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Product Design and Development

Design of Python-Based Expert System for Healthy Diet Recommendations Using Forward Chaining

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A B S T R A C T

A healthy diet is an important factor in maintaining overall health. However, many people still have difficulties determining their weight status, daily calorie requirements, and appropriate dietary patterns based on their individual conditions. In addition, the variety of diet information available on the internet may make it difficult for users to select appropriate recommendations. This study aims to design an expert system that calculates Body Mass Indes (BMI), determines calorie requirements, and provides dietary recommendations and health advice based on user conditions. The inference method used is Forward Chaining, supported by a knowledge base consisting of user facts and IF-THEN rules based on nutritional expertise. Specifically, the IF-THEN rules map user inputs (such as age, height, weight, target weight, and meal frequency) to evaluate BMI classification thresholds (e.g., if $25 \leq BMI \leq 30$, the system triggers an Overweight status and assigns an 1800 kcal target) along with supplementary goal-adjustment rules. The validation of these rules and the system's mathematical accuracy were verified through clinical test scenarios. The results show that the system can automatically calculate BMI, determine BMI status, provide calorie requirement information, and generate meal recommendations and health advice based on predefined rules. However, the system's scope is strictly limited to general BMI-based nutritional estimation and does not account for biological sex, physical activity levels, or pre-existing medical conditions; therefore, its automated outputs serve solely as a practical supporting tool and do not replace professional medical or nutritional consultation.

1. INTRODUCTION

Over the past few decades, global epidemiology has undergone a significant paradigm shift, with the incidence, morbidity, and mortality of non-communicable diseases (NCDs) or chronic conditions surpassing those of infectious diseases worldwide. Major chronic pathologies including cardiovascular disease, cancer, cerebrovascular disease, and diabetes mellitus have emerged as the leading causes of mortality globally. This public health crisis is further compounded by the rising prevalence of obesity, with over two-thirds of the adult population classified as overweight or obese ($BMI \geq 25.0$ kg/m^2). Obesity functions not only as an independent chronic condition but also as a primary driver for secondary metabolic disorders [1].

The etiology of chronic diseases is complex and intrinsically multifactorial, involving non-modifiable variables (such as age, family history, and genetic predisposition) as well as modifiable risk factors (including lifetime weight trajectory, physical activity levels, smoking, alcohol consumption, and dietary patterns). Among these, dietary modification offers the greatest potential for public health intervention. Consequently, the nutritional science community carries both a professional and moral obligation to actively engage in mitigating the burden of preventable diet-related chronic conditions [1].

Advances in information technology and modern lifestyle dynamics have driven a shift in public dietary patterns toward the consumption of fast food. Coupled with irregular eating habits and a low awareness of balanced nutrition, this trend ultimately escalates the risk of non-communicable diseases such as obesity, diabetes, and hypertension, thereby undermining overall public health [2]. Poor dietary patterns significantly increase the risk of various chronic diseases, such as obesity, cardiovascular disease, cancer, and type 2 diabetes. However, nutritional epidemiology research often faces major challenges in accurately assessing dietary exposure due to the complexity of modern food supplies, shifting eating patterns, and the heavy reliance of most studies on

self-report instruments that are prone to both random measurement error and systematic bias.[3].

Poor dietary quality is strongly associated with an increased risk of cardiovascular morbidity and mortality, as well as various other chronic conditions. Although evidence-based guidelines recommend adopting healthy dietary patterns such as increasing the consumption of fruits, vegetables, and whole grains, while limiting added sugars, salt, and saturated fats many individuals face significant challenges in adhering to these patterns due to environmental factors such as targeted marketing of unhealthy foods, food and nutrition insecurity, neighborhood segregation, and structural racism. These barriers complicate the achievement of ideal body weight and energy balance, thereby exacerbating the risk of cardiometabolic disorders and long-term health problems.[4].

