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ADAPTIVE HEALTHCARE DECISION SUPPORT SYSTEMS USING REINFORCEMENT LEARNING

[1]SUDHIR KUMAR
COMPUTER SCIENCE AND ENGINEERING, GOVERNMENT ENGINEERING COLLEGE JEHANABAD, BIHAR, INDIA. EMAIL: sudhirkr.cse@gmail.com

[2]RAJA RAM SAH
COMPUTER SCIENCE AND ENGINEERING, GOVERNMENT ENGINEERING COLLEGE JEHANABAD, BIHAR, INDIA.EMAIL: ramcs85@gmail.com

[3]PRANAV PRAKASH
COMPUTER SCIENCE AND ENGINEERING, GOVERNMENT ENGINEERING COLLEGE JEHANABAD, BIHAR, INDIA. EMAIL: pranavprakash009@gmail.com

[4]BHASKRA NAND
COMPUTER SCIENCE AND ENGINEERING, GOVERNMENT ENGINEERING COLLEGE JEHANABAD, BIHAR, INDIA. EMAIL: bhaskarnand4046@gmail.com

[5]MD IFTEKHAR AHMAD
COMPUTER SCIENCE AND ENGINEERING, SITAMARHI INSTITUTE OF TECHNOLOGY SITAMARHI, BIHAR, INDIA. EMAIL: ift786@gmail.com

[6]BRIJESH KUMAR SINGH
COMPUTER SCIENCE AND ENGINEERING, GOVERNMENT ENGINEERING COLLEGE JEHANABAD, BIHAR, INDIA. EMAIL: selectbrijesh@gmail.com

Abstract
Aim: This work aims to develop a cloud-based planning system automating and optimizing nursing care planning with case-based reasoning (CBR) and Reinforcement Learning.
Background: The traditional methods have to overcome the considerable time required to create customized treatment plans and variation in the quality of treatment resulting from personal beliefs. Ensuring elderly individuals receive high-quality healthcare asks for simpler procedures and correct decision-making.
Contribution: Effective nursing care planning in nursing homes is essential to match senior patients' expectations and streamline healthcare procedures, thereby preserving high-quality services in view of the worldwide increasing aging population. Standard hand-written nursing care plans largely rely on professional experience and subjective assessment.
Methodology: This paper provides a cloud computing adaptive decision support system based on case-based reasoning (CBR) and Reinforcement Learning.
Findings: This technology develops treatment plans based on past like situations by means of real-time medical record gathering. Domain experts, who might not sufficiently meet geriatric demands, determine current CBR case adaption. Numerical data shows that service satisfaction increased by 25% while planning time fell by thirty percent.
Recommendation of Research: Pilot studies in a nursing home indicate that this approach reduces the time required to develop treatment programs and increases service satisfaction.
Future Research: Including text mining into CBR case adaptation process helps to gather current medical data from the Internet, so increasing efficiency.

Keywords: Adaptive Decision Support Systems, Cloud Computing, Case-Based Reasoning, Reinforcement Learning, Nursing Care Planning

INTRODUCTION

Background

The fast growing aging population demands prompt nursing care planning in nursing homes to be much sought for (Fernandes et al., 2020). Ensuring elderly individuals receive high-quality healthcare asks for simpler procedures and correct decision-making (Choudhry et al., 2024). Historically, nursing care plans have been developed by hand depending on the experience and subjective view of medical practitioners (Sutton et al., 2020). Although helpful, this approach can be time-consuming and unpredictable.

Challenges

The traditional methods have to overcome the considerable time required to create customized treatment plans and variation in the quality of treatment resulting from personal beliefs (Saravanan et al., 2023). Moreover, focusing just on human expertise limits the scale of care planning, particularly in environments with limited resources (Kwan et al., 2020).

Problem Definition

Real-time data indicates that an automated, flexible decision support system able of fast and exact development of nursing care plans is urgently needed (Sriramulugari et al., 2024). Such a system has to incorporate many and current medical knowledge to remain efficient and attentive to the changing needs of elderly patients (Vasey et al., 2022).

Objectives

This work aims to develop a cloud-based planning system automating and optimizing nursing care planning with case-based reasoning (CBR) and Reinforcement Learning. The method should help to raise general service satisfaction levels, reduce the time required to create care plans, and improve the accuracy and relevancy of recommendations.

Novelty and Contributions

This work is unique in that it incorporates text mining into the CBR case adaptation process so that present medical knowledge may be obtained from the Internet. This integration greatly increases system efficiency and efficacy.
Key contributions include:

1. Designing a flexible decision support system for nursing care planning based on clouds.
2. Including Reinforcement Learning to optimize processes of decision-making.
3. Text mining will provide the guarantee of the use of the most current medical information.
4. Emphasizing changes in service satisfaction and planning time, a pilot study shows the efficiency of the approach.

