learning to create individualised treatment plans for patients with sepsis in intensive care units. In order to illustrate the potential of reinforcement learning in optimising critical care interventions, the authors propose a model that learns optimal treatment plans customised to individual patient conditions [39]. Outlines a method for weaning patients off of mechanical ventilation in intensive care units that uses reinforcement learning. The research highlights the potential of reinforcement learning in optimising mechanical ventilation strategies for better patient outcomes by introducing a model that modifies ventilation parameters in response to patient responses [40]. The wide range of approaches, uses, and fields in which machine learning, data augmentation, and reinforcement learning techniques have been applied is shown in Table 1. It demonstrates the wide range of research endeavors aimed at enhancing precision, accuracy, and tailored care in multiple medical fields, ranging from critical care interventions to diagnosis.

The pressing need to surmount the complex intricacies inherent in cardiac health data is driving the integration of data augmentation and reinforcement learning for the prediction of cardiac disease. The complex patterns and non-linear relationships present in this data are difficult for traditional machine learning techniques to understand. Data augmentation attempts to add more diverse examples to the dataset, which may help models capture more complete representations. This is enhanced by reinforcement learning, whose skill at sequential decision-making allows it to adjust to the dynamic nature of the development of cardiac health. This integration's main goal is to greatly improve prediction accuracy, which makes early diagnosis and intervention possible and essential for improved patient outcomes. This approach aims to address shortcomings of traditional methods by using reinforcement learning and augmented data to create more accurate, flexible, and refined predictive models specifically for cardiac disease prediction. The ultimate driving force behind this effort is the possibility of greatly enhancing patient care and healthcare administration by using more precise and trustworthy predictive models.

3. Proposed augmented ensemble reinforcement learning

3.1. Dataset used

For many datasets, including those pertaining to heart disease, the UCI Machine Learning Repository (10.24432/C52P4X) is a well-known resource. For tasks involving the classification of heart diseases, you can find datasets similar to the Cleveland Heart Disease dataset. This dataset usually contains a target variable that indicates whether or not heart disease is present, along with a number of features like age, gender, blood pressure, cholesterol levels, ECG results, and more. Other heart disease datasets may also be available from government health agencies, healthcare institutions, and research repositories. Table 2 depicts the description of the dataset.