Furthermore, these complexities and measurement errors make it difficult to accurately estimate nutritional needs and intake. This issue is compounded by the widespread difficulty individuals face in accurately calculating and determining their daily nutritional needs. The inability to independently design a balanced dietary plan frequently leads to uncontrolled body weight fluctuations, which poses additional long-term health risks. Consequently, these challenges necessitate newer, more objective approaches such as the use of nutritional biomarkers and metabolomics to improve the validity of dietary assessments and the prevention of related disease risks.

On the other hand, scientific evidence demonstrates that dietary patterns emphasizing high-quality foods, adherence to nutritional guidelines, and a focus on plant-based intake significantly reduce the risk of cardiovascular disease (CVD), type 2 diabetes, cancer, and all-cause mortality. Grounded in this evidence, international frameworks such as the 2015–2020 Dietary Guidelines for Americans propose Healthy U.S.-Style, Mediterranean-Style, Vegetarian, and Dietary Approaches to Stop Hypertension (DASH) diets as exemplary models [5]. However, practical implementation remains challenging for the general public due to a lack of accessible tools to translate these nutritional guidelines into daily meal plans tailored to individual health profiles.

To address this challenge, the application of artificial intelligence, particularly Expert Systems, serves as a strategic solution by transferring nutritionist expertise into computer systems to facilitate precise dietary planning. The efficacy of expert systems in healthcare management has been supported by prior research, such as the implementation of the RetinaNet method for meal selection in hypotension management [6] and the application of the Dempster-Shafer method integrated with Body Mass Index (BMI) assessment for diabetes mellitus patients [7].

Building upon these foundations, this study develops an Expert System for Health-Based Diet Menu Selection utilizing the Forward Chaining inference method.

The Forward Chaining method was chosen for this study because a data-driven approach is ideally suited for determining dietary menus and nutritional status, where reasoning begins with a set of initial user input facts such as age, body weight, height, target weight, and meal frequency to be systematically matched against IF-THEN rules within the knowledge base. Specifically, this study aims to design an expert system capable of calculating Body Mass Index (BMI), determining daily caloric requirements, and providing personalized dietary recommendations and health advice tailored to individual user conditions.

The differentiating aspect of the PolaSehat system compared to similar systems lies in its utilization of the Python programming language with the CustomTkinter library to deliver a modern, interactive, and responsive desktop graphical user interface (GUI). Furthermore, the system not only classifies BMI status and caloric requirements but also integrates supplementary rules to evaluate target weight discrepancies and perform iterative daily menu filtering based on the remaining caloric target per meal session.

2. LITERATURE REVIEW

2.1. *The Relationship Between Healthy Dietary Patterns and Healthy Aging*

Based on a journal article by [8], the shift in nutritional research from analyzing single nutrients to evaluating total dietary patterns has proven to be a more effective approach for understanding healthy aging and preventing non-communicable diseases (NCDs). Various traditional dietary patterns rich in plant-based foods, fiber, phytochemicals, and unsaturated fats such as the Mediterranean Diet, Japanese Diet, Okinawan Diet, Vegetarian Diet, and New Nordic Diet have consistently been shown to reduce total mortality risks, cardiovascular diseases, cognitive decline, and metabolic disorders. The common thread among all these diets lies in the consumption of nutrient-dense foods while restricting red meat, ultra-processed foods, and added sugars, where the synergistic interactions of these components actively suppress oxidative stress and chronic inflammation. Consequently, the consistent adoption of plant-forward diets combined with prudent caloric restriction represents a primary evidence-based strategy to extend disability free life expectancy and enhance overall quality of life in older populations.

2.2. *The Relationship Between Diet Quality and Body Mass Index (BMI)*

A 20-year longitudinal study by [9] involving 1,860 participants from the Multiethnic Cohort (MEC) demonstrated that higher diet quality is consistently inversely associated with Body Mass Index (BMI), where every 10-point increase in the Healthy Eating Index-2015 (HEI-2015) score significantly correlated with a BMI reduction of 0.47 to 0.92 kg/m^2 and a lower prevalence of overweight and obesity over time. Notably, the protective effect of diet quality against higher BMI was most pronounced as participants reached older age (mean age of 69 years). Although this inverse relationship was consistent across diverse ethnic groups including Japanese American, White, Latino, and Native Hawaiian participants it was not statistically significant in African American individuals, pointing to potential ethnic variations in biological responses or dietary behaviors. Consequently, these findings reinforce the critical role of long-term diet quality improvements as a primary weight management strategy for midlife and older adults while highlighting the necessity for culturally tailored nutritional interventions.

