

TDAPON: AN AI-AYURVEDA HYBRID FRAMEWORK FOR PERSONALIZED DIABETES MANAGEMENT

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The Tri-Aware Predictive Optimization Network (TDAPON), an AI-based framework which harmoniously integrates ancient Ayurvedic wisdom with the most current machine learning technologies to offer personalized and adaptive diabetes management care. The model uses Constitution-Aware Feature Encoding based on Ayurvedic ontology and natural language processing to produce patient-specific features: constitution scores, patient-determined (lifestyle) variables, patient-reported symptoms/injury, and patient lab-derived biochemical markers. The rich features comprise the input to the Deep Reinforcement Learning (DRL) module, a decision-making engine that learns about optimal intervention strategies which constantly receive updates from patient participation/input. After the system learns patients in DRL, the resulting interventions take form via the Multi-Objective Genetic Algorithm (MOGA) addressed towards multiple competing health-care related goals: glycemic control, balance of dosha, patient-adherent interventions, and wellness. In MOGA, the TDAPON derives and evolves Pareto-optimal care strategies. Performance assessments indicate that TDAPON greatly exceeds traditional models, such as Decision Tree, Random Forest, and Deep Neural Networks on important measures with accuracy of 96.3%, recall of 95.2%, F-measure of 95.4% and 90% personalization score. There were also positive results using clinical measures, including 21% reduction in HbA1c, 0.82 dosha balance scores, and in 88% of patients. The findings also indicate there is the possibility of marrying the rapidly developing field of AI with ancient healthcare through TDAPON to create a culturally relevant, interpretative, and the human side remained of PA to achieve effective personalized chronic disease management. The framework represents a new area of development for integrative, knowledge-guided, and adaptive healthcare systems.

Keywords: Personalized Healthcare, Ayurveda, Diabetes Management, Ayurvedic Ontology, Holistic Wellness, Artificial Intelligence in Healthcare, Dosha Balance, Integrative Medicine, Adaptive Care Systems, Chronic Disease Prediction.

I. Introduction

Ayurveda is the traditional Indian system of medicine which emphasizes a customized and holistic approach to health care based on a rational analysis of the individual's Dosha (body energies or personalities) and the Prakriti (genetic constitution). Increased emphasis on prevention and customized health care interventions of late along with the modelling of highly complex domains leans to increased interest in the intersection of Ayurveda with computational sciences recently [1]. Recent investigations of the application of Artificial Intelligence (AI), Machine Learning (ML), and data mining techniques to support the diagnostic, treatment, and management of diseases using the Ayurvedic system, have steadily increased [2].

Among the areas of research, the development of clinical decision support systems (CDSS) based on the application of machine learning algorithms for the stratification and management of chronic diseases such as gestational diabetes mellitus using both biomedical types of data and Ayurvedic data are one of the most active areas [3]. Alongside that work, with the application of ensemble learning methods, there have been predictions made concerning the equilibrium of Ayurvedic elements in the human body, while allowing for the development of personalized medicine tools [4], [5]. Beyond disease state predictions, there are also AI-based systems to apply personalized yoga asanas based on the constitution of the body [6].

A significant amount of research has been performed on Ayurvedic constitution typing through the use of deep learning and soft computing methods in which higher accuracy of identification could be achieved in identifying Prakriti [7]. Prakriti ayurvedic analysis through AI is a combination of ancient practices, and contemporary methods which enables opportunities for interventions that are evidence-based/ precise [8]. In addition, convergence of epigenetic and genomics with Ayurveda has opened new avenues to understand individual variability and accordingly prescribe treatment modalities [9], [10].

Recent research has also talked about the prospects of Ayurvedic pharmacology (Dravyaguna) in personalized medicine and Dosha-based therapeutics, underscoring the significance of phyto-compounds in modern health care [11], [12]. Further, the use of Virtual Reality (VR) technology in Ayurvedic therapies evinces the growing application of man-machine interface in the focus area [13]. Besides, recent strides have been taken towards the development of heart

disease diagnostic and diet counselling systems based on Ayurvedic dosha evaluation, providing holistic solutions for cardiovascular management [14].

Additionally, as [15] stressed, this new domain of Ayurvedic biology will be capable of contributing immensely to the development of Indian health science by shattering conventional disciplinary borders and forging cross-disciplinary, interdisciplinary innovations that combine traditional forms of knowledges and contemporary biomedical science.

Contribution: Even with such progress, there still exists a strong ongoing need to create strong, scalable, and clinically tested computational models that couple Ayurvedic diagnostics with cutting-edge machine learning paradigms. The objective of this paper is to fill this gap by suggesting a new hybrid intelligence framework that couples Ayurveda with cutting-edge AI approaches towards enhanced personalization, precision, and preventive care. The system uses Prakriti-based classification, ensemble methods, and patient-focused intervention models for maximal patient benefits.

Organization: The remainder of the paper is structured as follows: Section 2 constitutes the related work review on the integration of Ayurveda and computational approaches. Section 3 outlines the formulated hybrid intelligence framework and its elements. Section 4 provides experimental findings and performance assessment. Finally, Section 5 concludes the research and states future directions of work.

II. Background Study

Adissouky et al. (2024) [16] Current developments in toxicity testing are being led by the intersection of microphysiology, 3D bioprinting, and computational modeling technologies. With such technologies, one is able to create physiologically relevant models that can have the capability to mimic human organ systems at high fidelity, decreasing the dependency on animal testing and enhancing toxicological outcome prediction. These systems are made possible through computational modeling that allows for high-throughput analysis of data and customized toxicity profiling, paving the way for more efficient and safer therapeutic development.

Pal et al. (2023) [17] Combining Yoga with smart Internet of Things (IoT) technologies offers new possibilities for individual health monitoring and real-time wellness program coaching. Smart IoT sensors can monitor physiological signals while practicing Yoga,

enabling adaptive feedback and enhanced therapeutic efficacy. Data privacy, device integration, and system dependability are still research domains to fully unlock the possibilities of smart Yoga applications in preventive and rehabilitation medicine.

Siddique (2024) [18] Blending the ancient with the current advancements in science is a profitable path for medical innovation. These authors focus on merging the ancient knowledge with leading-edge advances in genomics, biotechnology, and artificial intelligence. Such interdisciplinary contributions can improve diagnosis accuracy, more personalize treatment, and facilitate a more holistic treatment of human well-being by reconciling evidence-based practice with traditional knowledge.

