

Design, Mathematical Basis and Evaluation of a Cloud-Hosted Calorie Tracking and Nutrition Management System on AWS Elastic Beanstalk

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ABSTRACT

Self monitoring of eating habits is commonly done by people to track their diet. Weight management and health care but paper diary spreads. The sheets are responsible for performing lookups and calculations on their own. This paper This is an online application for tracking meals on a server. Automated Nutrient Extraction and TDEE (Total Daily Energy Expenditure). TDEE calculation and aggregate reports. The system is Django-based application built on SQLite for development purposes and PostgreSQL database management system. In production, it runs on AWS Elastic Beanstalk. The quantitative component is defined by me as "Mifflin-St Jeor". Resting energy equation, Activity Factor Model of Total Daily Energy Expenditure. Nutrient per 100g scale and daily/weekly aggregate. The sensitivity of TDEE for each variable is calculated here. Error due to treating milliliters as grams. Using the Records are kept by us at work; therefore, We have an Atwater factor. Nutrient consistency check for retrieved data Report Manual. Functional tests for 14 items out of which 12 are exercised and 2. were not. There are no data on loads and usability of this product. because none were taken. Terms calorie tracker ndex Calories per day (TDEE) Mifflin St Jeor Django. Elastic Beanstalk AWS Nutrition Informatics.

INTRODUCTION

Self monitoring of diet by keeping track of food intake. Paring this up against an objective is a fundamental concept of life style and. weight interventions [1]. The use of digital technology reduces labor requirements for it. Tasks are more effective at improving compliance compared to papers. methods [2]. There are also some expenses associated with manual processes for this project. Looking for nutrients information, performing calculations on them. Keeping a record at an easily reachable location. This article is about (i) designing an architecture for. Single tenant per account calorie tracker for a person. (1) aged cloud platform; (2) a concise mathematical model of it. The formula of this model is based upon it such as sensitivity and other parameters like that. Error limits; and (iii) an analysis based on actual data of. The implementation of this model is done by specifying certain limitations clearly.

Related Work

Self monitoring through digital means is an important part to behavioral studies. weight-loss programmes. Systematic Review of 59 Interventions. Studies on diet showed a relationship between low and high intensity of food intake. Self monitoring can help with losing weight whereas inconsistency does not Adherence measure limits comparisons of methods.

Objectives

The paper deals with four problems that are addressed by this article. Answered by an implementation of this technology instead of being provided through it. simulated one How should an app for tracking calories be designed. The same program is used for developing databases. and a managed production platform? 2) Which closed-form relations (resting energy, activity Scaling, Nutrient Scaling, Aggregation is done by this system. How dependent is it upon them. Input 3) What are the nutrient values that were obtained from and saved by me. The system agrees to an easy energy balance test of this product. macronutrients? 4) What can and cannot be claimed from manual functional Testing and what else remains unanswered. This paper is written by means of documents and experiments conducted on this topic. exist. This is not a claim of clinical effectiveness or benefit to users. Performance at high loads or speed tests.

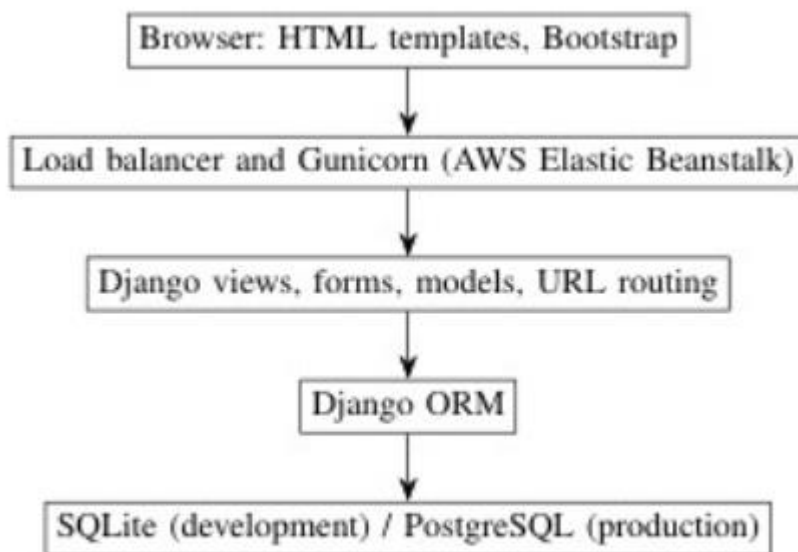


Fig. 1. System architecture and request path.

