



Blood Sugar Level Indication Through Chewing and Swallowing from Acoustic MEMS Sensor and Deep Learning Algorithm for Diabetic Management

S. Krishna Kumari¹ · J. M. Mathana²

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Abstract

Diabetes, a metabolic disorder due to high blood glycemic index in the human body. The glycemic index varies in the human of improper diet and eating pattern such as junk foods, variation in the quantity of food, swallowing of food without chewing and stress. However, the diagnose of increase or decrease in the glycemic index is a challenging task. Similarly, the regulation of glycemic index without regular exercise is a major problem in day to day life. In this paper, we propose a novel SCS method to regulate glycemic index without exercise through changing the eating method. The proposed SCS eating method consists of Size of the food, Chewing style and Swallow time (SCS) of the food to regulate glycemic index. Furthermore, the proposed SCS method evaluate and validate through the acoustic signal acquired and processed with deep learning algorithm to analyze the chewing pattern of food to formulate a standard procedure for eating style and to reduce the glycemic level. The validation of diabetes done by measurement of blood glycemic through AccuChek Instant S Glucometer. Furthermore, the SCS method of eating style from 50 diabetes persons reduces the blood glucose level drastically by 85% after following the proposed method of eating style.

Keywords Chewing · Swallowing · Acoustic sensor · Diabetic measurement

Introduction

Diabetic, a metabolic disorder arise in the human body due to irregular food habits and stress. The diabetic person increases day to day of about 4.7% in 1980 to 8.5% in 2014 in the adult population according to statistics of the World Health Organisation (WHO). Diabetes damage the internal organs such as kidney, eye, pancreas, lung, and leg, and lead to complication such as heart attack, stroke, and blindness. Diabetic

during pregnancy affects the fetal and uncontrolled blood glucose level leads to death.

The diabetic has the direct impact on the economy of the country and development due to the medical cost and loss of wages. Furthermore, managing diabetes in day to day life is a challenging task. The blood glucose level maintenance is done with proper and regular diet, medications, Insulin delivery parallel with regular exercise. However, the above-mentioned methods to be followed in daily activities fails due to changes in lifestyle. The Pancreas has the small cluster of cells scattered over them called islet cells as shown in Fig. 1.

The islet comprises many cells including beta cells. The beta cells produce insulin, deploy in the bloodstream after a meal. The cells in the body absorb glucose with insulin for energy. In diabetes patients pancreas stop producing beta cells resulting in increased Glycaemia index.

Motivation

In this paper, we solve the above problem with novel procedures in an eating pattern. Furthermore, the contributions of the paper as follows:

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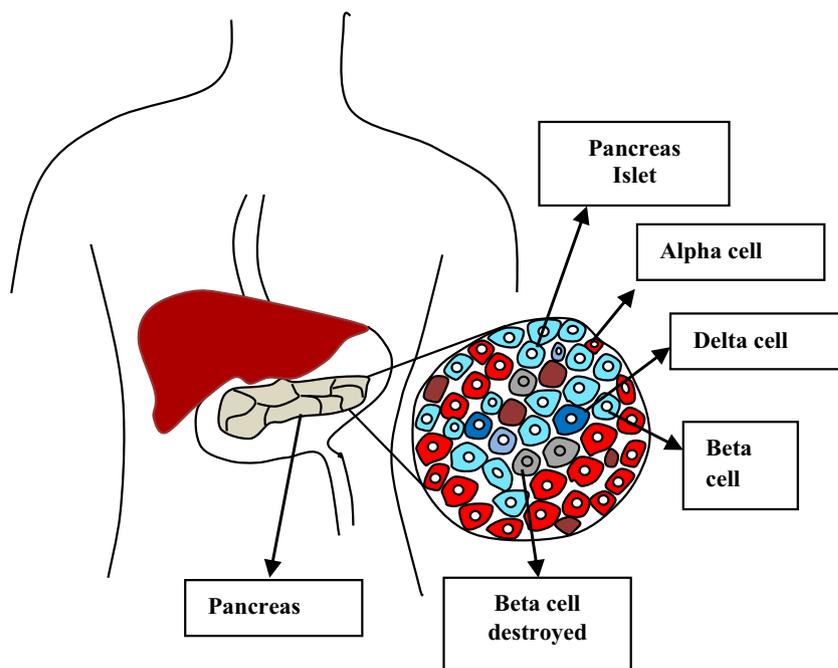
✉ S. Krishna Kumari
skrishnakumarireserach@gmail.com