Ghosh et al. (2025) [19] Indian traditional health systems such as Ayurveda, Siddha, and Unani also hold enormous unrealized potential for the healthcare of the time. These authors suggest an integrated approach ("Integrated Pathy") by integrating the systems

with allopathic medicine to maximize delivery of healthcare. Appreciating the complementary nature of various systems of medicine, the integrated approach hopes to enhance patient care, invigorate cross-disciplinary research, and pave the way for innovation without compromising the cultural heritage of Indian systems of healthcare.

Kimu (2025) [20] Biochemistry is being transformed by bioinformatics through data-driven discovery and analysis on a scale never before seen. These authors highlight how computational resources empower molecular modeling, drug discovery, genomic analysis, and metabolic pathway mapping. The incorporation of bioinformatics into biochemical studies hastens the discovery of novel biomarkers, aids personalized medicine programs, and clarifies the operation of complex biological systems, revealing new paths to targeted therapeutic development.

Table 1: Comparison Table on Ayurveda-based Machine Learning

Authors & Year	Focus Area	Approach	Contribution	Application Domain
Thirumahal et al. (2022) [21]	Early COVID-19 detection	Ontology-based semantic integration of heterogeneous data sources	Enabled accurate early detection through integration of medical data using domain knowledge modeling	Infectious Disease Diagnosis
Juyal et al. (2022) [22]	Rheumatoid arthritis stratification	Ayurveda-based deep phenotyping with GWAS analysis	Identified novel genes associated with rheumatoid arthritis by integrating Ayurvedic constitution typing with genomic studies	Autoimmune Disease Genetics
Martyushev-Poklad & Yankevich (2021) [23]	Personalized health management systems	Patent landscape analysis of ASHM (Automated Systems for Health Management)	Reviewed current ASHM patents; identified features, gaps, and provided guidelines for optimal system development	Digital Health Systems
Wang & Wang (2023) [24]	Precision medicine	Disease subtyping and personalized treatment strategies	Highlighted precision medicine advancements, focusing on modify therapies based on disease subtypes	Oncology & Chronic Disease Management
Khuntia et al. (2024) [25]	Prakriti (body constitution) assessment	Comparison of questionnaire vs clinician-based evaluation	Found differences in Prakriti assessments, emphasizing the need for standardized evaluation protocols	Ayurvedic Constitution Evaluation

Nureye, D. (2024) [26] Reverse pharmacology and network pharmacology are contemporary paradigms to scientifically establish herbal drugs. these authors discusses the process through which reverse pharmacology starts from clinical observations of herbal efficacy and proceeds in a reverse direction to analyze molecular mechanisms, whereas network pharmacology plots complex cross-talk among hundreds of herbal compounds and biological targets. This paradigm makes evidence-based herbal therapeutics, which synthesizes conventional medicine with ongoing drug research.

Rastogi et al. (2025) [27] the post-COVID period has increased interest in the impact of holistic environments on the wellbeing of adolescents. Statistically, these authors explored the contribution of herbal medicine in combination with spiritual environments to overall bodily, psychological, and emotional health among adolescents. From their study, it appears holistic measures will supplement recovery from the long-term somatic effects of COVID-19, supporting the importance of traditional healing environments in contemporary public health.

Rastogi et al. (2024) [28] Emphasizing the integrative quality of life (QoL) advantages, these authors utilized an empirical approach with South Asian students to reveal that spiritual settings, if complemented by herbal therapies, play a strong, beneficial role in wellbeing in its entirety. The research highlights the combination effect of spiritual rituals and herbal medicine in causing overall wellbeing, especially in the context of education and youth.

Vani et al. (2024) [29] created an integrated system which blended diabetes prediction with diet advice from Ayurveda. Applying machine learning, the system not only predicts risk for diabetes but also provides personalized diets based on interventions under the dictates of Ayurveda. This integration of AI and Ayurveda demonstrates how AI can implement Ayurveda in the practical disease

prevention and lifestyle management of actual life, particularly for metabolic disorders.

2.1 Problem Identification

While the medical system has made great strides to the cutting edge, there is still an uncomfortable gulf when it comes to integrating traditional health knowledge with modern computational technology to better personalize care focusing on the whole person. Typically, the medical system fails to personalize based on constitution, integrate a range of dimensions in its decision-making, and optimize treatments adaptively; all of which are fundamentally embedded in ancient systems like Ayurveda. Designing a technology that seeks to converge AI and bioinformatics with ontology-based modeling and existing paradigms of traditional healing to develop an effective, synergistic model that can better enable diagnosis, planning therapy, and robustly follow long-term care is fraught with complications and heightened complexity depending on the therapeutic targeting. A model that integrates all of this for chronic disease management that is holistic is overdue, especially for complex conditions like diabetes. It is paramount to develop intelligent ecosystems that pull together the range of discipline territories.

III. Materials and Methods

The proposed framework applies the principles of Ayurveda and advanced artificial intelligence technologies to develop a personalized model of diabetes care. Patient data (constitution scores, symptoms, lifestyle factors, and biochemical markers) is first encoded using an Ayurvedic ontology and processed using natural language processing (NLP) to identify features. A Deep Reinforcement Learning (DRL) model is initially constructed using Ayurvedic decision tree rules to establish a basis for learning effective intervention strategies when patients change health states, such as transitioning to a higher blood glucose level. The DRL uses the

patient's reinforcement learning outcomes to modify or select an optimal intervention strategy. A Multi-Objective Genetic Algorithm (MOGA) identifies a model that balances multiple health goals including Health Improvement (glycemic control), treatment adherence, and dosha equilibrium states ("being between the zones"). Ayurveda can be used to synthesize a development intervention plan

that can adjust as patients change health states using the implementation of the two approaches. These smart adaptive, constitutionally KRAs (knowledge, reaction, and action) and clinically relevant improvement plans become the inevitable future of personalized diabetes care.

