Avrupa Bilim ve Teknoloji Dergisi
Özel Sayı 32, S. 1168-1174, Aralık 2021

Araştırma Makalesi

www.ejosat.com ISSN:2148-2683

European Journal of Science and Technology
Special Issue 32, pp. 1168-1174, December 2021

Research Article

Smartphone-based Multi-parametric Glucose Prediction using Recurrent Neural Networks

Zeki Palaz*, Vakkas Doğan, Volkan Kılıç,

İzmir Katip Celebi University, Faculty of Engineering and Architecture, Department of Electrical and Electronics, İzmir, Turkey (ORCID: 0000-0002-1058-2935, 0000-0001-5934-4156, 0000-0002-3164-1981), zzekipalazz33@gmail.com, vkksdgn2@gmail.com, volkan.kilic@ikcu.edu.tr

(International Conference on Design, Research and Development (RDCONF) 2021 – 15-18 December 2021)

(**DOI:** 10.31590/ejosat.1041547)

ATIF/REFERENCE: Palaz, Z., Doğan, V., & Kılıç, V., (2021). Smartphone-based Multi-parametric Glucose Prediction using Recurrent Neural Networks. *European Journal of Science and Technology*, (32), 1168-1174.

Abstract

Diabetes Mellitus causes many deadly diseases, including pancreatic cancer as irregularity of glucose level triggers dysfunctions like unchecked cell growth. The critical stages in glucose irregularity are categorized as hyperglycemia (high blood glucose) and hypoglycemia (low blood glucose) which needs to be detected in advance for the quality of human life. In that sense, many tools have been developed based on artificial intelligence (AI) systems which mostly consider the glucose measurement as a prediction parameter. However, in this study, we propose to employ multi-parameter in glucose prediction based on a Recurrent Neural Network (RNN), a subset of AI, to enhance predictability. The proposed system utilizes a Long-Short Term Memory (LSTM) based RNN to handle complex memory operations caused by multi-parametric prediction. Training and validation scores on the OhioT1DM dataset show the advantage of our proposed system over the baseline systems for predicting glucose levels with a significantly reduced error. The system is later integrated with our custom-designed Android application, *BffDiabetes PRO*, capable of reading the glucose levels from the sensors via Bluetooth. The *BffDiabetes PRO* transfers the current glucose level, acceleration, and baseline skin temperature to the server via a cloud system to predict the next level. It receives the prediction result to evaluate whether the glucose level tends to reach the critical stages. In case of this tendency is detected, the *BffDiabetes PRO* alerts the user for necessary precautions.

Keywords: Artificial Intelligence, Recurrent Neural Networks, LSTM, GRU, Glucose Prediction, Smartphone Application

Tekrarlayan Sinir Ağlarıyla Akıllı Telefon Tabanlı Çoklu Parametrik Glikoz Tahmini

Öz

Diabetes Mellitus, glikoz seviyelerindeki düzensizliğin kontrolsüz hücre çoğalması gibi işlevsel bozuklukları tetiklediği için pankreas kanseri gibi birçok ölümcül hastalığa neden olmaktadır. Glikozun düzensizliğndeki kritik seviyeler, insan yaşam kalitesi için önceden tespit edilmesi gereken hiperglisemi (yüksek kan şekeri) ve hipoglisemi (düşük kan şekeri) olarak sınıflandırılır. Bu anlamda, genellikle sadece glikoz verisini kullanarak tahmin gerçekleştiren yapay zeka (AI) tabanlı birçok araç geliştirilmiştir. Ancak bu çalışmada, glikoz tahmininde öngörülebilirliği artırmak için yapay zekanın bir alt kümesi olan tekrarlayan sinir ağında (RNN) çoklu parametre kullanılması önerilmiştir. Önerilen sistemde, çoklu parametreli tahminin neden olduğu karmaşık bellek işlemlerini üstesinden gelmek için uzun-kısa süreli bellek (LSTM) tabanlı bir RNN kullanılmıştır. OhioT1DM veri setindeki eğitim ve doğrulama sonuçları, önerilen sistemin çok düşük bir hatayla glikoz seviyesini tahmin ederek temel sistemlere göre avantajını göstermiştir. Sistemimiz daha sonra Bluetooth aracılığıyla sensörlerden gelen glikoz seviyelerini okuyabilen özel tasarladığımız Android uygulamamız *BffDiabetes PRO* ile entegre edilmiştir. *BffDiabetes PRO*, bir sonraki glikoz seviyesini tahmin etmek için mevcut glikoz seviyesini, akselerasyon ve temel cilt sıcaklığı gibi parametreleri bulut üzerinden sunucuya aktarır. Uygulama, tahmin edilen değeri, glikozun kritik seviyelere ulaşma eğiliminde olup olmadığını değerlendirir. Bu eğilimin tespit edilmesi durumunda *BffDiabetes PRO* gerekli önlemler için kullanıcıyı uyarı göndermektedir.

Anahtar Kelimeler: Yapay Zeka, Tekrarlayan Sinir Ağları, LSTM, GRU, Glikoz Tahmini, Akıllı Telefon Uygulaması.

