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ORIGINAL

# Personalized Medical Diet Recommendations for Disease Management and Improved Patient Outcomes

## Recomendaciones dietéticas médicas personalizadas para el tratamiento de enfermedades y la mejora de los resultados de los pacientes

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## ABSTRACT

Personalized health diets play a crucial role in infection management by tailoring diet recommendation systems to routine data, genetic factors, and specific medical conditions. Research introduces the Intelligent Nutcracker Optimized Effective Decision Tree (INO-EDT) model, designed to provide individualized nutritional guidance for managing chronic illnesses, particularly diabetes and heart disease. Medical files, questionnaires, wearable devices, and food journals serve as sources of patient data standardization and cleaning to ensure accuracy and stability. Machine Learning (ML) techniques analyze individual patient profiles to develop personalized nutrition plans that are effective, sustainable, and adaptable. The INO-EDT model incorporates a nutcracker-inspired optimization technique to enhance decision tree accuracy, fine-tuning diet recommendations based on patient-specific factors. This optimization ensures proper diet interventions with enhanced efficacy of dietary interventions in disease organization. The outcome confirms that the INO-EDT model was more accurate (98,40 %), demonstrating its ability to generate proper, data-backed dietary advice. By optimizing personalized nutritional interventions, the INO-EDT model enables healthcare providers to offer more effective, patient-centered solutions, reducing complications connected with chronic diseases. This approach enhances patient outcomes by integrating intellectual algorithms that consider multiple health parameters to create a customized diet strategy. The results highlight the potential of AI-driven dietary recommendation systems in enhancing disease management, improving adherence to medical diet systems, and elevating overall quality of life. Future research will aim to expand the model's capabilities by integrating additional health markers for broader clinical applications.

**Keywords:** Medical Diet Recommendations; Disease Management; Intelligent Nutcracker Optimized Effective Decision Tree (INO-EDT); Patient Outcomes.

## RESUMEN

Las dietas sanitarias personalizadas desempeñan un papel crucial en la gestión de las infecciones al adaptar los sistemas de recomendación de dietas a los datos rutinarios, los factores genéticos y las afecciones médicas específicas. La investigación presenta el modelo INO-EDT (Intelligent Nutcracker Optimized Effective Decision Tree), diseñado para proporcionar orientación nutricional individualizada para el tratamiento de enfermedades crónicas, en particular la diabetes y las cardiopatías. Archivos médicos, cuestionarios, dispositivos wearables y diarios de alimentación sirven como fuentes de estandarización y limpieza de datos de pacientes para garantizar la precisión y la estabilidad. Las técnicas de aprendizaje automático (ML) analizan los perfiles individuales de los pacientes para desarrollar planes de nutrición personalizados que sean eficaces, sostenibles y adaptables. El modelo INO-EDT incorpora una técnica de optimización inspirada en el cascanueces para mejorar la precisión del árbol de decisión, ajustando las recomendaciones dietéticas en función de factores específicos del paciente. Esta optimización garantiza intervenciones dietéticas adecuadas con una mayor eficacia de las intervenciones dietéticas en la organización de la enfermedad. El resultado confirma que el modelo INO-EDT fue más preciso (98,40 %), lo que demuestra su capacidad para generar consejos dietéticos adecuados y respaldados por datos. Al optimizar las intervenciones nutricionales personalizadas, el modelo INO-EDT permite a los profesionales sanitarios ofrecer soluciones más eficaces y centradas en el paciente, reduciendo las complicaciones relacionadas con las enfermedades crónicas. Este enfoque mejora los resultados de los pacientes al integrar algoritmos intelectuales que tienen en cuenta múltiples parámetros de salud para crear una estrategia dietética personalizada. Los resultados ponen de relieve el potencial de los sistemas de recomendación dietética basados en IA para mejorar la gestión de las enfermedades, mejorar el cumplimiento de los sistemas dietéticos médicos y elevar la calidad de vida en general. En futuras investigaciones se tratará de ampliar las capacidades del modelo integrando marcadores de salud adicionales para aplicaciones clínicas más amplias.

**Palabras clave:** Recomendaciones de Dietas Médicas; Gestión de Enfermedades; Árbol de Decisión Eficaz Optimizado por Intelligent Nutcracker (INO-EDT); Resultados de Pacientes.