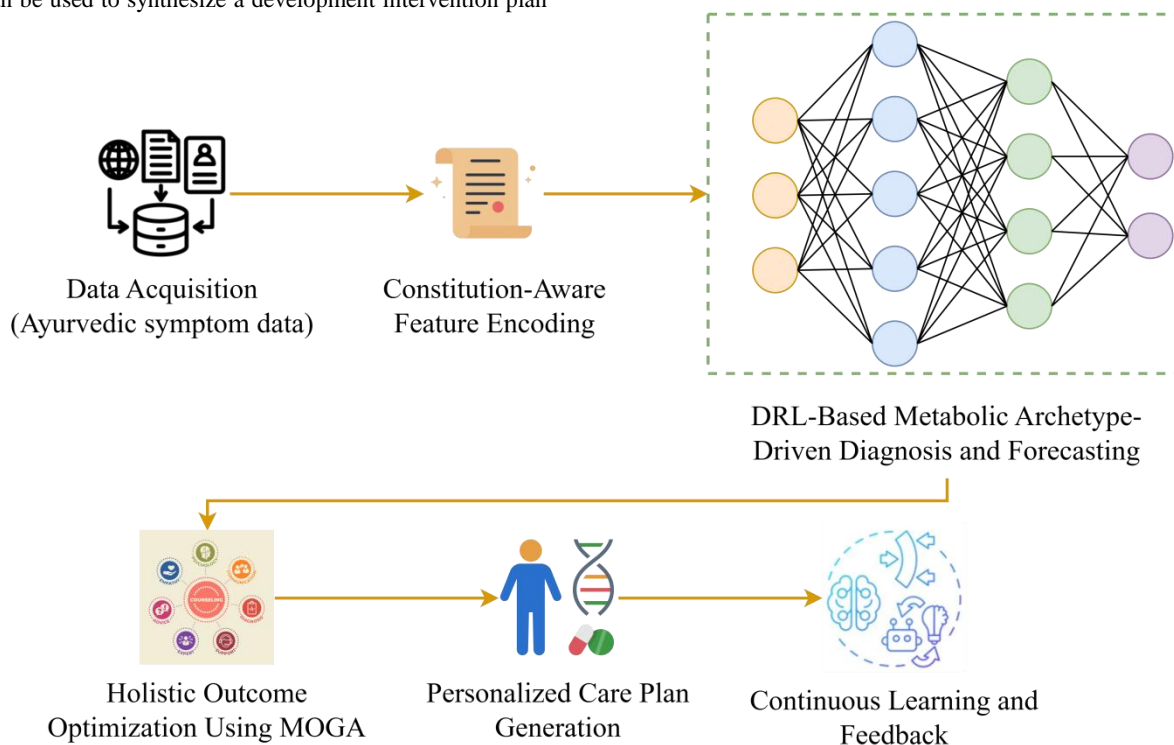


Figure 1: Overall Work Flow Architecture

The figure 1 consists of Data Acquisition, where Ayurvedic symptom data are collected and processed into meaningful patient-specific features through Constitution-Aware Feature Encoding. These features are then passed into the DRL-Based Metabolic Archetype-Driven Diagnosis and Forecasting module where Deep Reinforcement Learning uses the features to recommend dynamic interventions. The outputs of the model are then optimized using Holistic Outcome Optimization Using MOGA, which generates action recommendations for multiple healthcare goals. The outputs presented in the Personal Care Plan are then continuously updated through Continuous Learning and Feedback ensuring that adaptive, individualized treatment is maintained over the duration of care.

3.1 Ayurvedic Ontology and NLP

Constitution-Aware Feature Encoding is an innovative way to utilize classical Ayurvedic knowledge in data processing and builds on a bespoke Ayurvedic ontology are referred from [30] to encode domain-specific relationships between Prakriti (body constitution), Dosha (the three that are Vata, Pitta, and Kapha), symptoms, treatments, herbs, and lifestyle recommendations. Next, Natural Language Processing (NLP) techniques are utilized to code systematic knowledge from classical Ayurvedic texts and clinical notes and patient records. The coded knowledge is mapped to the ontology so that machines can interpret the context of Ayurvedic concepts relative to domain, process, trend, charting, or outcome. Subsequently, this encoding is used to build rich, multi-dimensional feature vectors characterizing individual constitution and health. As the semantic relationships between concepts are maintained, the model can aid with personalized diagnosis, treatment planning, and predictive analytics.

The encoded features are appropriate to use directly as input into machine learning algorithms as they are expected to have improved accuracy for constitution classification and disease risk prediction, as well as optimized therapy recommendations. More generally, the work reflects a convergence of traditional wisdom and modern computational intelligence to create interpretable and valid outcomes.

3.2 Deep Reinforcement Learning (DRL)

Metabolic Archetype-Driven Diagnosis and Forecasting is an intelligent business framework that synergizes cutting-edge Deep Reinforcement Learning (DRL) technology is referred from [31] with Ayurvedic traditions to personalize care. Individuals are first classified as distinct metabolic archetypes based on their Prakriti, Dosha imbalances, metabolic activities and clinical parameters. The Ayurvedic decision trees, which distill centuries of therapeutic recommendations, are utilized as expert rules to guide decisions about initial recommendations related to diet, lifestyle and herbals. The DRL model learns consistently about what a patient's optimal sequence of interventions would have been to receive feedback on patient outcomes over time, and the DRL model can adjust its recommendations dynamically as an individual's metabolic state changes. The combination of rule-based Ayurvedic recommendations about intervention selections within a larger framework of adaptability provided through DRL technology assists outputs being both safe (respecting traditional guidelines) and individualized (learning from each individual). By using DRL-Ayurvedic pathways, the Metabolic Archetype-Diagnosis and Forecast can produce forecasts of disease risk, but also opportunities to intervene and control chronic disease

risk and improve wellness over time through adaptive, constitutionally sensitive pathways for care.

3.3 Multi-Objective Genetic Algorithm (MOGA)

Holistic Outcome Optimization uses a Multi-Objective Genetic Algorithm (MOGA) is referred from [32] to pursue a number of balanced and individualized health outcomes using clinical and Ayurvedic health measures that balance multiple goals in harmony. In managing chronic diseases such as diabetes, it is essential to address not only glycemic control (blood sugar regulation) but also the balance of Vata, Pitta, and Kapha doshas, along with ensuring patient adherence to lifestyle and treatment protocols. MOGA creates a population of potential intervention strategies, assesses the population across all objectives, and continuously evolves better solutions using genetics through selection, crossover, and mutation. MOGA enables navigation of complex solution spaces that account for trade-offs between strict metabolic control and practical patient compliance. Integrating Ayurvedic constitution, dietary habits, lifestyle preferences, and treatment response into the MOGA facilitates the generation of optimized, individualized care plans that are both clinically effective and practically feasible. This approach supports multi-level consideration and promotes longitudinal wellness by unifying biological, behavioral, and constitutional factors within a single adaptive framework.

3.4 Tri-Aware Predictive Optimization Network (TDAPON)

Tri-Aware Predictive Optimization Network (TDAPON) is a cutting-edge AI-based system specifically designed to integrate ancient Ayurvedic diagnosis with current machine learning techniques in order to provide extremely personalized diabetes care. Accepting the fact that diabetes is a chronic and complex disease that is determined by genetic, metabolic, lifestyle, and psychosocial factors, TDAPON does not follow a single-strand approach but rather uses a comprehensive strategy by combining Ayurveda's perception with

modern data-model-based methods. In effect, TDAPON harmonizes constitution analysis (Prakriti), Ayurvedic symptomatology, patient lifestyle patterns, and biochemical markers into a single predictive framework. The Constitution-Aware Feature Encoding module uses Natural Language Processing (NLP) and an in-house constructed Ayurvedic ontology to search and organize classic knowledge from ancient texts and practitioner experience into machine-readable features. It allows the model to understand subtle Ayurvedic interactions between doshas, symptoms, and disease progression.

