

Article



Training Performance Indications for Amateur Athletes Based on Nutrition and Activity Lifelogs

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Abstract: To maintain and improve an amateur athlete's fitness throughout training and to achieve peak performance in sports events, good nutrition and physical activity (general and training specifically) must be considered as important factors. In our context, the terminology "amateur athletes" represents those who want to practice sports to protect their health from sickness and diseases and improve their ability to join amateur athlete events (e.g., marathons). Unlike professional athletes with personal trainer support, amateur athletes mostly rely on their experience and feeling. Hence, amateur athletes need another way to be supported in monitoring and recommending more efficient execution of their activities. One of the solutions to (self-)coaching amateur athletes is collecting lifelog data (i.e., daily data captured from different sources around a person) to understand how daily nutrition and physical activities can impact their exercise outcomes. Unfortunately, not all factors of the lifelog data can contribute to understanding the mutual impact of nutrition, physical activities, and exercise frequency on improving endurance, stamina, and weight loss. Hence, there is no guarantee that analyzing all data collected from people can produce good insights towards having a good model to predict what the outcome will be. Besides, analyzing a rich and complicated dataset can consume vast resources (e.g., computational complexity, hardware, bandwidth), and this therefore does not suit deployment on IoT or personal devices. To meet this challenge, we propose a new method to (i) discover the optimal lifelog data that significantly reflect the relation between nutrition and physical activities and training performance and (ii) construct an adaptive model that can predict the performance for both large-scale and individual groups. Our suggested method produces positive results with low MAE and MSE metrics when tested on large-scale and individual datasets and also discovers exciting patterns and correlations among data factors.

Keywords: lifelogs; sensory data fusion; model fusion; data analysis; pattern mining; fuzzy logic

1. Introduction

Everyone's health can benefit from regular exercise and good nutrition, especially amateur athletes [1]. To determine health trends across various age groups, the research introduced in [2] pointed out that people pay a great deal of attention to which type of nutrition and physical activities they need to perform during exercising to gain better performance. In [3], the authors mention people's interest in the correlation between nutrition, sleeping qualification, training regimen, and health. With hard training without eating or sleeping healthily, people cannot improve their performance, and their health will probably deteriorate.

Beyond this, people want to predict training performance for various objects (e.g., professional and amateur athletes, college students, older people) based on people's daily



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Copyright: © 2023 by the authors. Licensee MDPI, Basel, Switzerland. This article is an open access article distributed under the terms and conditions of the Creative Commons Attribution (CC BY) license (https:// creativecommons.org/licenses/by/ 4.0/). routines, such as nutrition, sleeping, physical activities, habits, and demographic data. In [4], a model built by neural networks and chaos theory is proposed to predict the training performance of college students. The model's accuracy is over 90%, and most of the data pertain to athletic performance measurements. In [5], a neural network model using player performance data is built to forecast the performance of cricket athletes. An LSTM model is introduced in [6] to predict soccer athletes' performance. These studies focus on a narrow domain that rarely shares the same common points, such as professional athletes and college students. Moreover, these studies do not consider nutrition, one of the most critical factors impacting training performance.

It cannot be denied that the mentioned datasets are very helpful in supporting professional athletes to improve their training. Unfortunately, due to a lack of resources, ordinary people or amateur athletes cannot afford such datasets for their training.

Recently, lifelogs have become a new trend to monitor the daily activities of individuals by utilizing both friendly and economic IoT and wearable devices (e.g., Fitbit, camera, smartphone, ECG) and conventional diaries (e.g., self-reports, multi-choices, tags) to collect personal data reflecting all aspects of personal life [7]. Such datasets can be an excellent resource for building a personal coaching application. In recent decades, many challenges and tasks aimed at obtaining insights into lifelog data have been organized, such as LSC (Lifelog Search Challenge) [8], NTCIR (NII Testbeds and Community for Information access Research—Lifelog task) [9], and CLEF (Conference and Labs of the Evaluation Forum—ImageCLEFlifelog task) [10]. Few studies have been performed related to understanding the association between daily life activities and sports performances, such as imageCLEFlifelog—SPLL task (Sport Performance Lifelog).

