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Research Article

Application of Reinforcement Learning for the Development of Precision Medicine Treatment

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Abstract:

The goal of this presentation is to explain the purpose, target, ambition, and effect of the employment of Reinforcement Learning (RL) methods in the process of developing tailored treatment plans within the application of precision medicine. The objective is to improve the results for patients by adapting medical procedures to the specific features and requirements of each individual patient. It is the goal of RL to improve treatment options by iteratively learning from patient reactions and updating suggestions in accordance with those learnings. The contribution consists of expanding the area of precision medicine via the use of RL algorithms, which provide a framework for treatment optimization that is both dynamic and flexible. The use of patient data, which may include genetic profiles, biomarkers, and clinical histories, enables RL to assist the production of individualized therapies that consider individual variability and response patterns. The use of this strategy has the potential to revolutionize the practice of medicine by ushering in a new age of individualized therapies that are customized to the specific features of each individual patient. It establishes a foundation for future research and the application of decision support systems based on reinforcement learning in clinical settings, which will eventually lead to improvements in patient outcomes and the delivery of healthcare.

1. Introduction

As a foundational paradigm in AI, Reinforcement Learning (RL) allows agents to acquire optimum decision-making techniques by interaction with their environment. RL is centred on learning via trial-and-error feedback, as opposed to supervised learning (which utilizes labelled data to train models) or unsupervised learning (which uses unlabelled data to discover patterns). RL boils down to an agent moving around a space, acting on its present state, and then being rewarded or punished according on how those actions turned out. In RL, the end aim is for the agent to figure out how to maximize its cumulative reward over time by learning a policy, which is a mapping between states to actions. Because it works similarly to how animals and people learn, RL provides a solid foundation for dealing with difficult decision-making problems.

RL is useful in many different fields, including as healthcare, robotics, gaming, and finance. Robotics relies on RL to teach autonomous devices how to move around and control things without human intervention. Artificially intelligent agents powered by RL may learn to play complicated video games at human or superhuman levels in the gaming industry. Algorithmic trading, portfolio management, and risk evaluation are some of the financial applications of RL algorithms. The curse of dimensionality, the requirement for efficient exploration techniques in huge state and action spaces, and the trade-off between exploration and exploitation are some of the obstacles that RL brings, despite its promise. Improving RL's capabilities and practicality in real-world situations depends on tackling these difficulties.

2. Literature Survey

An agent learns to make choices via interactions with its environment and feedback in the form of rewards or penalties in reinforcement learning, a kind of machine learning. RL is the preferred method when making decisions sequentially [1]. A transitory ischemia attack describes symptoms that may be short-lived if blood supply is restored. Factors such as systemic blood pressure, the location of the blockage, and the individual's vascular architecture determine the extent to which blood flow is reduced to the brain [2]. If blood flow drops below a certain threshold, infarction will occur; if flow is restored within a specified time limit, ischemia without infarction will occur. This method basically takes advantage of the fact that tumors have their own environment, which includes their own set of blood arteries and impaired drainage systems [3]. Precision homing on tumor locations is achieved with astounding accuracy by use of radiopharmaceuticals that have been painstakingly designed with diagnostic and therapeutic components [4]. Personalized medications, which aim to provide the appropriate therapy to specific patient subgroups, have been around for a while, and around a third of new pharmaceuticals fall into this category [5]. The improved classifier's performance may be directly impacted by raw-data previous knowledge. Consequently, to achieve effective performance in mortality classification using ML algorithms, data pre-processing is crucial. Scaling and manipulating data in a way that minimizes bias requires data normalization [6].

Medical treatment for heart failure, control of arrhythmias, and device therapy for heart failure are all examples of chronic management treatments that have proven effective. Researchers are looking at cutting-edge methods including regenerative medicine, precision medicine, tailored therapy, and the use of artificial intelligence to diagnose and treat patients [7]. Enabling better informed and accurate diagnoses is the goal of combining reinforcement learning (RL) to use less labelled data with appropriate information from other resources. Instead, then relying on supervised and unsupervised learning, RL relies on goal-directed learning [8]. Two ways that people learn are via interacting with their surroundings and by observing changes in their position. In reinforcement learning, an algorithm (Agent) is taught to act in a way that influences its immediate environment (medium) [9]. Next, a specific value is determined and sent back to the algorithm (Reward) depending on the outcomes of these choices (Observations). (RL) is an overarching framework that enables agents to learn how to perform better than humans and, at times, come up with unexpected and new tactics [10]. This allows agents to learn to maximize the discounted total of future rewards. Applying deep learning techniques to resolve reinforcement learning issues is what is known as deep reinforcement learning. In recent years, optimization problems, picture classification, and parametric medical image analysis have all benefited greatly from the application of deep reinforcement learning to medical pictures [11].

