BGMonitor: Towards an Ubiquitous Blood Glucose Tracking for Daily Use

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Abstract here

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1 INTRODUCTION

Blood glucose level plays a significant role in personal health. Hyperglycemia results in diabetes, leading to the health risks such as pancreatic function failure, immunity reduce and ocular fundus disease, etc [**?**]. According to the World Health Organization, there are approximately 171 million people in the word suffering from diabetic patients. The number of diabetic patients is expected to increase by more than 100% by the year 2030 [**?**]. Meanwhile, hypoglycemia also brings lots of clinical symptoms (*i.e.*, confusion, shakiness, anxiety, nervousness, and even loss of consciousness) [**?**]. Therefore, tracking and predicting the blood glucose variance is of great importance.

Current continuous glucose monitors (CGM) either rely on the electrochemistry [**? ?**] or light reflection [**?**] to track the variance of blood glucose. Both of them, however, are usually limited to clinical uses. Complicated operations and physical intrusive requirement make them hard to be accepted by the public. Accordingly, it is not convenient for people to wear this kind of products at all times.

To this end, we propose BGMonitor, a non-intrusive and pervasive mobile service for abnormal blood glucose track in daily use. The key insights of BGMonitor are based on the following aspects. On one hand, the blood glucose level is impacted by the outer contextual factors, including the physical activities (*e.g.*, running and walking), intakes of food and clinical drugs, time and user's sleep quality [**?**]. Such factors can be detected via off-the-shelf smartphones. On the other hand, the blood glucose is also determined by the physical genetic factor. The genetic factor is usually different between crowds yet same in each person or similar within a group of people [**?**]. Accordingly, BGMonitor models the blood glucose trend of each user based on the historical blood glucose values while he/she is not wearing the CGM. When BGMonitor detects the abnormal points of blood glucose, it reminds the user of measuring his/her blood glucose values by the clinical CGM for a double-check. By combining the clinical CGM and BGMonitor, users are able to acknowledge their blood glucose variance at any moment.

The implementation of BGMonitor is very challenging.

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First, the blood glucose measurement of the professional CGM device is for a short-term usage. The glucose oxidase stored in the CGM device usually cannot supports to the blood measurement more than 4 to 5 days. Moreover, most of the users are not willing to wear CGM devices again within a short period because of pains. The limited mount of data makes the ad-hoc personal blood glucose analysis hard. Second, the high or low blood glucose level is relative less than the normal level, resulting in the weak ability of BGMonitor to recognize these two levels. However, monitoring the high and low blood levels is of significant importance, how to promise their detection accuracy is great essential. Third, the traditional physiological model of tracking the blood glucose variance [**?**] cannot be applied to BGMonitor directly. It assumes that the impact of external factors (*e.g.*, food intake, calories cost of exercises, drug and insulin intake) are same to all the people, but ignores the individual differences. Meanwhile, the prediction intervals of BGMonitor is inconsistent with that of the traditional physiological model. The unified parameters of physiological, therefore, cannot well handle with the blood glucose variance of different individuals and different predict time.

To address the aforementioned issues, we track the blood glucose of a person through a data-driven perspective, by building up a multi-task deep RNN model to merge the blood glucose data of persons but still guarantee its characteristics of each single person.

The key contributions of our work are listed as follows:

- A non-intrusive and ubiquitous approach is proposed to monitor the blood glucose variance with smartphones. It monitors the user's blood glucose level when he/she does not wear clinical professional monitor devices. Once BGMonitor detects the abnormal points of blood glucose level, it reminds the user of blood glucose measurement by CGM for a further control.
- Two dimensional types of blood glucose features (*e.g.*, physiological factors and temporal factors) are well considered to infer the blood glucose levels. In particular, the physiological factors described in the physiological model are encoded in the Multi-task deep RNN model, using for quantifying the impact of physiological factors on the blood glucose levels. We also translate the historical data to infer the current blood glucose level. By measuring the influence of these factors on the blood glucose, BGMonitor can well infer the variance of the blood glucose.
- By sharing the blood glucose data in the information representation layer and temporal dynamic deep learning layer, BGMonitor can well copy with the limited data of single user, but enables to keep the individual blood glucose characteristics in the personality learning layer. Meanwhile, the deep Recurrent Neural Networks (RNN) adopted in BGMonitor, is able to encode the temporal relationships between the sensed outer contextual factors and blood glucose level. With the assistance of the multi-task deep RNN model, BGMonitor can infer the blood glucose trend with high accuracy.

