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Calorie Intake Monitoring Application Using the Mifflin–St Jeor Algorithm

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ABSTRACT

Unbalanced dietary habits are a major factor contributing to health problems such as obesity, malnutrition, and metabolic disorders. This study developed a calorie monitoring application to help users accurately and efficiently manage their nutritional balance. The system applies the Mifflin–St Jeor algorithm to estimate daily energy requirements based on personal data, age, gender, height, and weight, integrated with Body Mass Index (BMI) and Total Daily Energy Expenditure (TDEE) to provide adaptive calorie recommendations according to activity levels. The application was built using Flutter for the mobile interface and Flask for backend computation, utilizing the Kaggle Nutrition Dataset as a reference for food data. Validation results showed a deviation of less than 1% between manual and system-based calculations, confirming the algorithm's precision. The system delivers personalized, data-driven calorie recommendations and real-time monitoring of food intake. These findings demonstrate the potential of algorithm-based mobile systems to improve dietary self-management and support healthier lifestyle behaviors.

Keywords: *Calorie Intake, Mifflin–St Jeor Algorithm, Body Mass Index (BMI), Basal Metabolic Rate (BMR), Total Daily Energy Expenditure (TDEE), Android Application, Nutrition*

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INTRODUCTION

Modern lifestyle changes have led to a growing imbalance in dietary intake. Increased mobility and the widespread availability of fast and processed foods have encouraged unregulated eating behaviors, making it increasingly difficult for many individuals to maintain a balance between energy intake and metabolic expenditure (World Health Organization, 2010). Public awareness of calorie management remains limited, while manual methods for estimating daily energy needs are often inaccurate and inconsistent in everyday use (Kementrian Kesehatan Republik Indonesia, 2022).

The health consequences of inadequate calorie regulation are significant. Conditions such as obesity, malnutrition, and metabolic disorders, including type 2 diabetes and hypertension, are becoming more prevalent and now account for a major portion of global non-communicable diseases (World Health Organization (WHO), 2025). Worldwide, more than 2.5 billion adults are overweight, and over 890 million are classified as obese, a trend that has sharply increased since 1990 and is mirrored in developing countries such as Indonesia (World Health Organization, 2025). In Indonesia, the prevalence of adult obesity rose from 14.8% in 2013 to 21.8% in 2018, according to the 2018 Basic Health Research (Riskesdas) survey, underscoring an urgent public health concern (Kementrian Kesehatan Republik Indonesia, 2022).

In response to these challenges, technology-based interventions have emerged as promising solutions for improving the accuracy and consistency of calorie monitoring. Prior studies have introduced mobile and web-based applications to enhance calorie awareness and dietary planning, emphasizing the importance of reliable estimation methods supported by user-friendly interfaces (Sulaiman et al., 2023). However, many of these systems rely on static calculations, offer limited personalization, and lack adaptive feedback mechanisms that consider user-specific activity levels or behavioral patterns (Rusliyawati et al., 2020). This gap highlights the need for a more intelligent, integrated system that not only performs accurate energy estimation but also adapts dynamically to individual lifestyles and user data.

Algorithmic estimation forms the core of such systems. The Mifflin–St Jeor equation is widely recognized for its superior accuracy in estimating the Basal Metabolic Rate (BMR) from key physiological parameters like weight, height, age, and sex (Febrianta, 2021). This estimation is further refined for personalization using complementary indicators such as Body Mass Index (BMI) and Total Daily Energy Expenditure (TDEE). BMI helps classify a user's weight status, while TDEE allows for calorie recommendations to be adjusted based on activity levels (Qamaruzzaman et al., 2022). Integrating these components into a unified framework bridges the gap between generic estimation and individualized guidance (Septiana et al., 2024).

Beyond computational accuracy, the literature underscores that user-centered design and system usability are critical for long-term adoption. Research demonstrates that system design spanning from Android applications with machine-learning toolkits to expert systems built on classical software life cycles significantly influences user experience and acceptance (Bunyamin et al., 2022). Moreover, features such as well-structured nutritional databases, practical logging workflows, and adaptive recommendations are essential for fostering sustainable behavioral change (Ulhaq et al., 2025). Collectively, these findings suggest that technical precision alone is insufficient it must be complemented by usability and contextual relevance to achieve meaningful outcomes (Bisma et al., 2021).