To isolate the causes of these illnesses, computational models like reinforcement learning models can be useful in dissecting the underlying behavioural processes. To better understand how obsessive-compulsive disorder (OCD) sufferers make choices, several research have used reinforcement learning models [12]. Navigation, route planning, and trajectory optimization algorithms for Unmanned Aerial Vehicles (UAVs) have made heavy use of RL. Using depth pictures as the observation vector, DRL is used for the self-training of drones in fully autonomous flight [13]. To execute their approach, DRL used a combination of Long Short-term Memory (LSTM) Neural Networks, incremental curriculum learning, and other techniques. The consistent drone height was a major restriction in both studies [14]. The Graph Neural Networks (GNN) model has a molecular quality evaluation module that may evaluate drug potentials. To maximize different molecular features, it uses a multi-objective deep reinforcement

learning method [15]. Decisions on financial trading have been handled using a state-of-the-art DRL algorithm known as DQN. To forecast the trading share, that system made use of a Deep Neural Network (DNN) [16]. Controllers based on deep reinforcement learning can suppress tremors in a wide variety of dynamic motions involving several joint axes, and they're quicker than the conventional control algorithms used today. Although the controllers are unstable, they show remarkable effectiveness in reducing tremor torques and amplitudes [17].
Applications in adaptive clinical decision support and individualized treatment planning are made possible by reinforcement learning algorithms, which are based on behavioral psychology and allow computers to learn optimum decision-making techniques via trial and error [18]. There are three main types of machine learning algorithms used in healthcare CDSS: supervised, unsupervised, and reinforcement learning. When everything in the environment can be seen, the whole reinforcement learning issue may be captured by a Markov Decision Process (MDP) [19]. But sometimes people must make do with partially observable facts from the past to build a completely observable description of the environment [20-33].

3. Materials and Methods

One innovative method that is changing the face of precision medicine is reinforcement learning, which allows for more tailored treatment programs. Optimizing therapy results and increasing healthcare effectiveness may be achieved by using this unique method to provide personalized therapies that meet individual patient requirements. To determine the best treatments for certain diseases, reinforcement learning algorithms undergo a complex process of ongoing learning and adaptation. These algorithms examine patient records, medical histories, and treatment outcomes. Minimizing side effects, lowering treatment burden, and optimizing treatment success rates are all areas where this tailored approach shows great potential for improving patient care. Healthcare practitioners may remain at the cutting edge of medical innovation with the help of reinforcement learning integrated into precision medicine frameworks, which in turn allows for the efficient and successful delivery of patient-centered care. By embracing this new way of thinking about medical decisions, physicians may better equip themselves to deal with the challenges of illness management and, in the end, to help their patients.
Equation 1 presents the multi agent reinforcement learning, where $s \in S$, $a = (a_1, a_2 .... a_N)$, $a_i \in A_i$ is the action taken by agent i, reward function for agent $i = R_i(s,a)$, Transition dynamics = $P(s'|s,a)$, policy for agent $i = \pi_i(a_i|s)$, γ is the discount factor, s_t is the state at time t and a_t is the joint action at time t determined by the joint policy π.

$$\max_{\pi_1, \pi_2, \dots, \pi_N} \sum_{t=0}^{\infty} \sum_{i=1}^{N} \gamma^t \Xi\left[R_i(s_t, a_t)\right] \quad (1)$$