## INTRODUCTION

Infectious diseases continue to represent the biggest health burden in poor nations, notwithstanding the rise in non-communicable diseases like diabetes and heart attack. In the industrialized world, there are extremely reliable diagnostic tests for the majority of infectious diseases that are significant for public health, but people in developing nations cannot afford or obtain these tests.[1] The majority of health systems at present combine phone and video visits; interestingly, online interaction is linked to improve patient comprehension and experience than phone conversations. This is especially crucial to take into account in primary care, where successfully managing chronic conditions depends on long-term relationships and transparent communication, as well as among populations that are already less likely to use digital health services due to limited digital access or low digital literacy (the capacity to use and comprehend data obtained from digital gadgets).[2] One of the major causes of loss on the earth nowadays, cancer is a difficult illness that arises from some connections between genes and the environment. Cancer recovery and recuperation can be impacted by metabolic and nutritional changes, such as cachexia, sarcopenia, and malnutrition.[3] The effects of concurrently having multiple diseases on one's health and diet are different from the comparable connections between aging and disease. In contrast to the geriatric environment, when multimorbidity is always accompanied by functional limits and other age-related degenerative manifestations, polymorbidity is frequently, but not always, encountered in older adults. Polymorbidity is one of the biggest issues facing many social and medical services globally as life expectancy rises and people develop a range of chronic conditions.[4] The primary goal of nephrologists and nephrology-dedicated nutritionists is to monitor clinical reactions and medication compliance, whereas clinical profiling 20 is a crucial tool for proper food management in this patient type.[5] Consuming fruits, whole grains, vegetables, lean protein sources, legumes, dairy, nuts, and healthy fats is emphasized in dietary guidelines that promote excellent health while consuming fewer processed foods and energy-dense carbohydrates.[6] Even in public with a higher genetic risk for obesity, healthy food treatments are essential for encouraging weight defeat and preventing metabolic syndrome.[7]

High-performance computing (HPC) can be used to accurately forecast hazards using multidimensional clinical and biological datasets. Clinicians can at present carefully customize early therapies for each patient due to AI-powered precision medicine.[8] Based on their knowledge of treating patients with Familial Chylomicronemia Syndrome (FCS) and a review of recent research on the subject, registered diet nutritionists (RDNs) came together to create this statement. A patient's perspective on life with FCS was shared by one individual.[9] Children on ketogenic dietary treatments (KDT) should be managed according to a published expert consensus guideline that addresses client choice, pre-KDT therapy and assessment, diet decision and qualities, execution, supplementation, notes, side effects, and KDT discontinuation. Standardizing KDT for multicenter medical trials, defining a state-of-the-art protocol, and pinpointing areas of debate and ambiguity for further research have all benefited from it.[10] Adopting a strong lifestyle can lower the risk of myocardial infarction by over 80 %, with diet being a major factor. A vegetarian diet lowers the threat of Coronary Heart Disease (CHD) and Cardiovascular Disease (CVD) death by 40 %.[11] Programs and research centered on food and lifestyle choices, as well as chronic illnesses like type 2 diabetes mellitus (T2DM), are becoming more and more necessary due to rising disease burden and prevalence. In a randomized forced trial, the impact of a 6-month web-based diet involvement on Fasting Blood Glucose (FBG), glycosylated hemoglobin (HbA1c), Dietary Knowledge, Attitude and Behaviour (DKAB), Dietary Stages of Change (DSOC), and patients with uncontrolled HbA1c (> 7,0 %) were assessed.[12] Patients and their many medical professionals must work closely together to manage it. To be able to actively participate in the management of their illness, patients must get a thorough grasp of Non-Alcoholic Fatty Liver Disease (NAFLD).[13] Epidemiological research has usually emphasized particular dietary individuals, which can direct to incorrect outcomes. The findings from research assessing the relationship among inundated heavy and CVD without attracting the substitute diets into account is one model of this, which has given rise to a large contract of debate.[14] Weight loss can result from a variety of food-based and macronutrient-based eating patterns. Reducing energy density is a crucial weight-management tactic that works with all food patterns.

According to clinical analyses, lowering energy density helps people lose weight and keep it off. A range of useful techniques and resources can support effective weight administration by lowering power density, controlling portion sizes, and enhancing the quality of diets. Patients can customize their eating patterns to lower energy consumption for lengthy lasting weight loss because of the flexibility of power mass.[15] The organization can make tailored suggestions (e.g., food intake and physical exercise) based on the unique socioeconomic, educational, and geographic rank, especially for AI patients, by combining the ontological profile of American Indian (AI) users with general medical diabetes recommendations and guidelines.[16] Diet recommendation for disease management involves tailored nutritional strategies designed to prevent, manage, or improve specific health conditions. The INO-EDT model introduces a novel optimization approach, enhancing decision tree accuracy for precise dietary planning.

## METHOD

The Nutcracker Optimization algorithm optimizes attribute selection and split points for increased accuracy. The INO-EDT model is implemented in Python and creates personalized dietary recommendations for managing chronic diseases like diabetes and heart disease. Patient data is gathered from wearable devices, dietary logs, medical records, and lifestyle surveys. Figure 1 displays the methodology flow.