In [11], the authors introduce an interesting multimodal lifelog dataset that includes individuals' dietary habits, sports participation, and health status with the aim of studying human behavior via their daily activities. This dataset contains different factors, including food pictures, heart rates, sleep qualification, exercises, and feelings. The primary motivation of this study is to combine information on various aspects of daily activities, including exercises and nutrition, to recognize human activities and extract daily behavior patterns with the aim of discovering five representative models for understanding human behavior. Although the dataset contains some information relating to sports, the authors do not aim to analyze how nutrition and physical activities can impact sports activities.

In contrast to the mentioned methods and datasets, PMData [12] aims to collect lifelog data from ordinary people who want better health by exercising independently without personal trainers. These people could be considered amateur athletes. The motivation of the person who created this dataset is to provide a playground for those who want to create a tool that can support amateur athletes to gain better training performance by monitoring their daily routines. This motivation is expressed to the public via the ImageCLEFlifelog 2020 challenge [10], where participants are required to predict the change in running speed and weight after monitoring the amateur athlete's dataset for a while.

Recent multimodal lifelog datasets have succeeded in collecting diverse data types that reflect daily human activities. The ambition of these datasets is to collect as much data as possible. Unfortunately, this leads to significant challenges in data analysis and prediction model construction, such as high-dimensional data, computational complexity workload, data samplings, and redundant data. Although lifelog data help to serve individual demands (e.g., searching, recommendation, activity/behavior prediction), the community needs more than that: a prediction model that can work for a large-scale group of people, and that model can easily and quickly adapt to a new coming individual who joins the community. In other words, given a set of lifelog data collected from a group of diverse people, can we build a model that can work well for both groups and individuals? Moreover, can we explain the reason or causality of the model's output?

To meet these challenges and discover valuable and interesting insights, we propose a new method to achieve the following:

- Find different optimal subsets of data types from multimodal lifelog datasets that can help to reduce the computational complexity of the system;
- Discover daily nutrition and activity patterns that significantly impact exercise outcomes including endurance, stamina, and weight loss; and
- Predict exercise outcomes based on daily nutrition and activities, both for a group and an individual.

The main contributions of our work are as follows:

- We apply the periodic-frequent pattern mining technique [13] to discover subsets of factors that appear with a high periodic-frequent score throughout the dataset. We convert nutrition and physical activity data into a transactional table by converting continuous data into discrete data using fuzzy logic. We hypothesize that these subsets can characterize a particular group of people who share the same common points that do not appear in other groups.
- We estimate the portion of healthy and unhealthy foods from food images and treat them as numeric data. The data can enrich the nutrition factor besides food-logs reported by people. Estimating a portion of healthy food could overcome the challenge of precisely calculating calories from food images since object detection and semantic segmentation algorithms currently work better than image-to-calories approaches.
- We create a stacking model to forecast people's weight and running speed changes based on their daily meals and workout habits. The model can adapt to different general and individual cases that suit understanding training performance throughout the nutrition and physical activities of a large-scale people group.

The rest of the paper is structured as follows: Section 2 introduces the data-driven approach with which we build the model. Section 3 presents the evaluation and comparison of our model together with necessary discussions. The last section concludes the paper and proposes the next research step on the same topic.

2. Methodology

This section introduces the data-driven approach with which we build our model. First, we introduce the dataset and how to discrete it into a transactional table ready for mining periodic-frequent patterns. Then, we briefly introduce the periodic-frequent pattern mining algorithm and how to utilize it to discover valuable subsets of data factors (i.e., feature selection) with which we can discriminate among people groups. Next, we present the data-driven stacking-based model running on mined subsets of data factors. Finally, we explain how the model can work on different general and individual cases. Figure 1 illustrates the overview of the proposed method. Each component will soon be described in the following parts.

2.1. The PMData Dataset

Simula Lab, Norway introduced PMData, the first sports logging dataset [12]. Several researchers have utilized this dataset for their investigations into ordinary people's sports activities, such as activity eCoaching [14] and the analysis of the performance of physical activities [15] and other human behaviors [16]. Therefore, we decide to select this dataset for our study.