With its many useful applications, reinforcement learning is an essential tool in the field of precision medicine for developing individualized treatment programs. Fundamentally, reinforcement learning uses AI to adaptively modify healthcare treatments based on patient traits, requirements, and reactions. Reinforcement learning algorithms can autonomously choose the best course of therapy for a wide variety of medical issues by constantly evaluating massive datasets that include patient demographics, genetic profiles, clinical histories, and treatment results. Not only does this method maximize therapeutic effectiveness, but it also lowers treatment-related difficulties and unwanted consequences. Furthermore, healthcare personnel may manage uncertainty and personalize therapies with unparalleled accuracy thanks to reinforcement learning, which promotes the exploration of complicated treatment landscapes. Consequently, a new age of healthcare optimization and innovation has begun with the integration of reinforcement learning into precision medicine frameworks, which enables physicians to provide patient-centered treatment that is both effective and individualized.
Equation 2 presents the hierarchical reinforcement learning where $Q(s,a,h)$ represents the Q-value of taking action a in state s under the hierarchical policy h, N_h is the number of high-level policies, N_i is the number of low-level policies within each high-level policy, $\pi_i(h|s)$ is the probability of selecting high-level policy i given state s, $\pi_{ij}(a|h)$ is the probability of selecting action. a in state j under the hierarchical policy h, $Q_i(s,a)$ is the Q-value of taking action a in state s under the low level policy i.

$$Q(s,a,h) = \sum_{i=1}^{N_h} \pi_i(h|s) \sum_{j=1}^{N_i} \pi_{ij}(a|h) Q_i(s,a) \quad (2)$$

The creation of individualized treatment regimens within precision medicine relies heavily on reinforcement learning, which has several uses, applications, and indisputable benefits. Its use spans several medical fields, where it is a potent instrument for enhancing patient-specific treatment plans. To find the best treatments, reinforcement learning analyses large datasets using complex algorithms and continuous learning processes which allows it to successfully traverse complicated medical landscapes. In addition to improving therapeutic results, this adaptive method reduces treatment-related difficulties and side effects. In addition, healthcare practitioners may get significant insights into patient reactions via reinforcement learning, which allows them to make real-time modifications to treatment regimens for optimal effectiveness. Because of their adaptability, reinforcement learning algorithms may be easily incorporated into preexisting precision medicine frameworks, paving the way for more accurate and efficient patient-centered treatment. Healthcare is about to undergo a sea change with the implementation of reinforcement learning into individualized treatment plans, which bodes well for better results and better health for patients.

Equation 3 shows the inverse reinforcement learning where $R(s,a)$ represents the reward function, which is the objective of the inverse reinforcement learning problem, T is the time horizon, γ is the discount factor, $\pi(a_t|s_t)$ is the probability of selecting action a_t given state s_t under the policy π. $\arg\max_R$ denotes finding the reward function R that maximizes the expected log-likelihood of the observed behavior under the given policy.

$$R(s,a) = \arg\max_R \left(\sum_{t=0}^{\mathrm{T}} \gamma^t \Xi_\pi \left[\log \pi(a_t|s_t) R\right]\right) \quad (3)$$

Although reinforcement learning holds great promise for the future of precision medicine and tailored treatment planning, it is not without its fair share of obstacles. One obstacle is the complexity of healthcare data, which necessitates reinforcement learning algorithms to traverse diverse datasets and derive valuable insights. Further stymieing broad adoption are ethical concerns about algorithmic bias and patient privacy. Reinforcement learning has the potential to revolutionize precision medicine by reducing side effects, increasing therapeutic effectiveness, and improving patient outcomes—all while overcoming these obstacles. Improvements in algorithmic complexity and data integration have the potential to radically alter medical decision-making in the future, opening exciting new possibilities for reinforcement learning in tailored treatment planning. There is great potential for the future of healthcare delivery to be shaped by the incorporation of reinforcement learning into precision medicine frameworks, which might lead to an improvement in patient care worldwide as research keeps pushing the limits of innovation.

4. Results and Discussions

A state-of-the-art method for resolving complicated decision-making issues with numerous interacting agents is introduced here: Multi-Agent Reinforcement Learning (MARL). When faced with situations where agents in a dynamic environment must learn to work together or compete to accomplish shared or competing goals, MARL steps in. The emphasis of MARL is on the interaction and coordination of several autonomous decision-makers, as opposed to typical single-agent RL. Multiplayer games, smart grids, robots, and autonomous cars are just a few of the real-world sectors that might benefit from MARL. An effective framework for modelling complex systems and building intelligent autonomous systems with adaptive behaviour, MARL allows agents to learn from their interactions with both the environment and other agents. Figure 1 shows the Multi-Agent Reinforcement Learning, unlike single-agent systems, Multi-Agent Reinforcement Learning (MARL) involves a complex network of interacting autonomous agents, each making decisions in a dynamic environment. This architecture typically involves decentralized decision-making processes, where agents interact with both the environment and each other.