* Corresponding Author: zzekipalazz33@gmail.com

1. Introduction

Diabetes Mellitus is a chronic disease that occurs due to less production or ineffective use of insulin which causes irregularity in glucose levels (Kılıç, 2021; Mellitus, 2005). Failure to keep the glucose level at a normal range (80-130 mg/dL) causes damage to many organs, including the heart, blood vessels, brain, and kidney (Mercan, 2020; Mercan, Doğan, & Kılıç, 2020).

Many tools have been developed to monitor the regularity of the glucose level, such as continuous glucose monitoring (CGM) devices to minimize the problems experienced by diabetes patients and to improve their life quality (Doğan & Kılıç, 2021; Kap, Kilic, Hardy, & Horzum, 2021; Mercan, Kılıç, & Şen, 2021). CGM devices measure blood glucose periodically, like every 5 minutes, which allows controlling the glucose irregularity (Strollo et al., 2021). However, knowing the current glucose value is not enough to maintain a life quality. The user may not have sufficient time to stabilize the glucose once critical stages are exceeded too far. Therefore, sophisticated systems that predict glucose levels before exceeding critical stages are required to maintain the stability of metabolism. In this regard, artificial intelligence (AI) based systems have been proposed due to their ability to deal with the processing of current and past values to predict the future (Daniels, Herrero, & Georgiou, 2020; K. Li, Liu, Zhu, Herrero, & Georgiou, 2019; Martinsson et al., 2018; Martinsson, Schliep, Eliasson, & Mogren, 2020; Q. Sun, Jankovic, Bally, & Mougiakakou, 2018; X. Sun et al., 2020; Şahin & Aydın, 2021). A personalized artificial neural network (ANN) model was used to predict glucose levels at 30 and 60-minutes (Şahin & Aydın, 2021). To remove the uncertainty in the prediction, a deep neural network model is proposed that predicts glucose levels for up to 60 minutes using a univariate Gaussian output distribution (Martinsson et al., 2020). GluNet was developed for Type 1 diabetes, which provides short-term monitoring of glucose levels using a CGM device to prevent hyperglycemia and hypoglycemia (K. Li et al., 2019).

The RNN model was developed to process sequential data, and the same data transfer process applies the same variable weights to the inputs at each step. The hidden state vector emerging at each step is calculated based on the previous and new input. The neural network has a memory that develops itself from previous calculations with persistent storage. This hidden state vector is processed with the corresponding weight vector and bias value to generate the output. The gradient value of each output is based on calculations and operations at the previous step, which makes a large RNN model challenging to train. To overcome this issue, the back-propagation through time (BPTT) method has been proposed (Lillicrap & Santoro, 2019). This method limits the gradient and the computational load for each output from the previous time steps used in the time series. Exceeding the computational load limit with the BPTT method for long-term learning causes the problem of exploding and vanishing gradients. Gate mechanisms of LSTM and GRU, which are the solutions to these problems, include memory and hidden state vectors similar to the RNN model.

A multi-tasking approach was developed using the multi-tier conditioning recurrent neural networks (MTCRNN) to make short-term predictions (Daniels et al., 2020). The LSTM-based RNN model was trained with the OhioT1DM dataset to predict glucose at the next 30 and 60-minutes (Martinsson et al., 2018). A retrospective analysis was performed using a sequential model with an LSTM, a bidirectional LSTM, and several fully connected layers to predict future glucose levels (Q. Sun et al., 2018). A multivariate statistical technique based on latent variables was developed using the principal component analysis to predict glucose levels at the next 30 and 60-minutes (X. Sun et al., 2020). Recently, smartphones have found applications in AI-based systems as technological advances offer more computing power to process complex data. Many applications for predicting glucose levels have been developed, such as *Diabits* (Kriventsov, Lindsey, & Hayeri, 2020), MobiDiaBTs (J. Li & Fernando, 2016), and *BffDiabetes* (Kılıç, 2021). *Diabits* predicts glucose levels for up to 60-minutes based on CGM data and provides statistical analysis of historical data (Kriventsov et al., 2020). A machine learning classifier is proposed to predict glucose levels, integrated with the *MobiDiaBTs* application (J. Li & Fernando, 2016). In this study, a multi-parametric glucose prediction system is proposed and integrated with *BffDiabetes PRO*, an upgraded version of our previous application, *BffDiabetes* (Kılıç, 2021), where prediction is based on a single parameter. The *BffDiabetes PRO* notifies the users before their glucose level reaches a critical stage. Furthermore, the *BffDiabetes PRO* stores the real and prediction glucose values, allowing the user to access the history of glucose variation.

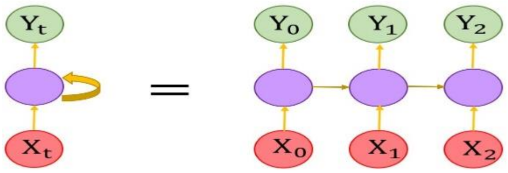
The rest of this study is structured as follows: The dataset and proposed system are described in Section 2, experimental evaluations are presented in Section 3, and the conclusion is given in Section 4.

