Proceedings of the Nineth International Conference on Communication and Electronics Systems (ICCES-2024)
IEEE Xplore Part Number: CFP24AWO-ART; ISBN: 979-8-3503-7797-2

Personalized Food Nutrient Recommendations for Kids using AI and Behavior Analysis

C.Anjanamma
Department of CSE,
Sridevi Women's Engineering college,
Hyderabad,Telangana, India.
anjanareddychappidi@gmail.com

G.Sirisha
Department of IT,
Sridevi Women's Engineering college,
Hyderabad,Telangana,India.
gangasireesha@gmail.com

B.Sravani
Department of CSE,
Malla Reddy Engineering College,
Secunderabad, Telangana,India
sravani.morla001@gmail.com

K.Shilpa
Department of CSE,
Gokaraju Rangaraju Institute of Engineering and Technology,
Hyderabad, Telangana,India
kancharla12.shilpa@gmail.com

C V Lakshmi Narayana
Department of CSE(AI&ML),
Annamacharya University,
Rajampet,India.
cvlakshminarayana@gmail.com

V.Vivekanandhan*
Department of CSE,
Malla Reddy College of Engineering,
Secunderabad,Telangana,India
acevivek7677@gmail.com

2024 9th International Conference on Communication and Electronics Systems (ICCES) | 979-8-3503-7797-2/24/$31.00 ©2024 IEEE | DOI: 10.1109/ICCES63552.2024.10859422

***Abstract*—This article introduces a custom-made dietary recommendation system for children that harnesses artificial intelligence (AI) and the Internet of Medical Things (IoMT) to provide adaptable, context-sensitive nutrition plans. It integrates a Decision Tree-based Nutritional Assessment, employs Reinforcement Learning (RL) for dietary modification, and incorporates a Context-Aware Recommendation Model to flexibly modify dietary advice based on individual health profiles and environmental variables such as ambient weather. Constructed using Python and evaluated on a robust computing platform featuring IoT-enabled wearables for real-time monitoring of calorie intake, the model exhibited notable advancements over pre-existing methods, achieving 92% accuracy, 90% precision, 91% recall, and an F1-score of 91%. These metrics affirm its effectiveness in providing pertinent dietary guidance. During a 30-day evaluation, compliance with diet plans rose from 75% to 90%, in contrast to other models with a top adherence of 85%. Furthermore, the context-aware feature of the model offered efficient caloric adjustments that boosted adherence by 10% in cooler climates compared to models lacking contextual inputs. User satisfaction surveys revealed that 80% of participants reported being "Very Satisfied" or "Satisfied," illustrating the system's versatility and user-oriented approach. These results suggest the model's significant promise for real-world utilization in personalized child nutrition, enhancing dietary compliance, precision, and user involvement by fusion of context-driven modifications and RL.**

Keywords*—Personalized Nutrition, Dietary Recommendation System, Artificial Intelligence, Reinforcement Learning, Internet of Medical Things (IoMT)

I. INTRODUCTION

Globally, the frequency of childhood obesity and associated health issues has been increasing, making focused interventions that promote healthy eating habits from a young age necessary. People find it challenging to maintain balanced diets that take into account their specific health profiles, dietary preferences, and lifestyle circumstances because traditional dietary advice frequently lack personalization. Artificial intelligence (AI) and the Internet of Medical Things (IoMT) have showed great promise for revolutionizing dietary planning and health management as public health research advances. Dietary advice can be made to each person's needs using personalized diet recommendations, especially those that use AI and machine learning. This could enhance adherence and promote long-term health results.

AI-based nutritional planning and personalized diet recommendations have demonstrated great promise in tackling public health concerns, especially in childhood nutrition and obesity control. Essential insights about AI's expanding involvement in this subject can be gained from foundational efforts. Iwendi et al. [1] demonstrate how IoT can improve diet management and produce customized health outcomes with their IoMT-assisted diet advice system that uses machine learning. A comprehensive evaluation of AI applications in nutrition is provided by Armand et al. [2] who highlight the adaptability of machine learning in illness prevention, dietary assessment, and customized diet planning. Furthermore, Singar et al. [3] explore genetic insights in personalized nutrition, talking about the significance of bioinformatics for optimal dietary guidance and gene-diet relationships. "ChatDiet," a Large Language Model (LLM)-enhanced chatbot framework for personalized nutrition, is presented by Yang et al. [4]. Bastida et al. [5] examine OCARIoT's IoT platform, which lowers the prevalence of obesity through individualized coaching and real-time health monitoring, demonstrating the potential for tech-enabled health management in kids.