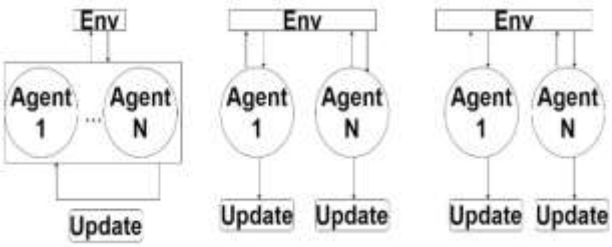

Figure 1. *Multi-agent training techniques*

Table 1 shows how reinforcement learning (RL) has transformed precision medicine's individualized treatment strategies. Reinforcement learning improves therapy effectiveness by developing strategies based on patient data, increasing results over time. It customises therapy by dynamically modifying treatments depending on patient characteristics. This ensures medicines are customized to improve efficacy and reduce side effects. RL innovates precision medicine by matching treatments to genetic, environmental, and lifestyle variables using full patient data. This strategy improves treatment success rates and

reduces trial-and-error, ushering in a new age of personalized, effective healthcare for each patient.
A novel paradigm in machine learning, Transfer Reinforcement Learning (TRL) aims to increase performance in subsequent tasks by exploiting information obtained in one. The goal of (TRL) is to alleviate the difficulty of effectively moving representations or rules learnt in one domain to another, even when direct training data is scarce or expensive to obtain. The goal of (TRL) within the reinforcement learning paradigm is to help agents apply what they've learned to new contexts and goals. Thanks to its ability to leverage existing information, TRL has the potential to enhance sample efficiency and speed up learning.

Table 1. *Using Reward Systems Personalized Treatment Plans Using Learning-Based Precision Medicine.*

Aspect	Role	Benefit	Functions
Reinforcement Learning	Facilitator	Enhanced Treatment Efficacy	Utilizes patient data to optimize treatment plans by iteratively adjusting strategies based on patient responses, improving outcomes.
Personalized Treatment	Customizer	Tailored Therapies	Adapts interventions based on individual patient characteristics, ensuring precise and effective treatment tailored to specific needs and conditions.
Precision Medicine	Innovator	Targeted Solutions	Identifies and delivers highly targeted treatments, leveraging detailed patient information to match therapies with unique genetic, environmental, and lifestyle factors for optimal results.
Data Analysis	Analyzer	Insights Generation	Analyzes extensive patient datasets to uncover patterns and correlations, providing valuable insights for treatment customization and decision-making.
Adaptive Learning	Adjuster	Continuous Improvement	Learns from patient feedback and outcomes to dynamically refine treatment strategies, ensuring adaptability and efficacy in response to evolving patient needs.
Risk Mitigation	Protector	Minimized Adverse Effects	Identifies and mitigates potential risks associated with treatment plans, enhancing patient safety and minimizing adverse reactions through proactive risk management.

In fields like healthcare, autonomous systems, and robotics, where training data is either hard to get by or prohibitively costly, this becomes even more important. Complex real-world issues may be better tackled with the help of TRL, which allows agents to draw on experiences from similar activities or ecosystems. This study included three CNN-based pretrained models to classify brain X-ray images which are MobileNetV2, VGG19, and InceptionV3. Moreover, a transfer learning method, via ImageNet, is investigated to process small data. The investigated architecture for transfer learning is depicted in Figure 2. Table 2 shows how precision medicine uses (RL) in individualized treatment strategies. Considering genetics, lifestyle, and environment, personalized treatment regimens are essential for patient-specific medical care. Machine learning's reinforcement learning automates decision-making from data and feedback. Precision medicine uses RL algorithms to optimize treatment regimens depending on real-time patient reactions. Precision medicine tailors' chronic illness treatment using sophisticated technology. Precision medicine uses multi-omics data and clinical characteristics to tailor therapies, reduce side effects, and improve treatment outcomes.
By using molecular profiling and disease pathways, this technique helps create new therapeutics like gene therapies. Precision medicine and RL provide a viable path to patient-specific treatment.