The dataset was created by continuously collecting data from 3 women and 13 men from November 2019 to March 2020. The data were collected with various methods and devices such as Fitbit (objective biometrics and activity data), PMSys (subjective wellness, training load, and injuries), Google Forms (demographics, food, drinking, and weight), and food images. The dataset provides detailed information on calories consumed, distance and steps taken by athletes, minutes of activity at various intensities, and descriptions of exercise activity. We also can find information on meals eaten, the number of glasses drank, current weights, and alcohol ingested. Only three people took pictures of every meal they



ate for two months (February and March 2020). Table 1 and Figure 2 illustrate an overview of PMData and an example of food images.

Table 1. Overview of the PMData dataset [12].

Categories	File	Rate of Entries	Number of Entries	
SRPE	srpe.csv	Per exercise	783	
Injury	injury.csv	Per week	225	
Wellness	wellness.csv	Per day	1747	
Steps	steps.json	Per minute	1,534,705	
Calories	calories.json	Per minute	3,377,529	
Distance	distance.json	Per minute	1,534,705	
Exercise	exercise.json	When it happens (100 entries per file)	2440	
Heart rate	heart_rate.json	Per 5 s	20,991,392	
Lightly active minutes	lightly_active_minutes.json	Per day	2244	
Sedentary minutes	sedentary_minutes.json	Per day	2396	
Moderately active minutes	moderately_active_minutes.json	Per day	2396	
Very active minutes	very_active_minutes.json	Per day	2396	
Resting heart rate	resting_heart_rate.json	Per day	1803	
Sleep	sleep.json	When it happens (usually daily)	2064	
Sleep score	sleep_score.csv	When it happens (usually daily)	1836	
Time in heart rate zones	time_in_heart_rate_zones.json	Per day	2178	
Google Forms reporting	reporting.csv	Per day	1569	

Figure 1. The method's overview.



Figure 2. Examples of the captured food and drinks images [12].

2.2. Periodic-Frequent Pattern Mining

In this subsection, we briefly review the fundamental terminologies of periodicfrequent pattern mining techniques, show an example of how they produce periodicfrequent patterns, and explain how to interpret these patterns.

Periodic-frequent patterns are patterns (e.g., a sequence of items) that (1) appear in a dataset with its frequency less than or equal to the predefined threshold (i.e., minsup) and (2) repeat themselves with a specific period in a given sequence [17].

For example, the pattern *meat*, *vegetables*: [4, 3] expresses that if a 2-pattern happens (i.e., *meat* and *vegetables* are items of the pattern), then within three periods, it will appear again with a probability (or *sup*) of 3.

In general, if $PA = \{pa_i\}_{i=1..L}$, where *L* is the number of mined patterns, is a set of mined patterns, the format of a mined pattern *i*th is

$$pa_i = (\{item_i\}) : [sup, maxPer].$$
(1)

Periodic-frequent pattern miningtries to discover all periodically occurring frequent patterns in a temporal database. In our research, we want to mine such periodic-frequent patterns from an uncertain temporal dataset, as mentioned before.

Let $I = {I_i}_{i=1..N}$ denote the itemset. Let $T_j = {I_m}_{m \in [1,N]}$ denote a transaction that is a set of items of the itemset. Let $P_k = {\{I_n\}_{n \in [1,N]}, \text{support}(\%), \text{ periodicity}(\%)\}$ denote a periodic-frequent pattern where the set of items ${I_n}_{n \in [1,N]}$ has the frequency expressed by support(%), and how regularly this pattern appear within a database is depicted by periodicity (%).

The periodic-frequent pattern mining algorithm introduced by Uday et al. [13] gets $\{T_j\}_{j=1..M}$, where *M* is the total transactions, as the input and generates $\{P_k\}_{k=1..P}$, where *P* is the total patterns, as the output. The *minSup* (i.e., select only patterns with their support larger than *minSup*) and *maxPer* (i.e., choose only patterns with their periodicity smaller than *maxPer*) must be declared beforehand to limit the searching scope.