However, while previous studies have successfully introduced calorie monitoring systems, most of them emphasize computational or interface design aspects separately, rather than integrating them into a unified, intelligent framework. Several works apply machine-learning or traditional estimation models, but lack continuous monitoring and adaptive personalization aligned with user activities and goals. This indicates that existing approaches still provide fragmented user experiences and limited scalability across diverse populations (Sulaiman et al., 2023; Ulhaq et al., 2025). Therefore, a comprehensive model that combines algorithmic accuracy, behavioral adaptation, and user-centered design remains limited in the current literature.

Despite these advancements, most existing systems still operate in isolation, failing to combine Mifflin–St Jeor–based estimation with BMI- and TDEE-driven personalization in a cohesive mobile workflow. Fragmented nutritional databases and manual input mechanisms further reduce user consistency and long-term engagement (Ulhaq et al., 2025). Therefore, this study focuses on bridging this gap by developing a calorie monitoring application that integrates algorithmic estimation with adaptive feedback, providing accurate, personalized, and user-friendly nutritional recommendations (Sulaiman et al., 2023). Addressing these limitations, this study proposes an integrated calorie monitoring framework that not only automates energy estimation using the Mifflin–St Jeor algorithm but also dynamically personalizes calorie recommendations based on BMI and TDEE metrics. This integration highlights the novelty of this work, bridging the gap between theoretical precision and practical usability.

This study aims to address these gaps by developing a calorie monitoring application that integrates algorithmic estimation with personalized feedback. The system applies the Mifflin–St Jeor algorithm to calculate daily energy requirements based on user attributes (age, sex, height, and weight), classifies weight status using Body Mass Index (BMI), and adjusts calorie recommendations through Total Daily Energy Expenditure (TDEE) according to each user's activity level and health goals whether to lose, maintain, or gain weight (Qamaruzzaman et al., 2022). The system architecture consists of a mobile front-end and a service-oriented back-end, integrating a nutrition dataset from Kaggle as the food information source for calorie and nutrient computation, along with a logging module to support continuous monitoring (Bunyamin et al., 2022).

Accordingly, this study aims to design and implement a calorie monitoring application that calculates user-specific daily energy requirements using the Mifflin–St Jeor equation, generates calorie recommendations tailored to each user's BMI category and activity-derived TDEE, and provides a practical tool for daily monitoring to help users achieve targeted health goals such as weight loss, maintenance, or gain (Septiana et al., 2024). The primary contribution of this work lies in an integrated, data-driven system that combines accurate estimation, activity-aware personalization, and structured nutrition logging within a single mobile-first platform designed to promote healthier dietary behaviors (Ulhaq et al., 2025).

METHOD

This research employs a quantitative experimental design to develop and evaluate a mobile calorie monitoring application. The development adopts the Agile–Kanban approach within the Software Development Life Cycle (SDLC) framework, chosen for its flexibility and iterative process. According to Huss, Herber, and Borky (2023), Agile methods address the limitations of traditional SDLC by emphasizing adaptability, continuous improvement, and visual task management. In this study, the system combines a mobile front-end and a Flask-based back-end to calculate daily energy needs using the Mifflin–St Jeor equation.

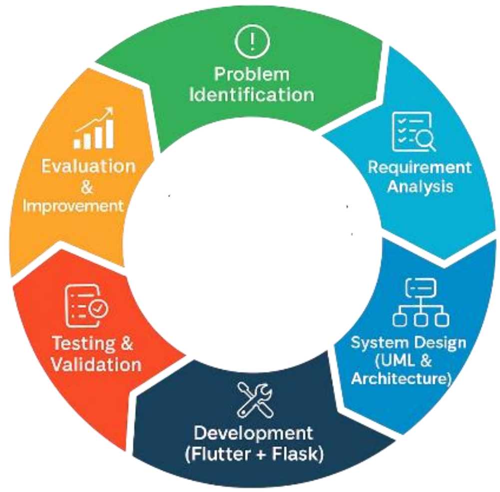

Figure 1. Research Methodology Framework

This study utilized data provided by users through the mobile application's interface, including personal information such as age, sex, height, weight, and physical activity level. The system processed these inputs to calculate the Basal Metabolic Rate (BMR) using the Mifflin–St Jeor equation, which estimates daily energy requirements based on these parameters (Meidiawati et al., 2024). This formula, originally proposed by Mifflin et al. (1990), is widely regarded as one of the most accurate methods for determining BMR, outperforming earlier models like the Harris–Benedict equation, particularly across varied body compositions. The system then multiplied the resulting BMR by a physical activity factor (ranging from sedentary to very active) to determine the Total Daily Energy Expenditure (TDEE). Furthermore, the system computed the Body Mass Index (BMI) to classify the user's weight status according to World Health Organization (WHO) (2025) standards. This compiled dataset served as the primary sample for evaluating the system's functional performance and the accuracy of its caloric recommendations.