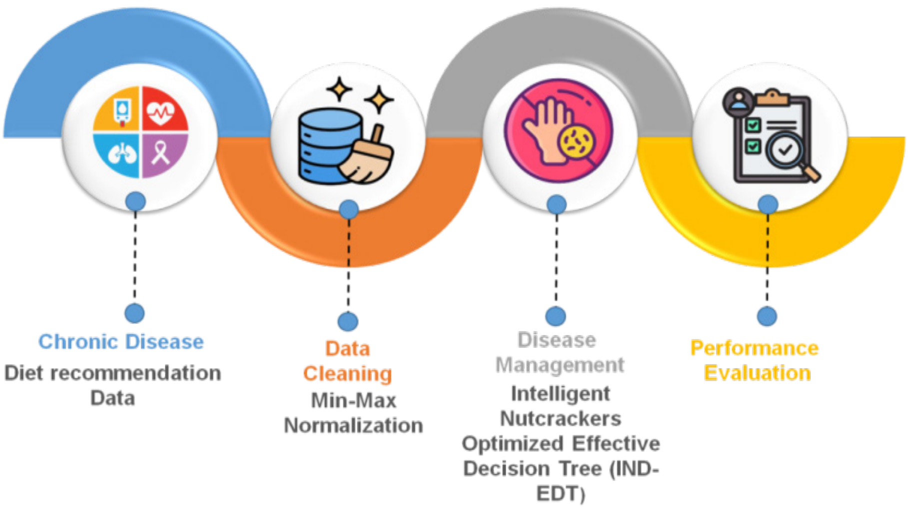


**Figure 1.** Methodology flow

### Data collection

The personalized medical diet recommendation dataset is designed to facilitate the development of data-driven, intelligent dietary interventions aimed at improving patient outcomes and enhancing disease management. It also accounts for lifestyle factors such as sleep patterns, dietary intake, and physical movement stage. The systematic organization of the dataset aids in sophisticated ML models to optimize diets for individual chronic diseases, such as diabetes, cardiovascular disease, hypertension, and metabolic syndrome. Considering diet choice, drug interaction, and personal health measures, it enables customized nutrition counselling and encourages precision medicine methods in dietary control. The dataset of diet recommendations was obtained from the Kaggle platform https://www.kaggle.com/datasets/ziya07/personalized-medical-diet-recommendations-dataset/data.

### Data preprocessing using Min-Max Normalization

Min-max normalization is a numerical data scaling processing technique applied in scaling data in a given interval, usually [0, 1] or [-1,1]. Preprocessing the feature scaling in such a manner maximizes the performance of ML algorithms, particularly for chronic disease diagnosis and enabling customized healthcare applications, as shown by equation (1).

$$W_{new} = \frac{W - \min(W)}{\max(W) - \min(W)} \quad (1)$$

$W_{new}$= the adjusted value derived from the normalized outcomes.
W = elderly amount.
max(W)= the dataset's maximum value.
min(W)= the dataset's minimum value.

**Personalized Medical Diet Recommendations using Intelligent Nutcracker Optimized Effective Decision Tree (INO-EDT)**

Intelligent Nutcracker Optimized Effective Decision Tree (INO-EDT) model utilizes systematic reasoning to generate personalized diet recommendations and enhances control of diseases such as diabetes and cardiovascular disease. After the data preparation, a decision tree-based model is developed with health factors such as blood glucose, cholesterol, and BMI being decision nodes. Tree branches create dietary recommendations and leaves provide individual diet suggestions corresponding to particular health states. For precision improvement, the Nutcracker Optimization algorithm optimizes split points of the decision tree for improving diet planning precision by the model. The optimization does not sacrifice clarity and efficiency and dynamically modifies diet thresholds according to individual patient parameters.

**Effective Decision Tree (EDT)**

Decision tree algorithms play a critical task in model management strategies and diagnosing illness. The ID3 measurement, one of the more widely used decision tree approaches, is based on data theory and choice features using information gain. However, its tendency to favour attributes with more values can introduce biases. The C4,5 measurement improves ID3 by incorporating the information gain ratio, which mitigates these issues and develops decision-making in medical diagnosis.

$$\text{Entropy(T)} = \text{Entropy}(o_1, o_2, \ldots, o_n) = -\sum_{j=1}^{n} o_j log_2 o_j \quad (2)$$

Given a clinical parameter l with g possible amount $o_1$, $o_2$,..., $o_n$, partitioning patient information file T based on L outcome in g diagnostic groups. Each o group contains patients' results, forming a subset denoted as $t_j$. The data entropy of $t_j$, is then computed to evaluate uncertainty in patient classification. Since the number of patients varies across measurement groups, the facts gained from using B for classification are determined by weighting the entropies of these subsets accordingly. This approach aids in optimizing diagnostic decision-making and developing patient results.

$$\text{Entropy}_B(T) = \sum_{j=1}^{l} \frac{|t_j|}{|t|} \text{Entropy}(T_j) \quad (3)$$

C4,5 develops investigative decision-making by utilizing the facts gain ratio rather than depending only on data gain, as the details increase criterion prioritizes attributes with a better number of possible values. By lowering biases and raising the precision of illness analysis and treatment planning, this modification aids in the choice of the most pertinent clinical criterion for the patient category. The information gain ratio improves the selection of clinical parameters by information gain using the split information value. This adjustment establishes a more equitable criterion for determining the most relevant attributes in disease diagnosis and treatment optimization. The definitions are provided in equation (4).