Figure 3 illustrates a toy sample of an itemset, transaction, and periodic-frequent patterns. The terms ts, P, Sup, and Per are acronyms of transaction, pattern, support, and periodicity, respectively. Readers could refer to the original paper [13] for more details.

We assume we have 10 receipts of customers from a small grocery in town, where each receipt records the list of food purchased by a customer. Then, we want to understand how frequently and periodically one food type is purchased. Figure 3a illustrates these 10 receipts; each receipt is considered as one transaction (ts). Figure 3b depicts the result from the periodic-frequent pattern mining. We can see that "meat" is bought with high frequency (i.e., 6/10), and after every three transactions, "meat" is repurchased.

2.3. Data Pre-Processing: Fuzzy Logic and Transactions

We apply fuzzy logic to discretize the data since we utilize a periodic-frequent pattern data mining algorithm to discover people's daily nutrition and activity patterns with the aim of selecting valuable subsets of features to build a prediction model. The algorithm requires the input of the transactional table. Since the transactional table is built on pointwise data (i.e., itemset), we need to convert continuous values to level values. For example, the traditional transactional table of a supermarket problem contains a set of items (milk,

\mathbf{ts}	Items		Р		\mathbf{Per}
1	meat, vegetables		meat	6	3
2	meat, fruit, nuts,	ve	getables	5	3
	sugar_sweetened_beverages				
3	fruit, eggs, fish, Fast_food		fruit	5	3
4	meat, vegetables, fish,		nuts	4	3
	dairy_products, refined_grains				
5	vegetables, fruit, nuts		eggs	4	3
6	6 nuts, eggs, fish		fish	4	3
7	7 meat, vegetables,		, vegetables	4	3
	sugar_sweetened_beverages				
8	³ fruit, nuts, eggs		uit, nuts	3	3
9	9 meat, vegetables, eggs, fish		ggs, fish	3	3
10	meat, fruit, dairy_products				
(a) Transactional table		(b)	Periodic-f	reque	\mathbf{nt}

vegetable, meat, bread), not the quantity of these items. Therefore, if we want to apply transactional tables to our data, we must convert them into item sets.

patterns mined from (a)

Figure 3. A toy example of periodic-frequent patterns mining.

We decide to apply fuzzy logic with three levels to discretize the data. The reason for choosing three levels (low, medium, high) is to adapt human habits when talking about the quality of something. We can determine more levels (e.g., 5, 7); however, we found that three levels are enough to explain the cognition of people and more straightforward to explain the meaning of the patterns.

Since we pay attention to nutrition and physical activities, we first filter out irrelevant data, convert different measure units into one, and synchronize data by temporal dimension. Finally, we get a new dataset containing only cleaned nutrition and physical activities synchronized by timeline.

People have studied the association between food categories and calorie intake for a long time. Moreover, food categories also provide information on healthy and unhealthy meals that people should take for personal purposes. In [18–20], the authors provide food categories built upon different criteria (e.g., food colors, iodine, fast-food vs. slow-food, calorie intake). These studies offer a hint for us to create our food categories: (1) refined_grains, (2) vegetables, (3) fruits, (4) nuts, (5) eggs, (6) dairy_products, (7) fishes, (8) meats, (9) sugar_sweetened_beverages, and (10) fast_food. We first manually locate and determine the portion of each food category in each food image. Then, we apply fuzzy logic to divide each portion into one of the three levels of low (less than 20%), medium (between 20% to 50%), and high (over 50%). Finally, we attach these labels as the prefix of portion categories to generate the itemsets.

For example, there is a dish with whole grain bread, steamed broccoli, boiled egg, and strawberries. We assign categories "refined_grains", "vegetables", "eggs", and "fruits". Then, we estimate how large each category is compared to the whole dish. Suppose we have 55% of "refined_grains", 30% of "vegetables", 10% of "eggs", and 5% of "fruits"; then, we will have a set of items {high_refined_grains, medium_vegetables, low_eggs, low_fruits} for the dish.