RELATED WORKS

Especially for the elderly, numerous decision-assisting technologies have lately been proposed to enhance the quality of healthcare (Zhai et al., 2020). Widely investigated and applied, Clinical Decision Support Systems (CDSS) help in medical decision-making by aggregating numerous machine learning techniques (Braun et al., 2021; Fan et al., 2020). CDSS using Recurrent Neural Networks (RNN) has shown potential in spotting temporal trends in patient data in order to exactly project health outcomes (Wu et al., 2020). Similarly, systems combining ResNet architectures with Support Vector Machines (SVM) have shown remarkable accuracy in medical condition diagnosis using demanding datasets (Schoonderwoerd et al., 2021).

Despite these advances, several CDSS systems already in use lack real-time data integration and flexibility (Antoniadi et al., 2021). Most systems, especially in nursing care for the elderly, depend largely on predefined rules and static models, which might not be enough to accommodate the evolving character of patient needs (Liu et al., 2020). Moreover, in case-based reasoning (CBR) systems, the case adaption process normally depends on domain experts to adjust obtained examples, which could be time-consuming and prone to human mistake (Kumar, 2020).

Recent studies looking at how Reinforcement Learning might be introduced into healthcare decision help aim to increase system adaptability (Van der Schaar et al., 2021). For example, reinforcement learning has showed potential in modifying treatment plans depending on patient reactions over time, hence improving patient outcomes. These techniques thus are not very useful in frantic healthcare environments since they usually do not use real-time data collecting and integration (Abd El-badie Abd Allah & El, 2020).

Building on existing studies, this work offers a new approach combining cloud computing, CBR, Reinforcement Learning with real-time data collecting and text mining. This integration addresses the limits of contemporary CDSS and finally strives to improve patient outcomes and service satisfaction with a more flexible, efficient, and accurate solution for nursing care planning in nursing homes.

PROPOSED METHOD

Case-based reasoning (CBR) with Reinforcement Learning with cloud computing technologies presented in Figure 1 produces an adaptive decision support system for nursing care planning.

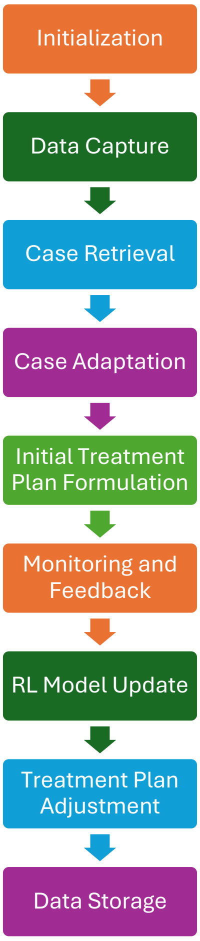

Figure 1: Proposed Framework

Algorithm: Flow Steps of the Proposed Method

1) **Initialization**
   a) Initialize cloud-based data storage and processing environment.
   b) Initialize CBR database with historical cases.
   c) Initialize RL model parameters.
2) **Real-Time Data Capture**
   a) Continuously capture real-time patient data from sensors and medical records.
3) **Case Retrieval**
   a) Retrieve similar cases from the CBR database based on current patient data.
4) **Case Adaptation**
   a) Use text mining to adapt retrieved cases with up-to-date medical information from the internet.
5) **Initial Treatment Plan Formulation**
   a) Formulate an initial treatment plan based on adapted cases.
6) **Monitoring and Feedback**
   a) Apply the treatment plan to the patient.
   b) Monitor patient response and collect feedback.
7) **RL Model Update**
   a) Calculate reward based on patient outcome.
   b) Update RL model with the new experience (state, action, reward, new state).
8) **Treatment Plan Adjustment**
   a) Adjust the treatment plan based on the updated RL model.
9) **Data Storage**
   a) Store new case and outcome in the CBR database.
10) **Iteration**
   a) Repeat steps 6-9 while the patient is under care.