$$Gain(T, b) = \text{Entropy(T)} - \sum_{u=1}^{u} \frac{|T^u|}{|T|} \text{Entropy}(T^u) \quad (4)$$

This amount quantifies the data made when the patient information T is divided into b subsets, according to the results of the clinical parameter pp exam. The data gain ratio is then defined as follows in equation (5).

$$\text{SplitInf}_{P_B}(T, b) = -\sum_{i=1}^{u} \frac{|T_i|}{|T|} \times log_2(\frac{|T_i|}{|T|}) \quad (5)$$

The clinical assessment with the largest gain ratio serves as the key criterion for patient categories and diagnosis.

$$\text{GainRatio(T, b)} = \frac{\text{Gain(T,b)}}{\text{SplitInfo(T,b)}} \quad (6)$$

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**Intelligent Nutcracker Optimization (INO)**

The Intelligent Nutcracker Optimization (INO), a novel method approach, has been put forth to develop disease finding and treatment preparation. NOA simulates the data-driven choice, archiving, and retrieval of the most excellent analytic and action approaches. This plan can be divided into two primary stages: diagnostic feature selection and storing, which are detailed as follows.

*Diagnostic feature stage: Exploration Phase 1*

During this stage, the optimization agents start by initializing their locations in the solution space at random. Every agent assesses the initial set of parameters for diagnosis or treatment. It is saved for later examination and improvement if a very pertinent clinical characteristic or successful treatment plan is found. The agent searches several areas of the medical dataset for potential solutions if it is unable to identify an ideal parameter. The position update approach listed below can be used to quantitatively depict this behavior:

$$\vec{W}_j^{s+1} = \begin{cases} W_{j,i}^{s} \;\; if\ \tau_1 < \tau_2 \\ \begin{cases} W_n^s + \gamma^{\cdot}\left(W_{B,i}^s - W_{A,i}^s\right) + \mu(q^2.V_i - K_i)\ if s \le S_{max}/2{,}0 \quad Otherwise \\ W_{D,i}^s + \mu^{\cdot}\left(W_{B,i}^s - W_{A,i}^s\right) + \mu(q_1 < \delta.(q^2.V_i - K_i), Otherwise \end{cases} \end{cases} \tag{7}$$

In $W^{\rightarrow(s+1)}_j$ a healthcare optimization process, the updated treatment strategy for the ith patient at iteration t+1; $W_j^s$ is determined based on previous treatment outcomes and adaptive optimization mechanisms. The jth parameter of the ith treatment plan at iteration S; $K_i$ and $V_i$ is represented mathematically. The up and down bounds of the jth parameter in the method issues are denoted as $K_i$ and $V_i$, ensuring clinically feasible solutions. A numerical factor γ gamma, generated randomly through Lévy flight, introduces adaptive adjustments for personalized treatment optimization. The best-known treatment outcome's jth parameter is used to guide convergence toward improved patient responses. Three treatment plans, indexed as A, C, and B, are chosen randomly from the population to enhance the search for optimal interventions. Random real numbers $\tau_1$, $\tau_2$, $q_1$ and $q_2$ are drawn from the range [0,1]; $W_n$ to introduce variability in treatment strategies. The mean of all treatment plans in the recent dataset for the jth parameter at iteration is calculated to balance the exploration of new approaches and refinement of existing protocols. The parameter S; μ is estimated using the following equation (8).

$$\mu = \begin{cases} \tau_3, if q_1 < q_2 \\ \tau_4, f q_2 < q_3 \\ \tau_5, f q_1 < q_3 \end{cases} \tag{8}$$

In optimizing treatment strategies, the parameters $\tau_3$, $\tau_4$, and $\tau_5$ are real numbers randomly generated within the range [0,1] influencing individualized patient care adjustments. The value $\tau_4$ follows a normal distribution, allowing for natural variations in treatment responses, while $\tau_5$ is derived from a Lévy flight distribution to enhance adaptive optimization in personalized medicine.

*Storage technique: Exploitation Phase 2*

Decision-making in the first level of therapy optimization is based on before-together patient health information that corresponds to earlier evaluations. Important clinical indicators are examined and saved for later improvement during this stage. This phase makes it possible to recognize the best therapeutic techniques and conduct a methodical assessment of the efficacy of the cure. This process can be expressed mathematically as follows in equation (9).

$$\vec{W}_j^{s+1(new)} = \begin{cases} \vec{W}_j^s + \mu.\left(\vec{W}_{best}^s - \vec{W}_j^s\right).|\lambda| + q_1.\left(\vec{W}_B^s - \vec{W}_A^s\right) if\ \tau_1 < \tau_2 \\ \vec{W}_{best}^s + \mu.\left(\vec{W}_B^s - \vec{W}_A^s\right)\ if\ \tau_1 < \tau_3 \\ \vec{W}_{best}^s.k \quad Otherwise \end{cases} \tag{9}$$