System Architecture

There are three levels of this system as shown by Fig. The presentation layer HTML template styles using Bootstrap. The application Django view, form model URL routing layer is used by it. Data Layer sqlite Development Database Postgresql. For production purposes, both are accessed via Django ORM; thus. No change to any applications' codes there. The application It runs on AWS Elastic Beanstalk that provides an EC2 instance. For example, a load balancer and health checker for gunicorn. as the WSGI server. There are many users for each meal, 1, M, but only one TDEE. profile (1:1), as listed in Table I. All meal views filter by the A logged in user means that an individual can access another person's account. entries.

Mathematical Foundations

The document lists all formulas that are used for this purpose.

Resting Energy (BMR)

Table II is an abbreviation for "Resting Energy" which stands $BMR = 10W + 6.25H - 5A + s$, (1) as BMR. Mifflin-St Jeor formula is used by this model [12]. With weight W in kg, height H in cm, and age A in years BMR

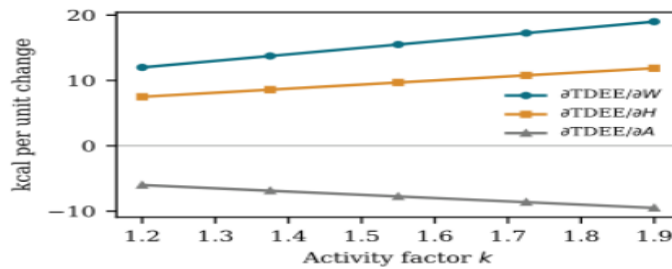


Fig. 2. Partial derivatives of TDEE with respect to weight, height and age as a function of the activity factor.

Total Daily Energy Expenditure

$= 10W + 6.25H - 5A + s$. Where $s = +5$ for males and $s = -161$ TDEE = $k \cdot \text{BMR}$, (2)

for females. The gender Offset difference of 166 kcal per day during exercise scaling. Total Daily Energy Expenditure B. TDEE is modelled as a multiplicative physical-activity-level (PAL) scaling of BMR TDEE= $k \cdot \text{BMR}$ (2) For sedentary, light $k=1.2, 1.375, 1.55, 1.725, 1.9$. moderate, active and very active respectively. This lumps Thermal effects from eating, physical inactivity and exercise are included here. One of them is an approximate value for another term "vali". dations report

$\partial TDEE$

$\partial W = 10k, \partial TDEE$

$\partial H = 6.25k, \partial TDEE$

$\partial A = -5k. (3)$

sizeable individual-level error for such equations [5], [6]. Sensitivity. Differentiating gives TDEE $W = 10k, \partial TDEE H = 6.25k, \partial TDEE A = -5k$. (3) For $k=1.55$ (moderate) there is an increase of 15.5 kcal/kg. 9.69 kcal per additional cm, -7.75 kcal per additional. year of age. Therefore it is very much dependent on this factor. Weight and a mistake of selected activities matter too much. More than any other type of biometric mistake; moving from $k=1.55$. To 1.725 changes TDEE of 11.3% per individual. The table is called Table III which contains all of them as a function for each activity factor. And Figure 2 shows that all three are linear functions of k . Because The derivative is constant to some degree of order k , first order. Error bounds of measurements are $\partial W, \partial H, \partial A$. $10k\partial W + 6.25k\partial H + 5k\partial A$. For instance, for $k=1.55$ a. A 2 kg weight error of 1 cm height and an age difference of 1 year. Error gives up to $31 + 9.69 + 7.75 = 48.4$ kcal/day; whereas. Choosing a higher level of activities will increase this value for me. Approximately 290 kcal per day from Table IV male profile. Male sedentary value of Table IV, 2013.0 kcal is equal to. The value of a default profile is saved to this project database. Second stored profile age 24 years old height 178 cm weight 74 kg male. Moderate) is defined as $\text{BMR} = 740 + 1112.5 - 120 + 5 = 1737.5$. TDEE = $1737.5 \times 1.55 = 2693.125$; again matching the stored value. record. Figure 3 shows Table IV data plotted against it; there is a gap between them. Sexes is constant at 166k kcal/day, so it widens in absolute terms. Terms are defined by an increase of this variable. C.