In [21], the authors provide interesting information related to US adults' typical daily calorie needs by demographic and other characteristics. Hence, we can estimate the average calories for adults daily. Based on that, we define low (less than 2000 calories/day), medium (between 2000 to 3000 calories/day), and high (over 3000 calories/day) levels for the daily calorie intake for each person.

For the rest of the data types, we determine their levels based on popular criteria of the value ranges. Table 2 describes how we determine levels for each data types.

By adding the prefix "low", "medium", and "high" to each feature's name associated with its value, we generate the itemset. Then, all items appearing during one person's day are utilized to create a transaction set.

Table 2. Data Level Determination.

Features	Low Level	Normal Level	High Level	
Calories_all_day	0–2000	2000-3000	3000–6000	
exercise_calories	0–200	200-450	450-6000	
distance	0–7000	7000–9000	9000–25,000	
exercise_distance	0–4000	4000-7000	7000–25,000	
lightly_active_minutes	0–1800	1800–2100	2100-42,000	
exercise_lightly_minutes	0–1800	1800-2100	2100–42,000	
steps	0–10,000	10,000–18,000	18,000–30,000	
exercise_steps	0–2000	2000-4000	4000–30,000	
moderately_active_minutes	0–6300	6300–6900	9000	
exercise_moderately_minutes	0–6300	6300–6900	9000	
sedentary_minutes	0–600	600–1800	1800–90,000	
exercise_sedentary_minutes	0–600	600–1800	1800–90,000	
very_active_minutes	0–15,000	15,000–15,600	15,600–120,000	
exercise_very_minutes	0–15,000	15,000–15,600	15,600–120,000	
exercise_averageHeartRate	0–95	95–170	170–2000	
exercise_speed	0–7	7–9	9–15	
exercise_duration	0–1500	1500-2100	2100-9000	
time_per_kilometer	0–1500	1500-2100	2100-9000	
exercise_elevationGain	0–15	15–100	100-300	
exercise_heartRateZones_FatBurn_minutes	0–3600	3600-5100	5100-120,000	
exercise_heartRateZones_Peak_minutes	0–11,220	11,220–12,000	12,000–30,000	
exercise_heartRateZones_Cardio_minutes	0–6180	6180–7500	7500–30,000	

2.4. Feature Selection

Feature selection is one of the most critical stages in machine learning. It aims to reduce the data's dimensionality and enhance any proposed framework's performance [22]. Many feature selection works have been reported from various applications and domains. These reports converge into one common sense: feature selection suffers from many factors, such as high dimensionality, computational and storage complexity, noisy or ambiguous nature, and high performance, to name a few. Despite the challenges mentioned, feature selections bring undeniable benefits to enhance machine learning models' productivity (e.g., accuracy, complexity).

This section discusses our feature selection mechanism, through which significant characteristics of a group and person are distributed into different discriminative sets. Our aim is to find a group of features that can leverage the common sense of one group's members while maintaining the uniqueness of each member of that group. This could contribute to developing a supervised model that could start with a few samples shared by a group of people to generate a primary instance and end with an adaptive instance when considering personal characteristics.

Our hypothesis for feature selections is based on the following observations and facts.

- People share common characteristics with their group and have personal characteristics that make them unique from a group.
- With the same exercise and nutrition plan, finding two people with the same outcome is problematic.
- People who prefer a self-training plan tend not to follow the plan strictly due to both subjective (e.g., tired, not in the mood) and objective reasons (e.g., busy working, unexpected meeting)

Based on the discussions above, we created three personal, intersection, and general features, where the first describes the uniqueness of one person, the second indicates the common concrete characteristics shared inside one group, and the third is involved in characteristics that two people at least share in a group.

It should be noted that we rely heavily on the periodic-frequent pattern mining results to build these three feature types. In other words, we consider people's habits and frequency of data factors, both for individuals and groups.

2.4.1. Personal Features

For each person, we apply periodic-frequent pattern mining to the relevant transactional dataset as explained in Section 2.3. Based on the output of the pattern mining, we select all patterns with high frequency (i.e., support) or high periodicity. In other words, we are interested in patterns that appear frequently and at regular intervals or rarely appear within the data. The union of these patterns provides a compact and discriminative feature set representing one person. Let PF_i denote the feature set of person p_i .