J. M. Mathana
drmathanajm@gmail.com

¹ Department of ECE, Vel Tech High Tech Dr. Rangarajan Dr. Sakunthala Engineering College, Chennai, India

² Department of ECE, Mangalam College Of Engineering, Kottayam, India

Fig. 1 Islet cells



- (i) To regulate the glucose level in the blood through the size of food, chewing style and swallow time.
- (ii) The acoustic signal during the swallow and chewing indicates the level for managing diabetes when to continue the chewing and swallow.
- (iii) The indication for the level of chewing to maintain diabetes in control done through deep learning algorithms.
- (iv) Validate the SCS method and diabetes management through clinical traits apart from test patients.

The arrangement of this article is as follows: Chapter 2 reviews the literature articles in chewing, swallowing and diabetic management by medications and its adverse effects. Chapter 3 explains the SCS methodology. Chapter 4 gives the results of the proposed SCS method for swallowing using deep learning. Chapter 5 explains the regression analysis.

Related work

The chewing and swallowing monitoring play a vital role in the detection of diabetes from an efficient algorithm. The strain gauge sensor identifies the time interval of food intake through a non-invasive method and develops a standard pattern of a signal. The strain gauge sensor captures the movement of the lower jaw and differentiates the non-overlap epoch in the signal acquired. The non-overlap identified through a fixed length of time and frequency in every epoch [1]. The jaw movement and

overlap epoch identify in robotic mouth model force analysis. The force analysis combines with Pythagorean theorem for inverse kinematic analysis during chewing. The inverse kinematic analysis of chewing analyze the jaw movement in the muscles, while closing and opening of the mouth [2]. The chewing analysis measures the salt content in the saliva during the intake of food. The salt content monitor through the electrodes placed in the mouth during chewing and swallowing. The chewing and swallowing of different foods vary the content of salt in saliva and parallel to the different individuals [3]. The chewing of food analyzes with sensors such as an accelerometer, PPG and microphone for false chewing. [4]. The author studies the effect of diabetes Type 1 and Type 2 on salivary gland functions in human. There is a higher Protein concentration in resting and stimulated saliva for diabetic patients compared to healthy age-matched controls(AMC). For Diabetic persons, the secretion of saliva from salivary gland varies with the diabetic level. The diabetic level is inversely proportional to the saliva Secretion and secretion varies according to the diabetic person's age [5].

Glycaemia index, control with implantable artificial pancreas system (APS) to deliver insulin. The artificial pancreas system needs human intervention for precise insulin secretion. Furthermore, implantable APS cause dehiscence, infection, rupture and hematoma. Moreover, pancreatic islet film transplant from a donor to the diabetic patient for Glycaemia index control. The Table 1 shows the critical analysis of diabetic, swallow and saliva for correlation.