2. Multi-parametric Glucose Prediction

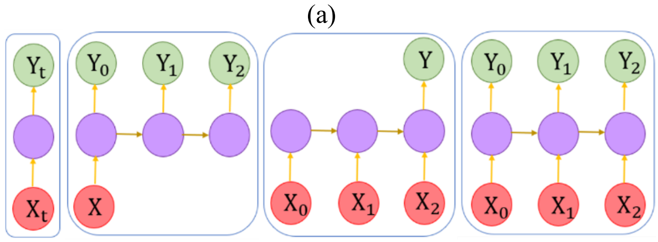
This section introduces RNN-based methods (LSTM and GRU) and our custom-designed *BffDiabetes PRO* application.

2.1. Recurrent Neural Networks

The general structure of folded and unfolded RNN has been shown in Figure 1 (a), where X_t and Y_t indicate input and output data sequences, respectively. Various structures of RNN can be categorized as one-to-one, one-to-many, many-to-one, and many-to-many, as illustrated in Figure 1 (b). These structures have been used in particular applications, including classification of images, text in images, recognition operations, language translations, and video summaries (Amidi & Amidi, 2020). Among these structures, here, a many-to-one structure was employed for multi-parametric glucose prediction.



(a)



(b)

Figure 1: General RNN structure is given in (a), and its extensions are given in (b), from left to right, one-to-one, one-to-many, many-to-one, and many-to-many.

As the conventional RNNs have vanishing and exploding gradients problems, they cannot handle long-term temporal dependencies (Hossain, Sohel, Shiratuddin, & Laga, 2019).

Therefore, LSTM and GRU models are proposed to overcome these problems, as explained next.

2.1.1. Long-Short Term Memory

LSTM is a type of RNN consisting of memory blocks that catch long-term dependencies, capable of dealing with vanishing and exploding gradients problems. The LSTM, which is illustrated in Figure 2, processes data in memory blocks in four steps.

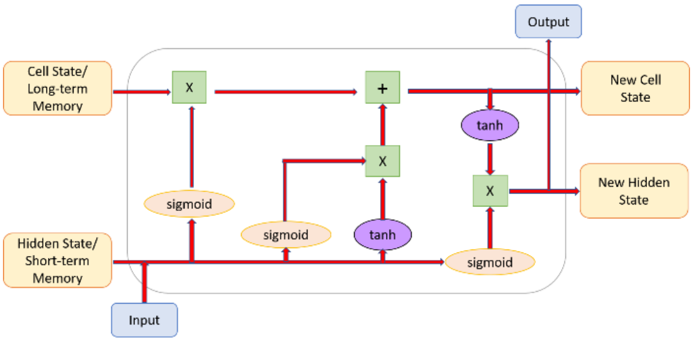


Figure 2: LSTM Model (Figure is adapted from (Loye, 2019b))

In the first step, the data to be kept or removed is decided in forget gate based on the Eq. (1) (Gers & Schmidhuber, 2001; Sak, Senior, & Beaufays, 2014):

$$f_t = \sigma\left(W_f \, . [h_{t-1}, x_t] + b_f\right), \tag{1}$$

where W_f defines the weights, b_f is the bias value of the forget gate, and σ represents the logistic sigmoid function. In the second step, the input layer is used to determine the new information, and then, the data (i_t) is updated with the sigmoid function using Eq. (2) (Tang, Qin, & Liu, 2015). Moreover, with Eq. (3) (Tang et al., 2015), the candidate information (C_t) that will create the new data is determined by the tanh function.

$$i_t = \sigma((W_i) * [h_{t-1}, x_t] + b_i), \tag{2}$$

$$\hat{C}_t = \tanh((W_c) * [h_{t-1}, x_t] + b_c), \tag{3}$$

where W_i and W_c represent the input and the memory cell weights, then, b_i and b_c refer to the bias value of the input gate and memory cell, respectively. In the third step, the old cell state C_{t-1} is multiplied by f_t to create the new cell state C_t. Then $\hat{C}_t$ is multiplied with the i_t to be updated and new information (C_t) is generated with Eq. (4).

$$C_t = f_t * C_{t-1} + i_t * \hat{C}_t, \tag{4}$$

In the fourth step, the sigmoid function is used to remove unnecessary information from the cell. Then the cell state is passed through the tanh and multiplied by the sigmoid function, removing only necessary parts. Finally, the output data (o_t and h_t) are obtained using Eq. (5) and (6) (Tang et al., 2015) in the output gate layer (Gers & Schmidhuber, 2001; Sak et al., 2014).

$$o_t = \sigma\left(W_{o,x} * x_t + W_{o,h} * h_{t-1} + b_o\right), \tag{5}$$

$$h_t = o_t * \tanh(c_t), \tag{6}$$

where, o_t and b_o define the activation vector and bias value of the output gate, respectively.