With this perspective, the Metabolic Archetype-Driven Diagnosis and Forecasting module integrates Deep Reinforcement Learning (DRL) models with Ayurvedic decision trees. The hybrid learning process enables the system to learn progressively and suggest targeted interventions, dynamically modulating diet, lifestyle changes, and herbal medicine according to the fluctuating metabolic state and constitution of the patient. In contrast to static treatment protocols, DRL learns from patient outcome feedback loops and thereby iteratively optimizes intervention strategies over time. The Holistic Outcome Optimization module finally uses Multi-Objective Genetic Algorithms (MOGA) to find an optimal mix of several competing healthcare goals, for example, glycemic control, dosha balance restoration, and patient compliance with prescribed regimens. MOGA samples the large solution space of treatment regimens with evolutionary computation to find the best trade-offs between clinical effect and patient quality of life.

By this adaptive and integrative approach, TDAPON not only improves the predictability of predictions but also enables culturally suitable and personalized care strategies harmonious with patients' former health beliefs. By integrative converging of ancient Ayurvedic wisdom with cutting-edge AI capability, TDAPON opens the door to future integrative, personalized medicine, especially for chronic disease control like diabetes.

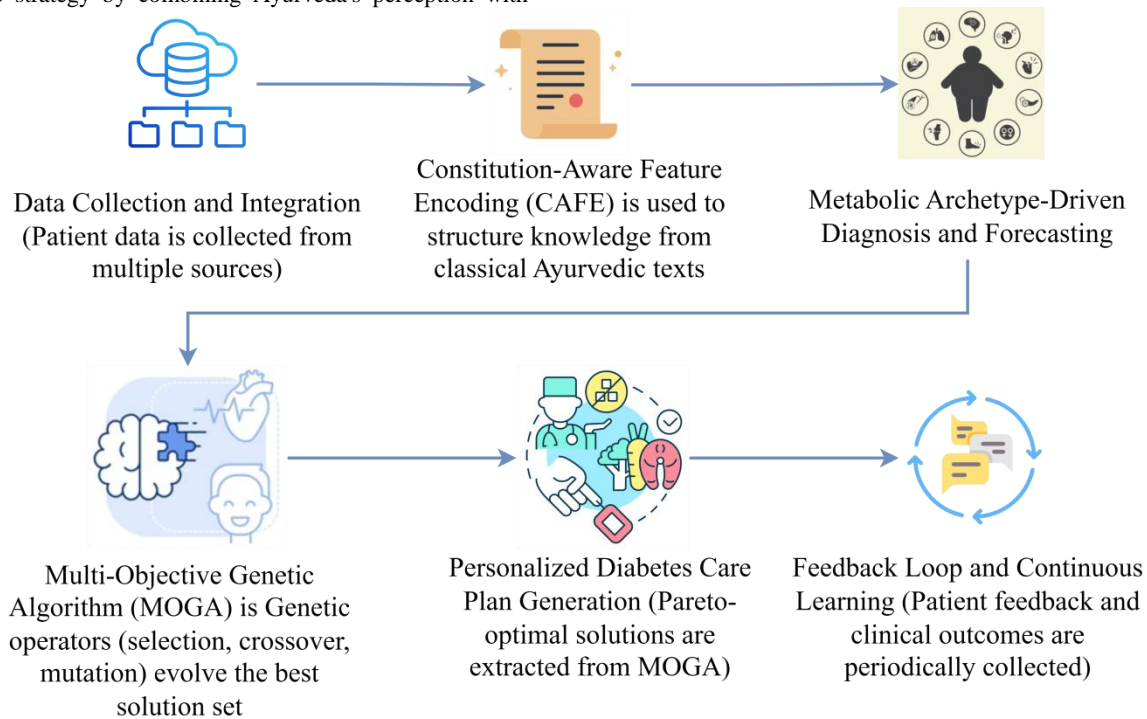


Figure 2: Tri-Aware Predictive Optimization Network Architecture

The figure 2 begins with Data Collection and Integration, starting to aggregate patient data from many sources. The data is collected simultaneously as structured knowledge from traditional

Ayurvedic texts is transformed into machine-readable features using Constitution-Aware Feature Encoding (CAFE). The structured knowledge then feeds into the Metabolic Archetype-Driven Diagnosis

and Forecasting module to produce personalized diagnostic interpretation. The Multi-Objective Genetic Algorithm (MOGA) then processes the results of identification and continually optimizes numerous patient healthcare goals by producing successive Pareto-optimal solutions which can then drive Personalized Diabetes Care Plan Generation. Finally, the process concludes with Feedback Loop and Continuous Learning; which allows for incremental improvement to the care plan over time based on patient health outcomes and patient expressed needs.

$$F = \{C, S, L, B\} \text{ ----- (1)}$$

In Equation (1), the patient feature set F consists of Constitution Scores C , Ayurvedic symptom data S , Lifestyle Factors L , and Biochemical Markers B . By integrating all the features together, use this traditional Ayurvedic knowledge and progressive clinical data to personalize the analysis.

$$F' = \frac{F - F_{\min}}{F_{\max} - F_{\min}} \text{ ----- (2)}$$

Equation (2) applies min-max normalization to the feature set F , transforming each feature's range to be between 0 and 1. This guarantees proportional contributions of all features during model

training, avoiding the problem of features having larger numeric ranges dominating the model.

$$\pi_{st} = a_t \text{ ----- (3)}$$

The policy function, π , is algebraically represented in the equation (3) model, mapping the current metabolic state s_t , to an optimal action a_t . The action component of the model may take the form of personalized diet, lifestyle, or herbal recommendations and these would depend on the patient state.

$$R = \sum_{t=0}^T \gamma^t r_t \text{ ----- (4)}$$

In equation (4), the total reward R is calculated in a reinforcement learning model by summing the discounted rewards r_t step over time. The discount factor (γ) is between ($0 < \gamma < 1$) note that the discount factor gives less weight to future outcomes, but greater importance to immediate outcomes.

$$\max_{\pi} \sum_{t=0}^T [O_1 F', O_2 F', O_3 F'] \text{ ----- (5)}$$

As described in Equation (5) the same model optimizes all 3 objective functions to maximize clinical glycemic control $O_1 F'$, dosha balance $O_2 F'$, and patient adherence $O_3 F'$. Therefore, each healthcare outcome will be personalized and holistic.