2 RELATED WORK

3 PRELIMINARY

Blood glucose level is determined by two factors: external and internal factors. The external factors are composed of the food intake, exercise, sleep quality and drugs or insulin input. The internal factors are determined by the genes.

4 OVERVIEW

The framework of BGMonitor is shown as Fig. 1, consisting of four major components. The first one is the external factors collection. The users are required to enter their basic information into application, including of the age, the gender, the diabetes type and the year of diagnosis.

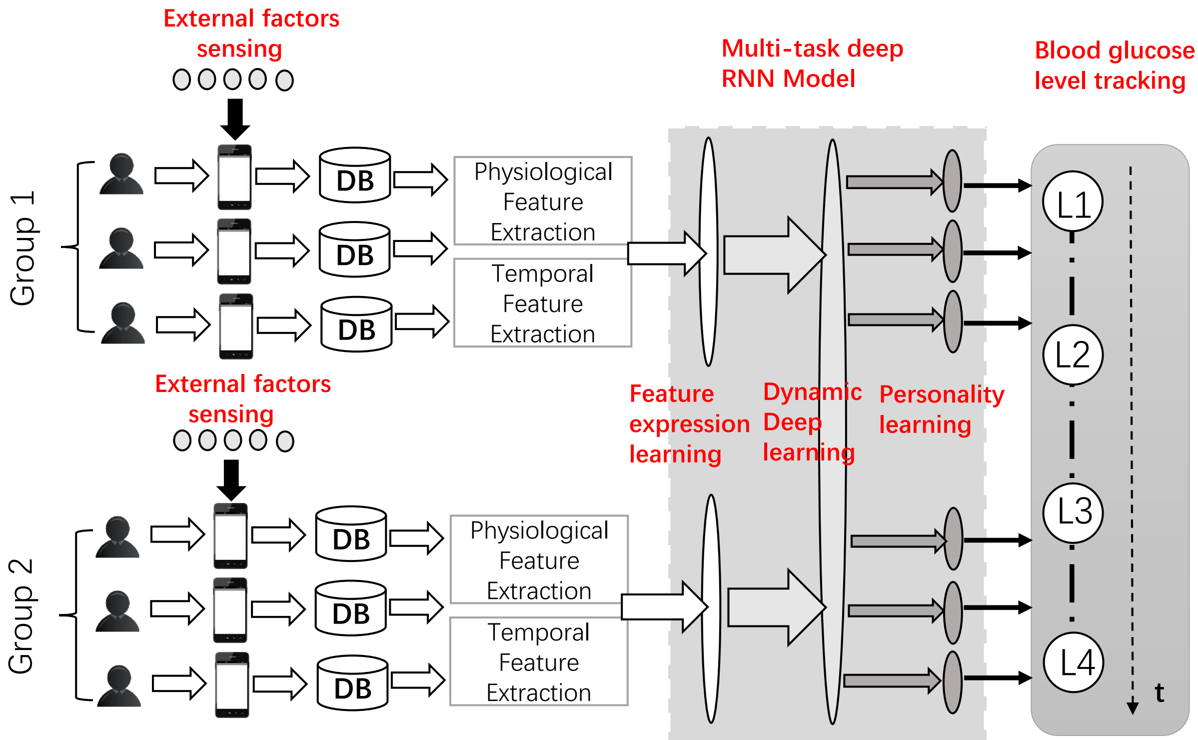

Fig. 1. The system architecture

After a user measures his/her blood glucose by a CGM, the records of the blood glucose along with the outer contextual factors occurred during the measurement are uploaded to an individual database automatically. Afterwards, a RNN model is trained based on the dataset to establish the relationships between the outer contextual factors and the corresponding blood glucose level. It then is fed into the user's smartphone. When the user does not wear the CGM, BGMonitor detects the outer contextual factors with embedded sensors in the smartphones, and infers the current blood glucose level based on the trained model. Once BGMonitor detects the abnormal points of blood glucose (*i.e.*, in a *high* or *low* blood glucose level), it reminds the user to measure the blood glucose by a clinical CGM for a further control.

The extraction mechanisms of outer contextual factors are detailed as follows.

Physical activity: BGMonitor leverages the accelerometer to detect the user's activities by the approaches in [**?**], as well as the corresponding time costs. BGMonitor then measures the calorie of user's physical consumption.

Food intake: BGMonitor measures the food's effect on a person's blood glucose level based on the glycemic index.

Clinical drug intake: BGMonitor records the name and amount of the drug that user eat.

Time: BGMonitor invokes the timer embedded in the smartphone to record the time.

Sleep quality: BGMonitor measures the user's sleep by the approach in [**?**].

Table 1. Details of the datasets

Blood Level	**Level 1**	**Level 2**	**level 3**	**Level 4**	**Total**
Number	75369	293530	235686	158054	762639
Testing days	**5 $\sim$ 10 days**	**10 $\sim$15 days**	**15 $\sim$20 days**	**20 $\sim$25 days**	**25 $\sim$30 days**
User number	48	24	20	13	7