Table 1 Critical analysis of diabetic, swallow and saliva for correlation

SL.NO	Author(Year)	Sensors/Algorithm	Advantages	Disadvantages	Remarks
6	Buisson and Garel (2003) [6]	Fuzzy Arithmetic and Heuristic Search	Regular measurement maintains the health.	Only 14 number of food items evaluated.	Country to Country food item changes.
[7]	Kiyomi et al. (2008)	Plate Reader (Model 550 Microplate Reader -	Saliva based mastication detected	Detects only the nerve health condition.	From saliva, other diseases such as acidity, digestion,ulcer can be detected.
[8]	Marios et al. (2014)	Camera	Food quality can be detected from nutrition tables	Food and diabetes relation correlates less.	Food and swallow relation need to be established
[9]	Sebastian et al. (2014)	Microphones	Sensor located in outer ear canal solves the mounting problem	Applicable in laboratory setting.	Not applicable for routine monitoring.
[10]	Joseph et al. (2017)	Implanted oxygen electrodes(Implanted and Telemetry)	Directly measures the glucose level from abdominal tissue	Truncation error due to telemetry approach.	Healing of surgical wounds is slow.
[11]	Temiloluwa et al. (2017)	Common sensors and Signal processing	Each sensor system and location varies the performance.	Each system has own error percentage.	A standard procedure required for measurement of swallowing related to diabetes.
[12]	Muhammad et al. (2017)	Piezoelectric Sensor	Located in glass and monitors temporal muscle to avoid speech and motion artifacts.	Only 10 samples considered.	The device need to be checked for various food items.
[13]	Qianyi et al. (2017)	EMG sensors	Located in glass to monitor the jaw muscle movements	Continuous wearing of glass affects the eye due to radiation.	Applicable for patients wearing glass.
[14]	Muhammad et al. (2018)	Tri axis Accelerometers	Comfortable for wearing the sensor in the glass.	Wearing glass continuously irritates the muscles and eating time changes from person to person leads to forget in wearing the glass.	Needs a different location with less radiation effect.
15	Proposed methodology	MEMS sensor, Deep Learning	Wide frequency response of the acoustic sensor and the inbuilt low cut-off frequency minimizes noise from surrounding environment while acquiring the signal.	-	-

In this paper, we propose a novel method to control postprandial Glycaemia index naturally by masticating meal. The mastication of food evaluates with near-field Omni directional MEMS acoustic sensor. The Omni directional MEMS acoustic sensor acquires the swallowing signal during intake of food. However, the MEMS acoustic sensor applies for various application such as Hearing aids, bone conduction devices, hearing protection and audiometers due to wideband frequency response. The inbuilt low cut-off frequency minimizes noise from the surrounding environment during food intake and swallowing. However, IASUS NT make throat microphone located over laryngopharynx has certain disadvantages such as muffling of sound signals between sounds generated by nasal cavity, tongue, and lips and absorbs the throat vibrations due to strapping over the neck.

Methodology

SCS signal acquisition and deep learning

The correlation of saliva secretion due to chewing and swallowing establishes the relation of blood sugar level. In this paper, the MEMS acoustic sensor place over the lower trachea for the acquisition of signal due to chewing, swallowing and saliva. Furthermore, the optimum location for lower trachea selected to avoid muffling and vibration. The other locations such as ear canal, jaw muscle, temporal muscle, neck, throat, wrist and ear show less performance during acquisition due to internal and external noise. The internal noise such as gurgling and clicking sound, external noise due to the surrounding

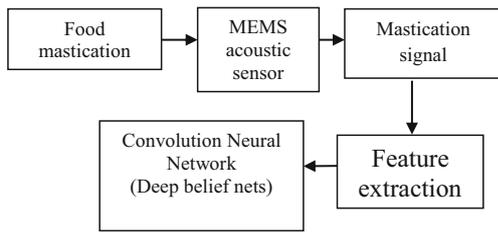


Fig. 2 Mastication signal and deep learning flow diagram

environment such as electrical and electronic devices. The proposed device of MEMS acoustic sensor to acquire the signal with suppressing the external and internal noises during various kinds of food intake such as solid and liquid. Figure 2 shows the flow diagram of the proposed SCS method.

In the SCS method initially, solid food for normal and abnormal mastication signal acquired with MEMS acoustic sensor. In addition, the glycemic level measures before and after solid food consumption through mastication. The mastication feature of solid food signals applies in Convolution Neural Network (CNN) for spatial and frequency of the signal with and without coherence.