Despite these developments, a large number of dietary advice systems now in use lack the thorough customisation required to meet the particular requirements of children. The nutritional needs of children vary with age, growth, activity level, and dietary choices, all of which can alter with time. Furthermore, general diet regimens sometimes don't involve young people or take behavior-driven aspects into consideration when making food decisions. A promising answer to these problems is an AI-driven food plan that adjusts to the unique requirements, habits, and behaviors of kids.

Current research identifies a number of shortcomings that restrict the effectiveness of child-specific nutrition guidance systems. Most systems fail to consider the behavioral factors that impact dietary adherence, especially in younger users. A lot of models are generic and don't include the modifications required for different stages of growth and development. Many platforms don't offer real-time monitoring and feedback, which could facilitate quick interaction and improvements. Few systems successfully use kid-friendly interactive interfaces that encourage consistent adherence to dietary guidelines. By putting forth an AI-based nutritional recommendation system for kids that combines behavioral analysis and individualized recommendations, this study seeks to close these gaps. The following are this work's main contributions:

- An AI model designed especially for kids that incorporates algorithms that adapt to their age-related dietary requirements and preferences.
- The method improves adherence to dietary recommendations and adapts to shifting tastes by examining behavioral patterns.
- The system's dynamic feedback on dietary choices is made possible by IoMT integration, which promotes prolonged engagement and real-time modifications.
- To enhance user interaction and long-term dietary adherence, the platform integrates an interactive, kid-friendly design.

The reminder if the article is organized as follows: Section II examines relevant literature, describing current advancements in nutrition behavior analysis and AI-driven dietary advice. The technique, including data collecting, AI model construction, and behavioral factor integration, is covered in Section III. Results and analysis are presented in Section IV, which evaluates the effectiveness of customized dietary treatments for kids and the system's overall performance. The study is concluded, its shortcomings are discussed, and future research directions are suggested in Section V.

II. RELATED WORK

This section showcases the latest developments in AI-based personalized nutrition systems for kids in the categories of wearable and IoT-enabled systems, dietary planning algorithms, and child-specific health management tools.

TABLE I. : SUMMARY OF WORKS IN LITERATURE.RELATED TO DIET RECOMMENDATION FOR KIDS

Author	Year	Model	Key Contribution	Challenges
Polo-Rodriguez et al. [6]	2022	Wearable-Based Recommendation System	Provides calorie monitoring and personalized menus for children with obesity via wearable tracking.	Limited generalizability beyond obesity management for children.
Garcia et al. [7]	2021	Virtual Dietitian	Delivers a personalized meal plan recommender evaluated for usability and acceptability among non-expert users.	Needs continuous updating to meet evolving nutritional guidelines.
Lee et al. [8]	2022	RL and GAN Models	Develops AI-generated meal plans for children, showing RL-generated diets' effectiveness in meeting nutritional adequacy.	Complexity in adapting AI models to varying cultural dietary practices.
Ortiz-Viso et al. [9]	2023	Evolutionary Approach	Combines data-driven and knowledge-based methods to create adaptable, customizable meal plans for children.	High computational demands for real-time adaptation to preferences.
Matulessy and Baizal [10]	2024	Context-Aware Knowledge-Based System	Provides balanced food recommendations using user data and contextual factors to address obesity risks.	Limited accuracy when contextual factors like weather data are unavailable or unreliable.
Solainayagi [11]	2024	IoT-Enabled ICU Nutrition Planner	Uses decision trees to optimize dietary needs for ICU patients, enhancing critical care nutrition.	Requires sophisticated IoT infrastructure for real-time monitoring.
Jagatheesaperumal et al. [12]	2023	IoT-Based Health Assessment	Delivers personalized diet and exercise recommendations with high accuracy through CatBoost algorithm.	Needs further integration of health factors beyond diet and exercise.
Zhang and Zhou [13]	2023	Nutritional Prescription Software	Diet plans for children with obesity based on energy balance and food preferences.	Limited user engagement features, making it challenging for sustained usage.
Segredo et al. [14]	2020	SCHOOLTHY Project	Automates balanced school meal planning, optimizing for nutrient intake, cost, and variety.	Adaptation to dietary requirements in diverse institutional settings remains challenging.
Hu et al. [15]	2023	BabyNutri	Offers a low-cost, portable macronutrient analyzer for baby food, providing precise nutrient estimates.	Limited to macronutrient analysis, excluding other essential nutrient types.