Health Status	**Health**		**Type I**		**Type II**
User number	35		38		39
Age	**15 $\sim$25**	**25 $\sim$35**	**35 $\sim$45**	**45 $\sim$55**	**55 $\sim$70**
User number	8	17	24	29	34
Weight	**30$\sim$45**	**45$\sim$55**	**55$\sim$65**	**65$\sim$75**	**75$\sim$90**
User number	18	21	32	22	19
Gender	**Male**		**Female**		
User number	57		55		

5 DESIGN

5.1 External factor collection

Sensing module is mainly designed for collected the external factors of users.

Activity factors. Since the carbohydrate in the body can be consumed by daily exercise, resulting to vary the blood glucose level, BGMonitor adopts an effective and power efficient approach [**?**] to recognize six common user's daily activities, and then calculates the total calories consumed .

5.2 Feature Engineering

5.3 Blood glucose level prediction

6 EVALUATION

6.1 Experimental Settings

6.1.1 Datasets. We collected the blood glucose dataset from July 2016 to January 2017. A total of 112 users joined in our experiments. During the experiments, each user wears a CGM device to collect the blood glucose sample every 3 minutes. Meanwhile, BGMonitor is installed in smartphones to sense the external factors. Table. 1 details the experimental dataset. As is shown, the data of blood level shows the number of users in the four levels. The testing days date shows the user number at different testing days. The data of health status illustrates the health status of participants. The age, weight and gender shows the corresponding basic information of volunteers.

6.1.2 Ground Truth and Metrics. The blood glucose samples collected by the CGM are regarded as groundtruth. We compare the prediction results of BGMonitor with the groundtruth, and the performance is measured in terms of the precision [], recall[] and accuracy[].

6.1.3 System Evaluation. To evaluate the BGMonitor performance, we provide CGM for each new user for one time usage, supporting more than 5 days. We take the former 4 days as the training data, and left days as the testing data. If the left days of one users are longer than 2 days, we calculate the user's average performance. Table 2 shows the results of testing dataset. As we can see, the recalls of four blood glucose levels are above 79%, and all the precisions of four blood glucose levels keep above 73%. In particular, the recalls of level 1 and level 3 are 83.13% and 85.23%, demonstrating the high sensitivity of

