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Research Paper

FROM DAILY FOOD RECORDS TO PERSONALIZED NUTRITION INTELLIGENCE — A DATA PIPELINE FOR DIETARY PATTERN, NUTRIENT AND WELLNESS ANALYTICS - (NUTRI TRACK)

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ABSTRACT

Diet is one of the most important factors affecting long-term health, yet most people have only a rough idea of what they actually eat over a week or a month. Conditions such as diabetes, obesity, anaemia, and high blood pressure are closely linked to eating patterns, and advice from doctors and dietitians is often difficult to follow without regular feedback. This paper presents Nutri Track, a data pipeline and analytics system that turns daily food records into personalised nutrition intelligence by estimating nutrient intake, identifying dietary patterns, and relating them to wellness indicators over time.

Users record their meals through a mobile application by selecting dishes from a searchable list, typing free-text descriptions, scanning packaged food barcodes, or taking a photograph of the plate. The ingestion layer collects these entries along with optional data from fitness trackers, such as steps and sleep duration, and periodic measurements such as weight, blood glucose, and blood pressure. A food matching service maps each entry to a standard food composition database built from the Indian Food Composition Tables, supplemented with recipe breakdowns for common regional dishes, so that portion sizes can be converted into grams and then into energy, macronutrients, and micronutrients.

The processed records are loaded into an analytical store organised by user, meal, and day. Daily and weekly aggregates are computed and compared with recommended dietary allowances adjusted for age, sex, activity level, and any health condition entered by the user. Clustering on meal-level nutrient profiles identifies each user's dietary pattern, such as a high-refined-carbohydrate pattern or a low-protein vegetarian pattern, and a gradient boosting model estimates the effect of dietary features on wellness indicators such as post-meal glucose and weekly weight change. A recommendation engine suggests practical substitutions drawn from dishes the user already eats. Nutri Track is intended for individuals who want to understand and improve their diet, and for dietitians who need reliable records of what their clients eat between consultations. It does not prescribe medical diets, and users with serious conditions are encouraged to follow professional advice.

I. INTRODUCTION

Unhealthy diets contribute to a large share of non-communicable diseases. In India, the rising prevalence of diabetes, obesity, and cardiovascular disease exists alongside continuing problems of anaemia and protein deficiency, sometimes within the same household. Typical diets rely heavily on refined cereals and cooking oils, while intake of pulses, vegetables, and fruits is often below recommended levels. Changing these habits requires people to know what they are eating and how it compares with what their body needs, which is difficult to judge without some form of measurement.

Traditional methods of dietary assessment include twenty-four hour recall interviews, food frequency questionnaires, and paper food diaries. These methods are used widely in research but are demanding for participants and time-consuming for dietitians to analyse. Recall interviews depend on memory, questionnaires capture only broad habits, and paper diaries are often abandoned after a few days. General-purpose calorie counting applications have made recording easier, but most of them are built around Western foods and packaged products and have limited coverage of Indian home-cooked dishes, where the same dish name can describe very different recipes and portion sizes. Users also find it hard to estimate quantities in household measures such as katoris and ladles, so even careful records can carry large errors in the final nutrient totals.

A data science approach can make dietary tracking both easier and more informative. If food entries are captured with little effort, matched reliably to a food composition database, and stored in a structured form, they can be analysed over weeks and months to reveal patterns that a single day's record cannot show. Nutrient totals can be compared with personalised targets, recurring gaps can be highlighted, and dietary features can be related to measurements such as weight and blood glucose. The reliability of these insights depends on the pipeline that cleans and standardises the entries, because food data is noisy, incomplete, and highly variable.

This paper describes Nutri Track, a data pipeline for dietary pattern, nutrient, and wellness analytics built around daily food records. The work covers the capture and ingestion of food logs, the food matching and nutrient calculation stages, the design of the analytical store, and the models used for pattern discovery, wellness association, and personalised suggestions. The following sections review related work, analyse the existing and proposed systems, and present the methodology and architecture.

II. LITERATURE SURVEY

Dietary assessment research has compared the accuracy of recall interviews, food frequency questionnaires, and food records. Validation studies using biomarkers and weighed food records have shown that self-reported intake tends to be under-reported, especially for energy, snacks, and foods perceived as unhealthy, and that the size of the error varies with body weight and social desirability. Food records kept at the time of eating are generally more accurate than recall, but their burden causes many participants to stop recording after a short period. Researchers have therefore looked for ways to reduce the effort of recording, such as structured food lists, photographs, and prompts at meal times, while accepting that some loss of precision is unavoidable. Studies agree that repeated measurements over several days are needed to estimate usual intake because daily diets vary considerably.