The data analysis stage comprised four primary computational components integrated into the system's algorithm, namely the calculation of Basal Metabolic Rate (BMR), Body Mass Index (BMI), Total Daily Energy Expenditure (TDEE), and daily calorie recommendations. Each of these components was implemented to support personalized energy estimation and dietary guidance.

Basal Metabolic Rate (BMR)

The BMR represents the amount of energy required by the body at rest. It was calculated using the Mifflin–St Jeor equation, which has been recognized as more accurate than the earlier Harris–Benedict formula for estimating resting energy expenditure across diverse body compositions (Mifflin et al. 1990; Meidiawati et al. 2024).

$$BMR_{male} = 10 \times W + 6.25 \times H - 5 \times A + 5$$

$$BMR_{female} = 10 \times W + 6.25 \times H - 5 \times A - 161$$

Where W is weight (kg), H is height (cm), and A is age (years).
These values serve as the baseline energy requirement before being adjusted by the activity factor to determine total daily energy expenditure.

Body Mass Index (BMI)

The BMI was used to classify weight status based on the ratio of body weight to height, following the standard formula defined by the World Health Organization (WHO) (2025):

$$BMI = \frac{W}{H^2}$$

Table 1. BMI Classification According to WHO

Category	BMI Range	Description
Underweight	< 18.5	Below ideal weight
Normal	18.5–24.9	Healthy range
Pre-obese	25.0–29.9	At risk of overweight
Obesity Class I	30.0–34.9	Moderate obesity
Obesity Class II	35.0–39.9	Severe obesity
Obesity Class III	≥ 40	Extreme obesity

Although BMI provides a general overview of nutritional status, it does not account for body composition variations, such as fat and muscle mass distribution.

Total Daily Energy Expenditure (TDEE)

The TDEE represents the total amount of energy required daily, combining basal metabolism, physical activity, and thermogenic effects. It was calculated by multiplying BMR by an activity factor. According to (Makarim, 2023), as published in HaloDoc, TDEE helps individuals better estimate their energy needs based on their daily activity level.

$$TDEE = BMR \times Activity\ Factor$$

Table 2. Activity Classification and Multipliers

Activity Level	Description	Multiplier
Sedentary	Minimal physical activity (e.g., office work)	1.2
Lightly Active	Light exercise or household tasks	1.375

Moderately Active	Moderate activity such as brisk walking	1.55
Very Active	Intense physical activity or labor	1.725
Super Active	Extremely heavy physical activity	1.9

Caloric Recommendation

Daily caloric recommendations were formulated based on TDEE values and BMI classifications. According to Umbu (Umbu Pati et al., 2023), daily calorie adjustments can be achieved through energy deficits or surpluses depending on health goals.

Table 3. Caloric Recommendation Strategy

BMI Category	Caloric Recommendation	Notes
Underweight	TDEE + 250–500 kcal	Gradual increase with nutrient monitoring
Normal	TDEE	Maintain energy balance
Pre-obese	TDEE − 500–1000 kcal	Mild deficit with regular exercise
Obesity I–III	TDEE − 500–1000 kcal	Requires medical supervision and periodic monitoring

These caloric recommendations were integrated into the application to provide adaptive feedback according to users' health goals and activity levels. To ensure the accuracy and reliability of these computational processes, the system underwent a structured testing and validation stage as described below.

System Testing and Validation

Although the system's calculation logic is based on established nutritional equations, it was essential to ensure the reliability and accuracy of its implementation within the application. Therefore, the system underwent a structured testing and validation process to verify both its functional performance and computational precision. The developed application was evaluated using the Black-box testing method to ensure that all features operated according to their functional specifications. This method focuses on testing the system's input-output behavior without analyzing internal code structures, thereby confirming that the user-facing functionality aligned with design requirements (Mahendra & Asmarajaya, 2022).

In addition, we conducted a manual calculation comparison to validate the algorithm's computational accuracy. We compared the results generated by the system for Basal Metabolic Rate (BMR), Body Mass Index (BMI), and Total Daily Energy Expenditure (TDEE) with manually computed values using identical user parameters. This approach assessed the validity (accuracy) and reliability (consistency) of the algorithmic implementation based on the Mifflin–St Jeor model, ensuring that the computation logic performs precisely and consistently across diverse user profiles (Mifflin et al., 1990).