2.4.2. Intersection Features

We take the intersection of relevant $\{PF_i\}$ for each group $IPF = \cap \{PF_i\}$. We hypothesize that the intersection features *IPF* represent the very discriminative characteristic among people in the same group. We believe that *IPF* has strong discrimination to distinguish a group from others.

2.4.3. General Features

We take the union of relevant $\{PF_i\}$ for each group $UPF = \bigcup \{PF_i\}$. We hypothesize that people still belong to a group, even though they have some points that differ from other group members, as long as they share the discriminative characteristic of the group.

2.5. The Data-Driven Stacking-Based Model

To utilize three different feature sets ideally, as mentioned above, we decided to use the stacking learning approach [23], which allows several "weak learners" to be combined into one "strong learner" in the end. That is because we want to balance the generalization and personalization of our prediction model so that it can leverage not only group data but also personal data.

In this work, we choose the stacking-based model [24] because it frequently takes weak learners into account in a heterogeneous manner, teaches them concurrently, and combines them by training a composite model to create a robust prediction model.

As depicted in Figure 4, we create three models associated with three feature sets. We use a BiLSTM model for general and personal feature sets and a standard LSTM for the intersection feature set. We use the full connection (FC) to normalize input data dimensions and enhance salient training features.

We choose BiLSTM for general and personal models and LSTM for the intersection model because BiLSTM can exploit and explore the context and utilize information from both directions (e.g., forward, backward); hence, it could compensate for the asymmetric nature of general and personal features. In contrast, the intersection feature set is symmetric, and we can apply the indirect flow of LSTM without losing any significant cues.

The primary idea of using the stacking model here is that we do not ensure which model and feature set can give the best result. Hence, we need to estimate the weight

set by which the balance of outputs from the three models can be reached so that the final output can achieve the highest accuracy. Moreover, depending on different circumstances, we can quickly and flexibly switch the output levels from stacking mode to personal/general/intersection mode to adapt our model to local datasets. Besides, this could support us in adjusting the computational workload and volume of data.



Figure 4. The data-driven stacking-based Model: an overview.

3. Experimental Results

We utilize the PMData dataset to evalute our model. Firstly, we conduct data preprocessing, including cleaning, polishing, and grouping of data. Secondly, we generate the itemset using fuzzy logic to construct transactional data for each person. Thirdly, we mine these transactional data to produce a periodic-frequent pattern set for each person. Fourthly, we create general, intersection, and personal feature sets for each group. Finally, we train, validate, and test our models accordingly.

Since the weight loss and running speed are reported in numeric format, we decided to use MAE and MSE as the metrics for evaluation. We use MAE to measure the accuracy and MSE to evaluate the sensitivity with outliers of our models.

3.1. Data Grouping

We hypothesize that our feature selection approach can alleviate the dependence on the data grouping strategy. We conduct our model on the full dataset and data groups made by different clustering strategies to prove our hypothesis. This subsection introduces how we divide data into different group types.

We cluster the dataset into various groups according to different criteria. The clustering is based on the hypothesis that if people are grouped based on some common factors (e.g., demographic data, habits, food interests), their data will be discriminative compared to others. Table 3 denotes data groups and related criteria used for grouping.

We use the prefixes "weight" and "speed" to denote the categories we have to predict change in weight and change in running speed—and the rest of each name expresses the group criteria. For example, "Speed_Group_A" denotes a group for predicting running speed change in which people generally wake up early (potentially also go to bed early, i.e,. type A in PMData), or "Weight_Group_Age_20_40_Male" describes a group for predicting weight change where people must be male and between 20 and 40 years of age.

3.2. Evaluations

Table 4 shows that our model produces accuracy with a low MAE (<0.5) and MSE (<0.4) in all groups (also compared to other often-used methods later in the article). Among models, the stacking model gives the best accuracy. Interestingly, we can see that the food images significantly strengthened the accuracy level, even though only three people took food pictures.