2.3. *Expert Systems and the Forward Chaining Method*

An expert system is a computer-based information system that integrates specialized knowledge from human experts such as physicians or psychologists to deliver accurate and targeted corrective recommendations. By leveraging logical reasoning, the system derives automated conclusions from predefined facts and input data. To execute this process, expert systems frequently employ *Forward Chaining*, a data-driven reasoning method that operates inversely to *Backward Chaining*. This technique initiates the inference process using available baseline facts and systematically evaluates them against *IF-THEN* rules to establish definitive conclusions or discover new relevant facts [10].

3. METHODOLOGY

The design of the Expert System for Diet Menu Selection Based on Health Conditions utilizes the *Forward Chaining* inference method, a data-driven approach that initiates the reasoning process from a set of input facts prior to reaching a final conclusion. Determining a dietary regime is uniquely suited for an expert system because it relies on structured rules and a knowledge base derived from medical journals and nutritional expertise. Unlike *Backward Chaining*, which traces backward from a hypothesis, *Forward Chaining* actively processes user input facts such as age, weight, height, gender, activity level, and health goals and matches them against *IF-THEN* rules in the knowledge base. During this operation, the system evaluates the rule premises; when a condition is satisfied (evaluated as *TRUE*), the rule is triggered to generate new facts or conclusions. Through this systematic rule matching, the system delivers precise, personalized outputs, including Body Mass Index (BMI) status analysis, daily calorie requirement calculations, tailored meal plan recommendations, and actionable health guidance.

4. RESULTS AND DISCUSSION

4.1. Fact Base Formulation and User Data Analysis

This section presents the implementation of the fact base collected from users to drive the *Forward Chaining* inference engine. The fact base serves as the initial input parameters interactively gathered through the system interface. The demographic and anthropometric parameters processed by the system include user name, age, body weight (kg), height (cm), target body weight (kg), and daily meal frequency (ranging from 1 to 5 times per day).

Upon acquiring the complete set of input data, the system automatically computes the user's nutritional status using the Body Mass Index (BMI) formula as a primary derived fact:

$$BMI = \frac{Weight\ (kg)}{\text{Height (m)}^2}$$

The calculated BMI value is subsequently integrated into the knowledge base as a new fact premise. Based on this BMI classification and other contextual input facts, the inference engine determines the user's nutritional category (e.g., underweight, normal, overweight, or obese), calculates total daily caloric requirements, formulates tailored meal plan recommendations matching the specified meal frequency, and generates actionable, personalized health advice.

4.2. Rule Base Modeling and Inference Logic

The expert system utilizes an *IF-THEN* structured rule base to map user input facts into precise nutritional status decisions and dietary recommendations. The rule base is categorized into three primary domains: Body Mass Index (BMI) status classification, weight goal strategy adjustment, and daily menu selection filtering algorithms.

The formal rule structure for BMI classification and daily caloric target allocation is detailed in **Table 1**.

Tabel 1. Rule Base Structure for BMI Classification and Primary Recommendations

Rule ID	*Premise /Condition (IF)*	*Status Outcome (THEN)*	*Caloric Target (kcal)*	*Tailored Advice & Recommendation*
R1	*BMI<18.5*	*Underweight*	*2500*	*Increase intake of healthy proteins and carbohydrates.*
R2	*18.5≤BMI<25*	*Normal*	*2200*	*Maintain a balanced and healthy dietary pattern.*
R3	*25≤BMI<30*	*Overweight*	*1800*	*Reduce consumption of greasy foods and added sugars.*
R4	*BMI≥30*	*Obese*	*1500*	*Increase dietary fiber intake and engage in regular exercise.*

