Personalized Meal Classification Using Continuous Glucose Monitors

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Abstract

Managing diabetes mellitus (DM) requires monitoring the glucose response to meals, also known as the postprandial glucose response (PPGR). The PPGR to a meal is significantly affected by the amount of carbohydrates, but other macronutrients (e.g., protein, fat, fiber) are also known to affect the PPGR. This suggests that the type of meal consumed can be automatically identified by analyzing the shape of the PPGR, as measured by a continuous glucose monitor (CGM). As a step towards this goal, this study proposes a metric-learning approach to learn personalized PPGR embeddings to account for the inherently large inter-individual variability in PPGRs. Metric learning is implemented with a Siamese neural network (SNN) that models the relative distance between meals consumed by a participant. Embeddings learned with the SNN outperform features directly extracted from PPGRs, yielding 50% and 77% accuracy on the considered tertiary and binary meal classification tasks, respectively. Findings from this work would ultimately help in designing intelligent user interfaces for assisting patients with DM in dietary monitoring.

Keywords

Personalization, metric learning, inter-individual variability, continuous glucose monitors, postprandial glucose response

1. Introduction

Diabetes mellitus (DM) is a chronic progressive metabolic disorder that requires significant self-management, including nutrition, exercise, and medication [1]. An important aspect of daily DM management lies in controlling patients' postprandial glucose responses (PPGR), mostly by monitoring diet. Current forms of dietary monitoring rely largely on manual input and memory recall, though new technologies based on food photography and wearable sensors are also being investigated, each with their own pros and cons in terms of accuracy and obtrusiveness [2, 3, 4, 5, 6, 7]. For instance, dietary monitoring through memory recall can be burdensome and is confounded by patients' bias [8]. Food photography can be less burdensome, therefore promoting user adherence [8, 9]. However, food photography methods still require manual patient input, which can be noisy and potentially result in missing values, especially in the case of smaller meals or snacks [9, 10]. The photos collected via food photography also need to be analyzed by an expert or an automated machine learning algorithm to obtain food intake estimates [11].

Continuous glucose monitors (CGMs) use is common in type I diabetes, and is rapidly

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increasing in type II diabetes, the most common form of the disease [12]. CGMs can be a valuable source of information to monitor diet accurately and in a relatively unobtrusive manner by measuring PPGRs, therefore they have the potential to accurately capture even small meals [13, 14]. CGMs can also help researchers gain valuable insights into the complex interplay between PPGRs and the macronutrient composition of a given meal, due to the fact that the shape of PPGRs depends on the macronutrient composition of a meal [15, 16, 17, 18, 19]. For example, carbohydrate-rich meals generally result in PPGRs with high and narrow peaks, whereas meals rich in fat cause wider peaks, and meals rich in protein depict lower and moderately broader peaks [20]. However, the anthropometric and metabolic characteristics of a person also significantly affect PPGRs, leading to large inter-individual variability to identical meals [20, 21]. This paper proposes an algorithm to automatically identify meals by analyzing PPGRs collected by CGM devices. Such way of meal back tracking, along with the popularly used methods of meal tracking would help us to build a fool-proof application for proper diet monitoring.

We propose a metric learning approach to achieve personalized meal classification based on PPGRs. The objective is to learn a transformation that embeds a glucose response while considering within-person distances of consumed meals. For this reason, we design a metric learning approach, implemented with a Siamese neural network (SNN) architectures, that 1) learns a transformation that projects PPGRs for a participant that belong to similar meals to the same region in the new feature space, while 2 also projecting samples from different meals to non-proximal regions of the new feature space. Our approach models pairwise distances between different types of meals within each participant, rather than absolute patterns, therefore taking into account individual differences. Metric learning is implemented with a SNN that learns a PPGR transformation to minimize the distance between samples of the same meal consumed by an individual and maximize the distance between different meals. The proposed pairwise similarity measure does not require us to estimate the distribution of PPGRs for each type of meal, so it can it is suitable for small-sample-size applications [22]. As an additional step toward personalization, we combine participants' anthropometric and metabolic information with the learned personalized embeddings of the SNN. We evaluate our approach on a publicly-available dataset with three types of meals. Results indicate that PPGR transformations learned from the proposed metric-learning approach outperform the conventionally used PPGR statistics for the task of meal classification. Namely, integrating participants' anthropometric and metabolic characteristics into classifier further increases its accuracy in certain cases.