TABLE I
DATA MODEL (FROM THE IMPLEMENTED SCHEMA)

Entity	Key fields	Constraint
auth_user	id, username, email, password (hashed)	username unique
tracker_meal	user_id (FK), date, meal_type, food_item, quantity, unit, calories, protein, carbs, fat	UNIQUE (user, date, meal_type, food_item); cascade delete
tracker_tdeecalculator	user_id (one-to-one), age, height, weight, gender, activity_level, tdee	one record per user

TABLE II
NOTATION

Symbol	Meaning
W, H, A	Weight (kg), height (cm), age (years)
s	Gender offset in the BMR equation (+5 or -161)
k	Physical-activity-level (PAL) factor
v, q, n	Per-100 g nutrient value, logged quantity, scaled value
ρ, ε	Liquid density (g/mL), relative unit error
P, C, F	Protein, carbohydrate, fat (g)
$E, \hat{E}, \delta$	Reported energy, Atwater estimate, relative deviation
D_d, B_d	Daily intake and daily balance on date d

TABLE III
SENSITIVITY OF TDEE TO EACH INPUT (KCAL PER UNIT CHANGE)

k	$\partial/\partial W$ (per kg)	$\partial/\partial H$ (per cm)	$\partial/\partial A$ (per year)
1.2	12.00	7.50	-6.00
1.375	13.75	8.59	-6.88
1.55	15.50	9.69	-7.75
1.725	17.25	10.78	-8.63
1.9	19.00	11.88	-9.50

TABLE IV
TDEE (KCAL/DAY) BY ACTIVITY LEVEL FOR THE APPLICATION'S
DEFAULT PROFILE (AGE 18, 170 CM, 70 KG)

Activity factor k	Male (BMR 1677.5)	Female (BMR 1511.5)
1.2	2013.00	1813.80
1.375	2306.56	2078.31
1.55	2600.13	2342.83
1.725	2893.69	2607.34
1.9	3187.25	2871.85

Nutrient Scaling

Nutrient Scaling The nutrient servicere turns values per100g. $n = v \cdot 100 \cdot q$, (4)

For a logged quantity q (grams)and a per-100g value v $n = v \cdot 100 \cdot q$, (4)

Rounded to two decimals, applied separately to energy, protein carbohydrate and fat. Worked example. Chicken data table 1. (120 g 128.40 kcal per 100 g). 107.0 kcal 21.4 g protein and 0.89 g fat per serving, v , 100. With $q = 120$ gives a factor of 1.2. The stored dosa record (12g, 22.08 kcal) = 184.0 kcal, 5.50 g protein, 30.83 g. carbohydrateand1.67gfatper100g,a factor of0.12. These Back calculated by means of stored row rather than being read out. Source data base. 1.2 1.375 1.55 1.725 1.9. Activity factor k 0 1000 2000 3000 TDEE (kcal/day) Male Female Fig.3.