Convolution neural network

The solid food mastication feature distributes between weights in CNN to determine spatial and coherence during mastication

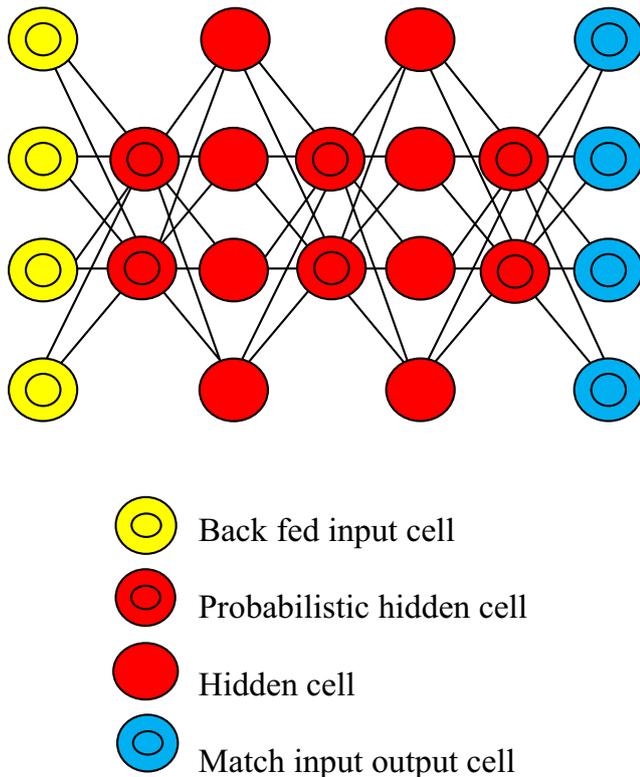


Fig. 3 Deep belief network (DBN)

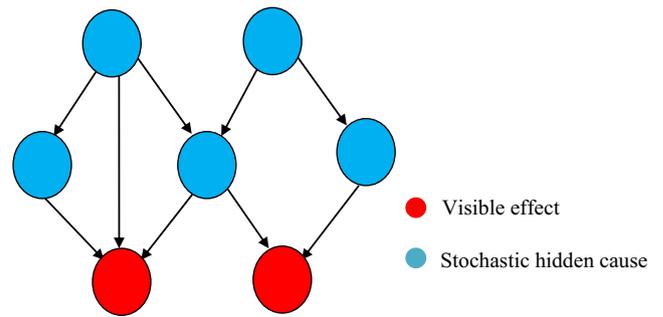


Fig. 4 Belief network (BN)

level. Furthermore, the deep learning - deep belief apply for mastication level analysis as explained below section.

Deep learning a part of machine learning develop and process raw input signal during chewing and swallowing. Deep learning applies in the pattern, Image matching and recognition for classification and identification of objects. Deep learning comprises multiple non-linear layers, where every successive layer performs with the previous layer. In deep learning, the supervise learning apply for pattern matching and unsupervised learning apply for pattern analysis. Both the learning scheme requires training data sets for classification or analysis. The data sets comprise of lower and higher levels to represent hierarchical data's for convolution. Deep learning classifies into different types based on an architecture such as Recurrent Neural network, Gated recurrent unit, Deep belief network, Convolutional Neural Network, and deep stacking network. Furthermore, the research emphasize on Deep belief network due to probabilistic in nature and which is required for SCS analysis. In a deep belief network, there exist multiple layers with undirected and directed edges. The multiple layers have hidden units, each layer connects to the next layer but the units are not connected as shown in Fig. 3.

The DBN combines Belief Net (BN) and Restricted Boltzmann Machine (RBM). The Fig. 4 shows the Belief Net and Fig. 5 shows the RBM network. The BN comprises of stochastic binary units connected to layers with weight. The binary unit value change depending on input from other units.