2. Prior work

Computational models for CGM signals have primarily focused on predicting hyper- or hypo-glycemic episodes [13, 23]. Prior work has further examined the prediction of the PPGR given a specific meal [20, 24, 25, 26, 27]. Zeevi *et. al.* showed that personal information related to dietary habits, physical activity, and gut microbiota can improve the prediction of PPGRs for specific meals, which has implications to personalized diet education interventions [20]. However, the inverse problem of predicting macronutrients from PPGRs has not been thoroughly examined, except for our own work [18, 19]. Anurag *et al.* proposed a sparse decomposition model for representing PPGRs, while Sajjadi *et al.* explored the use of machine learning mod-

els for predicting the amount of macronutrients in meals. Both works were evaluated in a set of 15 participants who consumed 9 predesigned meals with promising results.

Current methods for dietary monitoring primarily rely on computer vision algorithms that seek to detect the components of a meal by analyzing its photographs [4, 5, 6, 28]. However, food photography presents challenges for vulnerable populations, such as elderly adults, who may face challenges related to dexterity, coordination, and vision when using mobile devices [29]. In addition to food photography, other works have proposed wearable food monitoring technologies that rely on smart utensils and wearable sensors [7, 30]. These approaches tend to provide reliable measurements of the food quantity, but they cannot estimate the macronutrient composition. In addition, smart utensils might not always be readily available to the user, therefore potentially resulting in missing data.

Given the expanding use of CGMs in diabetic populations, our method can contribute to providing a feasible alternative to current food monitoring methods. Overall, our contribution to the existing literature is as follows: (1) While most studies have focused on predicting one's PPGR based on a given meal, the inverse problem of estimating the constituents of a meal based on the PPGR is relatively unexplored. Limited prior work from our group has investigated the problem of estimating macronutrient composition from PPGRs [31, 18, 19], but meal classification from PPGRs has not been yet examined; and (2) in contrast with the majority of work, which relies on modeling class-wise distributions of PPGRs [20, 24, 25], our work proposes a metric learning approach that models the pairwise distance between different meals consumed by each participant. The proposed metric learning approach does not require a large number of labelled samples,

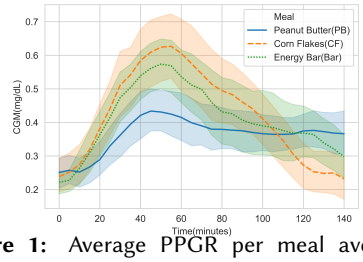

Figure 1: Average PPGR per meal averaged across participants for 140-minute analysis window (*AW*).

which is a significant benefit compared to other algorithms that tend to be more "data-hungry." In addition, the resulting model contains a small number of parameters, therefore it does not have large memory requirements or computational cost, and could be implemented as part of edge computing technologies, thus also promoting aspects of privacy preservation.

3. Data Description and Pre-Processing

We used a publicly available dataset of PPGRs contaning data from 30 participants (25-65 years) [21]. Individual glucose measurements were collected 5 minutes apart using a Dexcom G4 device. Each participant consumed three types of standardized meals at most twice, resulting in at most six meal samples per participant. The meals were isocaloric, but varied in the amount of protein, fat, and fiber [21]. The three meals were: (1) cornflakes and milk (CF), which were low in fiber and high in carbohydrates; (2) peanut butter sandwich (PB), which had a high amount of fat and protein; and (3) a PROBAR protein bar (Bar), which had moderate amounts of fat and protein. Fig. 1 illustrates the average PPGR across individuals for each of the three meals, which indicates that there are marked differences in PPGRs across the three types of meals. The data further include participants' anthropometric characteristics,