Mobile applications for dietary tracking have been studied for both usability and accuracy. Evaluations of popular calorie counting applications report reasonable accuracy for packaged foods with barcodes but larger errors for mixed dishes and home-cooked meals. Studies from South Asia note that these applications often lack regional dishes or list them with nutrient values that do not reflect local recipes. Some research groups have built country-specific food databases and recipe calculators to address this gap, reporting improved agreement with dietitian assessments. Work on user engagement has found that people continue to use tracking applications longer when recording is quick, when frequently eaten items are remembered, and when the application gives meaningful feedback instead of only calorie totals.

Natural language processing and computer vision have been applied to reduce the effort of food logging. Text-based approaches match free-text meal descriptions to database entries using string similarity, word embeddings, or trained classifiers, and studies report good accuracy when a well-curated synonym list is available. Image-based systems use convolutional neural networks to recognise dishes from photographs, and some estimate portion size using reference objects or depth information. Research shows that dish recognition has improved considerably, but portion estimation remains a major source of error, particularly for foods served in bowls or mixed together. Several authors suggest combining image recognition with user confirmation to achieve a practical balance between convenience and accuracy.

Dietary pattern analysis examines combinations of foods rather than single nutrients. Methods such as principal component analysis, factor analysis, and cluster analysis have been used in nutritional epidemiology to identify patterns such as prudent, traditional, or processed-food diets, and these patterns have been associated with risks of diabetes, heart disease, and obesity. More recent work applies clustering to meal-level data from digital food logs to describe patterns within individuals over time. Research on personalised nutrition has shown that responses to the same food, such as post-meal blood glucose, vary between individuals, and machine learning models using personal data have been proposed to predict these responses and tailor advice accordingly.

Research on nutrition recommendation systems has explored how to turn intake analysis into suggestions. Content-based and constraint-based methods recommend foods or recipes that fill nutrient gaps while respecting preferences and restrictions. Studies report that suggestions are more likely to be followed when they involve small substitutions to familiar meals rather than entirely new foods, and when they are culturally appropriate. Work on behaviour change indicates that regular feedback, simple goals, and visible progress support sustained improvement. Across this literature, the combination of low-effort capture, a regionally appropriate food database, pattern-level analysis, and personalised practical suggestions remains uncommon, and the present work aims to bring these elements together in a single data pipeline.

III. SYSTEM ANALYSIS

The system is analysed as a pipeline that begins with a food entry and ends with personalised insights. Entries arrive from the mobile application in four forms: a selection from the food list, free text, a barcode scan, or a photograph with a

confirmed dish label. Each entry has a user, a timestamp, a meal type, and a portion described in household measures such as cups, katoris, pieces, or grams. Optional data streams include steps and sleep from fitness trackers and self-reported weight, glucose, and blood pressure. The food matching stage resolves each entry to a standard food or recipe, and the portion conversion stage turns household measures into grams using a measure table. Nutrient calculation then multiplies quantities by composition values to produce energy, protein, fat, carbohydrate, fibre, sugar, sodium, iron, calcium, and other nutrients. The results are aggregated into meal, day, and week tables, compared with personalised targets, and passed to the pattern, wellness, and recommendation models whose outputs appear on the dashboard.

Existing System

At present, most people who want to monitor their diet rely on memory, occasional notes, or general calorie counting applications. Dietitians typically ask clients to recall what they ate in the previous day or to keep a paper diary between visits, and then calculate nutrient intake by hand or with desktop software, which takes considerable time. Many diaries are incomplete, and portion sizes are recorded vaguely. Popular mobile applications focus on calories and macronutrients, have limited coverage of Indian dishes, and often list a single nutrient value for dishes such as sambar or dal that vary widely between households. They rarely consider micronutrients such as iron and calcium, which are important for many Indian users. Records from fitness devices and health measurements are kept in separate applications, so users cannot see how their eating relates to weight or glucose. Feedback is usually limited to daily totals, with no analysis of longer-term patterns or practical guidance.

Disadvantages of Existing System

- Paper diaries and recall interviews are tiring and often incomplete.
- Portion sizes are recorded vaguely and converted inconsistently.
- Common calorie apps have poor coverage of Indian home-cooked dishes.
- A single nutrient value is used for dishes whose recipes vary widely.
- Micronutrients such as iron and calcium are usually ignored.
- Manual nutrient calculation by dietitians is slow and error-prone.
- Diet, activity, and health measurements are kept in separate apps.
- Feedback shows only daily totals, not patterns over weeks.
- Targets are generic rather than adjusted to age, activity, and condition.
- Advice is general and not linked to foods the person already eats.