Name of Group	Person in Group			
Weight_Group_Image_food	p01, p03, p05			
Weight_all_Female	p04, p10, p11			
Weight_all_Male	p01, p02, p03, p05, p06, p07, p08, p09, p12, p13, p14, p16			
Weight_Group_A	p01, p02, p03, p04, p05, p11, p12, p13, p14			
Weight_Group_B	p06, p07, p08, p09, p10, p16			
Weight_Group_Age_20_40_Male p16	p03, p05, p06, p07, p08, p09, p12, p13, p16			
Weight_Group_Age_20_40_Male_and_Female	p03, p04, p05, p07, p08, p09, p10, p11, p12, p13, p16			
Weight_Group_Age_41_60Male_and_Female	p01, p02, p06, p14			
Weight_all_people	p01, p02, p03, p04, p05, p06, p07, p08, p09, p10, p11, p12, p13, p14, p16			
Speed_Group_Image_food	p01, p03, p05			
Speed_all_Female	p04, p10, p11			
Speed _all_Male	p01, p02, p03, p05, p06, p07, p08, p09, p12, p13, p14			
Speed _Group_A	p01, p02, p03, p04, p05, p11, p12, p13, p14			
Speed _Group_B	p06, p07, p08, p09, p10			
Speed _Group_Age_20_40_Male	p03, p05, p06, p07, p08, p09, p12, p13			
Speed _Group_Age_20_40_Male_and_Female	p03, p04, p05, p07, p08, p09, p10, p11, p12, p13			
Speed _Group_Age_41_60Male_and_Female	p01, p02, p06, p14			
Speed_all_people	p01, p02, p03, p04, p05, p06, p07, p08, p09, p10, p11, p12, p13, p14			

Table 3. Data grouping.

There is an exciting observation of group "AAA_group_image_food" where the stacking model generates a better accuracy for the "weight" group than the "speed" group. This observation strengthens the role of nutrition in training performance: if you have a good nutrition regimen (both in healthy qualifications and regular meals eaten), you can improve your training performance. Another important and interesting discovery is that though people record the calories they took during the day, the food images they took are more informative.

From the observations mentioned, we discovered the following interesting facts: (1) to predict running speed change, we should focus on a group's common features rather than individual features; (2) to predict weight change, we must consider both common and individual features; and (3) to achieve high accuracy for each person, we have to use both common and individual features.

The final interesting observation is that our model can work well with different groups (i.e., using the entire data cohort or particular group data, the model still predicts well). Hence, our model can work independently with subjective clustering defined by individual people. This discovery is beneficial when applying our model to a new cohort because it means one does not need to worry about how to divide the data into suitable groups. This validates the idea that our feature selection approach can alleviate the problem of data grouping. Moreover, it points out that exercise outcomes are associated with daily habits, not people's demographic characteristics.

Name of Group	Genera	l Model	Intersection Model		ersection Model Personal Mode		Stacking Model	
Name of Group	MAE	MSE	MAE	MSE	MAE	MSE	MAE	MSE
Weight_group_image_food	0.416	0.256	0.408	0.235	0.458	0.367	0.006	0.002
Weight _all_Female	0.378	0.198	0.366	0.181	0.221	0.072	0.009	0.005
Weight_all_Male	0.322	0.138	0.376	0.167	0.391	0.237	0.003	0.001
Weight_Group_A	0.459	0.248	0.480	0.236	0.280	0.150	0.002	0.001
Weight_Group_B	0.238	0.090	0.509	0.290	0.237	0.088	0.007	0.003
Weight_Age_20_40_Male	0.371	0.169	0.443	0.205	0.225	0.075	0.005	0.001
Weight_Age_20_40_Male_Female	0.372	0.188	0.428	0.190	0.265	0.130	0.006	0.002
Weight_Age_41_60_Male_Female	0.270	0.127	0.293	0.122	0.203	0.061	0.000	0.000
Weight_full_version	0.231	0.082	0.371	0.158	0.263	0.122	0.005	0.002
Speed_group_image_food	0.169	0.039	0.126	0.024	0.225	0.086	0.107	0.020
Speed _all_Female	0.182	0.051	0.102	0.021	0.331	0.152	0.086	0.018
Speed_all_Male	0.134	0.031	0.078	0.014	0.349	0.181	0.067	0.012
Speed_Group_A	0.112	0.023	0.057	0.011	0.387	0.182	0.049	0.009
Speed_Group_B	0.175	0.043	0.171	0.034	0.463	0.286	0.145	0.029
Speed_Age_20_40_Male	0.150	0.037	0.073	0.012	0.454	0.247	0.062	0.010
Speed_Age_20_40_Male_Female	0.111	0.021	0.069	0.009	0.421	0.217	0.058	0.007
Speed_Age_41_60_Male_Female	0.151	0.038	0.253	0.077	0.322	0.153	0.128	0.033
Speed_full_version	0.119	0.024	0.095	0.016	0.345	0.170	0.081	0.013