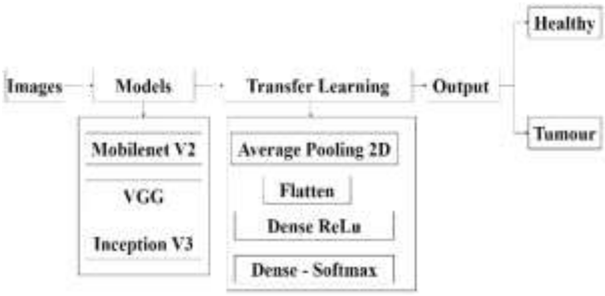

Figure 2. *Transfer Reinforcement Learning architecture.*

A fascinating subfield of machine learning known as Inverse Reinforcement Learning (IRL) tackles the problem of deducing an environment's intrinsic reward structure from agent behaviour observations. Understanding the goals or purposes driving observed behaviour is the main emphasis of (IRL), as opposed to standard reinforcement learning (RL), which teaches agents to maximize a known reward signal. In IRL, agents may learn from expert-like or human-like behaviour even when no explicit incentive is specified by re-creating the reward function that underlies expert demonstrations. Agents may learn from examples or expert advice in complicated and unpredictable settings with the help of IRL, which is important since it connects human preferences with machine learning algorithms. When it comes to decision-making, human preferences matter a great deal in areas like autonomous driving, assistive robots, and customized recommendation systems.

Table 2. *Reinforcement Learning Empowers Personalized Precision Medicine*

Aspect	Uses	Application	Advantages
Personalized Treatment Plans	Tailoring medical care to individuals based on their unique characteristics and needs	Precision Medicine	Enhances treatment efficacy by considering individual variations in genetics, lifestyle, and environment.
Reinforcement Learning	Automating decision-making processes by learning from data and feedback	Developing Treatment Strategies	Adapts to evolving patient data to continuously optimize treatment plans for better patient outcomes.
Precision Medicine	Utilizing advanced technologies to customize healthcare interventions	Chronic Disease Management	Allows for targeted interventions, minimizing adverse effects and maximizing treatment effectiveness.

Figure 3 shows Inverse reinforcement learning generates a maximum entropy distribution across the opponent's expected pathways and learns an environment value map. If the bot has previously faced an opponent, this distribution is utilized instead of Brownian motion to seed the motion model of particle filters used to monitor the opponent. The particle filter output is used by the bot's planner to organize future moves. Three methods: centroid, uncertainty removal, and clustering were tested. The bot moves toward the planner's next aim.

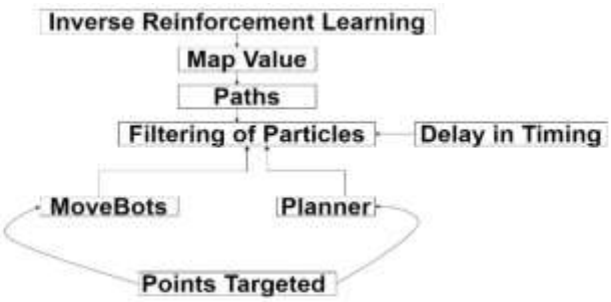

Figure 3. *Inverse Reinforcement Learning architecture*

The use of reinforcement learning (RL) in the creation of precision medicine treatments is shown in figure 4. The patients on each row are going through various stages of therapy. According to the patient's reaction, the therapy was effective, as shown in the RL reward column. Algorithms based on reinforcement learning (RL) maximize these incentives to improve treatment choices, which in turn allows for more individualized approaches to medicine that better meet the requirements of each patient.