Furthermore, the undirected edges limitation in Boltzmann machine overcomes with RDM, which comprises of hidden layer connections with hidden units. The connection provides the results of RBM learning accurately.

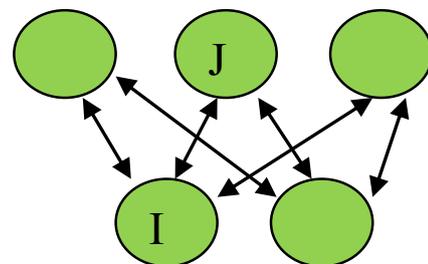


Fig. 5 Restricted Boltzmann machine

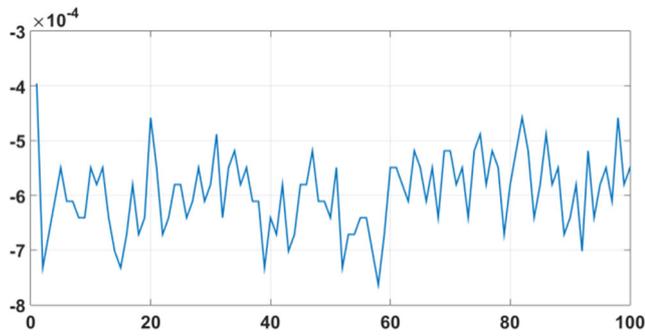


Fig. 6 A signal of 10-g food size, 10 s chewing and swallow

In addition, the multi-layer DBN comprises of belief networks, restricted with Boltzmann Machine order against each other for deep belief network. The DBN net uses contrastive divergence algorithm to train DBN. The trained features and visible units apply as the feature in the second hidden layer. Thus, the whole hidden layer train till the final hidden layer. The hidden layer comprises of complex functions to train data and the complex function improves the accuracy from the learning data of sample input.

For an n-layer system of $(\times 1, \times 2, \dots \times n)$ with ‘I’ input and ‘O’ output represent as $i \geq 1 \geq 2 \geq 3 \dots \dots \times n \geq$. O. In addition, the deep belief network, a probabilistic model, which relates neural network discrimination model and joint distribution. The relationship compares with conventional neural network discrimination model. Moreover deep belief net represent by

$$F(y_i; V) \tag{1}$$

Where,

- y_i the i th positive mastication signal
- v parametric model

The SCS training signal represented as in Eq. 2.

$$\sum_i D(F(y_i; V); x_i) \tag{2}$$

Where,

- x_i the correspondence mastication signal.

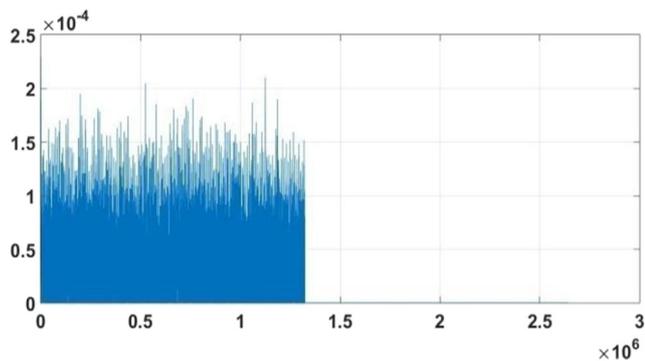


Fig. 7 Gabor filter of signal - 10-g food size, chewing of below 10 s and swallow