including age and body mass index (BMI), as well as metabolic characteristics, such as insulin, fasting blood glucose (FBG), an oral glucose tolerance test (OGTT), Hemoglobin A1c (HbA1C), high sensitive C-reactive protein (hsCRP), and triglyceride to high-density lipoprotein (HDL) ratio (tri/HDL). Anthropometric and metabolic characteristics were combined with the PPGR features and comprised the input of the proposed machine learning models as an additional step to personalization.

Prior to feeding PPGRs to the SNN, we performed data-cleaning procedures, including linear interpolation of missing samples and baseline correction. Baseline correction was done by subtracting the mean of the first 6 data points prior to meal consumption, which we assumed served as the fasting glucose level. Following prior work [20, 21, 31], we also experimented with various analysis windows (*AW*), including 140, 90, and 65 minutes. For the purpose of our experiments, we aim to model pairwise distances between the same meal and different meals. For this reason, our analysis included only those participants who consumed each meal at least twice. This resulted in 20 participants we could use to model pairwise distances between Bar and CF and, and 19 participants for the Bar vs. PB meal and PB vs. CF meals. The number of participants reduced to 11 when we considered all three meals for tertiary classification. When considering *AW* of 65 and 90 minutes, the number of participants became 14 and 16 for the tertiary combination, respectively.

4. Methodology

4.1. Glucose response feature extraction

We computed the maximum and minimum of each participant's baseline-corrected PPGR (Section 3). Then, we normalized the signal by subtracting its minimum value and dividing by the difference between the maximum and minimum value. Finally, we extracted the area under the curve (AUC) at 3, 5, and 8 distinct time points, following Huo et.al. [31], resulting in a total of 16 features. We experimented with these features extracted both in the normalized and non-normalized PPGRs. AUCs for 5-time points of the analysis window are illustrated in Fig. 2. These AUC features capture fasting glucose levels, as well as glucose rise and recovery patterns in various time resolutions.

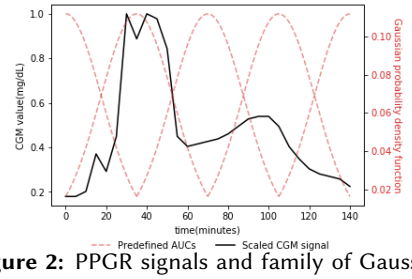

Figure 2: PPGR signals and family of Gaussian kernels centered at five-time points and used to compute the area under the curve (AUC) of the PPGR.

4.2. Personalized metric learning of PPGR embeddings

We designed a metric learning algorithm that models the pairwise distance between meals consumed by a participant (Fig. 3). The problem was formulated as both binary (i.e., CF/PB, PB/Bar, Bar/CF) and tertiary (i.e., CF/PB/Bar) classification tasks (Section 3). Inputs to the model consisted of the 16 AUC features of PPGRs (Section 4.1). Let $g_{\mathbf{W}}$ be a function parameterized by $\mathbf{W}$, which performs a transform of the original AUC space $\mathbf{x}$ and transformed embedding $g_{\mathbf{W}}(\mathbf{x})$. Also, let $\mathcal{X}_n^c$ be the set of samples belonging to class c from participant n. The parameters $\mathbf{W}$ are learned to minimize the distance of samples from the same meal-type and maximize the distance of samples from different meals