2.1.2. Gated Recurrent Unit

GRU is an RNN structure that predicts future information from past and present data (Chung, Gulcehre, Cho, & Bengio, 2014). The GRU model shown in Figure 3 (Dey & Salem, 2017; Pedamallu, 2020) includes reset (r_t) and update (u_t) gates that control the flow of information to solve the vanishing and gradient problem, protect hidden state information, and learn about long-term dependencies in the data (Shen, Tan, Zhang, Zeng, & Xu, 2018). The r_t (Eq. 8) allows deleting its previous hidden state h_{t-1}, and u_t (Eq. 7) enables to update its current hidden state with the new hidden state $\check{h}_t$ (Eq. 10). In network training, activations of the GRU are calculated and mapped from the input to the output sequence $y = y_1, \dots, y_t$ (Eq. 11). These equations of the GRU model are listed as follows:

$$u_t = \sigma(W_{u,x} * x_t + W_{u,h} * h_{t-1} + b_u), \tag{7}$$

$$r_t = \sigma(W_{r,x} * x_t + W_{r,h} * h_{t-1} + b_r), \tag{8}$$

$$h_t = (1 - u_t) * h_{t-1} + u_t * \check{h}_t, \tag{9}$$

$$\check{h}_t = tanh(W_{h,x} * x_t + W_{h,h}(r_t * h_{t-1} + b_h)), \tag{10}$$

$$y_t = \sigma(W_{y,h} * h_t + b_y), \tag{11}$$

where $W_{u,x}$, $W_{u,h}$, $W_{r,x}$, $W_{r,h}$, $W_{h,x}$, $W_{h,h}$, $W_{y,h}$ denote weight matrices, and finally b_u, b_r, b_h are bias vectors.

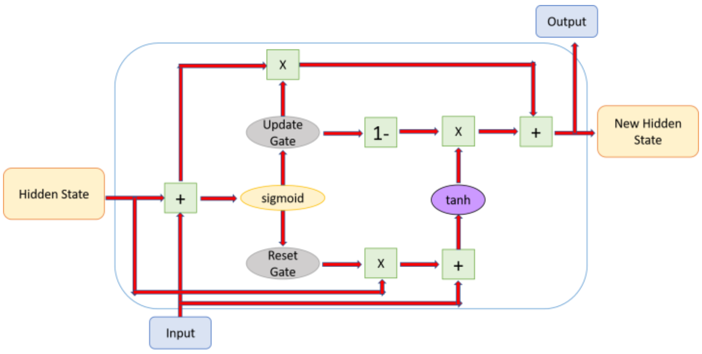


Figure 3: GRU Model (Figure is adapted from (Loye, 2019a))

2.2. Smartphone App: *BffDiabetes PRO*

The proposed multi-parametric glucose prediction system is integrated into the Android application to provide user- friendly environment for the users. Our custom-designed *BffDiabetes PRO* application was developed using Java language on the Android Studio. The application, capable of communicating wirelessly via Bluetooth with a glucose monitoring device, shows the current and past measurement on the plot together with the next four predicted values. Predicted values are evaluated whether there is a tendency to reach critical stages, and if so, it notifies the user of further precautions. Since the proposed system cannot be implemented on a human because of ethical issues, the system was tested with the data from the OhioT1DM dataset. The proposed system processes the data transferred to the server to make a prediction. Thus, the predicted value on the server is displayed on the *BffDiabetes PRO* screen. Firebase Realtime Database was used for data transfer which handles operations such as application management, usage tracking, data storage, sending notifications without needing an extra server, and server-side code writing (Kılıç, 2021).

