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Nutrition Control System Based on Short-term Personal Demands

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Abstract

Personalized nutrition considers an individual's unique genetic, metabolic, and lifestyle factors to create a customized dietary plan tailored to their needs. People seeking to optimize their health and wellness through diet and lifestyle changes can benefit from technological advances in machine learning and deep learning approaches to create personalized models of nutritional requirements that override traditional food plans. These models will provide users with an unprecedented decision tool for informing them of the impact of specific food intake and exercise on their goals. This article presents the architecture, implementation, and preliminary results of a deep learning-based control system for nutrition. It allows users to understand the impact of their food and exercise immediate choices on their goals while reducing user interaction demands. Preliminary results have shown that it is possible to predict BMI (Body Mass Index) accurately within a time window of three days.

Keywords: Deep learning; Machine Learning; Nutrition Control; Personalized Nutrition; Goal Prediction

1. Introduction

A seminal work by The American Nutrition Association involving pioneering thought leaders across disciplines [1] resulted in the following proposal for the definition of Personalized Nutrition (PN):

> ”*a field that leverages human individuality to drive nutrition strategies that prevent, manage, and treat disease and optimize health, and be delineated by three synergistic elements: PN science and data, PN professional education and training, and PN guidance and therapeutics.*”

Science and data are pillars of personalized nutrition used to create personalized models of the effect of food and exercise on the person's goals. However, data should be gathered with minimum interaction costs. When users encounter high interaction costs, they may become frustrated or disengaged, leading to a negative experience with the system. This can lead to low user adoption rates.

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IoT devices to monitor human physical parameters (e.g., heart rate, blood pressure, and oxygen levels) have appeared recently. One of the key benefits of these devices is the ability to reduce human interaction. Wearables such as smartwatches and smartbands can gather and process physical parameters in real time without or with limited human interaction. Several home appliances, such as smart scales, also extend the parameter set provided by wearable devices with additional parameters (e.g., weight, body mass index, body fat percentage, and muscle mass). In nutrition, smart scales may also help control food intake by measuring weight and registering food automatically.

This article presents the architecture, implementation, and preliminary work results of an approach that uses deep learning to predict time series of individualized goals based on food intake, exercise, and physical measurements. It addresses the following research questions:

- RQ1. What architectural elements constitute a system comprising data gathering, data processing, and user feedback presentation activities?
- RQ2. Which devices provide input metrics to predict the impact of food intake and exercise on a person's goals (weight and body mass index)?
- RQ3. What are the features required to predict a person's goals?
- RQ4. What is the person's goals prediction performance?

Previous work on physical goal prediction uses static features to determine the person's condition. Some work uses complex features such as facial images to predict BMI[2]. In contrast, others resort to simple features, such as height, weight, and ethnicity at certain ages, to predict obesity [3] and activities of daily living [4]. Our work addresses the problem of predicting the impact of instantaneous food and exercise on BMI and body weight in a continuum based on previous values of these metrics and food and exercise parameters. The problem is modeled as a time series that allows a person to project the impact of their actions today on the metric associated with their goal.

This paper is divided into several sections. Following this introduction, Section 2 will provide a comprehensive literature review. Section 3 will present the methodology used in this study, detailing the research design, data collection, and analysis techniques employed. The findings of this study will be presented in Section 4, followed by a discussion of the results and their implications. Finally, in Section 5 the paper summarizes the key findings, their contributions to the field, and potential avenues for future research.

2. Related Work

Related work on personalized nutrition has been rapidly expanding in recent years. Many studies have aimed to understand the impact of individual variability on nutrient requirements and how personalized nutrition can be tailored to meet individual needs.

Applying machine learning to nutrition to understand better the complex relationship between diet, genetics, and the microbiome was recently revisited in [5]. The study presented in [6] monitored the week-long glucose levels in an 800-person cohort, measured responses to 46,898 meals, and found high variability in response to identical meals, indicating that universal dietary recommendations may have limited efficacy. To overcome this challenge, the researchers developed a machine-learning algorithm that integrates various blood parameters, dietary habits, anthropometrics, physical activity, and gut microbiota, accurately predicting personalized postprandial glycemic response to real-life meals. An article in [7] explores the relationship between diet and the gut microbiome and how it impacts overall health. It discusses the importance of maintaining a balanced gut microbiome for optimal health and how an unhealthy diet can negatively impact the gut microbiome and lead to various health problems. It identifies a need for new tools to leverage this information for personalized nutrition. Machine learning and big data are proving helpful in developing these tools. The widespread adoption of smartphones presents an opportunity to integrate personalized nutrition into people's daily lives through interactive diet-related applications. The authors of [8] discuss the development of a wearable device for continuously monitoring glucose and lactate in sweat. The device is based on flexible and stretchable materials that can conform to the skin, and it integrates a biosensor that can detect glucose and lactate levels in real-time. The biosensor combines enzymes and nanomaterials to achieve high sensitivity and selectivity. The device was tested on human subjects during exercise and showed a good correlation with glucose and lactate levels in blood samples.