The Body Mass Index (BMI) classification used in the PolaSehat system refers to the international clinical standards for adults established by the World Health Organization (WHO). This standard is calculated based on the standard mathematical formula, which divides an individual's body weight in kilograms (kg) by the square of their height in meters (m^2). Within this expert system, the clinical thresholds of the WHO standard are translated into a knowledge base structured as IF-THEN rules (as presented in Table 1) to automate the assessment of nutritional status and the allocation of daily caloric targets with high precision. The categorized thresholds are detailed as follows:

1. Underweight Category: Applied for a BMI < 18.5, with a daily caloric target allocation of 2500 kcal and recommendations to increase the intake of healthy proteins and carbohydrates.
2. Normal Category: Applied for the range of 18.5 ≤ BMI < 25, with a caloric target of 2200 kcal and recommendations to maintain a balanced and healthy dietary pattern.
3. Overweight Category: Applied for the range of 25 ≤ BMI < 30, with a caloric target of 1800 kcal and recommendations to reduce the consumption of greasy foods and added sugars.
4. Obese Category: Applied for a BMI ≥ 30, with a caloric target of 1500 kcal and recommendations to increase dietary fiber intake and engage in regular exercise.

In addition to BMI criteria, the inference engine evaluates user weight goals and controls the meal selection loop using supplementary conditional rules, as summarized in Table 2.

Tabel 2. Rule Base for Weight Goal Adjustments and Menu Selection Filtering

Rule Domain	**Rule ID**	**Premise/Condition (*IF*)**
Weight Goal	RT1	Target Weight < Current Weight
	RT2	Target Weight > Current Weight
Menu Filtering	RM1	Menu Item Calories ≤ Remaining Caloric Target
	RM2	Remaining Caloric Target ≤ 30 kcal