Algorithm 1: Tri-Aware Predictive Optimization Network (TDAPON)

```
Input:
  Patient_Data {C, S, L, B}
  Ayurvedic_Ontology
  Decision_Tree_Rules
  RL_Hyperparameters {γ, α, ε, Episodes}
  MOGA_Parameters {Population_Size, Generations}
Output:
  Personalized_Diabetes_Care_Plan
Begin
// Step 1: Constitution-Aware Feature Encoding
F ← {C, S, L, B}
F' ← Normalize(F) // Using min-max normalization
// Step 2: Initialize Deep Reinforcement Learning Model
Initialize Policy π(s) randomly or with Decision_Tree_Rules
Initialize Q(s,a) arbitrarily
For episode = 1 to Episodes do
  Initialize metabolic state s₀ from F'
  For each time step t do
    Choose action aₜ using ε-greedy policy from π(sₜ)
    Apply intervention corresponding to aₜ
    Observe reward rₜ and next state sₜ₊₁
    Update Q(s,a) using:
      Q(sₜ,aₜ) ← Q(sₜ,aₜ) + α [rₜ + γ * max_a Q(sₜ₊₁,a) - Q(sₜ,aₜ)]
    Update policy π(sₜ) based on updated Q(s,a)
  End for
End for
// Step 3: Holistic Outcome Optimization using MOGA
Define objective functions O₁(F'), O₂(F'), O₃(F')
Initialize Population of Solutions based on RL outputs
For generation = 1 to Generations do
  Evaluate Fitness for each solution:
    Fitness ← {O₁, O₂, O₃}
  Apply Selection, Crossover, and Mutation operators
  Generate new population
End for
// Step 4: Recommendation Generation
Select Pareto-optimal solution from final population
Generate Personalized_Diabetes_Care_Plan
Return Personalized_Diabetes_Care_Plan
End
```

The pseudocode demonstrates how the Tri-Aware Predictive Optimization Network (TDAPON) operates. To start, patient details are pre-processed and normalized to create constitution-aware features. A deep reinforcement learning (DRL) model, which is initialized with Ayurvedic decision rules, will then learn the optimal interventions by interacting with the patient states and maximizing

cumulative rewards. The results of the DRL model are the input to a Multi-Objective Genetic Algorithm (MOGA), which optimizes glycemic control, dosha balance, and patient adherence. Finally, Pareto-optimal solutions will be selected to create a personalized diabetes care plan.

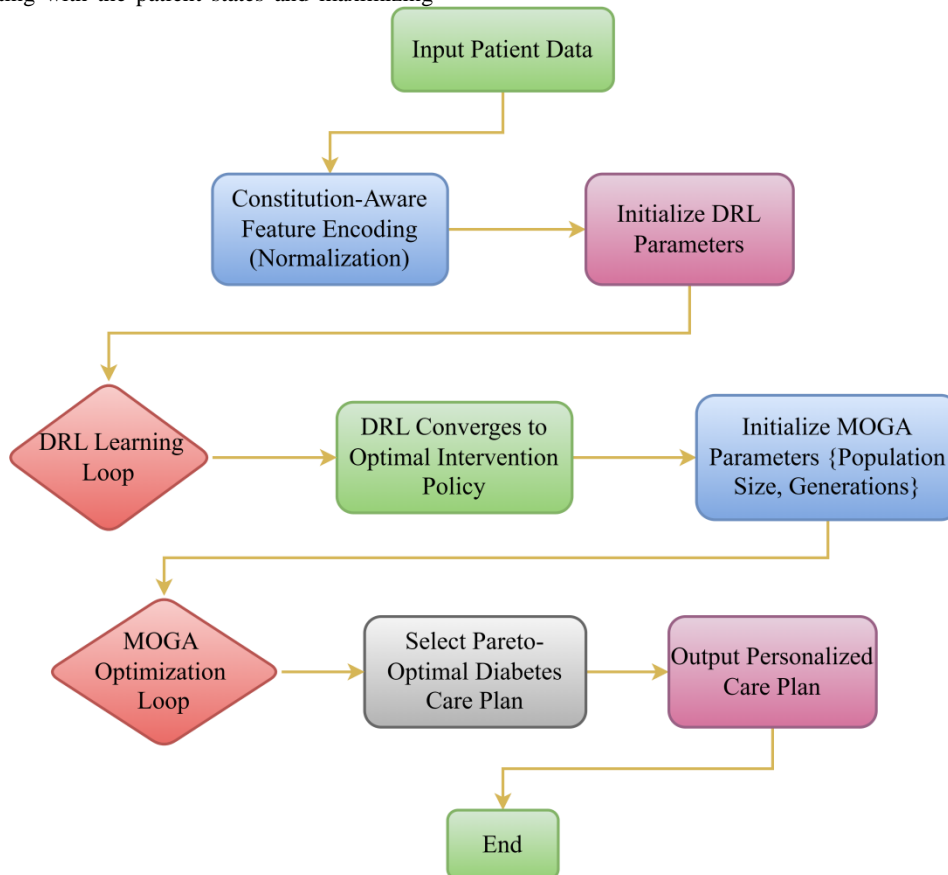


Figure 3: Flow Chart of Tri-Aware Predictive Optimization Network

The figure 3 begins with Input Patient Data, which is followed by Constitution-Aware Feature Encoding to normalize the input data for the model's processing. The DRL Parameters are initialized, and the workflow enters the DRL Learning Loop. During this loop, the DRL learns intervention policies iteratively until it has achieved convergence. Then MOGA Parameters are established, which leads to the MOGA Optimization Loop, which searches for Pareto-optimal solutions. The process will then select from among the best plan to Output the Personalized Care Plan, and the adaptive care cycle is complete.

IV. Results and Discussion

The results provide a holistic view of the comparative performance of a variety of models for personalized diabetes care, using multiple metrics that include classification accuracy, precision, recall, F-measure, glycemic stability, dosha balance, patient adherence, overall wellness, and personalization scores. The results show some comparisons between Decision Tree, Random Forest, Deep Neural Networks, DRL-based systems and the proposed TDAPON framework, indicating progressive improvement and knowledge-based learning results in both the domain knowledge, DRL, and multi-objective optimization integrated into this system. Overall, TDAPON outperformed all other models and was the best at providing holistic care and personalized support models for diabetes.