Personalized nutrition software can track an individual's nutrient intake, monitor physical activity, and provide personalized recommendations on healthy food choices, recipes, and meal plans. The authors of [9] present an application for nutrition control that uses smartwatches, smartphones, and smart bottles to reduce user interaction costs. The user can visualize the food plan created by a nutritionist and confirm the food intake or switch food to alternatives. In [10] discusses a computerized personalized nutrition (CPN) tool for hospital dietitians. It includes a rule-based expert feature given up by experienced dietitians and analyzes and reports on malnutrition to help dietitians understand a patient's nutritional trends and provide appropriate care. A survey found that 91.66% of dietitians reported that the CPN facilitates their work and saves 58% of processing time.

This article contributes to the state of the art by proposing a full stack architecture, considering data gathering and control, and considering continuous prediction of the impact of food and exercise on the goals metrics.

3. Architecture

To reduce the probability of user adoption, monitoring the person's goals should rely on an architecture that uses IoT devices to reduce interaction costs between end users and the system. Figure 1 presents the architecture proposed in this article that employs smart objects – such as scales and watches – to gather features and goals metrics data. A deep-learning algorithm processes these data to train the model and predict the next metric value.

Smart devices target the reduction of user interaction costs by measuring important parameters without user intervention. Nutrition devices can be divided into those that:

1. register **food intake attributes**, as the quantity and identification of food that allows the calculation of calories and macronutrients. Smart scales for measuring food intake fit this category.
2. measure the **person's goal accomplishment**. Smart scales for measuring weight, muscle mass, and body fat fit this category.
3. helps to determine **food intake requirements**. Smartwatches enter this category as they provide the calories the person burns during the day doing physical activities.

Smartwatches are valuable nutrition control devices that measure and collect essential metrics, such as the daily calories burned. These calories represent the variable component of energy expenditure associated with physical activity, which adds to the resting energy expenditure determined statically by the person's metabolism. Smart scales can measure the food weight and register the food type with minimum user interaction, using an app that supports the scale. Another type of smart scale measures body parameters (e.g., lean body mass, weight), helping follow the goal metrics (e.g., BMI, weight). The devices build a control system that, with the support of appropriate models, measures the impact of food intake on the person's goals.

3.1. Deep Learning

Deep learning is a subset of machine learning that involves training artificial neural networks to perform complex tasks. It is based on hierarchical learning, where the neural network learns to recognize patterns at different levels of abstraction. The fundamental advantage of deep learning is its ability to automatically learn features from raw data without manual feature engineering.

This article addresses a problem that fits the category of time series regression. We evaluate two different types of neural networks adequate for time series: LSTM (Long Short-Term Memory) and GRU (Gated Recurrent Unit). LSTM [11] are commonly used for time series analysis, such as stock price prediction, weather forecasting, and anomaly detection. They can capture the patterns and trends in sequential data, even in noise or missing data. LSTM uses memory cells to store information over long periods by resorting to three types of gates – input, forget, and output gates – to control the flow of information through the network. GRU is similar to LSTM but uses only two types of gates – reset and update gates – and a more straightforward mechanism called a *hidden state* to capture information about previous time steps.