FINDING AND DISCUSSION

RESEARCH RESULT

This section presents the results of the system development and implementation process, from problem identification through the application testing phase. The main problem addressed in this study is the lack of an automated and accurate method for calculating and monitoring daily calorie intake. To overcome this, a calorie monitoring application was developed using the Mifflin–St Jeor algorithm, which estimates energy needs based on user data such as age, sex, height, and weight. This algorithm was integrated with additional parameters, specifically Body Mass Index (BMI) and Total Daily Energy Expenditure (TDEE), to generate personalized calorie recommendations based on activity levels. The system was designed using the Unified Modeling Language (UML) approach, implemented with a mobile interface developed in Flutter, and supported by a Flask-based backend for data computation and retrieval of nutritional information from the Kaggle Nutrition Dataset.

System Design

The system design phase defined the application's overall structure and interaction flow. We modeled the design using the Unified Modeling Language (UML) to visualize components, actor relationships, and data processing in a structured, standardized form (Siska Narulita et al., 2024). The system utilizes two primary actors: the User and the System. Users begin by registering and inputting demographic and physical data, including age, sex, height, weight, and activity level. The system then processes this information via the Mifflin–St Jeor algorithm to calculate the Basal Metabolic Rate (BMR). Subsequently, BMR is multiplied by an activity factor to determine the Total Daily Energy Expenditure (TDEE). Concurrently, the Body Mass Index (BMI) is computed to classify the user's nutritional status. Finally, as Figure 1 illustrates, the Use Case Diagram details core interactions like registration, profile management, calorie calculation, and result visualization.

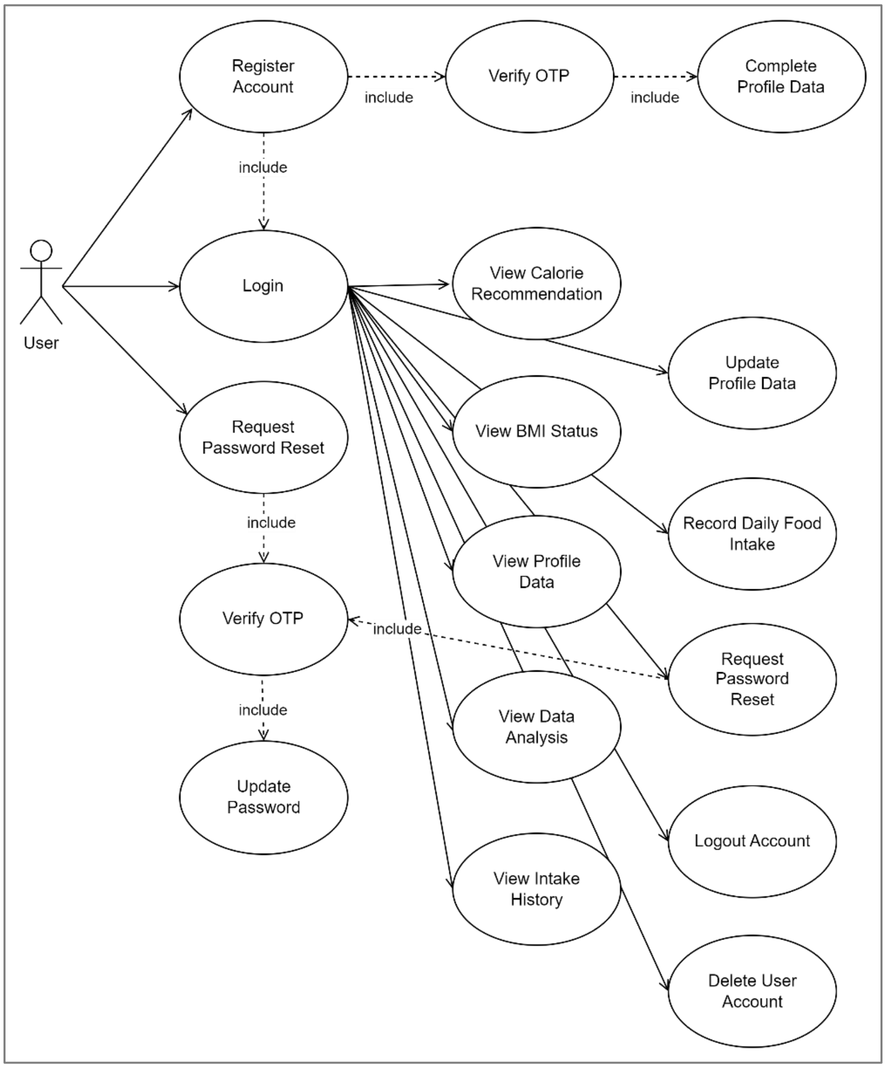

Figure 2: Use Case Diagram of the Calorie Monitoring Application

Application Display

The system development resulted in a functional mobile app for calorie monitoring. We used the Flutter framework for the user interface and Flask for backend data processing. The app's design is clear, accessible, and responsive. This ensures the best experience for all Android users. All features follow user-centered design principles for easy interaction and accurate results.