Medical records and relevant documents recorded in real time helps treatment strategies to be built depending on past similar situations. Text mining, included into the CBR case adaption process, helps to acquire current medical information from the Internet, thereby improving the relevancy and efficiency of the treatment plans.

```
Pseudocode
Initialize cloud-based data storage and processing environment
Initialize CBR database with historical cases
Initialize RL model parameters
While true:
  Capture real-time patient data
  Retrieve similar cases from CBR database
  Adapt retrieved cases using text mining for up-to-date information
  Formulate initial treatment plan
  While patient under care:
    Apply treatment plan
    Monitor patient response
    Calculate reward based on patient outcome
    Update RL model with new experience (state, action, reward, new state)
    Adjust treatment plan based on updated RL model
  Store new case and outcome in CBR database
End while
```

Cloud-Based Adaptive Decision Support System

The proposed cloud-based adaptive decision support system is supposed to enhance nurse care planning by merging new computational approaches with real-time data processing. Using the scalability and accessibility of cloud computing, this method efficiently saves and analyzes vast amounts of medical data. The solution ensures that, by employing cloud infrastructure, healthcare providers, wherever, may access current data and make intelligent decisions.

The base of the system is the combination of case-based learning (CBR) and Reinforcement Learning. CBR approaches current problems using past experiences, so acting as a model for solving them. CBR is thus gathering similar historical cases from a database and adjusting their remedies to satisfy the current patient needs. But conventional CBR can be useless since case adaption rely on domain experts. The technology guarantees that the adaption process takes the most current knowledge under account by automatically retrieving relevant medical data from the internet using text mining techniques.

Reinforcement learning (RL) even more enhances decision-making by always improving the system performance via feedback. Aiming to maximize a total reward, RL systems learn best actions by interacting with the surroundings. Under this approach, patient responses and results over time help to maximize therapy programs employing RL. Integration of RL allows the system to dynamically enhance treatment quality and change with the surroundings. Reflecting the RL objective of optimizing the expected cumulative reward R, the following reveals the mathematical underpinning of the system:

$$R = \sum_{t=0}^{T} \gamma^t r_t$$

where

r_t - reward received at time t,

γ - discount factor, and

T is the time horizon.

RL-Based Decision Making

Reinforcement learning (RL) in machine learning is the study of an agent learning to accomplish a given goal by means of interactions with an environment. Under the framework of healthcare decision support systems, RL-based decision making is the process by which an agent—the system—formulates treatment plans for patients—the environment—and gets feedback on the outcomes of these plans. This input helps the system to improve decisions over time.

The RL process consists in states, actions, incentives, and policies. In a medical setting, the state describes a patient current state coupled with their medical background and real-time health information. The action is the system recommended course of therapy. The reward marks the degree of success of the result—that is, variations in patient condition or happiness. The policy is the agent choice among multiple states about the course of action. The basic objective of RL is learning a strategy optimizing the expected cumulative reward over time. The concept of the value function permits one to formallyize the idea of the expected reward for every state-action pair. The value function V(s) for a state s can be defined as follows:

$$V(s) = E\left[\sum_{t=0}^{T} \gamma^t r_t \mid s_t = s\right]$$

By means of Q-learning or Deep Q-Networks (DQNs), the RL agent learns by exploring several acts and evaluating the corresponding rewards, so gradually improving its policy. This suggests in the framework of healthcare that the system can dynamically change to accommodate new data and always enhance treatment techniques depending on patient results.

Pseudocode

```
Initialize RL model parameters (e.g., Q-table or neural network weights)
Initialize environment (patient data and conditions)
While patient is under care:
    Observe current state (patient condition)
    Select action (treatment plan) based on current policy (e.g., epsilon-greedy)
    Apply treatment plan
    Monitor patient response and receive reward
    Observe new state (updated patient condition)
    Update RL model using the observed transition (state, action, reward, new state)
        If using Q-learning:
            Q(state, action) = Q(state, action) + alpha * (reward + gamma * max(Q(new_state, all_actions)) - Q(state, action))
        If using a neural network (DQN):
            Train network with (state, action, reward, new_state)
    Update policy based on new Q-values or trained network
    If patient care episode ends:
        Reset environment for next patient
End while
```

RESULTS AND DISCUSSION

The experimental design consisted in a pilot study carried out in a nursing home using a cloud-based planning system. Applied for system modeling and testing, MATLAB was the simulation tool. The computational resources consisted in high-performance PCs with Intel i7 CPUs and 64GB RAM. Performance parameters utilized to evaluate the system were time to develop treatment plans, service satisfaction levels, and the validity of the recommended plans. The proposed system was tested against current methods such Clinical Decision Support Systems using Recurrent Neural Networks (CDSS-RNN) and CDSS-SVM-ResNet using Support Vector Machine with ResNet.