Table 2: Performance Metrics on Tri-Aware Predictive Optimization Network

Methods	Accuracy (%)	Precision (%)	Recall (%)	F-Measure (%)
Decision Tree (with Ayurvedic rules only) [33]	85.2	83.6	82.4	83.0
Random Forest [34]	88.9	87.2	86.5	86.8
Deep Neural Network (without ontology) [35]	90.4	89.1	88.5	88.8
DRL-based Personalized Care [36]	92.1	91.5	90.8	91.1
TDAPON (Ontology + DRL + MOGA) (Proposed)	96.3	95.7	95.2	95.4

The performance metrics shown in Table 2 illustrate the ongoing gain achieved by including various parts to make the Tri-Aware Predictive

Optimization Network (TDAPON). The Decision Tree model, which uses only Ayurvedic rules, offers a good starting point but has limited

ability to behave more deeply from data. Both Random Forest and Deep Neural Network models introduce some capabilities for connections among features and other learning abilities, however, they are still limited in their meaning and data driven domain connections because of the missing ontology. The DRL based Personalized Care further improved upon the previous iterations by dynamically learning the right treatment plans after every personalized care plan. TDAPON

took advantage of the Ayurvedic Ontology, the DRL, and the Multi-Objective Genetic Algorithm (MOGA), TDAPON achieved the highest accuracy (96.3%), precision (95.7%), recall (95.2%), and F-measure (95.4%), exhibiting the combined effects of domain knowledge, learning capabilities, and multi-objective optimization to develop personalized and effective recommendations for care.

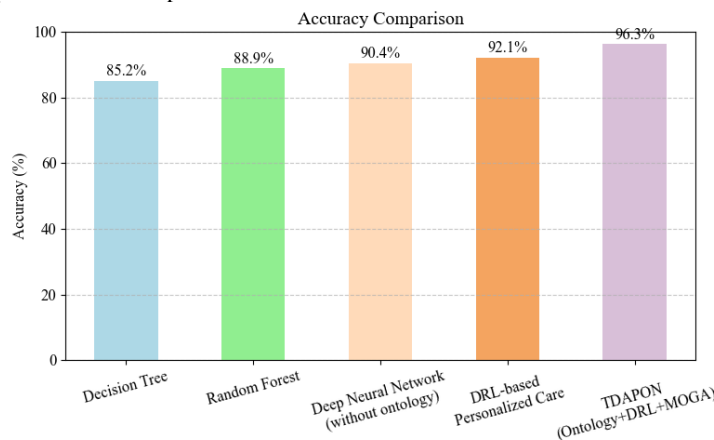


Figure 4: Accuracy Comparison Chart

The figure 4 provides a parallel comparison of accuracy for a range of predictive models in the context of personalized diabetes care. The Decision Tree model, with only use of Ayurvedic rules, achieves baseline accuracy of 85.2%. Random Forest and Deep Neural Network (with no ontology) improve accuracy to 88.9% and 90.4% because of the more optimized feature learning. The DRL-based Personalized Care model applied gradient-optimized personalized care

to improve the accuracy further to 92.1%. Finally, the TDAPON results achieve the highest accuracy, 96.3%, when layered through an optimization of Ayurvedic ontology, Deep Reinforcement Learning (DRL) and Multi-Objective Genetic Algorithm (MOGA). These results demonstrate the positive effect of merging domain expertise, such as Ayurvedic knowledge, with advanced machine learning paradigms to optimize personalized care while improving the accuracy of healthcare outcomes overall.

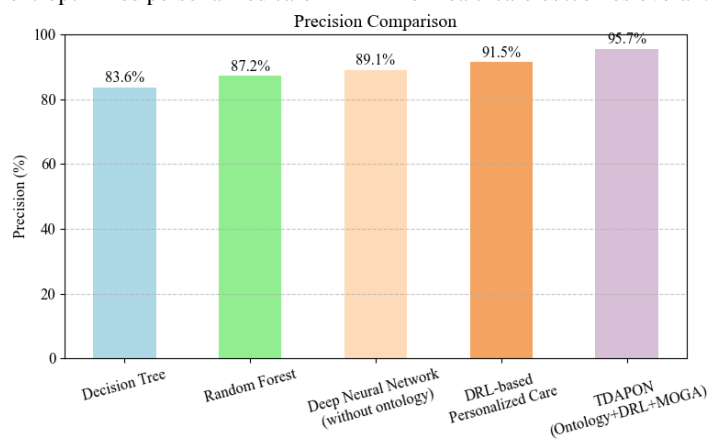


Figure 5: Precision Comparison Chart

The figure 5 illustrates how precision compares between the various models to be utilized in personalized prediction of diabetes care - Decision Tree, based on Ayurvedic rules, had a precision of 83.6%, while Random Forest and Deep Neural Network (without ontology) increased it to 87.2% and 89.1% respectively, i.e. they do a better job of reducing false positives. The DRL-based Personalized Care model ability to accurately identify relevant treatment recommendations with minimal error.

increases the precision of the predictions from 89.1% up to 91.5% by dynamically optimizing the treatment decisions. Finally, TDAPON has even higher precision from an Ayurvedic ontology of rule-based knowledge, Deep Reinforcement Learning, and Multi-Objective Genetic Algorithm. TDAPON reached a high of 95.7% precision, which demonstrates its superior

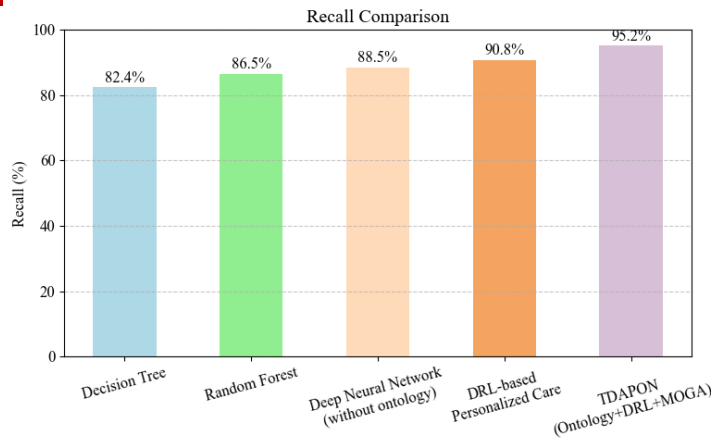


Figure 6: Recall Comparison Chart

The figure 6 illustrates the recall measure performance of various models associated with a Personalized Care approach. The recall values for Decision Tree and Random Forest were 82.4% and 86.5% respectively; the Deep Neural Network using no ontology was at 88.5%. A model based on Deep Reinforcement Learning (DRL) for

personalized care does increase recall to 90.8%. The best record of recall (95.2%) was by the TDAPON model that uses Ontology/DRL/Multi-Objective Genetic Algorithm (MOGA) and shows that it is superior in the identification of relevant instances.