In the optimization of treatment strategies, **λ** represents a random factor influenced by the Lévy flight distribution, introducing adaptive variability in therapeutic adjustments. The parameter / is a linearly decreasing factor ranging from 1 to 0, ensuring a balanced transition between broader exploration of potential treatments and focused refinement of effective interventions. The interaction between the evaluation section and treatment refinement is governed by the below equation, ensuring a balance between exploration and exploitation within the method program (equation 10).

$$\vec{W}_j^{s+1} = \begin{cases} Eq.(7), if\ \varphi\ < O_{b_j} \\ Eq.(8), Otherwise \end{cases} \qquad (10)$$

In treatment strategies, φ represents a randomly generated value within the interval [0, 1], introducing variability in adaptive treatment adjustments. The probability value represented, by the mathematical equation, decreases linearly from 1 to 0, and $Ob_j$ ensures a gradual transition from broad treatment exploration to focused refinement for improved patient outcomes. Finally, to maintain a balance between adaptive exploration of different treatment techniques and targeted intervention (exploitation) the adjustment and re-evaluation stages of the therapy process are randomly switched based on the following equation (11).

$$\vec{W}_j^{s+1} = \begin{cases} Eq.(19), if\ \varphi < O_{b_2} \\ Eq.(20), Otherwise \end{cases} \qquad (11)$$

Where, $Ob_2$ the mathematical equation represents a predefined value within the range [0, 1] to determine the probability of selecting a targeted treatment adjustment within the optimization process. However, in the adaptive treatment model, the current strategy remains unchanged if its effectiveness is superior to the newly proposed approach. This concept can be formally expressed by the following equation (12).

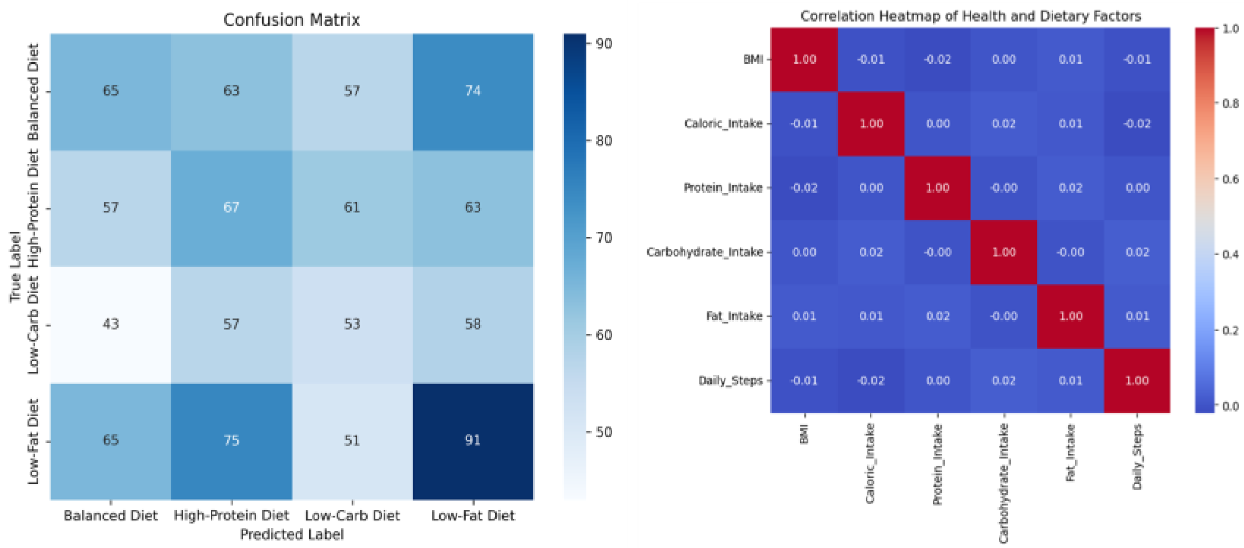
$$\vec{W}_j^{s+1} = \begin{cases} \vec{W}_j^{s+1}, if\ e\left(\vec{W}_j^{s+1}\right) < e(\vec{W}_j^{s}) \\ \quad \vec{W}_j^{s}, Otherwise \end{cases} \qquad (12)$$

## RESULTS

System requirements include a CPU of 2,40 GHz, and 8GB RAM, and the experiment is conducted in Python for implementing the INO-EDT model. This setup facilitates the performance analysis of the proposed method, enabling comparison with existing methods and providing valuable insights into how the INOP-EDT model optimizes personalized dietary planning to enhance patient health outcomes based on individual medical profiles.