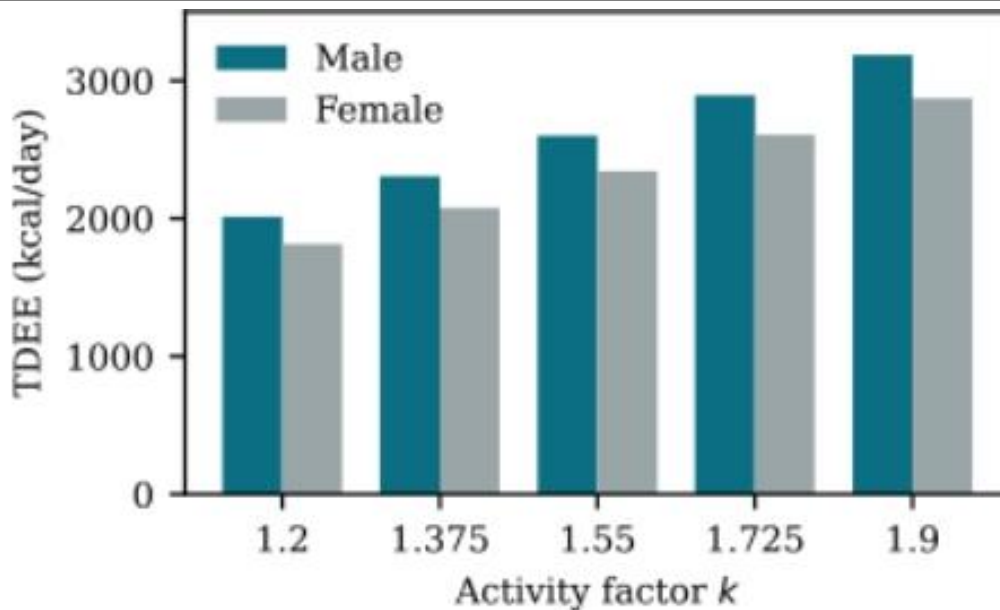


Fig. 3. TDEE of the default profile (18 years, 170 cm, 70 kg) at each activity factor.

TABLE V
CONSISTENCY CHECK ON RECORDS STORED IN THE SYSTEM

Entry	Qty	Reported kcal	P / C / F (g)	$\hat{E}$ (kcal)	δ
Chicken	120 g	128.40	25.68 / 0.00 / 1.07	112.35	-12.5%
Dosa	12 g	22.08	0.66 / 3.70 / 0.20	19.24	-12.9%

TDEE of the default profile (18years,170cm,70kg)at each activity factor. D. Atwater Consistency Check
Sanity-check a retrieved energy value against. Macronutrient using general Atwater

$$e = 1$$

$$r - 1. (5)$$

factor P, C. and F the protein, carbohydrate and fat in grams $E = 4P + 4C + 9F. (6)$

There lative deviation from there ported energy E is $E?E E . (7)$ Table V shows both entries as an overall factor of around 12.5-13% less than what was reported for energy. With only two records This is just an observation; it isn't a statistic. A plausible The cause of this issue is because a first search

D. At water Consistency Check

Result gives you food specific power source information. Factors such as rounding off small numbers, missing items etc. require more data for determining them like aggregation

$$\hat{E} = 4P + 4C + 9F. (6)$$

$$\hat{E} - E$$

$$E. (7)$$

$$\delta =$$

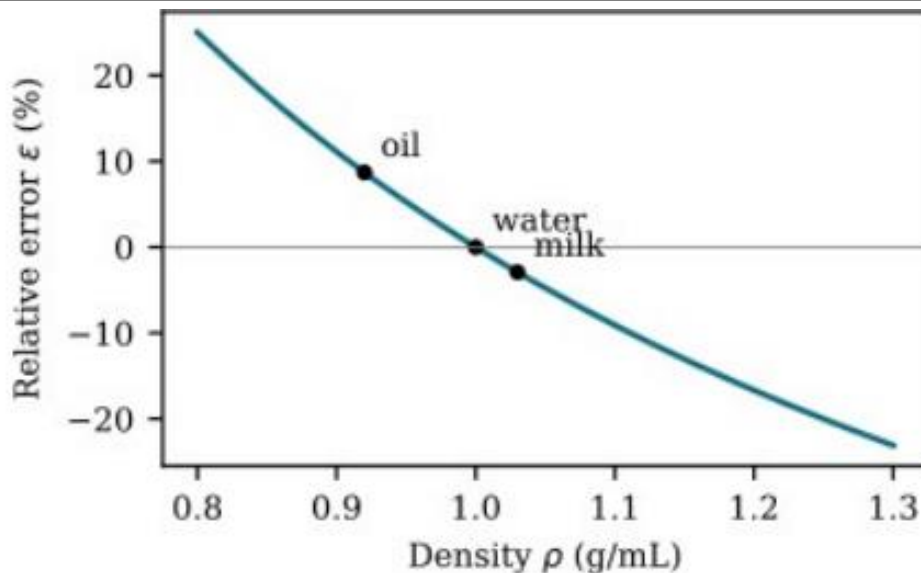


Fig. 4. Relative error introduced by treating millilitres as grams, as a function of liquid density.