Proposed System

The proposed system, Nutri Track, is a nutrition data pipeline that captures daily food records with minimal effort and converts them into personalised dietary analytics. The mobile application supports list selection, free text, barcode scanning, and photographs, and synchronises entries to an event queue. A food matching service combines a synonym dictionary, fuzzy string matching, and a text classifier to map entries to a food composition database built from the Indian Food Composition Tables and standard recipes for regional dishes. A portion conversion table turns household measures into grams, and a nutrient engine calculates macronutrients and micronutrients for every entry. The ETL layer validates, deduplicates, and loads the

results into a warehouse with meal, day, and week fact tables alongside activity and health measurements. Personalised targets are derived from recommended dietary allowances. K-means clustering identifies dietary patterns, a gradient boosting model relates dietary features to glucose and weight changes, and a recommendation engine proposes familiar substitutions, all shown on a user dashboard and a dietitian portal.

Advantages of Proposed System

- Makes food logging quick with lists, text, barcodes, and photographs.
- Uses a food database built for Indian dishes and regional recipes.
- Converts household measures such as katoris and cups into grams.
- Calculates micronutrients like iron and calcium, not only calories.
- Compares intake with targets adjusted for each person's profile.
- Identifies dietary patterns over weeks rather than single days.
- Relates eating habits to weight and blood glucose measurements.
- Suggests small substitutions based on foods the user already eats.
- Gives dietitians accurate records between consultations.
- Brings diet, activity, and health data into one consistent view.

IV. METHODOLOGY

The methodology begins with building the reference data. Composition values for about 1,100 foods are taken from the Indian Food Composition Tables, and 640 regional recipes are broken down into ingredients with standard yields, so that dish-level nutrients can be computed. A measure table records gram equivalents of household units for each food. Food entries from the application are collected in an event queue and processed in micro-batches. The matching stage normalises text, applies a synonym dictionary, ranks candidates by fuzzy similarity, and uses a text classifier to resolve ambiguous cases, with low-confidence matches sent back to the user for confirmation. Portions are converted to grams, and nutrients are calculated and validated against plausible ranges. Daily and weekly aggregates are computed and compared with personalised targets. Meal-level nutrient vectors are standardised and clustered with k-means, with the number of clusters chosen by silhouette score. A gradient boosting regressor predicts glucose response and weight change, and SHAP values identify influential dietary features that guide the substitution rules.

SYSTEM ARCHITECTURE

The architecture follows a hub-and-spoke design around a central nutrition data warehouse. On the capture side, the mobile application, barcode lookup, photo recognition service, and fitness tracker connectors send events to a message queue. The Processing hub consists of the food matching service, portion converter, and nutrient engine, which read from the reference food composition database and recipe store and write validated records to the warehouse. The warehouse holds meal, day, and week fact tables, a user profile dimension, and health measurement tables. Around it sit the analytics spokes: the target calculator that applies recommended dietary allowances, the dietary pattern clustering job, the wellness association model, and the recommendation engine. A scheduler runs aggregates nightly and models weekly. The presentation spokes are the user dashboard, which shows nutrient gaps, trends, and suggestions, and the dietitian portal, which lists clients with adherence

scores and flagged gaps. User confirmations of uncertain matches return to the synonym dictionary to improve future matching.