### Confusion Matrix and Correlation Heat Map

The confusion matrix evaluates the accuracy of the INO-EDT model in predicting personalized diet plans. The highest accuracy is observed for Low-Fat Diet (91 correct predictions), which Low-Carb Diet has the most misclassifications. The results suggest that the model is more reliable for certain dietary recommendations, highlighting areas for improvement in diet classification (figure 2a). The correlation matrix shows relationships between BMI, cholesterol levels, caloric intake, sleep patterns, and step count. Strong correlations indicate that higher BMI is associated with increased cholesterol levels and reduced physical activity, reinforcing the importance of personalized dietary recommendations using INO-EDT to mitigate health risks (figure 2b).




(a) (b)

**Figure 2.** Heat map: (a) Confusion and (b) Correlation Matrix

*BMI vs. Disease Prevalence and Cholesterol by Disease Type*

Figure 3a highlights the direct association between BMI and disease prevalence. Higher BMI categories correlate with an increased incidence of diabetes and hypertension, emphasizing the need for weight-based dietary adjustments through INO-EDT to prevent and manage metabolic disorders. The boxplot compares cholesterol levels across different diseases, revealing that patients with cardiovascular diseases have the highest cholesterol levels. The INO-EDT model optimizes diet plans by suggesting low-fat, heart-healthy diets to manage cholesterol and reduce disease progression (figure 3b).

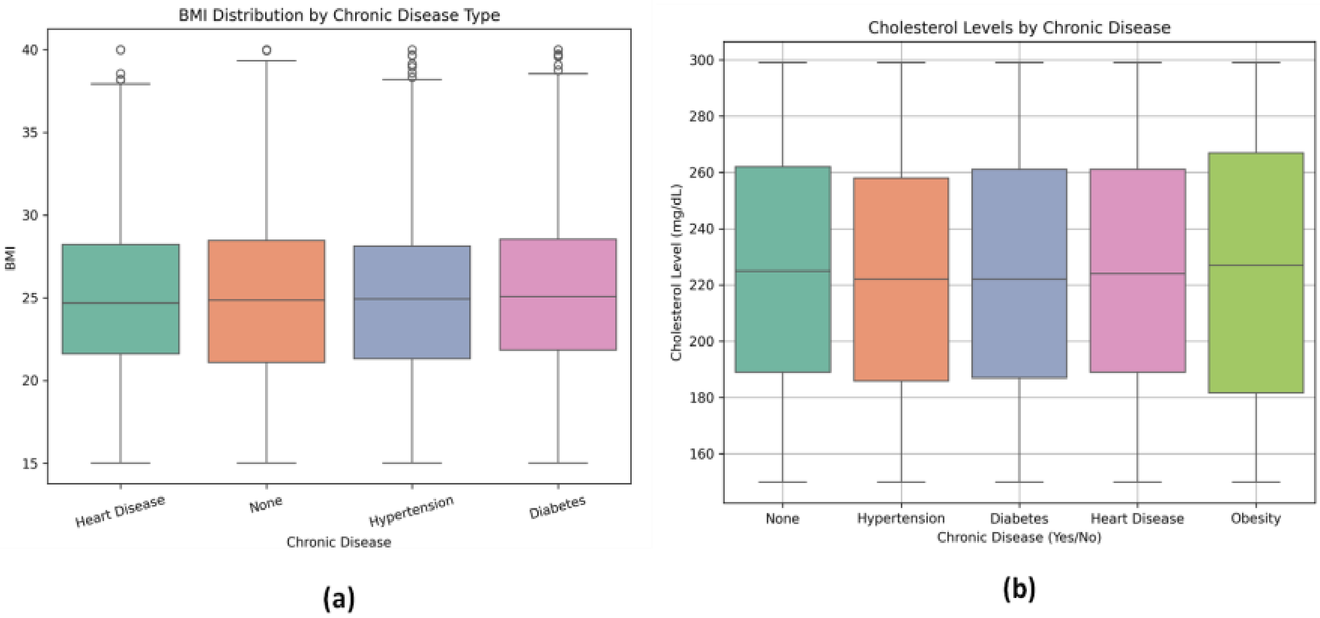



**Figure 3.** Disease type: (a) BMI vs. Disease Prevalence and (b) Cholesterol Levels

*Diet Plan Distribution*

Figure 4 illustrates the distribution of recommended diet plans by INO-EDT. The most prescribed plans are Low-Fat, Mediterranean diet (25,8 %) and Low-Sodium, DASH diet (25,2 %), indicating a significant focus on healthy diets. The Balanced Diet (25,1 %) and Low-Carb, Higher-Fiber Diet (23,9 %) cater to metabolic control and weight management.