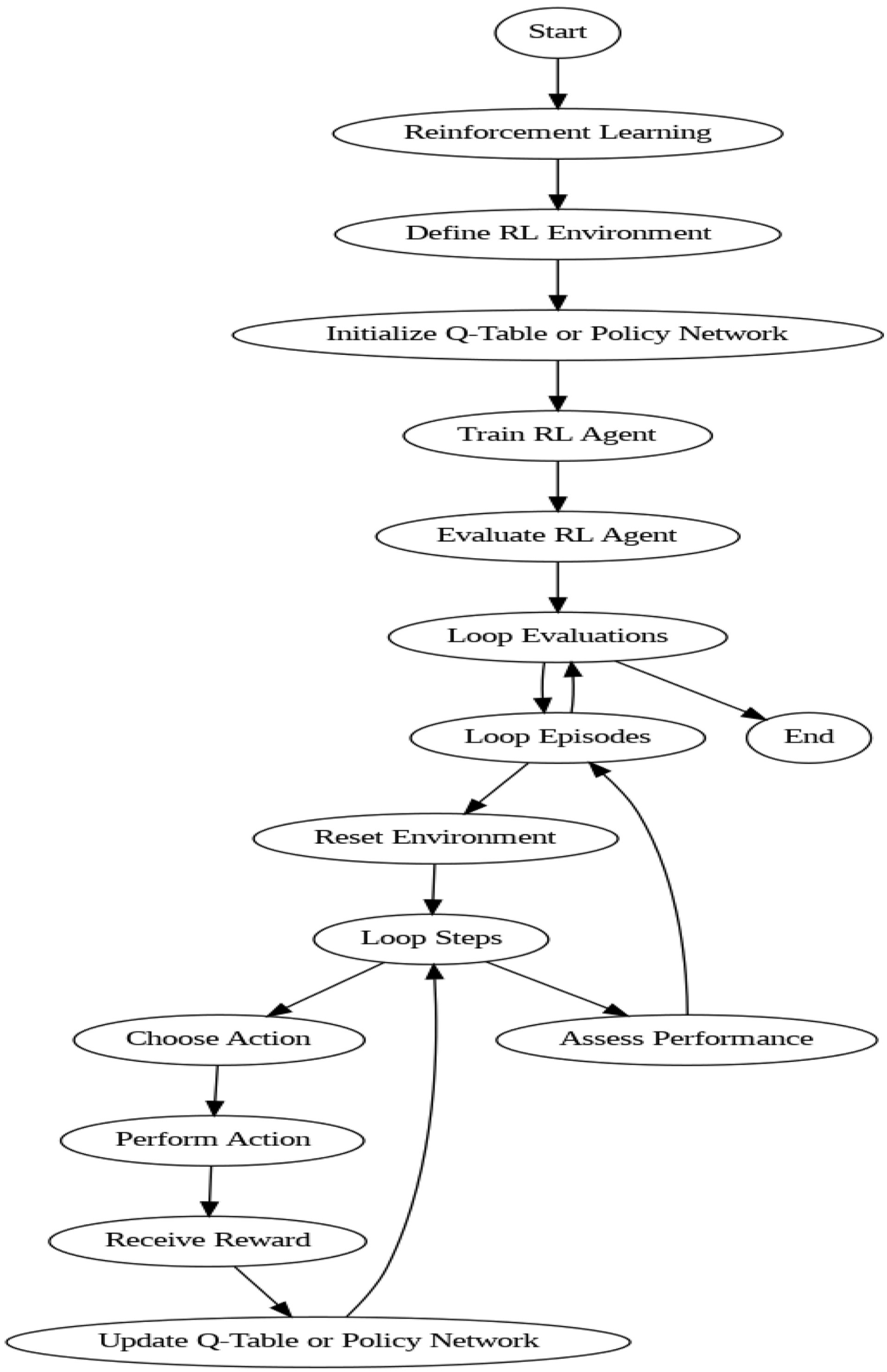

Fig. 7. General system architecture.

3.2. Data preprocessing

An essential first step in getting data ready for analysis and machine learning is pre-processing a dataset on heart disease. To make the data suitable for modeling and analysis, it must be cleaned, transformed, and organized. When cleaning the data, the first step is to deal with any missing data. Discover any missing values in your dataset and address them. Removal, imputation using the mean or median, or sophisticated techniques are available options. The duplicates should be checked for and removed if they are found. One-hot encoding and label encoding are two methods for converting categorical variables (like gender) into a numerical format. To ensure that numerical features have the same scale and enhance model performance, normalization or standardization is needed. Below Eq. (1) shows min-max scaling and Eq. (2) shows z-score scaling

$$A' = (A - A\_min)/(A\_max - A\_min) \tag{1}$$

$$X\_standardized = (X - \mu)/\sigma \tag{2}$$

Choose the most pertinent characteristics. To identify important variables for predicting heart disease, one can employ techniques such as feature importance scores or recursive feature elimination. Table 3 describes the feature details.

3.3. Proposed approach

The fundamental basis of this innovative approach lies in the utilisation of enhanced patient data. By incorporating additional instances of current patient data, the predictive model is exposed to a wider range of situations.The increased exposure allows it to adapt more efficiently to a wider range of patient profiles and to handle uncertainty with greater resilience.

For instance, a dataset of patients in which the majority of individuals are in their middle age, follow a well-balanced diet, and engage in regular exercise. Although this sample represents only a portion of the population, it may not fully encompass the wide range of lifestyle factors and demographic characteristics observed in real-life situations. Data augmentation techniques can incorporate artificial data instances that depict diverse age groups, dietary habits, or exercise patterns, thereby enlarging the training dataset of the model and enhancing its capacity to generate precise predictions for a broader spectrum of patients.