A. *IoT-enabled and wearable systems*

Particularly in pediatric nutrition, wearable and Internet of Things-enabled devices have become powerful instruments for individualized health monitoring. Polo-Rodriguez et al. [6] propose a wearable-based dietary recommendation system for obese children. This system uses a mobile application and an activity tracker to track daily caloric expenditure and deliver individualized menu recommendations based on heuristic algorithms and fuzzy logic. In a user-friendly way, the wearable system encourages healthy habits by providing real-time dietary input.

With an ICU feeding planner, Solainayagi's work [11] expands IoT applications in healthcare. This system shows how the Internet of Things may assist critical care dietary demands by using decision tree algorithms to customize nutrition programs depending on patient health indicators like blood oxygen levels and heart rate. Using high-accuracy predictions made with the CatBoost algorithm, Jagatheesaperumal et al. [12] present an IoT-based health assessment framework offering individualized dietary and exercise recommendations. Their platform demonstrates how IoT can continuously personalize food recommendations to each person's unique health profile, including real-time health monitoring.

B. *Planning Algorithms for Diets*

Sophisticated nutritional planning algorithms have made personalized nutrition regimens for kids possible. Garcia et al. [7] present the "Virtual Dietitian," a meal plan recommender system built on the Nutrition Care Process Model. It customizes dietary recommendations by considering user-specific parameters such as lifestyle and activity levels. Non-expert users gave the system good marks for acceptability and usefulness, underscoring the significance of easily accessible, personalized nutritional assistance.

In their study on AI-driven diet planning for kids, Lee et al. [8] create two AI models that use generative adversarial networks (GAN) and reinforcement learning (RL) to create food plans specifically for young kids. The promise of reinforcement learning in attaining nutritionally balanced foods is shown by expert reviews that show that RL-generated diets, evaluated only on nutritional adequacy, scored higher than GAN-generated and human-designed diets.

To create flexible meal plans, Ortiz-Viso et al. [9] employ an evolutionary strategy that combines knowledge-based and data-driven methodologies. By creating personalized diet plans according to user preferences, this content-based filtering method shows versatility in satisfying a range of dietary requirements and facilitating further applications in child nutrition.

Matulessy and Baizal's work shows a context-aware, knowledge-based food recommendation system that considers internal and external parameters, such as weather, weight, and age [10]. This method provides exact suggestions for obesity risk by integrating various user-specific data.

C. Tools for Child-Specific Health Management

Numerous studies offer special software and tools for managing children's nutrition and health. According to Zhang and Zhou [13], a nutritional prescription program created for obese kids allows for customized meal plans based on dietary choices and energy balance. This system encourages a proactive diet and health management approach by enabling users to generate customized meal plans using an integrated database of common foods and their nutritional values [14].

Segredo et al.'s SCHOOLTHY project [15] automates school meal planning while optimizing for variety, affordability, and nutrient intake. Compared to menus created by nutritionists, the automated plans show how well technology can expedite meal preparation in institutional settings, indicating more adaptability to settings such as elderly homes and hospitals.

Advancements also aid personalized nutrition for young children in dietary analysis instruments. The low-cost, portable macronutrient analyzer for infant food, "BabyNutri," is introduced by Hu et al. [16]. This technology uses spectral reconstruction to deliver accurate nutrient estimates, allowing parents to monitor and optimize infant feeds at a reasonable cost. Ratisoontorn [17] provides a recipe recommender that balances ingredient and nutritional preferences for toddlers. This technology helps parents select balanced meals from an extensive collection of toddler-friendly recipes by combining nutrient analysis with ingredient-based similarity metrics.