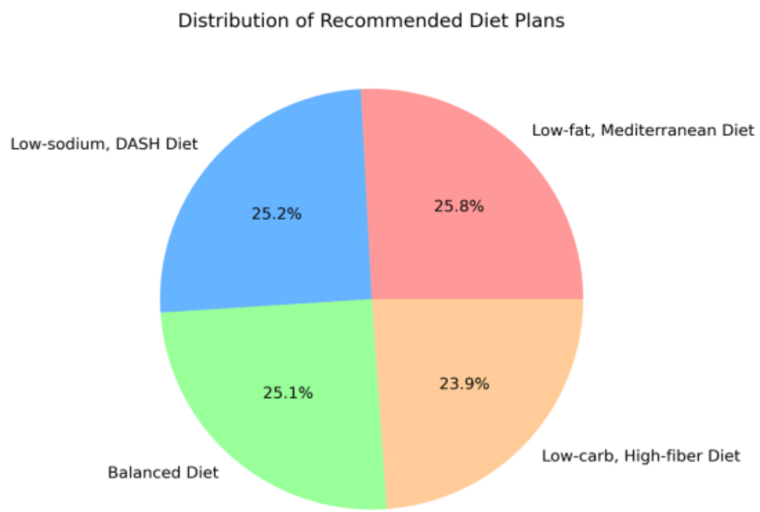



**Figure 4.** Diet Plan Distribution

*Caloric Intake Comparison and Caloric Intake Trends*

Figure 5a demonstrates caloric intake variations among different patient groups. Patients with diabetes and obesity tend to exceed recommended intake levels, while those with cardiovascular conditions follow stricter caloric restrictions. The INO-EDT model personalizes caloric adjustments based on health status. The trend analysis (figure 5b) reveals fluctuations in daily caloric consumption, highlighting dietary adherence inconsistencies. Patients with higher caloric intake deviations show poorer disease control, emphasizing the need for INO-EDT-driven mean planning to maintain dietary consistency for optimal health outcomes.

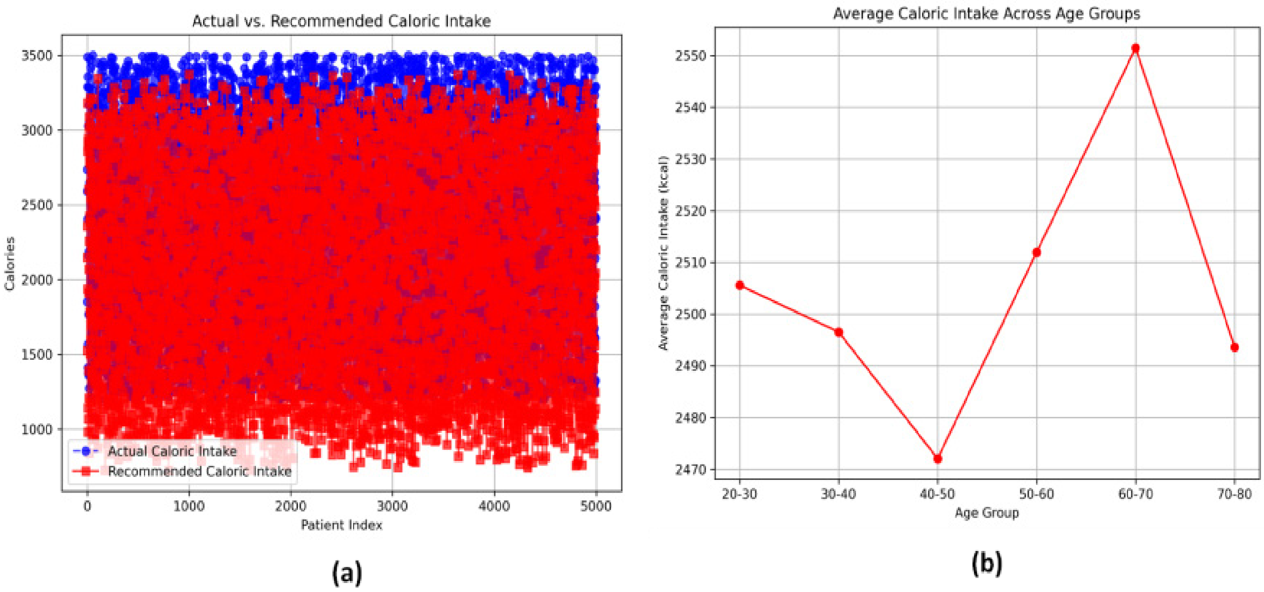



**Figure 5.** Patient groups:(a) Caloric Intake variations and (b) Caloric Intake Trends

*Stacked Diet Intake*

Figure 6 categorizes nutrient intake proportions (carbohydrates, proteins, fats) across different patient groups. Cardiac patients receive lower fat intake; diabetic patients follow low-carb, higher-fiber diets. The INO-EDT model ensures nutrient balance tailored to disease management.