1. Home Page

   The Home Page functions as the main activity center of the application, displaying the user's daily energy requirements based on personal data such as age, gender, weight, height, and activity level. As shown in **Figure 3**, this page allows users to monitor total calories consumed, remaining daily calories, and macronutrient distribution including carbohydrates, protein, and fat. The system also provides daily calorie analysis, including BMR (Basal Metabolic Rate), TDEE (Total Daily Energy Expenditure), and calorie recommendations tailored to the user's health goals.

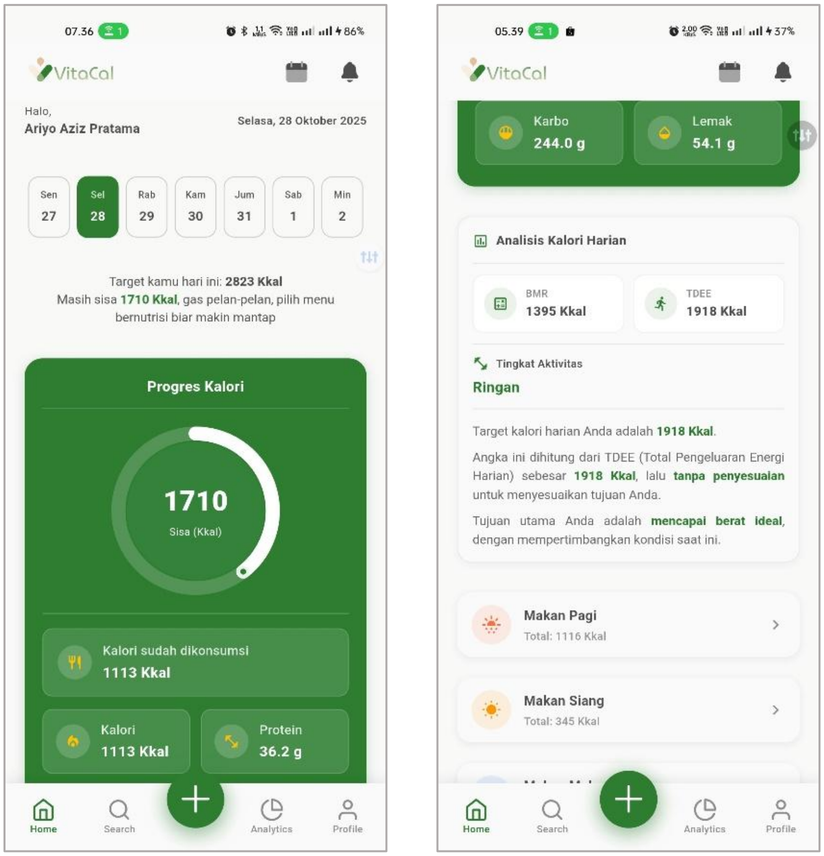

Figure 3. Home Page Interface

2. Registration and Profile Setup

The next component is the Profile Initialization Module, which manages user data input during the registration process. As shown in **Figure 4**, this module collects key user parameters such as age, gender, height, weight, and activity level. Upon completion, the system automatically calculates the Basal Metabolic Rate (BMR) using the Mifflin–St Jeor equation, as well as the Body Mass Index (BMI) and Total Daily Energy Expenditure (TDEE). All generated data are stored within the user's profile to enable real-time computation and continuous personalization without requiring repeated manual input.