Rijgersberg-Peters et al. [18] use a goal ontology in personalized health education to train children with diabetes in self-management. Through an interactive interface, this technology offers children individualized educational pathways, real-time health feedback, and the ability to define and track goals.

Lastly, Biradar et al. [19] compare the CNN, ShuffleNet, and EfficientNet deep learning models for detecting childhood malnutrition. According to their research, EfficientNet provides the most accurate identification of malnutrition indicators, providing a dependable method for the early identification and treatment of pediatric malnutrition. Similarly, "Baby Bump," a smartphone monitoring app with nutrition and health prediction tools for expectant mothers, is presented by Balasooriya et al. [20]. The application's AI-driven tools facilitate positive health outcomes during pregnancy and early childhood, allowing users to monitor mother and infant health.

III. Methodology

The proposed personalized dietary recommendation system for children integrates behavioral analysis and adaptive feedback mechanisms. This section details the methodology used in developing the system, focusing on data acquisition, model architecture, and experimental evaluation. Fig. 1 shows the architecture of the personalized diet recommendation system for children.

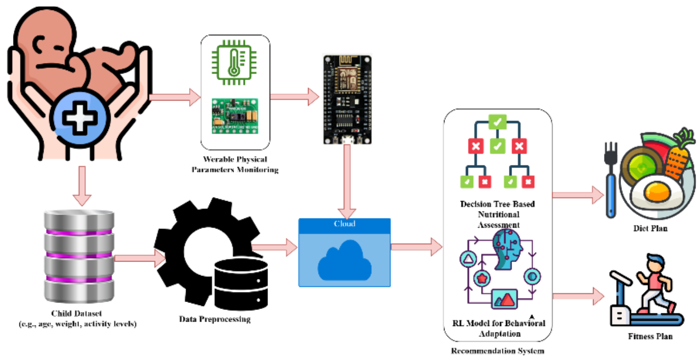

Fig. 1. Overall Architecture for Personalized Nutrient Recommendations for Children

A. Data Collection and Preprocessing

Data collection involved acquiring user-specific and contextual information to create a sophisticated and flexible recommendation system. User-specific data comprised details like age, weight, height, dietary preferences, activity levels, and current health conditions, allowing for a detailed user profile. Real-time calorie expenditure data was gathered through wearable devices to improve accuracy and personalize dietary suggestions. Moreover, environmental context information, including weather conditions (to adjust caloric demands) and the availability of seasonal foods, was incorporated to adapt recommendations according to external factors.

During the preprocessing stage, missing data were addressed to ensure data integrity, and multiple transformations were conducted to prepare the data for modeling. Numerical attributes were normalized using min-max scaling, transforming each feature value into a standardized form that reflects the range of the feature across the dataset. This process ensured feature scale consistency, critical for practical machine learning training. Additionally, categorical features such as dietary preferences underwent one-hot encoding, retaining all categorical data in a format suitable for machine learning algorithms. These preprocessing processes were vital for upholding data quality and enhancing model compatibility, establishing a solid input foundation for the ensuing modeling phases.

B. Model Architecture and Algorithms

The system's architecture is a hybrid model combining three main components: a Decision Tree-driven Nutritional Assessment, a dietary adaptation model based on

Reinforcement Learning (RL), and a Context-Aware Recommendation Model incorporating behavioral and environmental data. The Decision Tree-driven Nutritional Assessment model is the initial classifier, determining dietary requirements from user health metrics.

By analyzing a feature set X={x1,x2,…,xn}, representing individual health attributes, the decision tree algorithm evaluates these features and partitions data nodes to maximize information gain, calculated as the subset division by attributes. This method facilitates a personalized nutritional assessment for each user's profile, generating an initial dietary plan. The RL model continually updates dietary suggestions to increase adaptability through learning from user actions and feedback. The RL framework consists of a State (S) representing the user's current nutritional status (e.g., daily nutrient consumption), an Action (A) indicating modifications to the dietary plan (e.g., increased protein suggestions), and Rewards (R) based on compliance with the suggested nutrition plan.