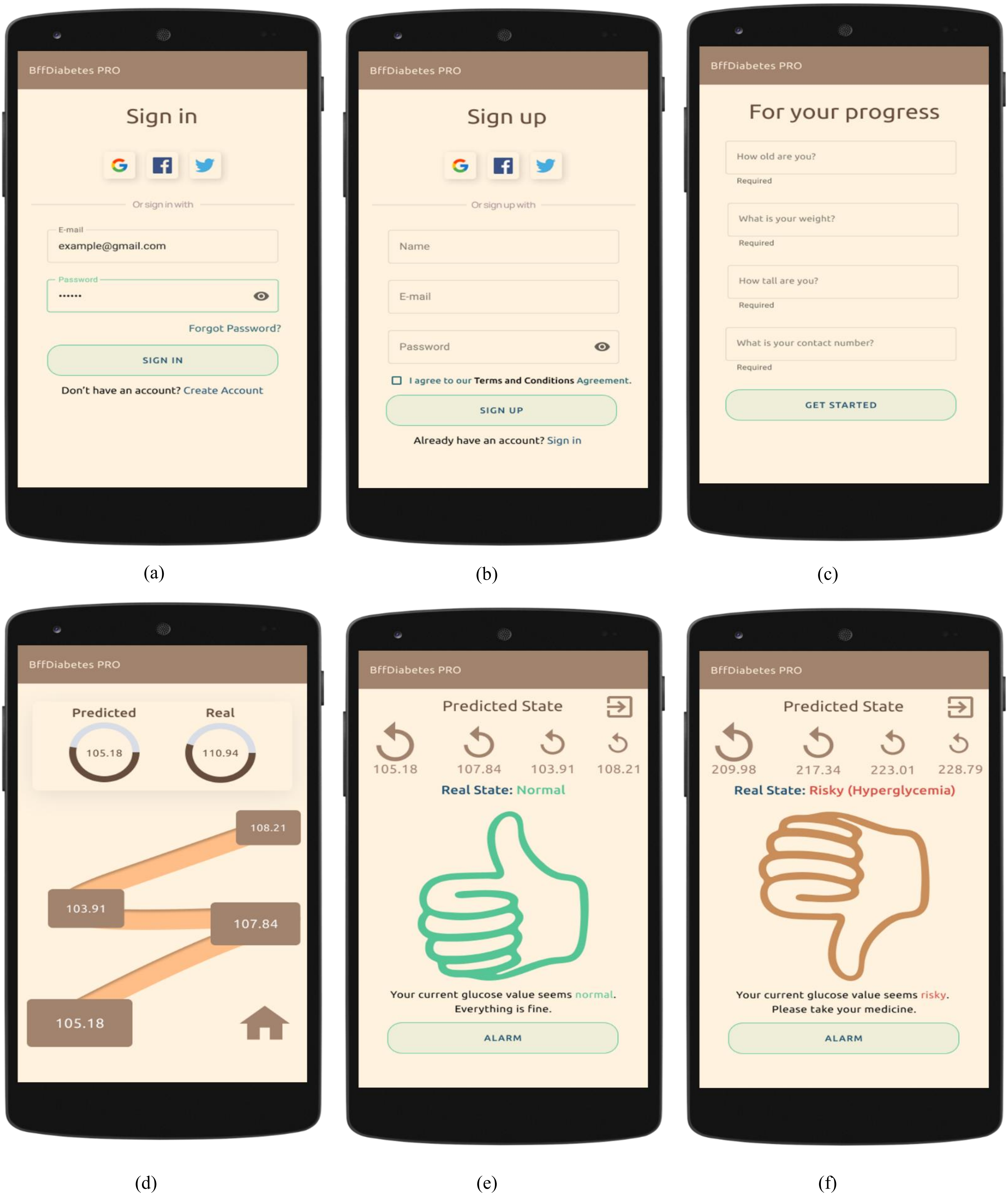


Figure 4: Screens of *BffDiabetes PRO* can be listed as follows: The sign in screen in (a), the sign up screen in (b), the information screen in (c), the main screen in (d), the predicted state screen for normal in (e), and the predicted state screen of risky (hyperglycemia) in (f) are shown.

3. Experimental Evaluations

In this section, the analysis of experimental evaluations and the OhioT1DM dataset are presented.

3.1. The OhioT1DM Dataset

The OhioT1DM dataset consists of eight weeks of data from 12 Type 1 diabetes measured in 2018 and 2020. While the cohort of the first six people in data released in 2018 wore the Basis Peak fitness bands, the second six people in data released in 2020 wore the Empatica Embrace. These patients were randomly numbered as 540, 544, 552, 567, 584, 596, 559, 563, 570, 575, 588, 591, and the personal data of the patients are shown in Table 1.

Table 1: OhioT1DM Dataset

ID	Gender	Age	Pump Model	Sensor Band	Cohort	Training Examples	Test Examples
540	Male	20-40	630G	Empatica	2020	11947	2884
544	Male	40-60	530G	Empatica	2020	10623	2704
552	Male	20-40	630G	Empatica	2020	9080	2352
567	Female	20-40	630G	Empatica	2020	10858	2377
584	Male	40-60	530G	Empatica	2020	12150	2653
596	Male	60-80	530G	Empatica	2020	10877	2731
559	Female	40-60	530G	Basis	2018	10796	2514
563	Male	40-60	530G	Basis	2018	12124	2570
570	Male	40-60	530G	Basis	2018	10982	2745
575	Female	40-60	530G	Basis	2018	11866	2590
588	Female	40-60	530G	Basis	2018	12640	2791
591	Female	40-60	530G	Basis	2018	10847	2760

All data were collected through CGM and insulin pump therapy. Patients wore Medtronic 530G or 630G insulin pumps during the 8-week data collection and used Medtronic Enlite CGM sensors. Provided physiological data from patients with the help of a fitness band were collected. The features given in the dataset are glucose level, finger stick, basal, basal temperature, bolus, meal, sleep, work, stressors, hypoglycemic event, illness, exercise, basis heart rate, basis GSR, basis skin temperature, basis air temperature, basis steps, basis sleep, and acceleration (Marling & Bunescu, 2020). Glucose level is recorded through CGM every 5-minutes. The magnitude of the acceleration is collected every 1-minute; however, the data are only available to people who wear the Empatica Embrace sensor band. Basis skin temperature is shown in Fahrenheit, and data are collected every 1 and 5 minutes for those wearing Basis Peak and Empatica Embrace, respectively. This study used glucose level, acceleration, and baseline skin temperature as their relationships were more correlated than other features illustrated in the correlation heatmap in Figure 4.