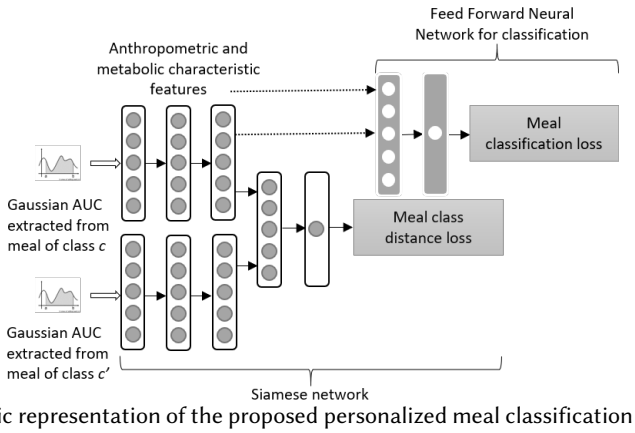

Figure 3: Schematic representation of the proposed personalized meal classification based on PPGRs. Metric learning learns PPGR embeddings based on pairwise meal distances within a participant. Anthropometric and metabolic characteristics are combined with the learned PPGR embeddings for the final meal classification.

within a participant:

$$\mathbf{W}^* = arg\min_{\mathbf{W}_1}\max_{\mathbf{W}_2}\Big(\sum_n\sum_c\sum_{\mathbf{x},\mathbf{x}'\in\mathcal{X}_n^c} d\left(g_{\mathbf{W}_1}(\mathbf{x}), g_{\mathbf{W}_1}(\mathbf{x}')\right) + \sum_n\sum_{c\neq c'}\sum_{\mathbf{x}\in\mathcal{X}_n^c,\mathbf{x}'\in\mathcal{X}_n^{c'}} d\left(g_{\mathbf{W}_2}(\mathbf{x}), g_{\mathbf{W}_2}(\mathbf{x}')\right)\Big) \quad (1)$$

where $d(\cdot,\cdot)$ was the $l2$–norm. Pairwise metric learning was performed via a SNN (Fig. 3). The SNN included 3 layers with 16 neurons each (i.e., siamese network; Fig. 3). The third layer of the SNN comprised of a 16-dimensional output, which represented the transformed PPGR input samples $g_{\mathbf{W}}(\mathbf{x})$ and $g_{\mathbf{W}}(\mathbf{x}')$ in each branch. Following that, the $l2$–norm between $g_{\mathbf{W}}(\mathbf{x})$ and $g_{\mathbf{W}}(\mathbf{x}')$ was computed. The learned glycemic embedding $g_{\mathbf{W}}(\mathbf{x})$ was fed into a set of fully-connected layers comprised of 16 neurons (i.e., feedforward neural network; Fig. 3), which learned a feature transformation between the PPGR embedding and the type of meal. Glycemic embeddings were learned based on the original PPGR, as well as the normalized PPGR using min-max normalization. Bayesian hyperparameter optimization [32] was used to optimize the dropout between layers (i.e., $\{0.0, 0.1, 0.2, 0.3, 0.4, 0.5\}$) and the $l2$–kernel regularization of each layer of the network (i.e., $\{10^{-1}, 10^{-2}, 10^{-3}, 10^{-4}\}$).

We compare the proposed personalized glycemic embeddings learned by the SNN architecture to the raw AUC features that comprised the input to two baseline models: a 1-layer feed-forward neural network (FNN) with 16 nodes and a logistic regression model. The architecture of the FNN was selected to be equivalent to the 16-node fully-connected layer following the output of the SNN architecture. We anticipate that the proposed model performs well in all scenarios where learning the original distribution is difficult due to the inherent inter- and intra-subject variability. However, because we do not have this data, comparing against deeper networks with larger numbers of tunable parameters would either underfit or overfit.

All classification experiments were performed using a leave-one-subject-out cross-validation. Simple classification accuracy was averaged over 40 iterations to remove random effects from parameter initialization and dropout. The classes considered here are balanced, therefore the chance accuracy is approximately 33.33% for the tertiary and 50% for the binary task. A paired t-test with the assumption of unequal variance among the two groups was used to calculate signifi-

Table 1
Accuracy (%) of tertiary meal classification, using the area under the curve (AUC) of PPGRs as an input to a feedforward neural network (FNN) and a logistic regression (LR) model, as well as the AUC embeddings learned by the proposed metric learning approach.