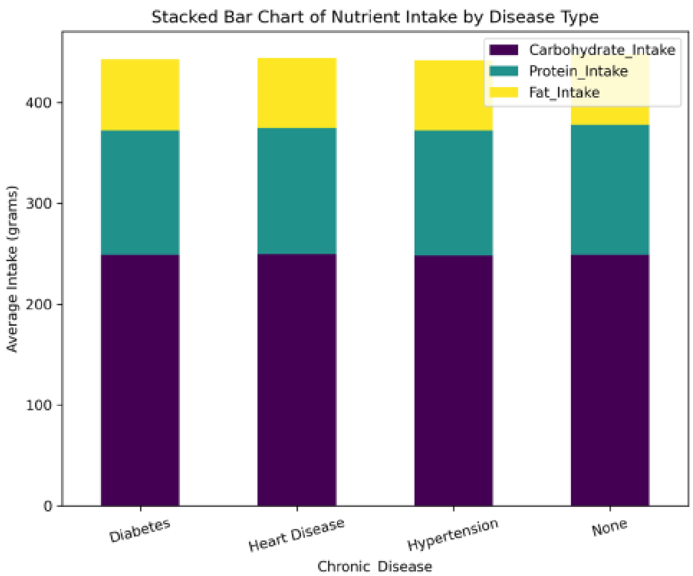



**Figure 6.** Stacked Nutrient Intake by Diet Type

## Comparison Phase

**Table 1.** Numerical outcomes of Accuracy

| Method | Accuracy (%) |
|---|---|
| LSTM[17] | 97,74 |
| RNN[17] | 95,24 |
| GRU[17] | 96,10 |
| INO-EDT (Proposed) | 98,40 |

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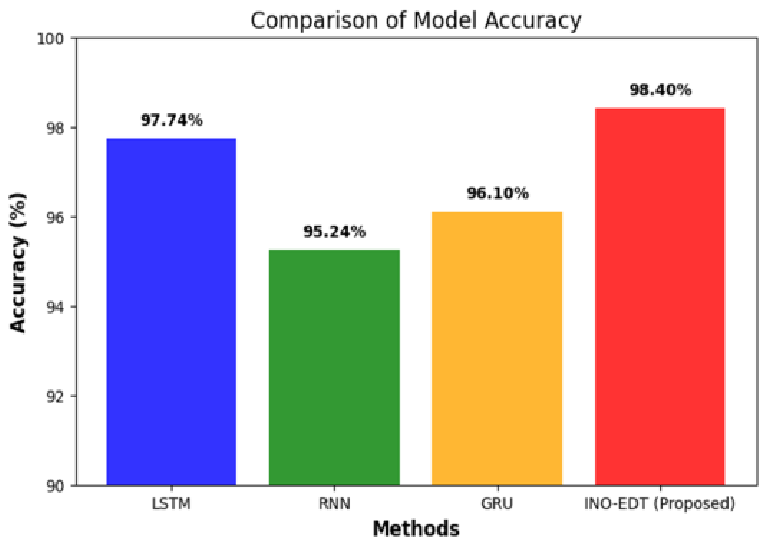


**Figure 7.** Comparison of Accuracy

Table 1 and figure 7 presents the accuracy performance of different deep learning models for personalized medical diet recommendations. The proposed INO-EDT method achieves the highest accuracy at 98,40 %, outperforming LSTM (97,74 %), GRU (96,10 %), and RNN (95,24 %). This demonstrates the effectiveness of the INO-EDT in optimizing dietary recommendations for disease management. The superior accuracy highlights its potential for improving patient-specific nutritional interventions.

## DISCUSSION

Comparative research focuses on deep learning-based dietary recommendations, using methods such as RNN,[17] GRU,[17] and LSTM[17] to estimate appropriate food for patients according to their nutritional and medical factors. While, these techniques have some limitations also such as LSTM powerful in capturing long-range dependencies, has high computational expense and slow training. RNN is plagued with vanishing gradients, which constrains its capability to learn long-term patterns from medical data. GRU is enhancing competence through LSTM, but its difficulty to completely capture involved nutritional dealings. The proposed INO-EDT technique overcomes these boundaries by combining an optimized decision tree structure with intelligent feature assortment, signifying higher accurateness, decreased computational weight, and enhanced correctness in dietary recommendations. This improves personalized diet scheduling, making it further competent for chronic management of disease.

## CONCLUSIONS

Personalized medicinal dietary recommendation involves patient-specific wellbeing information, such as medicinal history, way of life, and intaking habits, to expand individualized nutrition plans for disease control. Through the combination of AI and ML, these recommendations improve the efficacy of treatment for diseases such as diabetes and heart disease. This method enhanced patient outcomes by making diets scientifically optimized for individual health needs. The INO-EDT model improved AI-driven dietary recommendations, enhancing disease control and patient trust. It combines health information for an accurate, personalized dietary strategy and optimizes accuracy (98,40 %). However, its trust in high-quality patient data and computational difficulty can limit real-time uses. Future directions need to include other health markers and dietary preferences. Clinical validation should be included for ensuring real-time effectiveness. Increasing adaptability will enhance its position in precision nutrition and healthcare.

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## CONFLICT OF INTEREST

The authors declare that there is no conflict of interest.

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