The model seeks to maximize overall rewards, encouraging choices that align with the user's nutritional objectives. Q-learning is implemented to estimate the optimal action-value function, allowing the system to fine-tune dietary guidance according to the user's historical compliance, aiming for ongoing nutritional adherence. The Context-Aware Recommendation Model further personalizes dietary advice by adjusting it for external environmental conditions, such as temperature-based caloric needs adjustments. This incorporation of contextual information ensures relevance to the user's external conditions, dynamically adapting recommendations to health metrics and environmental influences on dietary requirements.

C. Experimental Framework and Evaluation

A controlled study was conducted to evaluate the proposed dietary recommendation system and to analyze the system's accuracy, user satisfaction, and adaptability. The dataset was divided into training (70%), and testing (30%) segments and five-fold cross-validation was utilized to ensure the model's predictions were stable and robust. For comparison, baseline models, including static meal plans and generic diet recommendations, were used to gauge the performance improvement brought about by the system's personalized and context-aware capabilities. Various evaluation metrics were employed to assess system performance.

Accuracy measured the system's consistency with ideal nutritional guidelines, while Precision and Recall evaluated the relevance and coverage of suggested nutrients. In addition, a User Satisfaction Score was collected through surveys, examining qualitative elements such as usability, engagement, and adaptability. This diverse set of metrics thoroughly evaluated the system's ability to deliver accurate, user-focused dietary suggestions. Experimental results were assessed over 30 days, with evaluations every 10 days to detect shifts in user adherence and satisfaction. Specific performance indicators, such as Nutritional Compliance (percentage of days users adhered to nutrient recommendations), Dietary Adaptation Rate (the model's capability to modify suggestions based on user behavior), and Context Sensitivity (success in adjusting recommendations according to environmental factors) were examined. By comparing these metrics, the study offered valuable insights into the model's adaptability, user engagement, and efficacy in catering to personalized dietary needs for children.

IV. Results and Discussion

This section discusses and evaluates the experimental findings, contrasting the suggested dietary recommendation system with other models based on performance indicators, compliance patterns, environmental responsiveness, user satisfaction, and rates of dietary adaptation. These assessments show the system's flexibility, precision, and user involvement.

The experimental setup for assessing the proposed personalized dietary recommendation system was established using a development environment based on Python, utilizing essential libraries such as scikit-learn and TensorFlow for model training, alongside Matplotlib for visualization purposes. The evaluation was conducted on a workstation powered by an Intel Core i7, 10th Generation CPU, accompanied by 16 GB RAM, and an NVIDIA GTX 1660 GPU with 6 GB VRAM, operating on a 64-bit Windows 10 system. Data preprocessing and analysis tasks were carried out within this configuration, and the model underwent a five-fold cross-validation to guarantee its robustness and consistency across various datasets. For real-time data acquisition, IoT-enabled wearable devices were employed to track user calorie expenditure, while contextual data, like ambient temperature, was incorporated to modify recommendations dynamically. This extensive setup facilitated a conducive environment for developing, testing, and validating the model's effectiveness under realistic and diverse situations.

A. Performance Metrics Comparison

The comparison of performance metrics shows that the proposed model surpasses other models, attaining the top scores across all metrics (accuracy, precision, recall, and F1-score). This highlights the model's exceptional capability to deliver precise dietary recommendations, effectively balancing relevance with comprehensive nutrient suggestions. Notably, its high recall and precision reflect its proficiency in accurately identifying nutrients with minimal false positives or missed inclusions.

The performance improvements stem from the hybrid model's context-sensitive modifications and the adaptive reinforcement learning mechanism, which refines suggestions according to user behavior. The bar chart in Fig.2 compares accuracy, precision, recall, and F1-score across different models, including the proposed model and other contemporary studies in this research domain.