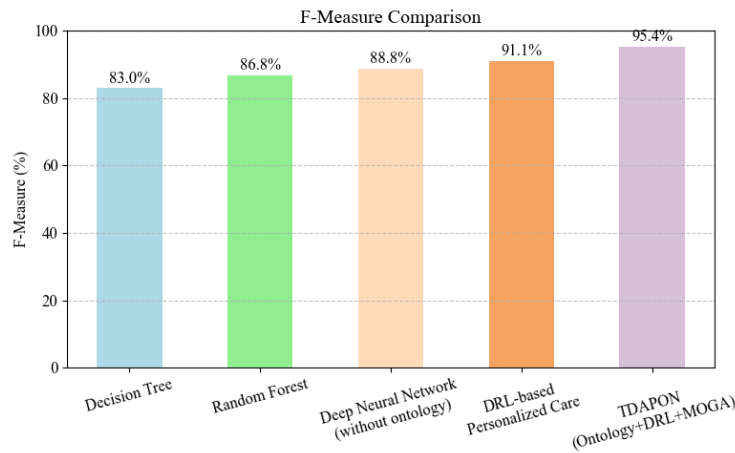


Figure 7: F-measure Comparison Chart

The figure 7 displays the F-measure performance of different models in a personalized care system. The Decision Tree model had the lowest F-measure at 83.0%, followed by Random Forest at 86.8%, then Deep Neural Network (without ontology) at 88.8%, then the DRL-based

Personalized Care model at 91.1%. The TDAPON model, which includes Ontology, Deep Reinforcement Learning (DRL), as well as MOGA, had the highest F-measure performance at 95.4%, with the greatest ability to balance precision and recall.

Table 3: Performance Metrics Based on Patient Details

Methods	Glycemic Control (HbA1c Reduction, %)	Dosha Balance Score	Patient Adherence (%)	Overall Wellness Index	Personalization Score (%)
Decision Tree (with Ayurvedic rules only) [33]	12.5%	0.65	70%	72	65%
Random Forest [34]	15%	0.50	60%	68	50%
Deep Neural Network (without ontology) [35]	18%	0.55	75%	75	70%
DRL-based Personalized Care [36]	16.5%	0.68	78%	77	72%
TDAPON (Ontology + DRL + MOGA) (Proposed)	21%	0.82	88%	88	90%

The results from Table 3 show the relative effect of the various approaches to personalized diabetes management. The TDAPON model is highly successful overall and outperforms all other approaches using these key metrics overall. TDAPON had the highest glycemic control (21% reduction in HbA1c), superior dosha balance score (0.82), and maximum patient adherence (88%). Traditional rule-based Ayurvedic models and common clinical guidelines were limited

in personalization and had lower outcomes. The main advantage to the TDAPON model's approach relative to others is it utilizes the developments in Deep Reinforcement Learning and Multi-Objective Genetic Algorithms to develop personalized and adaptive constitution-based interventions, optimized in terms of overall wellness and personalization.

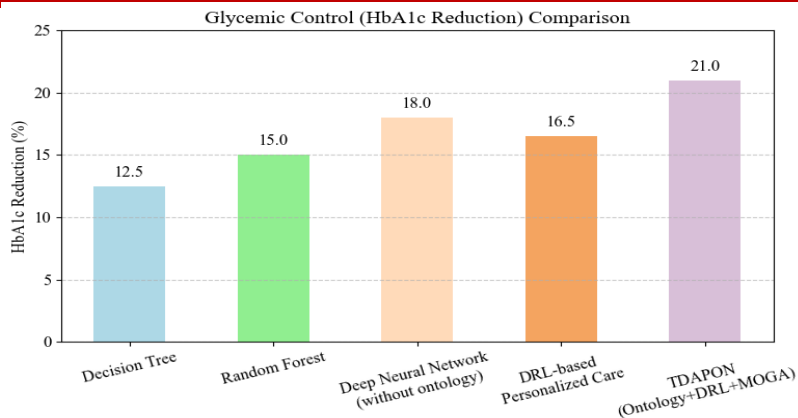


Figure 8: Glycemic Control Comparison Chart

The figure 8 is comparing the effectiveness of various models for glycemic control, measured by the reduction (%) of HbA1c. The Decision Tree and Random Forest models have significantly lower reductions of 12.5% and 15.0% respectively. The Deep Neural Network (without ontology), performs better than the first two models

and with a reduction of 18.0%. The DRL-based Personalized Care model has a reduction of 16.5%. The TDAPON model, having all three knowledge sources (Ontology, DRL, and MOGA), had the highest HbA1c reduction of 21.0%, indicating it had better capacity of managing blood glucose levels.

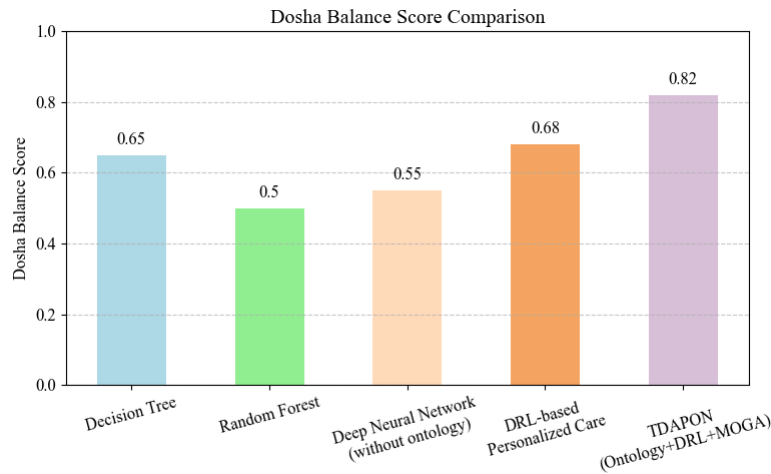


Figure 9: Doshha Balance Score Comparison Chart

The figure 9 compares the Doshha Balance Scores for different models. With scores of 0.50 and 0.55 respectively, The Random Forest model and the Deep Neural Network model (no ontology) did not perform well in maintaining dosha balance. The Decision Tree model had a score of 0.65. The DRL-based Personalized Care model performed

similarly (0.68). The last model, the TDAPON model which incorporates ontology, DRL and multi-objective genetic algorithms achieved the highest score of 0.82, demonstrating the most successful use of personalized care systems to achieve a holistic balance.