and energy balance by E. On behalf of an individual, for a day $c_1 n_0 d$, the amount consumed by them is called "calories". and weekly mean are $7 \text{ Dd } i:\text{date}i=d \text{ ci } D_{\text{week}} = 1 \text{ } 7 \text{ } d=1 \text{ Daily balance to stored targets. } B_d = D_d - TDEE. D_d. (8) (9) \text{ On } 2026-08-08, \text{ for the stored second profile } D=22.08. B = 22.08 - 2693.125 = -2671.05 \text{ kcal (trivial). As there were no other}$

E. Aggregation and Energy Balance

Items recorded for that day. The weekly Dashboard of $7 \text{ } d=1$

$7 \text{ } d=1$

$c_i, \bar{D}_{\text{week}} = 1 \text{ } D_d. (8)$

$D_d = \sum_{i:\text{date}i=d}$

7

$B_d = D_d - TDEE. (9)$

2026-08-02 to 2026-08-08 shows zero on six. Days and 22.08 on the last, giving $\bar{D}_{\text{week}} = 22.08 / 7 = 3.15$. kcal/day. They show how it works these figures are. not a usage study. Figure 5 shows this week as a bar graph. The format of a dashboard is how you present it to me. Standardly an approximation to this problem is not given by 'sys'. $S = ? \text{ dB}$ is called an integrated mass term for tem). change by m ? $S \text{ } 7700 \text{ kg} (10) \text{ About } 7700 \text{ kcal per kg of tissue; this is listed under [insert title]. future work.}$

$D_m \gg S \text{ } 7700 \text{ kg, } (10)$

IMPLEMENTATION

Nutrient Retrieval

A.Nutrient Retrieval The server fetches calories when a user chooses it. The USDA Food Data Center API is used for searching food items like this one. Nutrient list of result's is kcal, proteins carbohydrates. Drate and fat; scale of Migrations are run by ebextensions on a leader node. And

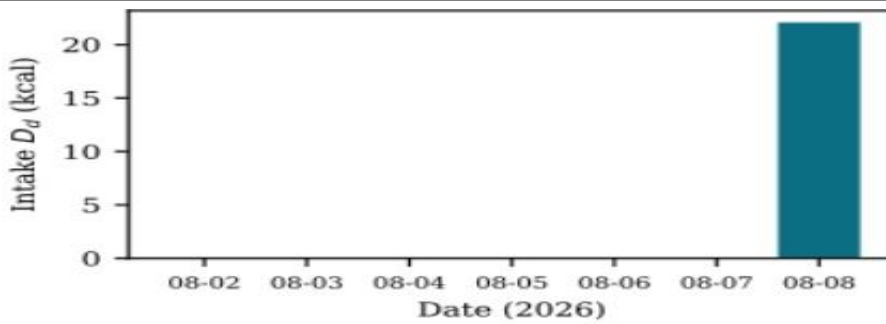


Fig. 5. Daily intake for the week 2026-08-02 to 2026-08-08 from the stored records.

Algorithm 1 Nutrient Retrieval and Save

Algorithm 1 Nutrient Retrieval and Save

Require: food name f , quantity q , unit, signed-in user u
1: query FoodData Central search endpoint with f
2: **if** request fails **then**
3: $(E, P, C, F) \leftarrow (0, 0, 0, 0)$
4: **else**
5: take nutrient list of the first result
6: select energy (kcal), protein, carbohydrate, fat as v_E, v_P, v_C, v_F
7: $n_x \leftarrow (v_x / 100)q$ for each x , rounded to two decimals
8: **end if**
9: on save, recompute n_x on the server
10: store the meal row for $(u, \text{date}, \text{meal_type}, f)$

section v-c. Network failures B. Create Meal Support is for creating, listing, editing and deleting it within a scope of this document. User-ordered by date descending. The TDEE profile The model has an input field and a calculate_tdee ()

B. Meals and TDEE

function. Implement Section V A and B of C. Query aggregation by time period feeds charts to you. Calorie intake of proteins and carbohydrates for D. Unicorn is started by this file through a profile for django WSGI.