3.1. Results and Discussion

The performance of the proposed system was measured with the root mean square error (RMSE) metric, which is commonly used to measure the difference between predicted real values [32], by Eq. (12),

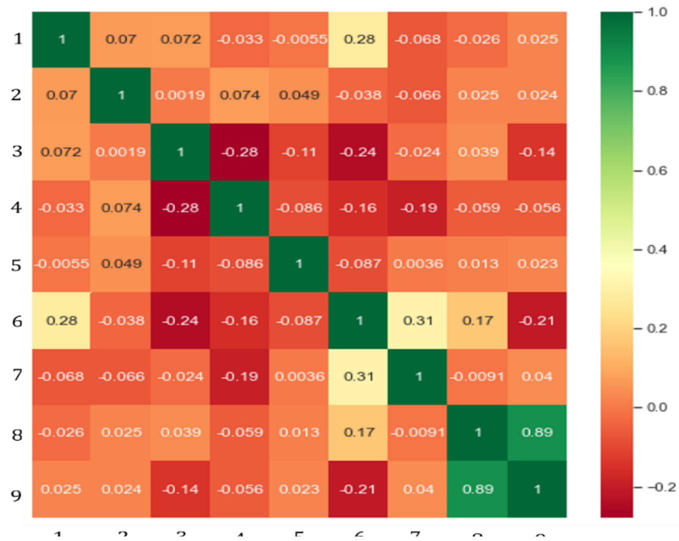


Figure 5: Correlation heatmap between features: (1) The glucose level, (2) The finger sticks, (3) The basal rate, (4) The bolus events, (5) The meal, (6) The reported sleep, (7) The basis GSR, (8) The basis skin temperature, and (9) The acceleration.

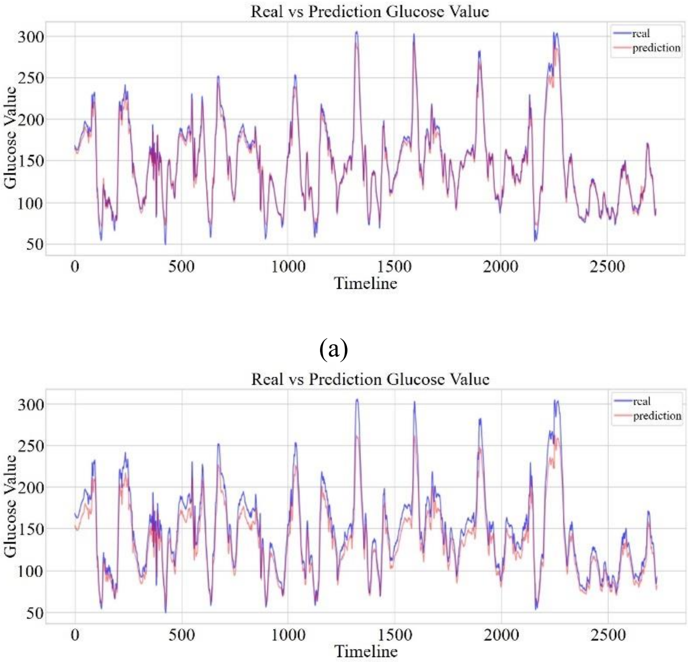
$$RMSE = \sqrt{\frac{\sum_{j=1}^{n} e_j^2}{n}}, \qquad (12)$$

where the n denotes the size of the measurement, and e_j is the difference between the real and predicted values.

Both LSTM and GRU were trained to determine which models gave fewer errors with the OhioT1DM dataset, and the results were analyzed with the RMSE shown in Table 2. Both models were trained with 200 epochs, a learning rate of 0.001, a batch size of 64, and a dropout of 0.2. Adam and stochastic gradient descent (SGD) optimizers were used for LSTM and GRU models, respectively. After the training, the prediction systems were tested and analyzed with the OhioT1DM dataset. The RMSE values were obtained at 5.74 mg/dl and 7.06 mg/dl for the LSTM and GRU models, respectively. Moreover, a minor error was attained from #570 Patient Id, and the graphs are shown in Figure 5. The LSTM model gives fewer errors than the GRU model, therefore the LSTM-based prediction system has been integrated into our smartphone application.

Table 2: The RMSE (mg/dl) Results Based on LSTM and GRU

PATIENT ID	LSTM	GRU
#559	5.79	7.03
#563	5.22	6.34
#570	**4.84**	**6.12**
#575	6.69	8.25
#588	5.51	6.73
#591	6.37	7.91
Average	**5.74**	**7.06**



(a)

(b)

Figure 6: Real and Prediction Glucose Values of Patient 570 Based on LSTM (a), and GRU (b)

The performance of the proposed system is also compared with similar studies as given in Table 3. The RMSE metrics such as 20.10 mg/dl, 19.79 mg/dl, 18.81 mg/dl, 18.68 mg/dl, and 11.63 mg/dl were reported in (Martinsson et al., 2018), (Daniels et al., 2020), (Şahin & Aydın, 2021), (Kriventsov et al., 2020), and (Q. Sun et al., 2018), respectively. Although the closest result to the proposed system was 8.88 mg/dl in (K. Li et al., 2019), our system gives more minor error with 5.74 mg/dl, which has shown that the proposed system outperforms the state-of-the-art methods.