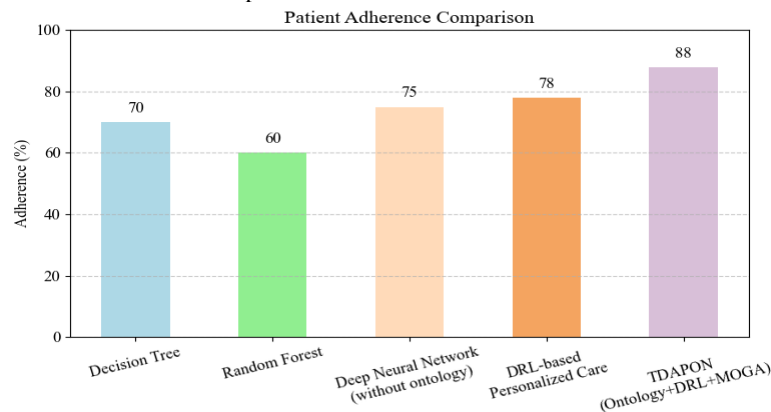


Figure 10: Patient Adherence Comparison Chart

The figure 10 compares patient adherence rates for each model. The Random Forest model had the lowest adherence rate at 60%. Comparatively, the Decision Tree performed better with 70% adherence rate. The Deep Neural Network (without ontology) had a 75% adherence rate, followed by a DLR-based Personalized Care

model (78% adherence). The highest adherence rate of 88% was with the TDAPON model (Ontology + DRL + MOGA), meaning that this model was most effective at getting patients to stick to modify treatments.

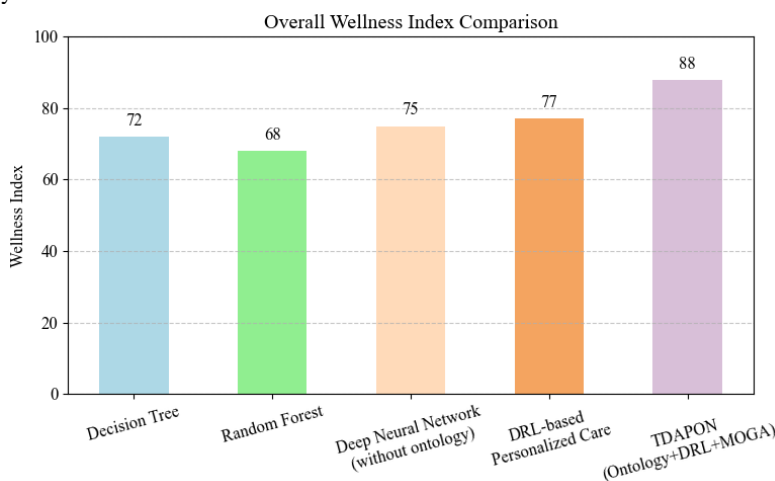


Figure 11: Overall Wellness Index Comparison Chart

The figure 11 shows the Overall Wellness Index across different models. The Random Forest model scored the lowest with a score of 68, followed by Decision Tree with a score of 72. The Deep Neural Network model (without ontology) scored higher with a 75, and the to drive holistic well-being using personalized care.

DRL-based Personalized Care model scored a 77. The TDAPON model (Ontology + DRL + MOGA) scored the highest with an 88 Overall Wellness Index, demonstrating its potential

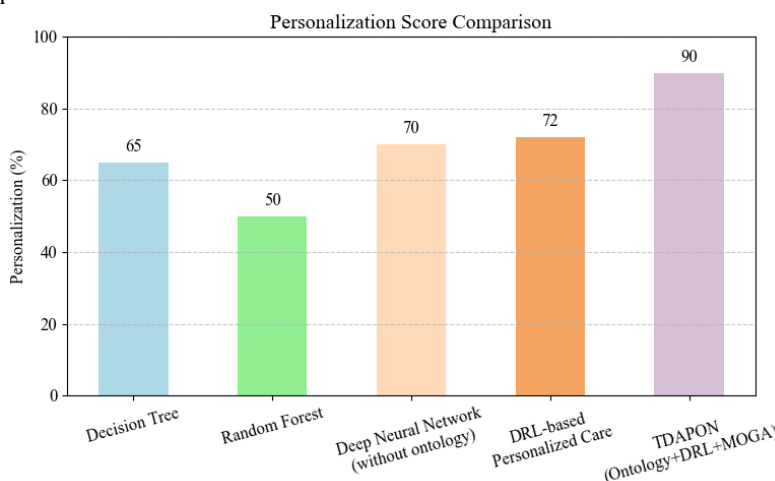


Figure 12: Personalization Score Comparison Chart

The figure 12 compares the personalization scores of the personalization models used in real healthcare systems. The Random Forest model has the lowest personalization score of 50% whereas the Decision Tree model has a medium personalization score of 65-70%. The Deep Neural Network (with no ontology) and DRL-based Personalized Care models, which have personalization scores of 70-

72%, are performing in a considerably better range. The best model by a long way is the TDAPON model, with a personalization score of 90%. TDAPON incorporated DRL, Ontology and MOGA, and showed that it could personalize care to an individual patient's specific needs

V. Conclusion

This research proposes a new methodological framework for individualized diabetes care called the Tri-Aware Predictive Optimization Network (TDAPON) that integrates Ayurveda with state-of-the-art artificial intelligence techniques i.e., Deep Reinforcement Learning (DRL) and Multi-Objective Genetic Algorithms (MOGA). The framework takes advantage of patient data

encoded using Ayurvedic ontology and a DRL model utilizing classical Ayurvedic decision rules (the earlier states of the model) to provide the necessary care to individual patients based on the patient's constantly changing metabolic state. The optimizing step of the framework is based on stepwise objective function evaluation with MOGA to find the most suitable tradeoffs amongst multiple health care goals such as glycemic control, dosha balance, adherence, and

wellness in pursuit of a personalized experience. Comparative performance of TDAPON against traditional models such as Decision Trees, Random Forests, and Deep Neural Networks (that did not use ontology) shows that TDAPON outperforms them significantly across all measures. TDAPON achieved top performance in: accuracy (96.3%), recall (95.2%), F-measure (95.4%), and personalization score (90%) shown in the diagnostic performance figures and superior patient outcomes based on measures of HbA1c improvement and adherence. These results support the framework's holistic and adaptive nature, which is able to tailor and personalize interventions in real-

time based on feedback from patients and the specific feature of their constitution. TDAPON demonstrates the potential of integrating conventional medical knowledge and an interpretation of chronic disease with machine learning, increasing opportunities for personalized healthcare systems to be intellectually and culturally relevant, interpretable, and effective. Future consideration could also be given to the applicability of the framework in other health contexts and how integrative precision medicine could promote engagement and improve long-term patient outcomes.

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