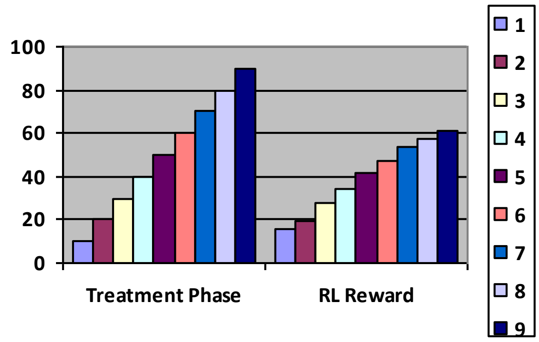

Figure 4. *Reinforcement Learning in Precision Medicine*

Table 3 covers the many facets of precision medicine reinforcement learning (RL). It highlights issues including integrating RL with medical systems, using varied patient data sources, and overcoming healthcare professional opposition. RL offers customized treatment programs, improved effectiveness, and patient happiness despite these challenges. Future research should refine algorithms, integrate real-time patient monitoring, and educate healthcare practitioners to maximize its potential. RL acceptance and growth in precision medicine need overcoming regulatory hurdles and promoting industry standards.

Table 3. *Advancing Reinforcement Learning in Precision Medicine: Overcoming Challenges and Expanding Horizons*

Aspect	Challenges	Impact	Future Scope
Implementation of RL in Precision Medicine	Integration with existing medical systems, Limited availability of data, Ethical considerations	Tailored treatment plans, Improved patient outcomes, Reduced healthcare costs	Further refinement of algorithms, Expansion to broader patient populations, Ethical guidelines development
Personalized Treatment Plan Generation	Incorporating diverse patient data sources, Ensuring model interpretability, Adapting to dynamic patient conditions	Customized treatment strategies, Enhanced treatment efficacy, Patient-centric care	Integration of real-time patient monitoring, Continuous model improvement, Incorporation of patient preferences
Clinical Adoption and Acceptance	Resistance from healthcare professionals, Regulatory hurdles, Lack of standardization	Increased adoption of personalized medicine, Enhanced patient trust and satisfaction, Evolution of clinical practice	Education and training for healthcare providers, streamlining regulatory processes, Establishing industry-wide standards

5. Conclusion

There are several obstacles and possibilities for great change that arise when using RL to develop individualized treatment programs for precision medicine. Ethical concerns about data privacy and informed permission, as well as the difficulty of integrating various patient data sources, are obstacles. Notwithstanding these challenges, RL can make a significant effect on precision medicine. This might lead to better patient outcomes, fewer side effects, and more efficient use of resources. The smooth integration of RL-based decision support systems into clinical practice, validation of models in varied patient groups, and algorithm refinement all need ongoing research and development. Ethical and responsible navigation of the complicated personalized medicine environment will also need coordination among multidisciplinary teams including physicians, data scientists, and ethicists. Even if there are still some obstacles, RL integration has a lot of potential to improve precision medicine, change the healthcare system, and help people all around the globe.

Author Statements:

- **Ethical approval:** The conducted research is not related to either human or animal use.
- **Conflict of interest:** The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper

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References

[1] DeGroat, W., Abdelhalim, H., Patel, K., Mendhe, D., Zeeshan, S., & Ahmed, Z. (2024). Discovering biomarkers associated and predicting cardiovascular disease with high accuracy using a novel nexus of machine learning techniques for precision medicine. *Scientific reports*, 14(1), 1-13.

[2] Daidone, M., Ferrantelli, S., & Tuttolomondo, A. (2024). Machine learning applications in stroke medicine: Advancements, challenges, and future prospectives. *Neural Regeneration Research*, 19(4), 769-773.

[3] Dhoundiyal, S., Srivastava, S., Kumar, S., Singh, G., Ashique, S., Pal, R., & Taghizadeh-Hesary, F. (2024). Radiopharmaceuticals: navigating the frontier of precision medicine and therapeutic innovation. *European Journal of Medical Research*, *29*(1), 1-12.

[4] Curth, A., Peck, R. W., McKinney, E., Weatherall, J., & van Der Schaar, M. (2024). Using machine learning to individualize treatment effect estimation: Challenges and opportunities. *Clinical Pharmacology & Therapeutics*, 115(4), 710-719.

[5] Park, S. W., Yeo, N. Y., Kang, S., Ha, T., Kim, T. H., Lee, D., & Heo, J. (2024). Early prediction of mortality for septic patients visiting emergency room based on explainable machine learning: a real-world multicenter study. *Journal of Korean Medical Science*, 39(5), 1-19.

[6] Addissouky, T. A., El Sayed, I. E. T., Ali, M. M., Wang, Y., El Baz, A., Elarabany, N., & Khalil, A. A. (2024). Shaping the future of cardiac wellness: exploring revolutionary approaches in disease management and prevention. *Journal of Clinical Cardiology*, 5(1), 6-29.