LSTM and GRU are two popular types of recurrent neural networks (RNN) [12] that have been widely used in various applications due to their ability to handle long-term dependencies in sequential data. These methods are

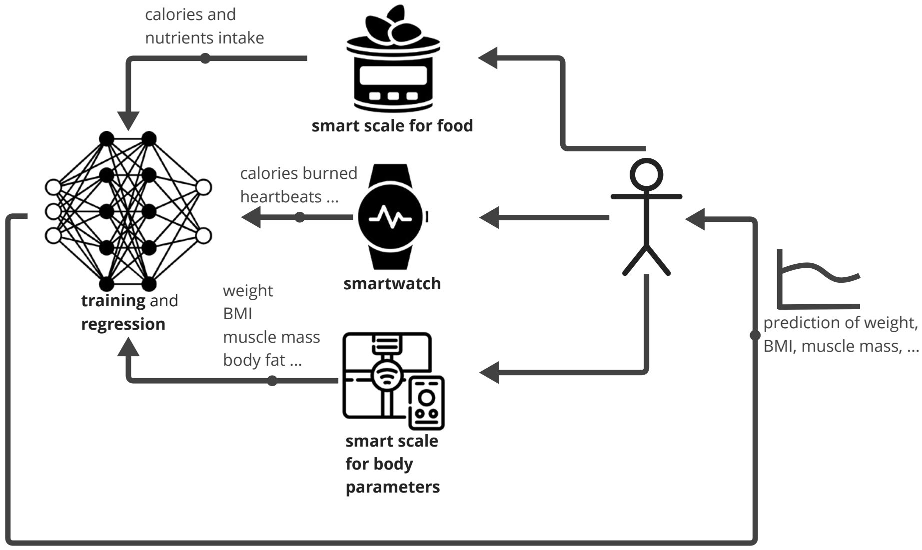


Fig. 1: Person's goals monitoring architecture.

adequate to model the relationship between the performance metric value of some day and the food intake, exercise and the performance metric values of the days preceding it, as defined in Equation 1 and Equation 2 for the Body Mass Index's performance metric (BMI).

$$BMI_t = predict(data_{i-1}, ...data_{i-n}) \tag{1}$$

$$data_i = \{bmi_i, caloriesIntake_i, nutrients_i, exerciseIntensity_i\} \tag{2}$$

4. Experimental Results

We chose a dataset available in [13] to evaluate BMI prediction. Table 1 lists the features chosen for the model inputs and outputs. Some of these features have discriminatory power to be used as predictors. We used the method [14] to filter irrelevant features. Those marked in the table with an asterisk were selected as relevant.

The dataset was broken down into 70% for training and 30% for validation. BMI is calculated as in Equation 3. A person with a BMI above or equal to 25 is overweight. The healthy range is between 18.5 and 24.9.

$$BMI = \frac{weight(kg)}{height^2(meters)} \tag{3}$$

Figure 2 presents the results of the validation phase. It shows only data regarding the validation phase. The time series represents the prediction of BMI at day t+i using the data of all features at day t. Figure 3 presents the BMI time series using the feature values at day t, t-1, and t-2 as predictors. The RMSE – calculated as in Equation 4 – is presented in Table 2.

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(\hat{y}_i - y_i)^2} \tag{4}$$

Two main observations are coming out from the analysis of results:

1. The BMI prediction performance is higher when it uses feature values of several days before the day predicted.
2. The prediction error increases when the prediction time window exceeds 3 days.

Another observation reveals that the prediction performance of methods is very similar.

Id	Date*	TotalSteps*	TotalDistance*	TrackerDistance	LoggedActivitiesDistance
1503960366	0	14727	9.71000003814697	9.71000003814697	0.0
1503960366	1	15103	9.65999984741211	9.65999984741211	0.0
2873212765	0	8859	5.98000001907349	5.98000001907349	0.0
2873212765	21	7566	5.1100001335144	5.1100001335144	0.0
4319703577	0	29	0.0199999995529652	0.0199999995529652	0.0

VeryActiveDistance*	ModeratelyActDistance*	LightActiveDistance*	SedentaryActDistance	Calories*
3.21000003814697	0.569999992847443	5.92000007629395	0.0	2004
3.73000001907349	1.04999995231628	4.88000011444092	0.0	1990
0.129999995231628	0.370000004768372	5.46999979019165	0.0099999997764825	1970
0.0	0.0	5.1100001335144	0.0	1431
0.0	0.0	0.0199999995529652	0.0	1464

VeryActMinutes*	FairlyActMinutes*	LightlyActMinutes	SedentaryMinutes*	WeightKg*	BMI*
41	15	277	798	52.59	22.64
50	24	254	816	52.59	22.64
2	10	371	1057	56.70	21.45
0	0	268	720	57.29	21.69
0	0	3	1363	72.40	27.45

Table 1: Features considered for training.