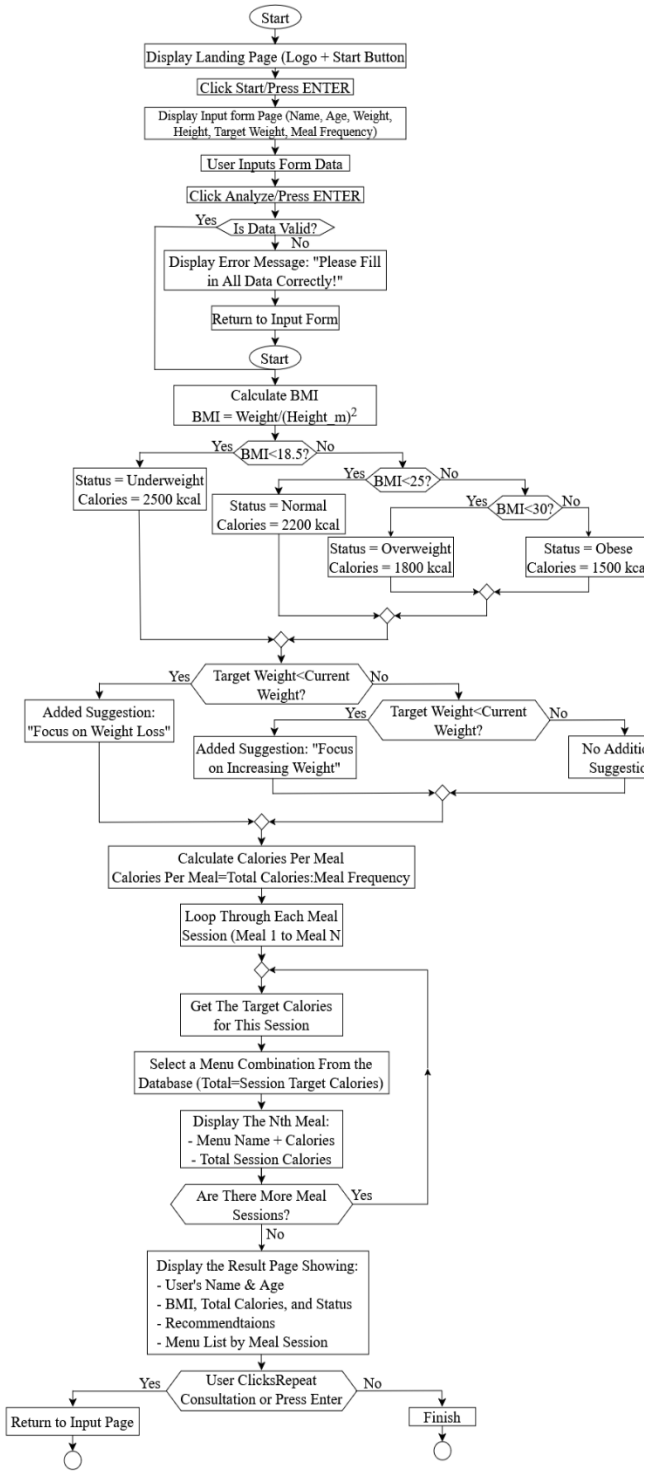


Figure 1. System Workflow *Flowchart* of PolaSehat Application

Operational Logic Explanation:

1. Target Evaluation Logic (RT1 & RT2): The inference engine evaluates the user's target weight relative to their current weight. If the target is lower, the system appends weight-loss guidance; if higher, it prompts a healthy weight-gain strategy.
2. Caloric Filtering Logic (RM1): Food items from the database are scanned iteratively. A meal item is added to the daily plan only if its caloric content does not exceed the remaining caloric quota.
3. Loop Termination Logic (RM2): To optimize computational performance and prevent infinite processing loops, the selection algorithm automatically terminates once the remaining caloric deficit falls within a tolerance threshold of ≤ 30 kcal.

4.3. *System Workflow and Implementation (System Flowchart)*

The operational execution of the PolaSehat expert system is structured to provide an intuitive self-consultation process for users regarding nutritional assessment and meal planning. The overall process flow of the system is illustrated in Figure 1.

4.4. *Graphical User Interface (GUI) Implementation*

The PolaSehat application was implemented using Python and the CustomTkinter library to deliver a modern, intuitive, and responsive Graphical User Interface (GUI). The interface design is structured into three main pages that seamlessly guide users through the health self-consultation process.

4.4.1 Landing Page Interface

The landing page serves as the welcome screen and the primary entry point to the consultation workflow. The layout of the Landing Page is presented in Figure 2.



Figure 2. Landing Page Graphical User Interface of the PolaSehat Application

Key functional elements of the Landing Page include:

1. Visual Branding & Identity: Features the application logo, the main title (PolaSehat), and a descriptive tagline (Aplikasi Konsultasi Pola Makan Sehat) to establish system identity.
2. Actionable Navigation: Provides a prominent MULAI (START) call-to-action button alongside keyboard event handling guidance (Tekan ENTER untuk mulai) to streamline user transition to the data acquisition form.

4.4.2 User Data Input Page (Form Input)

The second page acts as the fact acquisition interface, responsible for capturing primary input parameters from the user. These variables serve as the foundational inputs that drive the *Forward Chaining* inference engine. The layout of the Data Input Page is presented in Figure 3.



Figure 3. User Data Input Form Interface of the PolaSehat Application

Key functional components integrated into this interface include:

1. Demographic and Anthropometric Input Fields: Interactive text entry boxes designed to capture essential user data, including name, age, body weight (kg), height (cm), and target weight (kg).
2. Meal Frequency Selector: A set of numeric segmented choice buttons (ranging from 1 to 5) allowing users to intuitively specify their daily meal frequency.
3. Inference Execution Trigger: Features a prominent ANALISIS (ANALYZE) button along with keyboard shortcut handling (*Tekan ENTER untuk analisis*) to initiate data validation, BMI calculations, and rule-matching routines.

4.4.3 Consultation Result Page (Result Page)

The third page serves as the output display interface, presenting the complete analytical results generated by the *Forward Chaining* inference engine. The rendered information is structured systematically to provide clear insights into the user's nutritional status and dietary regimen. The interface layout of the Consultation Result Page is illustrated in Figure 4.