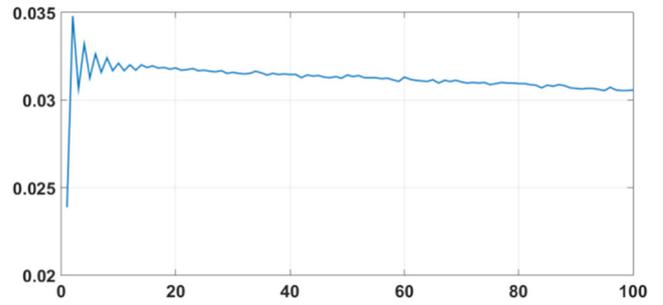


Fig. 8 A signal of 10-g food size, without chewing and swallow

$$D = -\sum_i p_i \log p_i - \sum_i (1-p_i) \log (1-\hat{p}_i) \tag{3}$$

In Eq. 3 the pi distance which represents solid food with deep chewing. In addition, the probability distribution calculates with cross-entropy as in Eq. 4.

$$D(Q, P) = -\sum_{k=1}^N q_k \log_2 \frac{q_k}{p_k} \tag{4}$$

Where Q, P represents N-dimensional feature space.

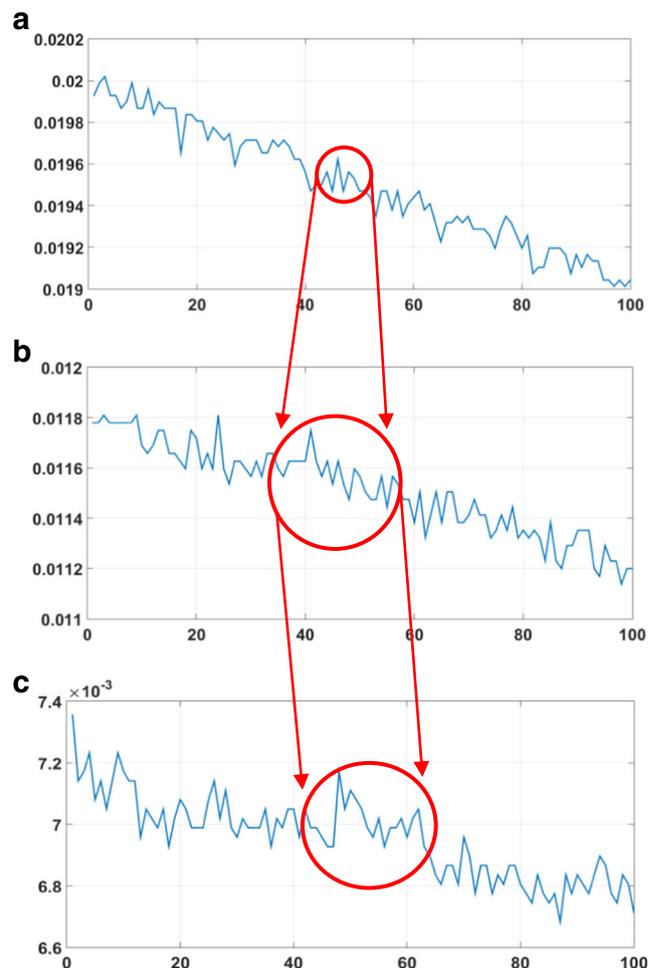


Fig. 9 a Layer 1 output of signal without chewing. b Layer 2 output of signal without chewing. c Layer 3 output of signal without chewing

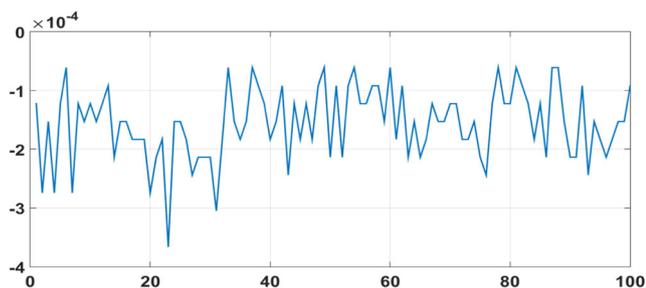


Fig. 10 Fast food consumption (no saliva secretion)

The Size of the food, chewing and swallowing varies for different individuals and the type of food. The feature of SCS represents with deep belief nets. The non-linear SCS features represent with Gabor kernel as defined in Eq. 5.

$$j_k(z) = I(Z) * \psi(k, z) - \tag{5}$$

The object function of $J_k(z)$ and $I(z)$ represented as

$$j_k(z) = A_k e^{i\Phi_k} \tag{6}$$

and $\Phi(k, z)$ is the Gabor feature of non-linear mastication signal.