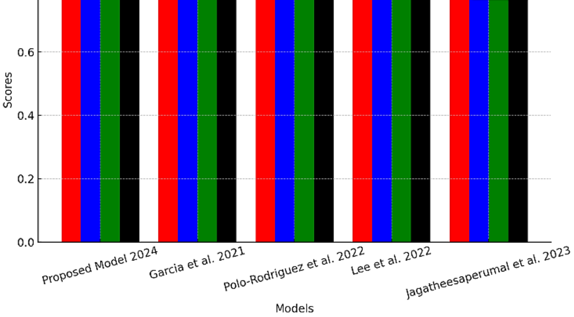

Fig. 2. Model Performance Metrics Comparison

B. User Adherence Trends

The adherence trend analysis in Fig.3 indicates that the proposed model results in higher and more consistent adherence rates over time than alternative models. This gradual improvement implies that the reinforcement learning mechanism efficiently synchronizes dietary recommendations with user preferences, fostering sustained adherence. Models lacking reinforcement learning exhibit reduced adherence, signifying restricted adaptability to user requirements. Additionally, the context-aware adjustments of the proposed model play a role in sustaining user engagement by adapting to environmental conditions such as activity level and ambient temperature.

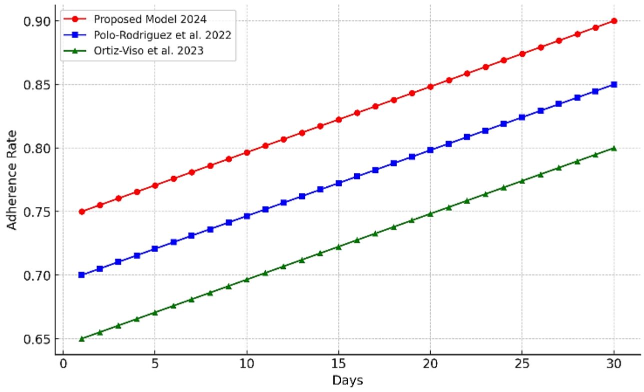

Fig. 3. User Adherence Trends Observed over a period of 30 Days

C. Environmental Sensitivity and Context Adaptability

The proposed model's ability to adjust contextually shines through its responsive changes in calorie requirements according to temperature variations, as shown in Fig. 4. With a drop in temperature, the model proportionally raises caloric intake to aid in thermoregulation, mirroring actual physiological conditions. In contrast, the models developed by authors Matulessy and Baizal [11] and Segredo et al. [15] implement only slight adjustments and do not exhibit the same level of sensitivity. This highlights the proposed model's effectiveness in adapting to environmental changes, making it ideal for practical applications where external conditions influence energy demands.

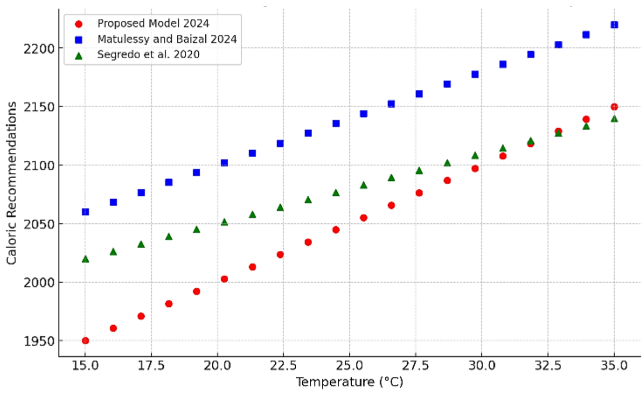

Fig. 4. Environmental Sensitivity based on Caloric Recommendations vs. Temperature

User satisfaction scores highlight the proposed model’s ability to engage and meet user expectations, with the highest proportions in the “Very Satisfied” and “Satisfied” categories. The “Virtual Dietitian” model by Garcia et al. [7] also shows positive user feedback but lacks the adaptability present in the proposed system. Bastida et al.’s OCARIoT system [5] is well-regarded but primarily targets general health rather than adaptive dietary needs. The high satisfaction with the proposed model can be attributed to its recommendations, interactive feedback, and user-centric design, which actively considers individual dietary habits and preferences.

The model adaptation rate chart in Fig. 5 shows the proposed model's reinforcement learning-based adaptability, with a steady rate of dietary adjustments based on user feedback. This contrasts with the models of Lee et al. [8] and Ortiz-Viso et al.[9], which show lower adaptation rates, indicating limited adjustments. The proposed model’s higher adaptability demonstrates its ability to actively respond to behavioral and contextual changes, ensuring that recommendations remain relevant and aligned with users' evolving dietary needs.