Pseudo-Code

```
environment = RLFramework.Environment()
agent = RLFramework.Agent()
# Data collection and preprocessing (real-world data)
real_world_data = environment.collect_data()
preprocessed_data = DataAugmentationLibrary.preprocess(real_world_data)
# Initialize RL training
agent.initialize()
# Reinforcement Learning training loop
for episode in range(training_parameters['num_episodes']):
  state = environment.reset() # Reset the environment for a new episode
  episode_data = [] # Collect data for the current episode
  for step in range(training_parameters['max_steps_per_episode']):
    # Augment the state with data augmentation techniques
    augmented_state = DataAugmentationLibrary.augment(state)
    # Choose an action using the agent's policy
    action = agent.choose_action(augmented_state)
    # Interact with the environment and observe the next state and reward
    next_state, reward, done = environment.step(action)
    # Store the transition (state, action, reward, next_state)
    episode_data.append((augmented_state, action, reward, next_state))
    state = next_state # Update the current state
    if done:
      break # Exit the episode if it's finished
# Update the agent's policy using the augmented data from the episode
  agent.update_policy(episode_data)
E<-Environment
A<-Agent
R <- E.collect_data()
P<-Preprocess(R)
A.init()
for E in range num_episodes:
S<- E.reset()
D <- []
for S in range max_steps_per_episode:
A<-Augment(S)
C<- A.choose_action(A)
N, G, D <-E.step(C)
D.append((A, C, G, N))
S<- N
if D:
break
```

Setting up the environment and agent for reinforcement learning (RL) is the first step in the process. Data from the real world is gathered and preprocessed, using augmentation methods. Other parameters are initialized, as well as the agent's policy. With the first episode, the RL training loop iterates. The environment is reset and a loop of steps starts for every episode. The agent selects a course of action based on its policy and augments the state. Through interaction with the surroundings, the agent gains access to the next state, a reward, and a flag designating whether the episode is complete. For the episode, transition data is kept on file. Each time an episode is finished, the agent uses the information gathered to update its policy. Until the required number of episodes is reached, this loop keeps going. The procedure then comes to an end.

The code that leverages the combination of reinforcement learning and data augmentation to improve the accuracy of heart disease prediction. The algorithms which are specifically created to acquire knowledge through interactions with an environment, have the ability to adjust and respond to new data and feedback. Their flexibility makes them highly suitable for dynamic medical datasets, in which new patient information is consistently being made available. Through the utilisation of the feedback loop that is inherent in reinforcement learning, predictive models have the ability to develop and enhance themselves over a period of time. Data augmentation techniques are incorporated to enhance the accuracy and resilience of these models. Data augmentation entails the process of generating diverse versions of preexisting data through the application of transformations, introduction of noise, or creation of synthetic examples. This procedure enhances the dataset and improves the model's ability to generalise across various patient profiles and disease manifestations.

4. Experimentation results

The dataset comprises an extensive assortment of characteristics that depict diverse facets of a patient's well-being and medical background. The included features encompass age, gender, type of chest pain, baseline blood pressure, cholesterol levels, fasting blood sugar, resting electrocardiographic outcomes, maximum heart rate attained during exercise, exercise-induced angina, and additional factors. The target variable for predictive modelling is the presence or absence of heart disease, typically represented as binary labels (0 for no disease, 1 for disease). Table 4 shows the classification description.

Evaluation metrics, such as F1-score, accuracy, precision, recall, and area under the ROC curve, are used to evaluate how well the model performs in correctly classifying people with and without heart disease. Interpreting and visualising the results offer valuable insights into the factors that impact the predictions. Utilising a variety of performance metrics is crucial for a comprehensive evaluation of machine learning models applied to the heart disease dataset. Precision, recall, F1-score, AUC-ROC, and AUC-PR are crucial metrics in medical diagnosis tasks, specifically for attaining accurate and balanced outcomes while minimising the risks involved with cardiovascular disease. Table 5 depicts the primary parameters.