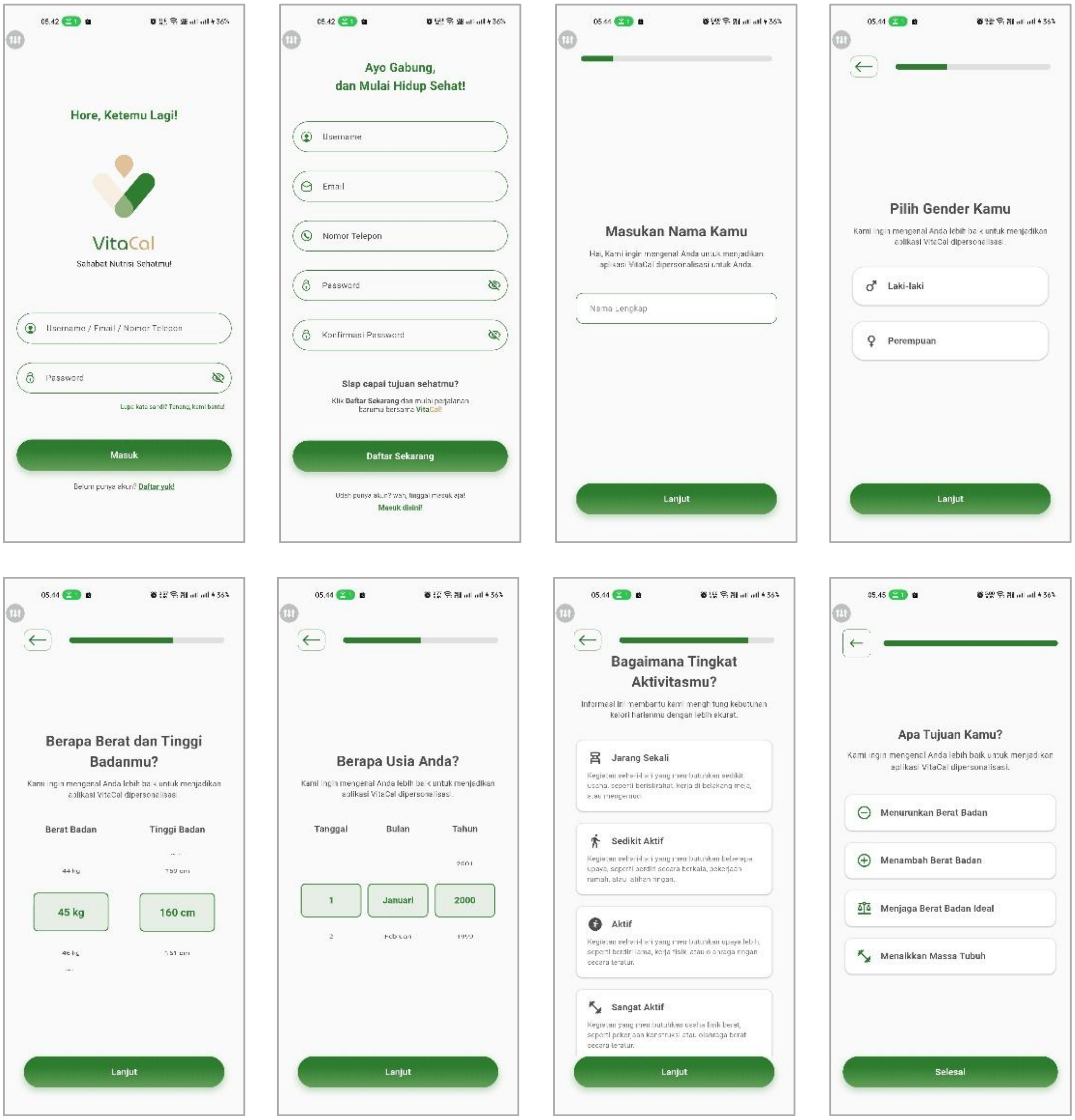

Figure 4. Registration and Profile Setup Interface

3. BMI Analysis Interface

The BMI Analysis Page, as shown in **Figure 5**, provides a visual representation of the user's Body Mass Index (BMI) based on the World Health Organization (WHO) classification standards (2020). The interface presents the calculated BMI value along with its corresponding weight status category, such as underweight, normal, overweight, or obesity levels I–III. This module helps users interpret their nutritional condition through an intuitive gauge indicator, supporting awareness and self-monitoring toward achieving a healthier body composition.