Where,

A_k amplitude of mastication signal

Φ_k phase of mastication signal

Materials and methods

The SCS signal $x(t)$ as shown in Fig. 6. For the food size of 10 g, chewing for 10 s and then swallowing.

The mastication amplitude and phase feature relate with non-linear mastication signal by Gabor feature filter matching. The non-linearity solve by enhancing mastication signal data sub-sets. The data enhanced data subsets remove redundancies in the signal of irregular food size i.e. more than 10 g and then chewing below 10 s and swallow as shown in Fig. 7.

For example, size, chewing and swallow signal represent as in Eq. 7

$$Y = [y_1, y_2, y_3, \dots, y_n] \tag{7}$$

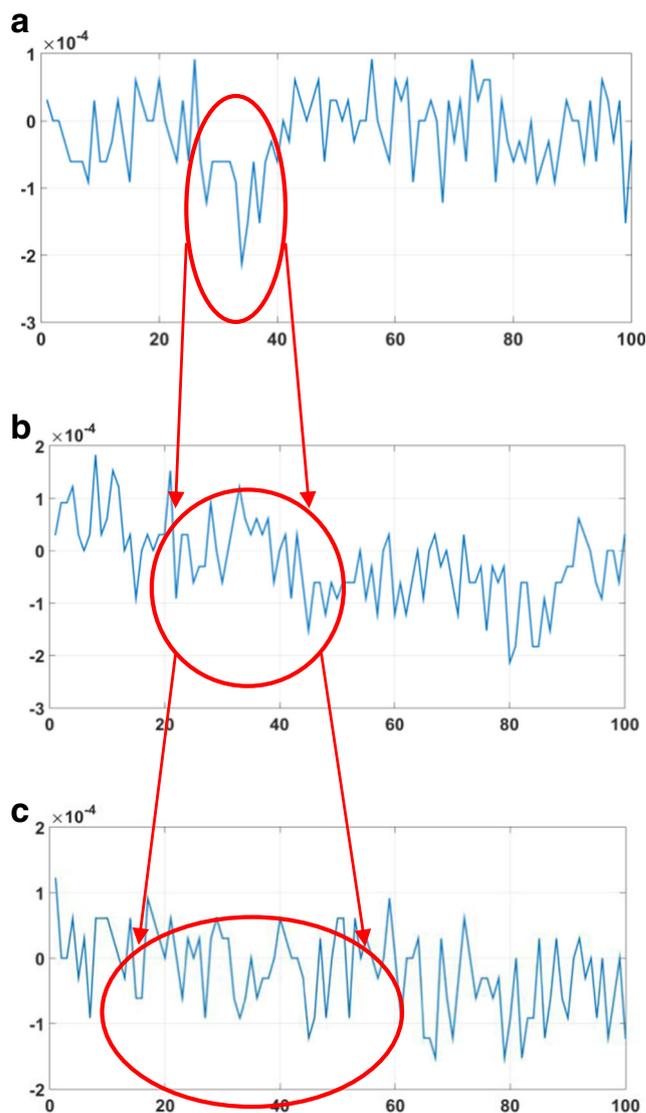


Fig. 11 a Layer 1 output of Fast food consumption (no saliva secretion). b Layer 2 output of Fast food consumption (no saliva secretion). c Layer 3 output of Fast food consumption (no saliva secretion)