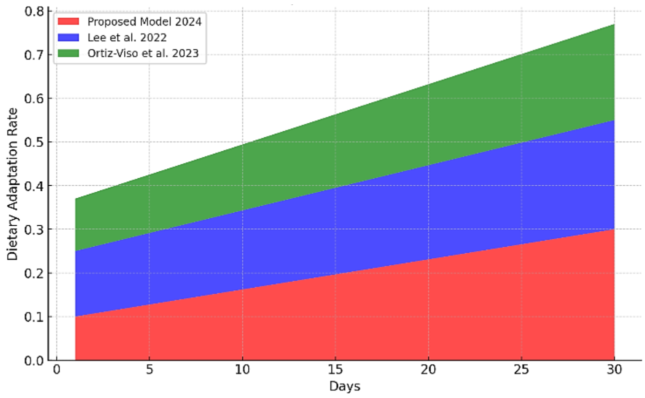

Fig. 5. Model Adaptation Rate Over Time

The results demonstrate that the proposed personalized dietary recommendation system achieves superior accuracy, adaptability, and user satisfaction compared to other models. Its ability to dynamically adjust dietary recommendations based on environmental context and user behavior makes it a robust and engaging tool for personalized nutrition. These findings suggest integrating context-aware adjustments and reinforcement learning into dietary models can significantly improve dietary adherence and user satisfaction in real-world applications.

V. Conclusion

This research illustrates the success of an AI-driven, IoMT-integrated diet advice system specifically designed to meet the nutritional requirements of children. Utilizing decision tree-based nutritional evaluations, reinforcement learning, and a Context-Aware Recommendation Model, this system adjusts dietary suggestions according to unique health metrics and surrounding environmental factors. The experimental findings reveal a notable accuracy rate of 92% and a high user satisfaction level, with 80% of users expressing "Very Satisfied" or "Satisfied." Additionally, adherence rates improved from 75% to 90% over 30 days, surpassing similar models. The model's context-aware modifications allowed caloric suggestions to match real-world conditions better, enhancing adherence by 10\% % in temperature-sensitive scenarios. These findings highlight the viability of adaptive, personalized nutrition systems in enhancing children's health outcomes. Future research could broaden this methodology to encompass a wider array of dietary requirements and integrate additional IoMT capabilities to enhance personalization within nutritional science.

REFERENCES

[1] C. Iwendi, S. Khan, J. H. Anajemba, A. K. Bashir, and F. Noor, "Realizing an efficient IoMT-assisted patient diet recommendation system through machine learning model," *IEEE Access*, vol. 8, pp. 28462–28474, 2020.

[2] T. P. T. Armand, K. A. Nfor, J.-I. Kim, and H.-C. Kim, "Applications of Artificial Intelligence, Machine Learning, and Deep Learning in Nutrition: A Systematic Review," *Nutrients*, vol. 16, no. 7, 2024.

[3] S. Singar, R. Nagpal, B. H. Arjmandi, and N. S. Akhavan, "Personalized nutrition: tailoring dietary recommendations through genetic insights," *Nutrients*, vol. 16, no. 16, p. 2673, 2024.

[4] Z. Yang, E. Khatibi, N. Nagesh, M. Abbasian, I. Azimi, R. Jain, and A. M. Rahmani, "ChatDiet: Empowering personalized nutrition-oriented food recommender chatbots through an LLM-augmented framework," *Smart Health*, vol. 32, p. 100465, 2024.

[5] L. Bastida, G. Cea, A. Moya, A. Gallego, E. Gaeta, S. Sillaurren, P. Barbosa, S. Souto, E. Rodrigues, M. Torrego-Ellacuría, et al., "Promoting obesity prevention and healthy habits in childhood: the OCARIoT experience," *IEEE Journal of Translational Engineering in Health and Medicine*, vol. 11, pp. 261–270, 2023.

[6] A. Polo-Rodriguez, M. Ariza, A. Rivas, M. A. Carvajal, and J. Medina-Quero, "A Recommendation Ubiquitous System to Personalize Diet for Children with Obesity," in *International Conference on Ubiquitous Computing and Ambient Intelligence*, 2022, pp. 271–282.