Normalized PPGR			
Analysis window	Metric learning	FNN	LR
140 minutes	50.00	47.84	50.00
90 minutes	46.14^{***}	42.71	42.85
65 minutes	45.89	45.2	45.83

*: p <0.05 ; **: p <0.01; ***:p <0.001

Non-normalized PPGR			
Analysis window	Metric learning	FNN	LR
140 minutes	44.86	47.84	50
90 minutes	45.59^{*}	42.7	44.04
65 minutes	45.63	45.21	45.63

*: p <0.05 ; **: p <0.01; ***:p <0.001

Table 2
Accuracy (%) of binary meal classification between pairwise combinations of peanut butter (PB), cornflakes (CF), and protein bar (Bar), using the area under the curve (AUC) of PPGRs in a feedforward neural network (FNN) and a logistic regression (LR) model, as well as the AUC embeddings learned by the proposed metric learning approach. The analysis window is 140 minutes.

Normalized PPGR			
Task	Metric learning	FNN	LR
PB-CF	74.79^{***}	72.29	72.22
PB-Bar	69.68^{***}	65.19	68.42
Bar-CF	52.49	53.59	56.25

*: p <0.05 ; **: p <0.01; ***:p <0.001

Non-normalized PPGR			
Task	Metric learning	FNN	LR
PB-CF	66.36	66.54	69.73
PB-Bar	61.92	60.39	64.47
Bar-CF	51.33	52.96	52.5

*: p <0.05 ; **: p <0.01; ***:p <0.001

cant differences between the proposed metric learning and the two baselines.

4.3. Integrating anthropometric and metabolic characteristics to the PPGR embedding

We incorporated the anthropometric and metabolic measurements of each participant to (1) the glycemic embedding $g_{\mathbf{W}}(\mathbf{x})$ learned by the SNN (Section 4.2), followed by a fully-connected layer (Fig. 3); and (2) the raw AUC features followed by the FNN and logistic regression models. We report the corresponding classification results in order to see whether the inclusion of these features further improves the meal classification performance. Anthropometric and metabolic features were included in five unique combinations according to their individual and group characteristics. Combinations 1 and 2 consisted of only anthropometric features (i.e., age, BMI) and only metabolic measurements (i.e., insulin, FBG, OGTT, HbA1C, hsCRP, Tri/HDL), respectively. Meanwhile, combination 3 included all features from both combinations 1 and 2. In combination 4, we only considered features that were significantly correlated with the AUCs extracted from PPGR (i.e., age, insulin, OGTT, HbA1C, Tri/HDL). The final combination 5 consisted of three metabolic measurements (i.e., FBG, OGTT, HbA1C), which were directly related to the participant's glucose level.

5. Results

We report the accuracy of the proposed metric learning and baseline models (Section 4.2). Table 1 presents the tertiary classification results over various analysis window (AW) lengths, while Table 2 presents the binary classification results for AW = 140 minutes for all meal combinations. We observe that the metric learning approach performs significantly better than the 1-FNN and logistic regression baseline in the majority of cases for the tertiary task (Table 1) and in many

Table 3
Accuracy (%) of binary meal classification between pairwise combinations of peanut butter (PB), cornflakes (CF), and protein bar (Bar), combining the PPGR embeddings learned by the proposed metric learning approach with anthropometric and metabolic characteristics. The analysis window is 140 minutes. The normalized PPGR was used.