Fig. 1 depicts the confusion matrix with sample values. The study demonstrates substantial improvements in prediction accuracy through the integration of reinforcement learning and data augmentation. Through the utilisation of the flexibility and iterative process of reinforcement learning, the predictive model consistently improves its parameters to match the evolving traits of the patient population. Data augmentation expands the variety of scenarios that the model encounters, thereby mitigating the possibility of overfitting to a particular subset of the data. Table 6 shows the comparison analysis of various conventional methods.

Figs. 2–6 depicts the experimentation results of various performance metrics. The combination of these two techniques results in more accurate heart disease predictions. The improved predictive precision not only advantages patients but also healthcare professionals, enabling more accurate risk evaluation and early intervention tactics. Enhanced precision enables healthcare providers to allocate resources more efficiently, guarantee prompt treatment for individuals at high risk, and reduce unnecessary procedures for patients at low risk. The possible computational complexity of reinforcement learning algorithms, especially when handling high-dimensional datasets frequently used in the prediction of cardiac disease or when training large-scale models, is one drawback of the suggested approach. This complexity may limit the approach's scalability and practical viability in real-world clinical settings by requiring more computational resources and lengthening training times. Furthermore, the quality and accessibility of the original dataset may have an impact on the efficacy of data augmentation techniques, which could lead to biases or inaccuracies in augmented data samples. Furthermore, the particular presumptions and design decisions supporting the reinforcement learning framework and data augmentation techniques may restrict the applicability of the suggested approach to various patient populations or clinical contexts (Fig. 7).

5. Conclusion

The versatility of reinforcement learning and the ability to generalise through data augmentation can be utilised in various medical diagnostic and predictive modelling tasks. This research aims to improve the precision of medical diagnoses by utilising advanced machine learning techniques. Reinforcement learning is utilized to optimize the model's decision-making process. The model was able to adapt its predictions in response to feedback from the environment through this reinforcement mechanism. Through assimilating knowledge from both accurate and erroneous predictions, the model acquired enhanced adaptability and the ability to enhance its classification proficiency progressively. Data augmentation techniques are implemented to enlarge the dataset and introduce variability into the training data. This not only augmented the magnitude of the dataset but also enhanced the model's capacity to extrapolate to unfamiliar data. Data augmentation encompasses various transformations, including feature scaling, rotation, and noise addition. The findings of our study revealed a significant enhancement in the precision of heart disease prediction models when compared to traditional methods. The accuracy rate of our models reached an impressive 94 %, representing a notable breakthrough in the field of cardiovascular disease prediction.The integration of reinforcement learning and data augmentation facilitated the models' ability to adjust and acquire knowledge from errors, ultimately resulting in enhanced dependability and accuracy in predictions. The integration of reinforcement learning and data augmentation in our novel approach has yielded substantial enhancements in the accuracy of heart disease prediction models. These technological advancements offer significant potential for the early detection and treatment of cardiovascular conditions. Nevertheless, the healthcare machine learning field is constantly changing, and continuous research and development are crucial to continually advance the limits of precision, comprehensibility, and practicality. Future improvements should prioritise the fine-tuning of current techniques, guaranteeing privacy and security, and conducting thorough clinical validation to establish these advancements as a central aspect of patient care.

Funding

HQ thanks the support of USA NSF Award under 1761839 and 2200138, a catalyst award from USA National Academy of Medicine.

CRediT authorship contribution statement

Gayathri R: Writing – original draft, Conceptualization. **Sangeetha S . K . B:** Writing – original draft, Conceptualization. **Sandeep Kumar Mathivanan:** Writing – review & editing, Methodology. **Hariharan Rajadurai:** Visualization, Validation, Data curation. **Benjula Anbu Malar MB:** Visualization, Validation, Data curation. **Saurav Mallik:** Writing – review & editing, Methodology. **Hong Qin:** Visualization, Validation, Supervision, Software, Resources, Funding acquisition.

Declaration of competing interest

The authors declare no competing interests.

Data availability

Data will be made available on request.

Acknowledgments

We thank all lab members for this work.

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