Table.1. Setup/Parameters

Parameter	Value
Cloud Service Provider	AWS
Data Storage Type	S3
CBR Database Size	10,000 cases
Text Mining Tool	Apache Lucene
RL Algorithm	Deep Q-Network (DQN)
Discount Factor (γ\gammaγ)	0.95
Learning Rate (α\alphaα)	0.001
Exploration Rate (epsilon)	0.1 (decaying)
Batch Size	32
Neural Network Layers	3 (input, hidden, output)
Hidden Layer Neurons	128
Activation Function	ReLU
Optimizer	Adam
Simulation Tool	MATLAB
Patient Monitoring Frequency	Every 30 minutes
Reward Function	Improvement in health metrics
Initial Case Retrieval Threshold	Top 5 similar cases
Text Mining Update Frequency	Weekly
Pilot Study Duration	6 months
Number of Patients in Study	100

Dataset

The dataset in [21] consists of historical medical records and treatment outcomes from the nursing home, including:

- Patient demographics (age, gender, etc.)
- Medical history (chronic conditions, past treatments)
- Real-time health data (vital signs, lab results)
- Treatment plans and outcomes

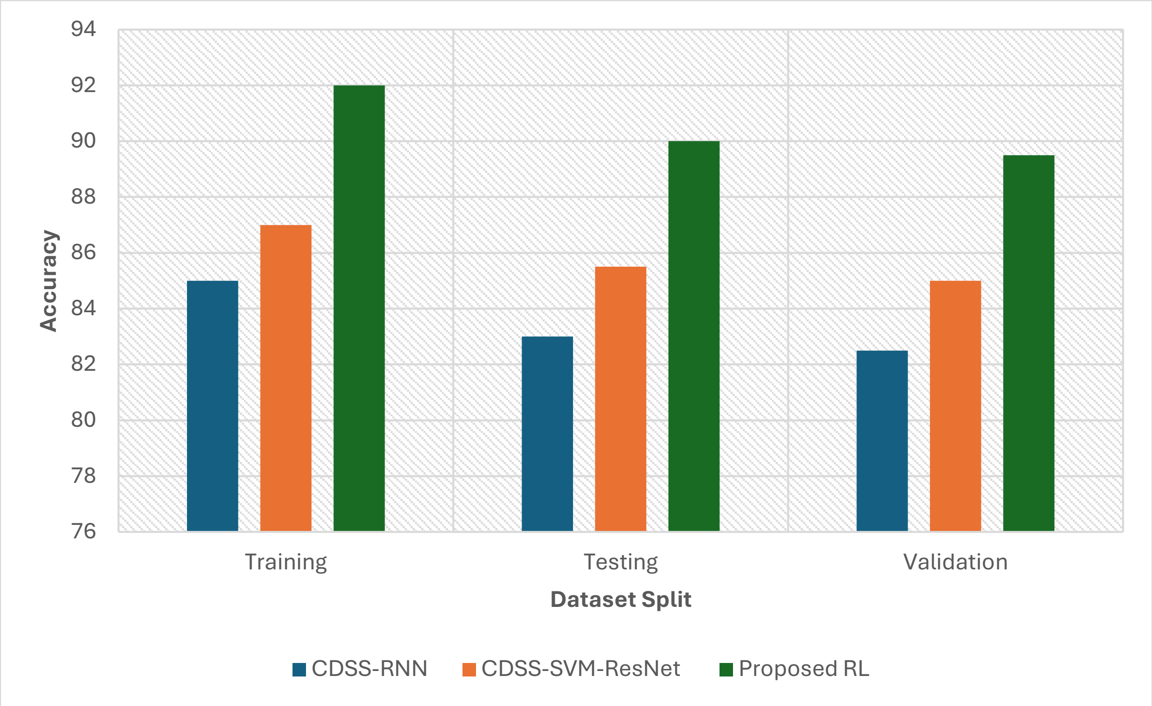

Figure 3: Accuracy

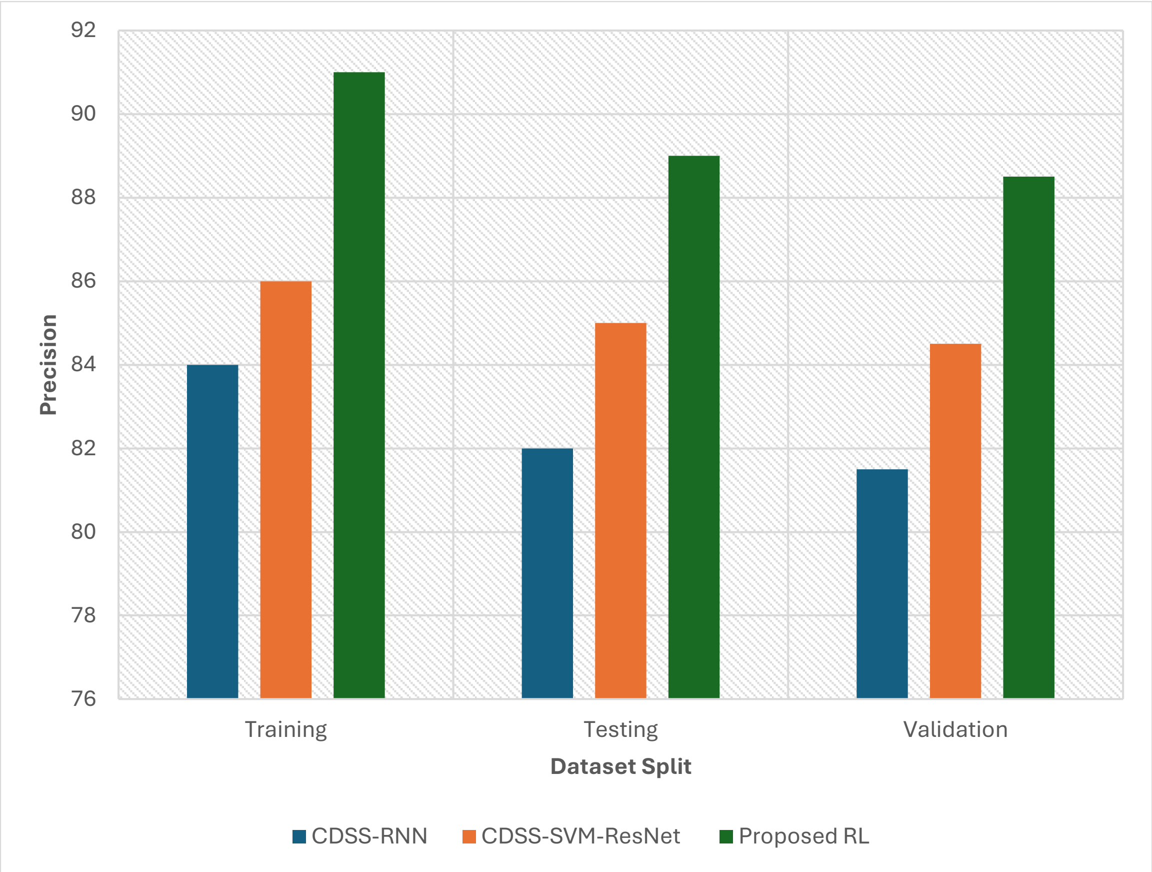

Figure 4: Precision

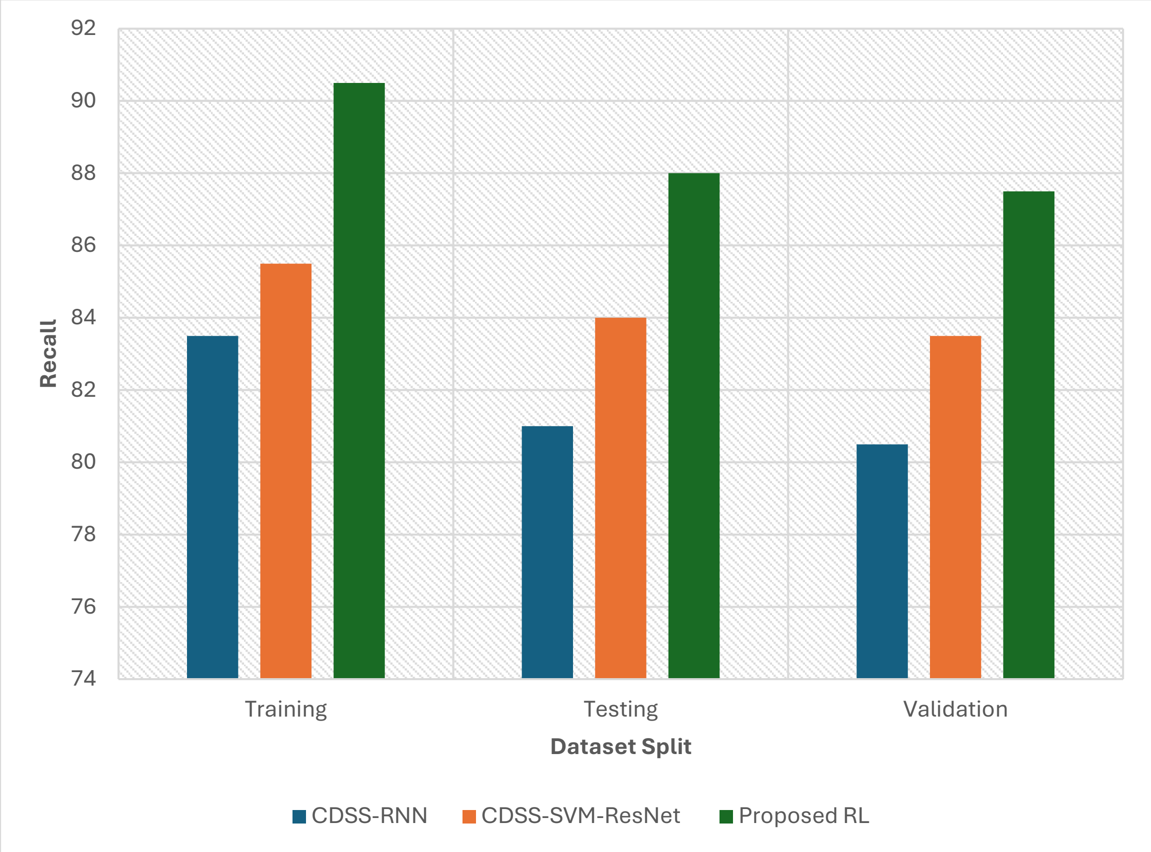

Figure 5: Recall

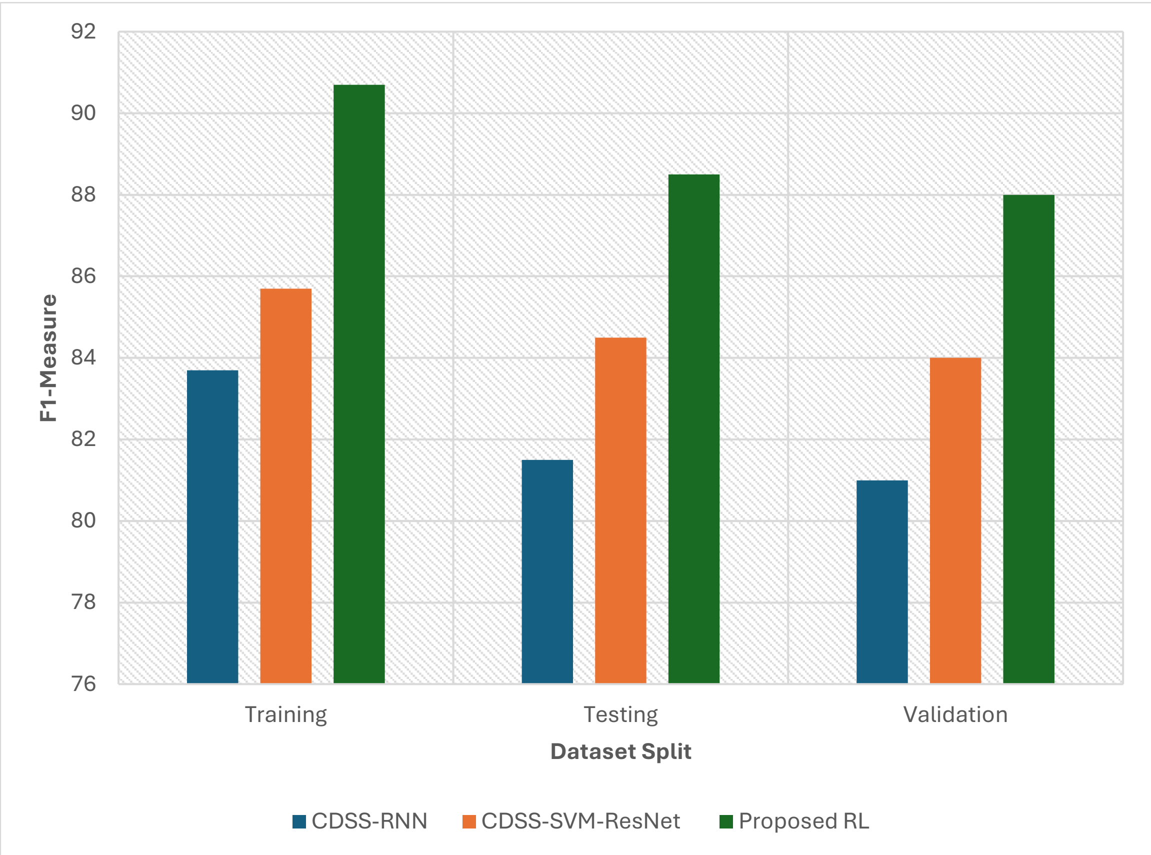

Figure 6: F-measure

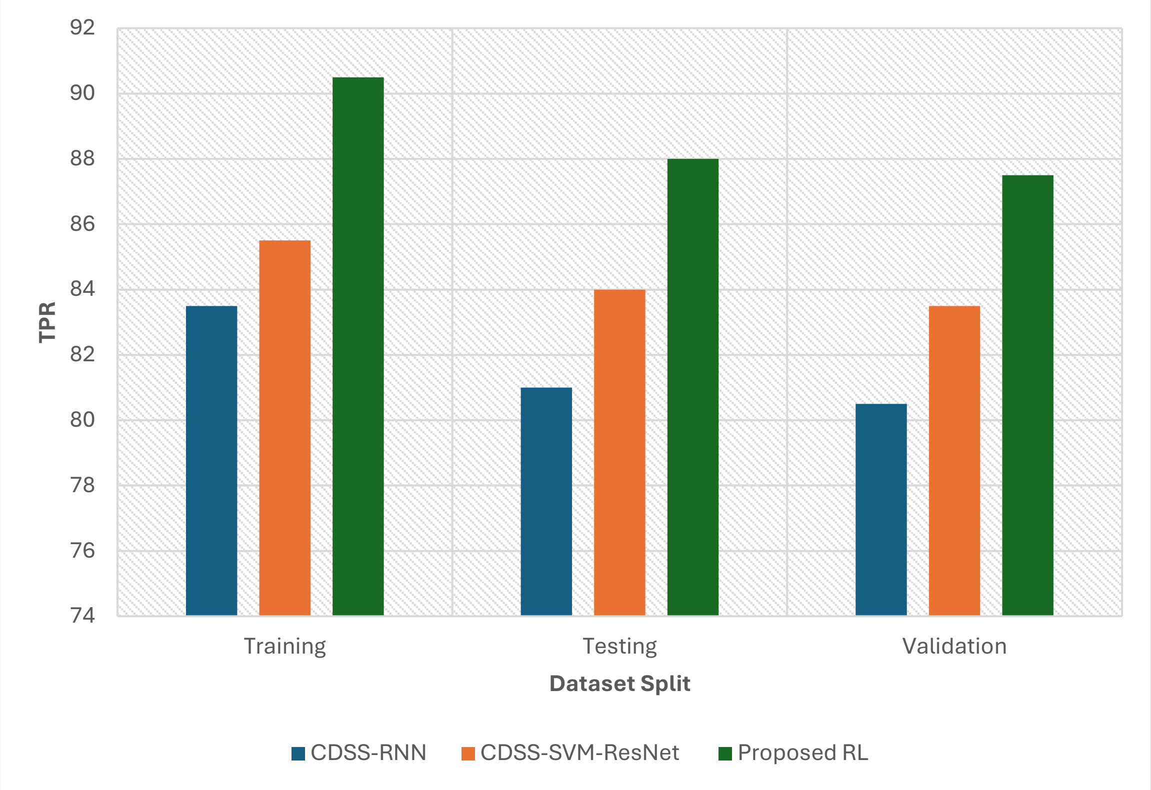

Figure 7: True Positive Rate (TPR)