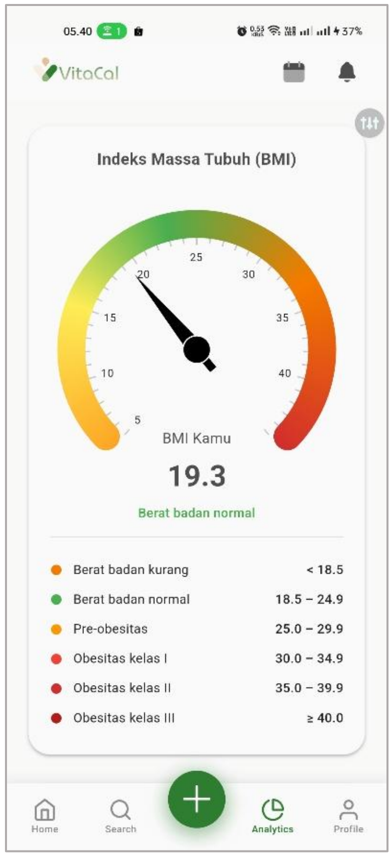

Figure 5. BMI Analysis Interface

4. Calorie and Weight Tracking Dashboard

The Calorie and Weight Tracking Page, illustrated in **Figure 6**, provides users with a historical overview of their nutritional and body weight progress. The upper section presents a bar chart comparing daily calorie consumption with the system's recommended intake, allowing users to evaluate adherence to their dietary targets. Meanwhile, the lower section displays a line chart visualizing body weight changes over time, enabling trend analysis and goal monitoring. This feature supports long-term self-assessment and helps maintain consistency in healthy lifestyle management.

Figure 6. Calorie and Weight Tracking Dashboard

5. Food Search

The Food Search Page, as illustrated in **Figure 7**, provides users with access to a comprehensive food database containing nutritional information for various meals. Through this feature, users can search for specific food items and view their corresponding calorie values, enabling accurate tracking of energy intake. The categorized meal options (breakfast, lunch, and dinner) simplify logging and ensure that daily consumption records remain structured and consistent.

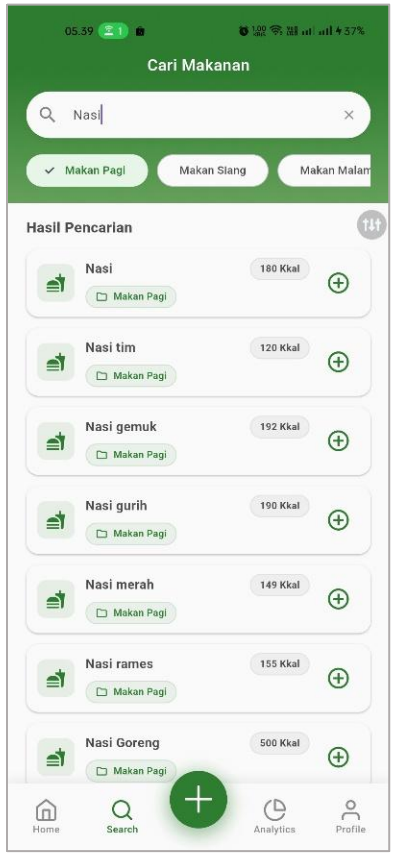

Figure 7. Food Search Interface

System Testing

This stage focused on verifying the functionality and computational accuracy of the developed calorie monitoring application. The evaluation process consisted of two main phases: functional testing and computational validation. In the first phase, we employed the Black-box testing method to assess system behavior based solely on input-output functionality without examining internal code structures (Mahendra & Asmarajaya, 2023). We tested each feature to ensure it performed according to predefined functional requirements and user expectations. The results of the functional testing are presented in **Table 4**.

Table 4. System Functionality Testing Results

No	Feature Tested	Test Scenario	Expected Result	Status
1	User Registration	User enters valid registration data	Account successfully created and stored in the database	Passed
2	OTP Verification	User enters the correct OTP sent to the registered number or email	OTP verified successfully and user redirected to the next step	Passed
3	Personal Data Input	User fills in personal data including age, gender, height, weight, and activity level	The system automatically calculates BMR, BMI, and TDEE values	Passed
4	Login	User enters valid login credentials	System authenticates successfully and navigates to the Home Page	Passed
5	Home Page	Displays daily energy requirements and macronutrient summary	Personalized dashboard matches user profile data accurately	Passed
6	Analysis Page	Displays BMI classification and calorie tracking visualization	Data visualized correctly and updated in real time	Passed
7	Profile Page	Displays and allows modification of stored personal information	Updated data saved successfully and recalculations performed automatically	Passed
8	Food Search	Retrieves food nutritional information from the Kaggle dataset	Nutritional data displayed accurately and search function operates properly	Passed

As shown in **Table 4**, all features successfully met the expected performance criteria during testing, confirming that the system operates smoothly and functions in accordance with its design specifications. No critical errors or failures were identified in either the user interface or data-processing layer.

In the second phase, comparative validation was performed to assess the accuracy of the system's algorithmic computation. This involved comparing the Basal Metabolic Rate (BMR), Body Mass Index (BMI), and Total Daily Energy Expenditure (TDEE) calculated by the system with manually computed values. The validation results are presented in **Table 5**, illustrating minimal deviation between manual and system-generated outputs.