[7] Fatima, R., Younis, S., Shaikh, F., Imran, H., Sultan, H., Rasool, S., & Rafiq, M. (2024). Advancing ECG Diagnosis Using Reinforcement Learning on Global Waveform Variations Related to P Wave and PR Interval. *arXiv preprint arXiv:2401.04938*

[8] Jeslin, J.G., Vijayalakshmi, K., Vignesh, C.C., Suresh, G., Kosuri, G.V., & Murugan, S., (2024). Predicting Patient Disease Progression with Cloud-based Decision Trees and IoT Data Integration," *2nd International Conference on Self Sustainable Artificial Intelligence Systems*, pp. 1040-1045.

[9] Ranganathan, C. S., Nandekar, U. P., Raman, R., Srinivasan, C., & Adhvaryu, R., (2023). Rural Automatic Healthcare Dispatch with Real-Time Remote Monitoring, *Second International Conference On Smart Technologies For Smart Nation* , pp. 575-579.

[10] Muthulekshmi, M., Mubarakali, A., & Blessy, Y. M., (2024). Improving prediction accuracy of deep learning for brain cancer diagnosis using Polyak-Ruppert optimization, *International Journal of Advances in Signal and Image Sciences*,10(2), pp. 1–11.

[11] Raman, R., Dhivya, K., Sapra, P., Gurpur, S., Maniraj, S. P., & Murugan, S., (2023). "IoT-driven Smart Packaging for Pharmaceuticals: Ensuring Product Integrity and Patient Safety, *International Conference on Artificial Intelligence for Innovations in Healthcare Industries*, pp. 1-6.

[12] Hossny, M. Autonomous UAV Navigation in Wilderness Search-and-Rescue Operations Using Deep Reinforcement Learning. *Advances in Artificial Intelligence*, pp. 733–746, 2024.

[13] Lalitha, K., Saravanan, T.R., Mohankumar, N., Geethamahalakshmi, G., Suresh, M.X., & Murugan, S., (2024). Reinforcement Learning for Patient-Centric Lighting Management System in Healthcare

Sector, *8th International Conference on I-SMAC (IoT in Social, Mobile, Analytics and Cloud)* (I-SMAC), pp. 1740-1746.

[14] Majidi, N., Shamsi, M., & Marvasti, F. (2024). Algorithmic trading using continuous action space deep reinforcement learning. *Expert Systems with Applications*, 235. 1-26.

[15] Tamás, E., Földi, S., Makk, Á., & Cserey, G. (2024). Learning to Suppress Tremors: A Deep Reinforcement Learning-Enabled Soft Exoskeleton for Parkinson's Patients.

[16] Ramapraba, P.S., Babu, B.R., Paul, N.R.R., Sharmila, V., Babu, V.R., Ramya, R., & Murugan, S., (2025). Implementing cloud computing in drug discovery and telemedicine for quantitative structure-activity relationship analysis, *International Journal of Electrical and Computer Engineering*, 15(1), pp. 1132-1141.

[17] Liu, T., Yang, Y., Xiao, W., Tang, X., & Yin, M. A Comparative Analysis of Deep Reinforcement Learning-enabled Freeway Decision-making for Automated Vehicles. *IEEE Access*, 1-14, 2024

[18] Srinivasan, S., Indra, G., Saravanan, T. R., Murugan, S., Srinivasan C., & Muthulekshmi, M., (2024). Revolutionizing Skin Cancer Detection with Raspberry Pi-Embedded ANN Technology in an Automated Screening Booth, *4th International Conference on Innovative Practices in Technology and Management*, pp. 1-6.