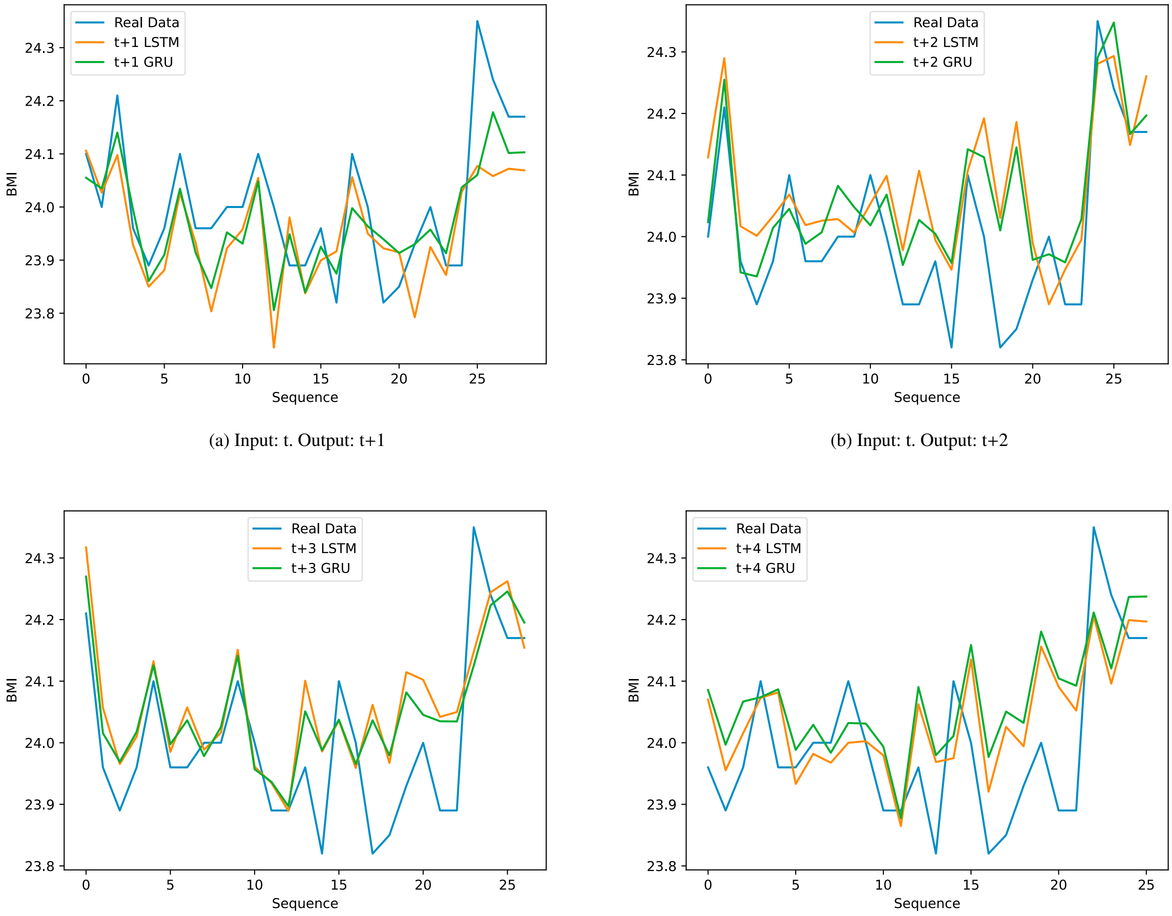
Input	Output	LSTM (RMSE)	GRU (RMSE)
t	t+1	0,02	0,01
t	t+2	0,02	0,01
t	t+3	0,02	0,02
t	t+4	0,01	0,02
t, t-1, t-2	t+1	0,00	0,01
t, t-1, t-2	t+2	0,00	0,00
t, t-1, t-2	t+3	0,00	0,01
t, t-1, t-2	t+4	0,01	0,00

Table 2: Performance metrics results.

5. Conclusion

Personalized nutrition using IoT has the potential to revolutionize the field of nutrition by providing customized recommendations based on real-time data, ultimately leading to better health outcomes for individuals. Traditional food plans demand discipline from the person, forcing them to eat specific food at specified times. Thus, they stop frequently following the food plan. Plus, using software to help people make food intake choices appropriate to their goals may require interaction effort to register and monitor their evolution. IoT can reduce interaction costs, automating many tasks that would otherwise require manual intervention. Interaction costs include the time, effort, and resources needed to complete a job, including information gathering, communication, and coordination. People can use intelligent scales and smartwatches to register food intake and control the accomplishment of their goals with minimum effort.