Table 4. Evaluation results of the data-driven stacking-based model.

Table 5 denotes some interesting patterns mined from the data of participant P03. We can consider this person as not active looking at the frequency of "not exercise" activities, which occupy a large portion of the data. Further, this person has a habit of drinking a lot of water regularly. In addition, this person has the habit of eating fast food (not in large portions, but regularly). The prediction results of a change in running speed and weight for this person are accurate, forecasting a weight increase and slower running speed. Together with the periodic-frequent patterns mined from this person's lifelogs, we can see the interesting correlation between nutrition, physical activities, and training performance. Based on that, the person could be recommended to adjust their food intake and activity level to achieve possible weight loss. This detailed example shows that our method can be used to provide recommendations based on the data and predictions, which could lead to possible health and performance benefits.

Table 5. Periodic-frequent pattern mining results for participant P03.

Patterns	Support (%)	Periodicity (%)
low_moderately_active_minutes, high_sedentary_minutes, low_very_active_minutes	0.99	2
low_glasses_of_fluid	0.96	6
Yes_Breakfast, Yes_Dinner	0.37	16
high_Fast_food	0.14	24

3.3. Comparisons

We compare our model to other models tested on the same dataset to obtain more objective evaluations. We select three models for this comparison: (1) the personalized adaptive model [25], (2) the Vanilla LSTM model [26], and (3) a one-dimensional convolutional neural network (CNN1D) model [26]. The first model also considers general and personal feature sets and applies a correlation matrix to select common and individual features. The purpose of this model is to predict sleeping quality using lifelog data. The second and third models use the whole dataset, not separating data into different groups. The target of these models is the same as ours.

Figure 5 illustrates the comparison between the personalized adaptive, CNN1D, and Vanilla LSTM models and our approach using the MAE metric. We can see that our model almost beats the adaptive model. The adaptive model utilizes a correlation matrix to group all high-correlation data factors with sleep quality and assumes that these data factors can influence sleep quality. Based on that, the researchers hope they can understand and predict sleep quality by monitoring the changes of these data factors. When applying this model to the PMData dataset, we guess that the correlation data factors are less discriminative than our feature sets that pay attention to intra and inter-correlation among people.

We also see that considering both group and individual datasets provides better accuracy than using the entire dataset. The personalized approach and our model work better than CNN1D and Vanilla LSTM, which deal with the whole dataset.



MAE of Our propose model with other models

Figure 5. Comparing the proposed model with others.

4. Conclusions and Future Works

In this paper, we introduce a method for indicating training performance for amateur athletes using nutrition and activity lifelogs. We apply the fuzzy logic to discrete data and transform them into transactional data, with which we can apply the periodic-frequent pattern mining technique to extract discriminative feature sets, i.e., union (general), intersection, and personal. We build a data-driven stacking-based model based on these feature sets to strengthen three weak learners with related feature sets. We evaluate our method on different groups that are divided subjectively using demographic data. We also compare our models to three other methods on the same dataset and metrics. The results show a comparable accuracy in addition to the exciting insights discovered with our approach.

In the future, we plan to develop a tool to detect food categories automatically. We will also compare the benefit of using correlation and pattern mining to establish discriminative feature sets. We will apply our approach to predict other factors such as sleep qualification, stress, and eating and drinking habits. We also intend to discover the relationship or association between nutrition and activity lifelogs with other factors.

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