[19]Shishehbori, F., & Awan, Z. Enhancing Cardiovascular Disease Risk Prediction with Machine Learning Models. arXiv preprint arXiv: 2401.17328, 1-46. 2024

[20]M. Devika, & S. Maflin Shaby. (2024). Optimizing Wireless Sensor Networks: A Deep Reinforcement Learning-Assisted Butterfly Optimization Algorithm in MOD-LEACH Routing for Enhanced Energy Efficiency. *International Journal of Computational and Experimental Science and Engineering*, 10(4). https://doi.org/10.22399/ijcesen.708

[21]Olola, T. M., & Olatunde, T. I. (2025). Artificial Intelligence in Financial and Supply Chain Optimization: Predictive Analytics for Business Growth and Market Stability in The USA. *International Journal of Applied Sciences and Radiation Research*, 2(1). https://doi.org/10.22399/ijasrar.18

[22]Vutukuru, S. R., & Srinivasa Chakravarthi Lade. (2025). CoralMatrix: A Scalable and Robust Secure Framework for Enhancing IoT Cybersecurity. *International Journal of Computational and Experimental Science and Engineering*, 11(1). https://doi.org/10.22399/ijcesen.825

[23]Ibeh, C. V., & Adegbola, A. (2025). AI and Machine Learning for Sustainable Energy: Predictive Modelling, Optimization and Socioeconomic Impact In The USA. *International Journal of Applied Sciences and Radiation Research*, 2(1). https://doi.org/10.22399/ijasrar.19

[24]Velmurugan Ayyamperumal, S. Prabu, R. Senthilraja, Ahmed Mudassar Ali, S. Jayapoorani, & M. Arun. (2025). AI-Driven Predictive Maintenance for Smart Manufacturing Systems Using Digital Twin Technology. *International Journal of Computational and Experimental Science and Engineering*, 11(1). https://doi.org/10.22399/ijcesen.1099

[25]Fowowe, O. O., & Agboluaje, R. (2025). Leveraging Predictive Analytics for Customer Churn: A Cross-Industry Approach in the US Market. *International Journal of Applied Sciences and Radiation Research* , 2(1). https://doi.org/10.22399/ijasrar.20

[26]Siva Satya Sreedhar P., I. Carol, Meenakshi, Helina Rajini Suresh, M. Thillai Rani, & J. Rejina Parvin. (2025). Optimizing Energy-Efficient Task Offloading in Edge Computing: A Hybrid AI-Based Approach. *International Journal of Computational and Experimental Science and Engineering*, 11(2). https://doi.org/10.22399/ijcesen.1268

[27]Hafez, I. Y., & El-Mageed, A. A. A. (2025). Enhancing Digital Finance Security: AI-Based Approaches for Credit Card and Cryptocurrency Fraud Detection. *International Journal of Applied Sciences and Radiation Research*, 2(1). https://doi.org/10.22399/ijasrar.21

[28]D. Naga Jyothi, & Uma N. Dulhare. (2025). Understanding and Analysing Causal Relations through Modelling using Causal Machine Learning. *International Journal of Computational and Experimental Science and Engineering*, 11(1). https://doi.org/10.22399/ijcesen.1018

[29]García, R., Carlos Garzon, & Juan Estrella. (2025). Generative Artificial Intelligence to Optimize Lifting Lugs: Weight Reduction and Sustainability in AISI 304 Steel. *International Journal of Applied Sciences and Radiation Research*, 2(1). https://doi.org/10.22399/ijasrar.22

[30]E.V.N. Jyothi, Jaibir Singh, Suman Rani, A. Malla Reddy, V. Thirupathi, Janardhan Reddy D, & M. Bhavsingh. (2025). Machine Learning-Based Optimization for 5G Resource Allocation Using Classification and Regression Techniques. *International Journal of Computational and Experimental Science and Engineering*, 11(2). https://doi.org/10.22399/ijcesen.1657

[31]Vishwanath Pradeep B. (2025). Ethnobotanical perspectives: conventional fever treatments of the gond tribe. *International Journal of Applied Sciences and Radiation Research*, 2(1). https://doi.org/10.22399/ijasrar.23

[32]R. Sundar, M. Ganesan, M.A. Anju, M. Ishwarya Niranjana, & T. Surya. (2025). A Context-Aware Content Recommendation Engine for Personalized Learning using Hybrid Reinforcement Learning Technique. *International Journal of Computational and Experimental Science and Engineering*, 11(1). https://doi.org/10.22399/ijcesen.912

[33] Muller, T. H., Butler, J. L., Veselic, S., Miranda, B., Wallis, J. D., Dayan, P., ... & Kennerley, S. W. (2024). Distributional reinforcement learning in prefrontal cortex. *Nature Neuroscience*, 27(3), 403-408.