Table 5. Validation of Manual and System Calculations

User	Gender	Age (yrs)	W (kg)	H (cm)	Activity	BMR (M/S)	BMI (M/S)	TDEE (M/S)	Dev (%)
1	Male	21	49.5	160	Light Active	1395 / 1395	19.3 / 19.3	1918 / 1918	0.00
2	Female	20	55	155	Sedentary	1258 / 1258	22.9 / 22.9	1509 / 1509	0.00
3	Male	21	70	170	Moderately Active	1673 / 1663	24.2 / 24.2	2593 / 2577	0.61
4	Female	19	60	162	Light Active	1357 / 1352	22.9 / 22.9	1866 / 1858	0.43
5	Male	21	50	170	Very Active	1463 / 1463	17.3 / 17.3	2523 / 2523	0.00

As presented in **Table 5**, the difference between manual and system-based calculations was consistently below 1%, confirming the high computational precision and reliability of the Mifflin–St Jeor algorithm's implementation.

To further verify the accuracy of the calorie recommendation logic, a comparison between manual and system-generated daily calorie recommendations was also conducted. The results, shown in **Table 6**, indicate that the system consistently produced near-identical calorie recommendations for all activity categories.

Table 6. Comparison of Calorie Recommendations

User	Activity	Manual (kcal)	System (kcal)	Dev (%)	Remark
1	Light Active	1918	1918	0.00	Maintain
2	Sedentary	1509	1509	0.00	Maintain
3	Moderately Active	2593	2577	0.61	Maintain
4	Light Active	1866	1858	0.43	Maintain
5	Very Active	2823	2823	1.15	Surplus +300

As seen in **Table 6**, all recommendations remain within an acceptable deviation margin of less than 1%, confirming the system's consistency and precision in producing personalized calorie targets. These findings validate that the system effectively applies the Mifflin–St Jeor algorithm and can reliably support user-specific nutritional monitoring.

DISCUSSION

The developed calorie monitoring application validates that the Mifflin–St Jeor algorithm can be effectively implemented to generate accurate and personalized energy recommendations. Validation results confirmed a deviation of less than 1% between manual and system calculations, indicating high computational reliability across diverse user profiles. These findings are consistent with studies by (Meidiawati et al., 2024) and

(Qamaruzzaman et al., 2022). Both studies also confirmed that the Mifflin–St Jeor model achieves higher accuracy than traditional methods such as the Harris–Benedict equation. Furthermore, the integration of BMI and TDEE into a single workflow enables the system to deliver adaptive feedback aligned with user activi ty levels and health goals, thereby enhancing usability and engagement in daily nutritional monitoring.

Compared to previous studies, this research provides a more comprehensive integration by combining Basal Metabolic Rate (BMR), Body Mass Index (BMI), and Total Daily Energy Expenditure (TDEE) into a single adaptive framework. Similar to the mobile applications developed by (Sulaiman et al., 2023) and (Ulhaq et al., 2025), the system emphasizes usability and real-time monitoring; however, it advances beyond these works by offering a data-driven personalization process that dynamically adjusts calorie recommendations according to user activity levels and goals. This integration strengthens the theoretical contribution by demonstrating that algorithmic precision and user-centered design can coexist effectively in health-monitoring systems.

However, the system's primary limitation is its nutritional dataset. The integrated data is sourced from a local Kaggle Nutrition Dataset, which lacks a wide variety of international foods. This limitation can compromise the accuracy of nutritional information, especially for users with diverse dietary habits. Future development will focus on integrating global food APIs, such as FatSecret or OpenFoodFacts, to expand data coverage. Additionally, development will include an image recognition feature, enabling users to upload food photos for automatic calorie and nutrient estimation. These integrations are expected to improve data entry efficiency and strengthen the application's adaptive functionality, ultimately evolving it into a more intelligent and globally adaptable, AI-based nutrition monitoring platform.

CONCLUSION

The developed calorie monitoring application successfully demonstrates the implementation of the Mifflin–St Jeor algorithm for calculating daily energy requirements with high accuracy. Validation testing revealed a deviation of less than 1% between manual and system-based calculations, confirming the algorithm’s precision across diverse user profiles. The integration of BMI and TDEE further enhanced personalization by providing adaptive calorie recommendations tailored to user activity levels and health goals.

Despite its effectiveness, the application's primary limitation is its reliance on a localized nutritional dataset, which limits food diversity. Therefore, future work will focus on integrating global food APIs (e.g., FatSecret or OpenFoodFacts) and developing a food image recognition feature for automatic calorie and nutrient detection. These enhancements are expected to improve the system’s adaptability, usability, and scalability, transforming it into a more intelligent, AI-based nutrition monitoring platform capable of serving users with diverse dietary patterns worldwide.

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