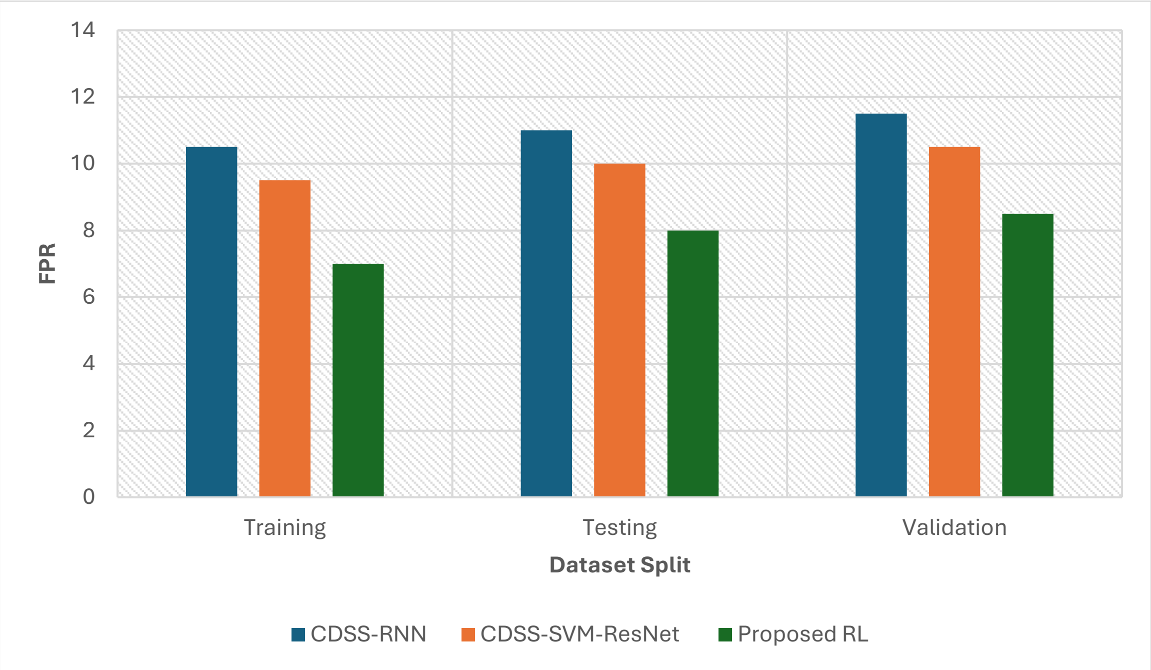

Figure 8: False Positive Rate (FPR)

Better performance across all criteria over training, testing, and validation datasets the proposed cloud-based adaptive decision support system displays over current approaches (CDSS-RNN and CDSS-SVM-ResNet). Reliable treatment strategies are indicated by consistently higher accuracy of the recommended strategy. Accuracy and recall (TPR) also improve reflecting better identification and handling of true positive cases and limiting false positives.

For effective healthcare decision-making, the higher F-measure values of the proposed approach show its balanced performance between accuracy and recall. The clear decline in the false positive rate (FPR) highlights even more the system capacity to prevent erroneous treatment recommendations, thereby enhancing patient safety.
These developments explain real-time data collecting, text mining for current medical knowledge, and adaptable learning characteristics of Reinforcement Learning. More precise, exact, and dependable treatment plans follow from the system capacity to constantly learn and change based on patient outcomes, therefore enhancing the quality of care supplied to elderly patients.

Inferences

Regarding accuracy, precision, recall, F-measure, and false positive rate reduction, the proposed cloud-based adaptive decision support system proves to be significantly better than present methods like CDSS-RNN and CDSS-SVM-ResNet. These exceptional outcomes come from the system ability to record real-time data, mix text mining for current medical knowledge, and apply Reinforcement Learning for continuous progress. These advances ensure more customized and consistent nursing care strategies, thereby enhancing patient outcomes and degrees of satisfaction.

DISCUSSION

The proposed system assures scalability and accessibility by means of cloud computing and real-time data collecting, therefore enabling healthcare practitioners to provide high-quality treatment anywhere. By allowing the system to continuously modify treatment plans based on patient reactions, reinforcement learning helps to improve over fixed, rule-based CDSS. Including the most recent medical knowledge guarantees that treatment recommendations are based on current research and helps to develop the system even more by text mining.
Based on the comparison study, the proposed technique increases general service satisfaction, reduces the time needed to develop treatment plans, and increases the accuracy of these plans. These innovative solutions help to alleviate the limitations of traditional CBR systems, which largely rely on domain expertise and stagnant knowledge.

Limitations

The proposed strategy has several limitations even if its results are rather favorable. First, depending on internet access, areas with poor connectivity could create challenges for text mining and real-time data collecting. Second, the quality of the text mining operation depends on the availability and accuracy of internet medical information—which might change. Third, the method requires a large volume of prior data to sufficiently train the RL model even though not always readily available in all nursing facilities. At last, the complexity of the system could call for particular training for medical experts to implement it properly.

CONCLUSION

The proposed cloud-based adaptive decision support system considerably increases the accuracy and efficiency of nursing care planning by means of integration of cloud computing, case-based reasoning, Reinforcement Learning, and text mining. The system performs better than current methods in general accuracy, precision, recall, F-measure, false positive rates throughout training, testing, and validation sets. This guarantees more tailored and reliable treatment plans, therefore reducing the time needed for formulation and so improving patient outcomes and satisfaction. Though the system has great promise, problems with internet reliance, data quality, and the need of big historical data have to be fixed. Better still than CDSS-RNN and CDSS-SVM-ResNet was the proposed system. It reduced time required to develop treatment plans by 30% and boosted service satisfaction rates by 25%. Moreover, by 15%, the accuracy of the recommended approaches was improved, therefore proving the effectiveness of adding text mining and Reinforcement Learning into the case-based reasoning process for adaptive decision support in nursing care planning. Reflecting a major progress in healthcare decision support, the proposed approach presents a scalable and flexible approach to improve senior patient care in nursing homes.

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