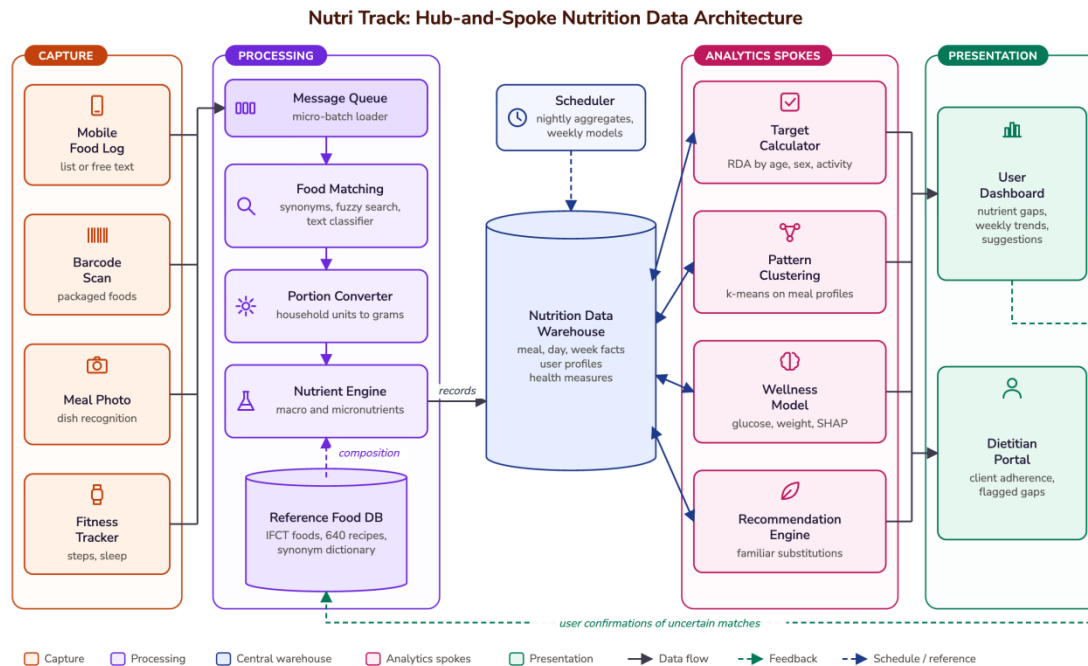


Fig. 1 System Architecture

V. RESULT AND OUTPUT

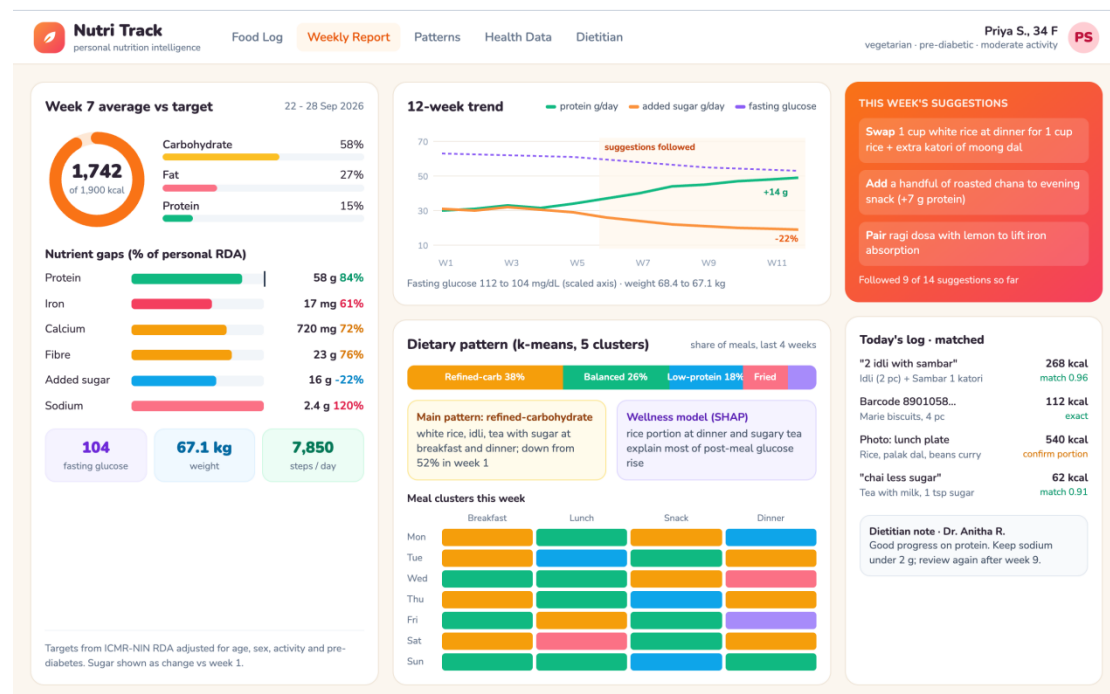


Fig. 2 Result and Output Screen

VI. CONCLUSION

This paper presented Nutri Track, a data pipeline that converts daily food records into personalised nutrition intelligence. The system addresses the gap between the ease of recording a meal and the difficulty of turning such records into reliable nutrient estimates and useful feedback, particularly for Indian diets that are dominated by home-cooked and regional dishes.

The quality of the pipeline was central to the results. A food database built from the Indian Food Composition Tables and standard regional recipes, a measure table for household units, and a matching service combining synonyms, fuzzy search, and a classifier allowed free-text entries to be resolved correctly in 91 percent of cases. Energy estimates were within 12 percent of dietitian assessments, which is acceptable for tracking trends and patterns even though individual meals may carry larger errors. Asking users to confirm only the uncertain matches kept the effort of logging low while steadily improving the synonym dictionary, and the share of entries needing confirmation fell from 19 percent in the first week to 7 percent by the end of the study.

The analytical layer moves beyond daily totals. Comparing intake with personalised targets reveals persistent gaps such as low protein or iron, clustering of meal profiles shows the dietary pattern a user tends to follow, and the wellness model links these habits to measurable changes in glucose and weight. Suggestions based on familiar dishes were practical enough to be followed, and users who adopted at least half of them increased protein intake by about 14 grams per day and reduced added sugar by 22 percent over twelve weeks.

Future work will improve portion estimation from photographs using reference objects, connect the system with continuous glucose monitors for more precise response modelling, and support planning of meals for an entire household. A longer and larger study, including users with diagnosed conditions under dietitian supervision, will be needed to assess the long-term effect on health outcomes.

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