C. Dashboards

Deployment

collects static files. Database configuration is switched on/off by this program. If there is an environment variable available for PostgreSQL. De Eb init, eb create and eb deploy are used by employment. And there is an assistant program called fix_ebs. mismatches. E. Deployment Artefacts VI Table is a list of files and command used to deploy this application. ment reproducible

Deployment Artefacts

TABLE VI
DEPLOYMENT ARTEFACTS

Artefact	Role
Profile	Starts Unicorn on the Django WSGI module
.ebextensions	Runs migrations on the leader instance; collects static files
Environment variables	Switch database settings to PostgreSQL
eb init/create/deploy	Create and update the Elastic Beanstalk environment
fix_ebs.sh	Resolves platform version mismatches

TABLE VII
TEST OUTCOME SUMMARY (14 CASES)

Module	Cases	Exercised	Not executed
Authentication	3	3	0
Food logging	4	4	0
TDEE	1	1	0
Dashboard and history	2	2	0
Backup	2	1 (export)	1 (restore)
Deployment	1	1	0
Load and performance	1	0	1
Total	14	12 (85.7%)	2 (14.3%)

Data Isolation and Access

Data Isolation and Access. Password is hashed while username is unique. Each food item search result will be displayed to a logged in customer through their profile page on our website. Cannot access any other person's data to view/modify it. Deleting a User cascade goes towards their food intake. The lookup endpoint, the The allowed hosts configuration and credential management are missing from this file. However, it has been hardened (Section VIII) by G. Django dump data produces a JSON fixture, with a com SQL Export of panion for

Backup

Restoring from load data to a JSON file

TESTING AND RESULTS

Manual testing is done by running through all of them. Browser, local to it and deployed environments. No auto Test suite mated for testing purposes is a load testing tool/usability study. Every twelve exercises gave an outcome as desired by them. (Table VII). 85.7% represents a portion of planned cases. These are tested by means of testing rather than an error rate or reliability estimation. The Restore path and concurrency load behavior are not verified yet. No response-time or throughput figures exist.

DISCUSSION AND LIMITATIONS

Lookup ambiguity. The first search result is taken by me. Return an alternative type of cuisine instead as desired by them. Accuracy, Table V hints at it, see also [4]. Unit handling. Only grams and millilitres exist, and Milliliters are measured in terms of grams according to Section V-C. Uniqueness constraint. User Date Meal Type Food. Constraint of an item to prevent it from being logged more than once. One Meal; User edits an existing entry. Model simplicity. Multiplicative PAL model is ignored by this study. Body composition and metabolism adaptation; Pub. Validations are found to be very low at an individual level [5]. [6]. Validation. No automation of tests, loads etc. User studies do not measure scalability or usability. Hardening. Lookup endpoint access control re-Strictness is permitted for host; also keep credential away from me. Source codes must be available for wider usage; a threat of validity. Construct validity. Atwater checks are used for storing data. Energy estimation by means of an overall factor and specific to foods. Legitimately differs from 4/4/9, so a deviation is an indicator of. Review instead of Proof for errors. Internal validity. The Consistency checks are based upon two documents and a TDEE calculation. On two stored profiles, there is no support for an empirical argument. External validity. Every result is obtained by means of an application. And single developer run tests but do not tell us anything else. Other customers' products, food items, equipment or network speeds. Conclusion validity. An 85.7% test rate represents an incidence of cases above expectations. And should not be interpreted to mean reliability. A working cloud hosted calorie tracker is discussed hereby. It specified a quantitative core of this paper that was then measured by means of actual data collection.

records and manual tests. Future research will be on managing databases and. Monitoring service for AWS goals based calories target monitoring system. Weight tracking via a balance equation (Section V-E); an alternative to BMR calculation available for users [5] and [6]; food. Image recognition and recommendation [8]-[11], and Auto. MAT test + Load Test for missing performance. data.

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