Table 3: Comparing Glucose Prediction Studies with Proposed System

	Methods	**RMSE (mg/dl)**
(Şahin & Aydın, 2021)	ANN	18.81
(K. Li et al., 2019)	**CNN**	**8.88**
(Daniels et al., 2020)	MTCRNN	19.79
(Martinsson et al., 2018)	LSTM	20.10
(Kriventsov et al., 2020)	SVM	18.68
(Q. Sun et al., 2018)	Bi-LSTM	11.63
Proposed System	**LSTM**	**5.74**

Furthermore, the proposed system is integrated with our custom-designed Android application called *BffDiabetes PRO*. This application has five basic screens: the user sign in and the sign up screen, the information screen, the main screen, and the predicted state screen. Screenshots of the application are given in Figure 4. Users can log in to the application after completing the sign in and sign up steps, as shown in Figure 4 (a) and (b). Moreover, users who will log in to the application for the first time must fill in the information on the sign up screen. In addition, users can also use Twitter, Facebook, and Google accounts to sign up, and then users can log in to the app with the sign in button. SharedPreferences property of Android Studio is used to keep some data when the app even is closed. As seen in Figure 4 (c), age, height, and weight information were requested from the user after logging in. In this way, the body mass index of the user will be calculated. Furthermore, a contact number is requested as a notification is sent to the contact information in an emergency.

Our proposed system generates four predictions at 5-minute intervals and displays these values on the graphical display in the smartphone app. As shown in Figure 4 (d), the main screen of the application contains current and predicted values. Predicted values are shown in more detail on the main screen with respect to the time. If the range of the time is small, the value displayed on the screen becomes larger, and also, the user can save these values historically. As shown in Figure 4 (e) and (f), two separate screens provide information about the predicted state of the glucose prediction graph.

Moreover, the user can have information about the current situation with hand signals and colors. Comparing the pictures in Figure 4 (e) and (f), they show that the real state condition of the user is normal and risky (hyperglycemia), respectively. A warning message is sent to the user before the predicted glucose level reaches a critical stage.

4. Conclusion

This paper proposed LSTM- based multi-parametric glucose prediction to increase predictability before glucose level reaches critical stages. The proposed system was used an LSTM-based RNN to handle complex memory operations caused by multi-parameter prediction. Training and validation scores in the OhioT1DM dataset demonstrated the advantage of our proposed system over baseline systems for predicting glucose levels with a significantly reduced error. After the training, the prediction system was tested and analyzed with the OhioT1DM dataset. The RMSE value for the LSTM model was obtained as 5.74 mg/dl. The system is then integrated with our custom-designed Android app, *BffDiabetes PRO*, which is transmitted the current glucose level to the server via a cloud system to predict the next level. It takes the prediction result to evaluate whether the glucose level tends to reach critical stages. If this trend has been detected, *BffDiabetes PRO* was notified to the user for necessary action. Finally, features such as finger stick, exercise, reported sleep, bolus events, the basal rate would be added in future studies to benefit the advantage of more parameters for improved predictions.

5. Acknowledge

This study is supported by the Scientific and Technological Research Council of Turkey (TÜBİTAK) under the 2209-B Industry-Oriented Undergraduate Research Projects Support Program with project number 1139B412100530.

References

Amidi, A., & Amidi, S. (2020). CS 230 - Deep Learning / Recurrent Neural Networks cheatsheet. Retrieved from https://stanford.edu/~shervine/teaching/cs-230/cheatsheet-recurrent-neural-networks

Chung, J., Gulcehre, C., Cho, K., & Bengio, Y. (2014). Empirical evaluation of gated recurrent neural networks on sequence modeling. J arXiv preprint arXiv.

Daniels, J., Herrero, P., & Georgiou, P. (2020). Personalised Glucose Prediction via Deep Multitask Networks. Paper presented at the KDH@ ECAI.

Dey, R., & Salem, F. M. (2017). Gate-variants of gated recurrent unit (GRU) neural networks. Paper presented at the 2017 IEEE 60th international midwest symposium on circuits and systems (MWSCAS).

Doğan, V., & Kılıç, V. (2021). Akıllı Telefon Kullanarak Yapay Zeka Tabanlı Farenjit Tespiti: Artificial Intelligence Based Pharyngitis Detection Using Smartphone. J Sağlık Bilimlerinde Yapay Zeka Dergisi, 1(2), 14-19.

Gers, F. A., & Schmidhuber, E. (2001). LSTM recurrent networks learn simple context-free and context-sensitive languages. J IEEE Transactions on Neural Networks, 12(6), 1333-1340.