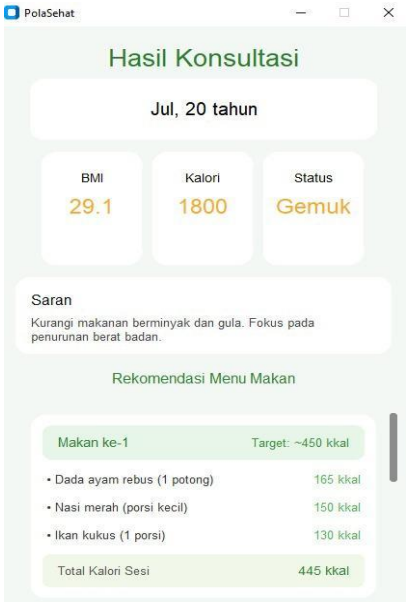




Figure 4. Consultation Result Graphical User Interface of the PolaSehat Application

The key functional elements of this page include:

1. User Identification Banner: Displays the user's name and age (e.g., *"Jul, 20 years old"*) to personalize the consultation outcome.
2. Nutritional Status Metrics Card: Highlights three derived core parameters: the calculated Body Mass Index (e.g., BMI 29.1), daily caloric requirement (e.g., 1800 kcal), and nutritional classification status (e.g., Overweight).
3. Personalized Health Guidance Box: Renders contextual health advice dynamically generated from the rule matching logic (e.g., *"Reduce greasy food and sugar intake. Focus on gradual weight loss."*).
4. Session-based Meal Recommendation Cards: Itemizes tailored meal plans categorized according to the selected daily meal frequency. Each meal session card (ranging from *Meal 1* to *Meal 4*) incorporates:
   a. Target session caloric threshold (e.g., Target: ~450 kcal).
   b. Detailed breakdown of food items with portion sizes and individual caloric contributions (e.g., *Boiled chicken breast - 165 kcal*, *Brown rice small portion - 150 kcal*, *Steamed fish - 130 kcal*).
   c. Total aggregated session calories (e.g., Total Session Calories: 445 kcal).
5. Session Reset Navigation: Positioned at the bottom, an interactive RE-CONSULT call-to-action button (*Press*

ENTER to re-consult) allows users to reset input facts and execute a new consultation cycle.

4.5. *Scenario Testing*

Scenario testing was conducted to evaluate and validate the numerical accuracy of the Body Mass Index (BMI) calculations, the execution correctness of the *IF-THEN* rules within the knowledge base, and the contextual appropriateness of the food menu recommendations and personalized health advice generated by the expert system.

4.5.1 Test Scenario 1

In the first scenario, testing was executed using a sample test case representing an overweight user aiming for weight loss. The detailed user input facts (*fact base inputs*) and the corresponding system output interface (*output display*) for this scenario are presented in Table 3 and Figure 5.

Table 3. Test Scenario 1 User Input Parameters

Input Parameter (*Fact Base*)	**Input Value**
User Name	ABC
Age	20 years old
Height	170 cm (1.70 m)
Current Weight	84 kg
Target Weight	80 kg



Figure 5. Consultation Result Output Interface for Test Scenario 1

Inference Logic Analysis and Proof (Scenario 1):