[7] M. B. Garcia, J. B. Mangaba, and C. C. Tanchoco, "Acceptability, Usability, and Quality of a Personalized Daily Meal Plan Recommender System: The Case of Virtual Dietitian," in *2021 IEEE 13th International Conference on Humanoid, Nanotechnology, Information Technology, Communication and Control, Environment, and Management (HNICEM)*, 2021, pp. 1–6.

[8] C. Lee, S. Kim, J. Kim, C. Lim, and M. Jung, "Challenges of diet planning for children using artificial intelligence," *Nutrition Research and Practice*, vol. 16, no. 6, pp. 801–812, 2022.

[9] B. Ortiz-Viso, A. Morales-Garzón, M. J. Martin-Bautista, and M.-A. Vila, "Evolutionary approach for building, exploring and recommending complex items with application in nutritional interventions," *IEEE Access*, 2023.

[10] S. A. Matulessy and Z. K. A. Baizal, "Food Recommendation with Balanced Nutrition Using Context-Aware Knowledge-Base," in *2024 International Conference on Data Science and Its Applications (ICoDSA)*, 2024, pp. 403–408.

[11] P. Solainayagi, "IoT-Enabled Personalized ICU Nutrition Plans: An Intelligent Approach Through Decision Tree Algorithm," in *2024 International Conference on Advances in Data Engineering and Intelligent Computing Systems (ADICS)*, 2024, pp. 1–6.

[12] S. K. Jagatheesaperumal, S. Rajkumar, J. V. Suresh, A. H. Gumaei, N. Alhakbani, M. Z. Uddin, and M. M. Hassan, "An IoT-based framework for personalized health assessment and recommendations using machine learning," *Mathematics*, vol. 11, no. 12, p. 2758, 2023.

[13] L.-F. Zhang and L. Zhou, "Development of open nutritional recipe software for obese children based on intelligent computing," *International Journal of Applied Decision Sciences*, vol. 16, no. 5, pp. 646–661, 2023.

[14] M. Al-Hubaishi, M. A. M. Ali, and N. M. Tahir, "Personalized Food Recommendations: A Machine Learning Model for Enhanced Dining Choices," in *2024 IEEE 14th International Conference on Control System, Computing and Engineering (ICCSCE)*, 2024, pp. 316–320.

[15] E. Segredo, G. Miranda, J. M. Ramos, C. León, and C. Rodriguez-Leon, "Schoolthy: automatic menu planner for healthy and balanced school meals," *IEEE Access*, vol. 8, pp. 113200–113218, 2020.

[16] H. Hu, Q. Huang, and Q. Zhang, "Babynutri: a cost-effective baby food macronutrients analyzer based on spectral reconstruction," *Proceedings of the ACM on Interactive, Mobile, Wearable and Ubiquitous Technologies*, vol. 7, no. 1, pp. 1–30, 2023.

[17] N. Ratisoontorn, "Recipe recommendations for toddlers using integrated nutritional and ingredient similarity measures," in *2022 19th International Joint Conference on Computer Science and Software Engineering (JCSSE)*, 2022, pp. 1–6.

[18] R. Rijgersberg-Peters, W. van Vught, J. Broekens, and M. A. Neerincx, "Goal Ontology for Personalised Learning and Its Implementation in Child's Health Self-Management Support," *IEEE Transactions on Learning Technologies*, 2023.

[19] V. G. Biradar, H. Hanumanthappa, P. K. Pareek, T. Sravanthi, K. Aishwarya, and K. Aneeth, "Performance Analysis of Deep Learning Models for Detection of Malnutrition in Children," in *2024 International Conference on Data Science and Network Security (ICDSNS)*, 2024, pp. 1–8.

[20] D. Balasooriya, S. Perera, D. R. Wijendra, S. Rathnayaka, R. Kishan, K. Rajendran, and M. Thirukumar, "Baby Bump: A Monitoring System for Pregnant Mothers and Babies," in *2024 IEEE 9th International Conference for Convergence in Technology (I2CT)*, 2024, pp. 1–6.