Table 2. Confusion matrix of BGMonitor performance

Ground Truth	**Predictions**					
	Level 1	Level 2	Level 3	Level 4		
Level 1	62657	5521	3672	3519	83.13%	**Recall**
Level 2	16346	240584	27563	9037	81.96%	
Level 3	2660	30905	188472	13649	79.97%	
Level 4	3443	5620	14278	134713	85.23%	
	73.62%	85.12%	80.55%	83.72%	Accuracy: 82.14%	
	Precision					

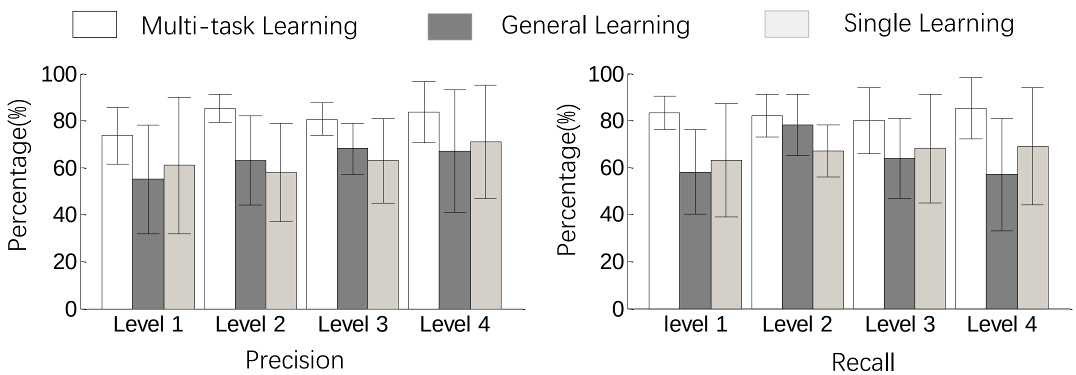

Fig. 2. The model comparison

BGMonitor towards these two levels. The 82.14% accuracy states the outstanding prediction performance of BGMonitor.

Evaluation with various training data. Since the users may wear CGM continuously, we evaluate the performance of BGMonitor with increasement of training dataset by five days. Under each system evaluation, we trained all the data of the users with before the testing date, and measured the system by calculating the average performance of those who have longer testing days.

Fig. 3 illustrates the results. We can see the system performance grow up with the increasement of training dataset, demonstrating the performance of BGMonitor will grow up with more training data.

Evaluation with various prediction duration. Considering the uncertainties of blood glucose increase while the time passing by, we detail the system performance by differentiating the prediction durations in Fig. 4. As expected, the system performance shows a decrease trend while the prediction duration leave longer away. It is possible due to the internal relevant factors of blood glucose changed with the time passing by. However, the system performance still can maintain an acceptable level for 30-days prediction.

6.1.4 Evaluation on Multi-task Model structure. To demonstrate the effectiveness of gsMTRNN structure, we compared our model over the following combinations.

- *General Learning*: All the users shared a same information representation, dynamic and personality layers, which assumes the blood glucose trends of all users can be tracked by a same model.