Hossain, M. Z., Sohel, F., Shiratuddin, M. F., & Laga, H. (2019). A comprehensive survey of deep learning for image captioning. J ACM Computing Surveys, 51(6), 1-36.

Kap, Ö., Kilic, V., Hardy, J. G., & Horzum, N. (2021). Smartphone-based colorimetric detection systems for glucose monitoring in the diagnosis and management of diabetes. J Analyst.

Kılıç, V. (2021). Yapay Zeka Tabanlı Akıllı Telefon Uygulaması ile Kan Şekeri Tahmini. J Avrupa Bilim ve Teknoloji Dergisi(26), 289-294.

Kriventsov, S., Lindsey, A., & Hayeri, A. (2020). The Diabits app for smartphone-assisted predictive monitoring of glycemia in patients with diabetes: retrospective observational study. J JMIR diabetes, 5(3), e18660.

Li, J., & Fernando, C. (2016). Smartphone-based personalized blood glucose prediction. J ICT Express, 2(4), 150-154.

Li, K., Liu, C., Zhu, T., Herrero, P., & Georgiou, P. (2019). GluNet: A deep learning framework for accurate glucose forecasting. J IEEE journal of biomedical health informatics, 24(2), 414-423.

Lillicrap, T. P., & Santoro, A. (2019). Backpropagation through time and the brain. J Current opinion in neurobiology, 55, 82-89.

Loye, G. (2019a). DEEP LEARNING Gated Recurrent Unit (GRU) With PyTorch. Retrieved from https://blog.floydhub.com/gru-with-pytorch/

Loye, G. (2019b). DEEP LEARNING Long Short-Term Memory: From Zero to Hero with PyTorch. Retrieved from https://blog.floydhub.com/long-short-term-memory-from-zero-to-hero-with-pytorch/

Marling, C., & Bunescu, R. (2020). The OhioT1DM dataset for blood glucose level prediction: Update 2020. Paper presented at the CEUR workshop proceedings.

Martinsson, J., Schliep, A., Eliasson, B., Meijner, C., Persson, S., & Mogren, O. (2018). Automatic blood glucose prediction with confidence using recurrent neural networks. Paper presented at the KHD@ IJCAI.

Martinsson, J., Schliep, A., Eliasson, B., & Mogren, O. (2020). Blood glucose prediction with variance estimation using recurrent neural networks. J Journal of Healthcare Informatics Research, 4(1), 1-18.

Mellitus, D. (2005). Diagnosis and classification of diabetes mellitus. J Diabetes care, 28(S37), S5-S10.

Mercan, Ö. B. (2020). Deep Learning based Colorimetric Classification of Glucose with Au-Ag nanoparticles using Smartphone. Paper presented at the 2020 Medical Technologies Congress (TIPTEKNO).

Mercan, Ö. B., Doğan, V., & Kılıç, V. (2020). Time Series Analysis based Machine Learning Classification for Blood Sugar Levels. Paper presented at the 2020 Medical Technologies Congress (TIPTEKNO).

Mercan, Ö. B., Kılıç, V., & Şen, M. (2021). Machine learning-based colorimetric determination of glucose in artificial saliva with different reagents using a smartphone coupled μPAD. J Sensors Actuators B: Chemical, 329, 129037.

Pedamallu, H. (2020). RNN vs GRU vs LSTM. Retrieved from https://medium.com/analytics-vidhya/rnn-vs-gru-vs-lstm-863b0b7b1573

Sak, H., Senior, A. W., & Beaufays, F. (2014). Long short-term memory recurrent neural network architectures for large scale acoustic modeling.

Shen, G., Tan, Q., Zhang, H., Zeng, P., & Xu, J. (2018). Deep learning with gated recurrent unit networks for financial sequence predictions. J Procedia computer science, 131, 895-903.

Strollo, F., Furia, A., Verde, P., Bellia, A., Grussu, M., Mambro, A., . . . Gentile, S. (2021). Technological innovation of Continuous Glucose Monitoring (CGM) as a tool for commercial aviation pilots with insulin-treated diabetes and stakeholders/regulators: A new chance to improve the directives? J diabetes research clinical practice, 172.

Sun, Q., Jankovic, M. V., Bally, L., & Mougiakakou, S. G. (2018). Predicting blood glucose with an lstm and bi-lstm based deep neural network. Paper presented at the 2018 14th Symposium on Neural Networks and Applications (NEUREL).

Sun, X., Rashid, M. M., Sevil, M., Hobbs, N., Brandt, R., Askari, M.-R., . . . Cinar, A. (2020). Prediction of Blood Glucose Levels for People with Type 1 Diabetes using Latent-Variable-based Model. Paper presented at the KDH@ ECAI.

Şahin, A., & Aydın, A. (2021). Personalized Advanced Time Blood Glucose Level Prediction. J Arabian Journal for Science Engineering, 1-12.

Tang, D., Qin, B., & Liu, T. (2015). Document modeling with gated recurrent neural network for sentiment classification. Paper presented at the Proceedings of the 2015 conference on empirical methods in natural language processing.