Task	Only PPGR	PPGR & Anthropometric/Metabolic Combination				
		1	2	3	4	5
PB-CF	74.79	77.41***	71.4	72.56	72.11	72.11
PB-Bar	69.68	68.1	61.6	61.44	60.85	65.54
Bar-CF	52.49	53.93	54.75*	55.01**	53.42	53.79

*: p <0.05 ; **: p <0.01; ***:p <0.001
Combination 1: [Age, BMI]; Combination 2: [Insulin, FBG, OGTT, HbA1C, hsCRP, Tri/HDL]; Combination 3: [Age, BMI, Insulin, FBG, OGTT, HbA1C, hsCRP, Tri/HDL]; Combination 4: [Age, Insulin, OGTT, HbA1C, Tri/HDL]; Combination 5: [FBG, OGTT, HbA1C]

cases for the binary task (Table 2). This indicates that learning a personalized embedding learning through metric learning can benefit meal classification performance, even after normalizing the corresponding PPGR. We further compare AUC features from the normalized and non-normalized PPGR through a paired t-test with the assumption of unequal variance. For tertiary classification with 140 minutes analysis window, we achieve accuracy up to 50% for the normalized signal, which is significantly higher (p < 0.001) than the 44% accuracy from the non-normalized signal (Table 1). Similarly, for the binary classification, results demonstrate the effectiveness of normalizing PPGR (Table 2), reaching 75% accuracy.

The combination of age and BMI with the PPGR embeddings learned by the proposed metric learning approach depicted the best results. Also, combinations 2 and 3, which include participants' metabolic characteristics, improve classification for the Bar-CF meal pair from 52.49% to 54.75% and 55.01%, respectively. Individual characteristics seem to benefit classification tasks that are difficult to learn solely from the PPGR, such as the CF and Bar which depicted similar PPGR patterns (Fig. 1), while no improvement is witnessed in other cases.

6. Discussion

Our results indicate that personalized PPGR embeddings through metric learning can effectively differentiate between meals. While the scope of our current work is limited due to the sparsity of datasets that include CGM signals with concurrent meal intake annotation, we believe that the ability to predict dietary intake has a broad range of applications in the context of automated real-life dietary monitoring and interventions. Particularly, these can have valuable implications for improving the accuracy of automatic diet monitoring based on CGM devices for people with (pre)(diabetes. The model requires small amount of data for personalization and also includes a small number of parameters, therefore making it ideal for a light user interface (UI). Moreover, the continuous PPGR collection through CGMs ensures that no meal–no matter how small–is overlooked, therefore can potentially accommodate users with non-routine eating patterns. Overall, the model could be easily added to the existing user platforms that are compatible with CGM signals, therefore allowing patients to monitor their PPGR patterns and better un-

derstanding the effect of each meal on their PPGR. These can be also beneficial for developing new technology-assisted dietary interventions, in which patients can visualize, understand, and internalize the interplay between meal intake and PPGR, therefore promoting positive behavior change [33].

Despite the encouraging results, this study presents various limitations. First, the standardized meals considered here are similar in terms of calorie intake and carbohydrate content, therefore rendering the PPGR similar across meals (Fig 1). This might be a potential reason why the final classification accuracies were modest. Second, our work is limited to binary and tertiary classification of standardized meals, while significantly more meal diversity exists in real-world settings. We note that the dataset that we have utilized is the only available dataset in which a given meal is administered to each participant twice, a component essential to our analysis. Third, the addition of anthropometric and metabolic characteristics marginally improves the classification performance. Given that the data were collected by healthy individuals, we observed little variation in their metabolic characteristics, which may be a potential factor contributing to the marginal increase in the system performance when such features were added. Prior studies also found that the HbA1C and FBG are the most highly correlated metabolic measurements with PPGR [21, 20], which is also reflected in our results.

7. Conclusion

We have shown that the personalized PPGR embeddings learned with the proposed metric approach outperform the original PPGR features for meal classification. PPGR normalization significantly ($p<0.05$) improves performance, while adding individual characteristics appears to partially help in certain cases. As part of our future work, we plan to explore the feasibility of this system in classifying diverse real-life meals, which can eventually contribute to effective dietary interventions. We also plan to collect data from 90 participants, which will provide us with the opportunity to evaluate our approach at a broader scale with a wider array of repeated meals.

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