1. BMI Mathematical Calculation (Primary Derived Fact):
$$BMI = \frac{Weight\ (kg)}{\text{Height (m)}^2} = \frac{84}{(1.70)^2} = \frac{84}{2.89} = 29.065 \sim 29.1$$
The system's computed BMI value of **29.1** is mathematically verified to be precise.
2. Rule Base Matching Execution:
   a. Rule 3 Execution (BMI Classification):
   Condition: 25≤BMI<30 (25≤29.1<30→TRUE)
   THEN Outcome: Status=Overweight, Caloric Target=1800 kcal, Menu Category=Overweight, Primary Advice = "Reduce greasy foods and sugar."
   b. Target Rule 1 Execution (Goal Adjustment):
   Condition:Target Weight<Current Weight (80<84→TRUE)
   THEN Outcome: Append Advice = "Focus on weight loss."
3. System Output Verification:
   c. Status & Caloric Metrics: The system accurately renders BMI 29.1, Calorie 1800, and Status Overweight.
   d. Menu Plan: Recommends calorie-controlled and low-fat meal portions (e.g., Fruit + yogurt, Brown rice + boiled chicken, Vegetable soup).
   e. Personalized Guidance: Dynamically combines outcomes from Rule 3 and Target Rule 1, producing: "Reduce greasy foods and sugar. Focus on weight loss."

4.5.2 Test Scenario 2

The second test scenario was executed using a user profile representing a normal/healthy weight individual with a target weight slightly below their current weight. The input parameter facts (*fact base inputs*) and the resulting output interface (*output display*) are presented in Table 4 and Figure 6.

Table 4. Test Scenario 2 User Input Parameters

Input Parameter (*Fact Base*)	**Input Value**
User Name	ABC
Age	20 years old
Height	170 cm (1.70 m)
Current Weight	60 kg
Target Weight	58 kg

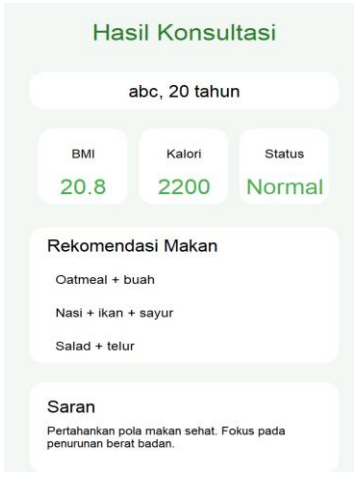


Figure 6. Consultation Result Output Interface for Test Scenario 2

Inference Logic Analysis and Proof (Scenario 2):

1. BMI Mathematical Calculation (Primary Derived Fact):
$$BMI = \frac{Weight\ (kg)}{\text{Height (m)}^2} = \frac{60}{(1.70)^2} = \frac{60}{2.89} = 20.761 \sim 20.8$$
The system's computed BMI value of 20.8 is mathematically accurate.
2. Rule Base Matching Execution:
   a. Rule 2 Execution (BMI Classification):
   Condition: 18.5≤BMI<25 (18.5≤20.8<25→TRUE)
   THEN Outcome: Status=Normal, Caloric Target=2200 kcal, Menu Category=Normal, Primary Advice = "Maintain a Healthy Dietary Pattern."
   b. Target Rule 1 Execution (Goal Adjustment):
   Condition:Target Weight<Current Weight (58<60→TRUE)

THEN Outcome: Append Advice = "Focus on weight loss."

3. System Output Verification:
   c. Status & Caloric Metrics: The system accurately renders BMI 20.8, Calorie 2200, and Status Normal.
   d. Menu Plan: Recommends balanced daily meals (e.g., Oatmeal + fruit, Rice + fish + vegetables, Salad + egg).
   e. Personalized Guidance: Dynamically combines outcomes from Rule 2 and Target Rule 1, producing: "Maintain a healthy dietary pattern. Focus on weight loss."

5. CONCLUSION

The desktop-based expert system PolaSehat was successfully developed using the Forward Chaining inference method and the CustomTkinter framework to automatically compute Body Mass Index (BMI) and daily caloric targets based on user inputs (height, current weight, and target weight). Through scenario testing, the system demonstrated logical consistency and reliability in executing nutritionist-validated IF-THEN rules, accurately evaluating BMI categories, adapting to weight goals, and generating practical meal plan recommendations and health advice to support healthy living. However, the current iteration is limited to BMI metrics and does not account for biological sex, physical activity levels, or pre-existing medical conditions. Consequently, future research should incorporate supplementary physiological variables, integrate dynamic external nutrition databases for richer menu variations, and transition the application to web or mobile platforms for broader user accessibility.

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