This article proposes an IoT architecture and a deep learning approach to minimize user interaction with the system. The deep learning model predicted the impact of daily food intake on the person's BMI during the subsequent days. An experimental model evaluation revealed that the best prediction performance could be achieved using a feature lookback of several days to predict the BMI in the following days. Plus, prediction errors increase when the prediction time window exceeds three days. We evaluated our approach by predicting BMI for the following days. Prediction of other person's goal metrics, such as lean and fat mass percentage, can be evaluated in the future.



(a) Input: t. Output: t+1

(b) Input: t. Output: t+2

(c) Input: t. Output: t+3

(d) Input: t. Output: t+4

Fig. 2: Prediction of BMI at time t+1, t+2, t+4 and t+4 using data known at time t.

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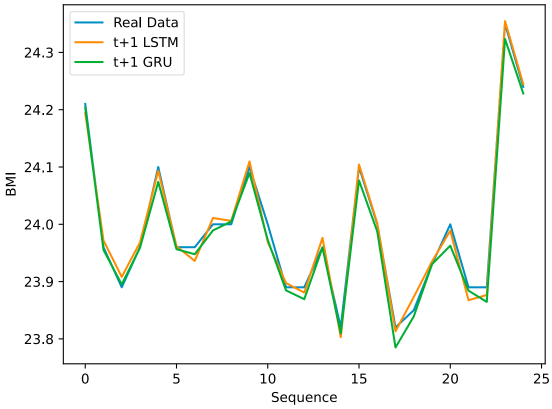
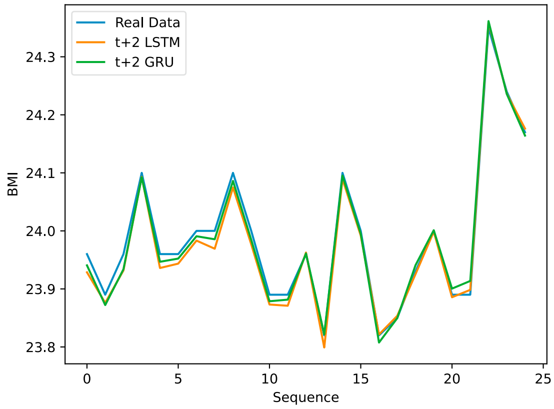
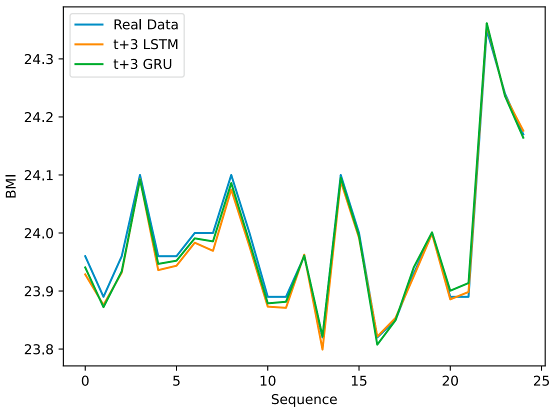


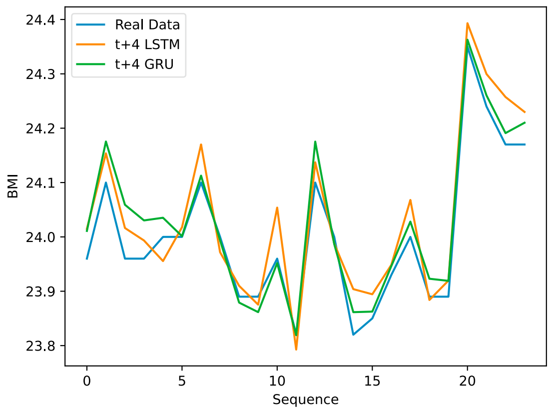
(a) Input: t, t-1, t-2. Output: t+1



(b) Input: t, t-1, t-2. Output: t+2



(c) Input: t, t-1, t-2. Output: t+3



(d) Input: t, t-1, t-2. Output: t+4

Fig. 3: Prediction of BMI at time t+1, t+2, t+3, t+4 using data known at time t, t-1, t-2.

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