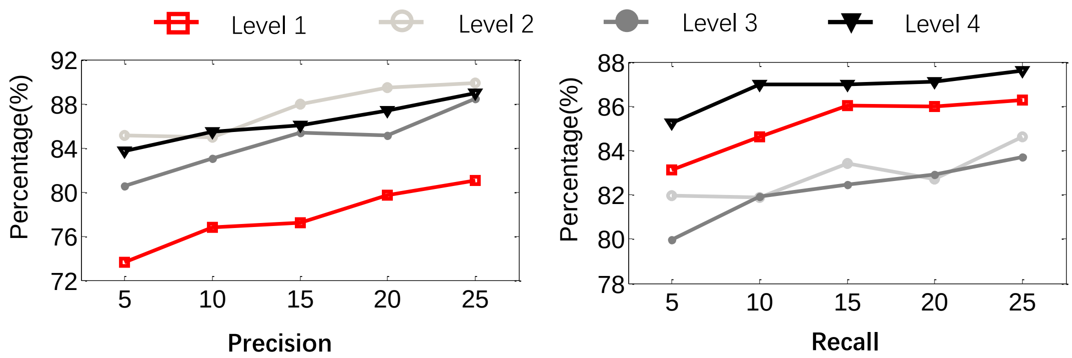

Fig. 3. System performance under different training date

under prediction longer.pdf

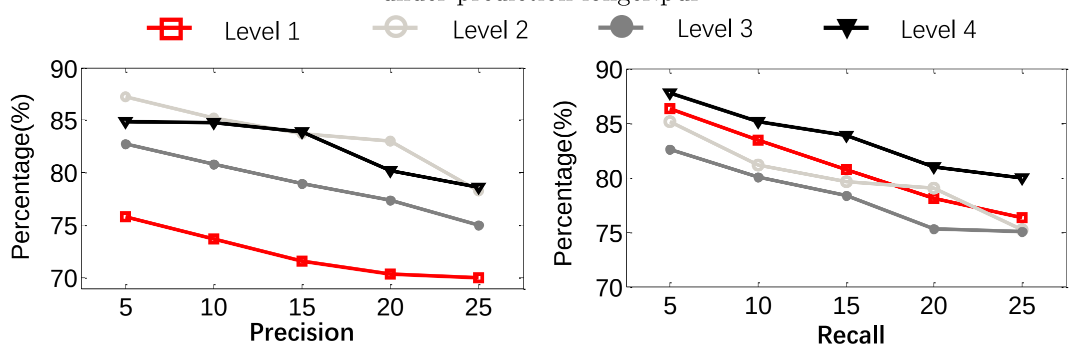

Fig. 4. System performance under different prediction duration

Table 3. Feature Evaluation

	Level 1		**Level 2**		**Level 3**		**Level 4**	
Features	**Precision**	**Recall**	**Precision**	**Recall**	**Precision**	**Recall**	**Precision**	**Recall**
F_p	43.37%	32.82%	46.03%	39.10%	51.79%	48.95%	56.30%	43.49%
F_p+F_{t1}	51.97%	58.11%	60.42%	58.90%	63.35%	53.59%	69.82%	55.16%
F_p+F_{t1}+F_{t2}	64.60%	73.08%	69.87%	61.23%	74.33%	67.81%	76.64%	72.32%
F_p+F_{t1}+F_{t2}+F_{t3}	73.62%	83.13%	83.13%	83.13%	80.55%	79.97%	83.72%	85.23%

- *Single Learning* : Each user is trained for a specific model.
  Fig. 2 shows the results.

6.1.5 Evaluation on Features. We show the effectiveness of four-dimensional feature in Table 3. Clearly, the tracking performance of BGMonitor improve a lot by adding one feature set into the model.

6.1.6 Blood glucose level predictions. Fig. 5 compares the predictive results of BGMonitor and true blood glucose level of a user over one day.

6.1.7 Model comparison. We compare gsMTRNN of BGMonitor over following baselines:

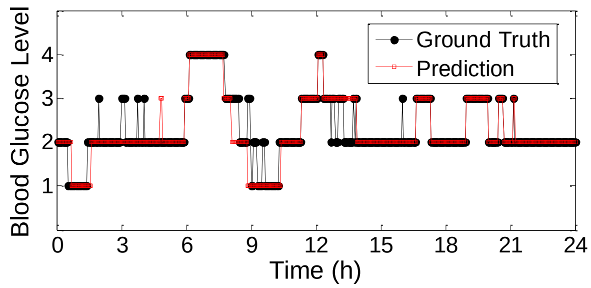

Fig. 5. The comparison of prediction and the ground truths of one user.

1) Gradient Boosting (GB):
2) Support Vehicle Machine (SVM):
3) Hidden Markov model (HMM):
4) Linear Regression (LR):
5) Random Forest (RF):
6) Gaussian Processes (GP):

7 CONCLUSION

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