The size, chew and swallow signal with redundancies in data subsets represent as

$$\psi(B_i) = [s(v_1, B_i), s(v_2, B_i), \dots, s(v_k, B_i)] \tag{8}$$

Table 2 Mastication and its relation to blood glucose

Blood glyceimic level(mg/dL)	With chewing		Without chewing	
	Left hand	Right hand	Left hand	Right hand
Before breakfast	128	132	177	171
After breakfast	181	197	205	228
Before lunch	145	149	132	129
After lunch	215	221	198	192

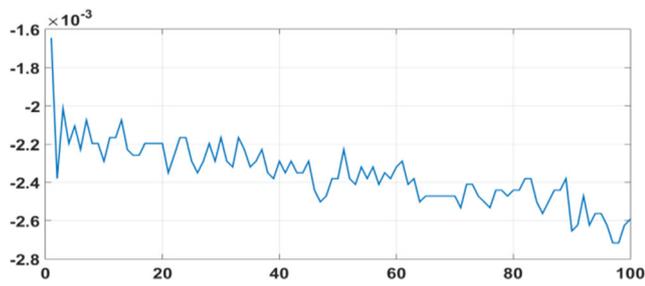


Fig. 12 Acoustic signal of only saliva swallow

The redundancies remove by Eq. 9.

$$\text{Redundancy rate} = \frac{\text{subsr}_i \cap \text{subsr}_j}{N_{fea} * N_{ins}} \quad (9)$$

Where subsr_i - data subset 1, subsr_j - data subset 2, N_{fea} - data set 1, N_{ins} - data set 1. The size, chewing and swallow signal removes the redundancies in the acquired signal and feature of the signal represented in Eq. 10.

$$s(v_i, B_i) = \max \exp_i \left(-\|X_{ij} - v_i\|^2 \right) \quad (10)$$

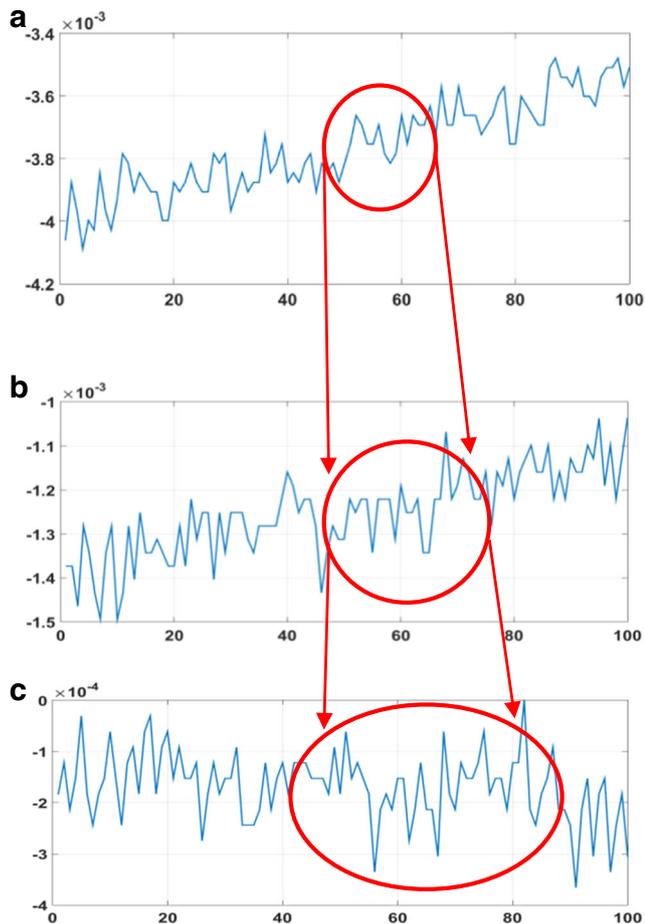


Fig. 13 a Layer 1 of Acoustic signal with only saliva swallow. b Layer 2 of Acoustic signal with only saliva swallow. c Layer 3 of Acoustic signal with only saliva swallow

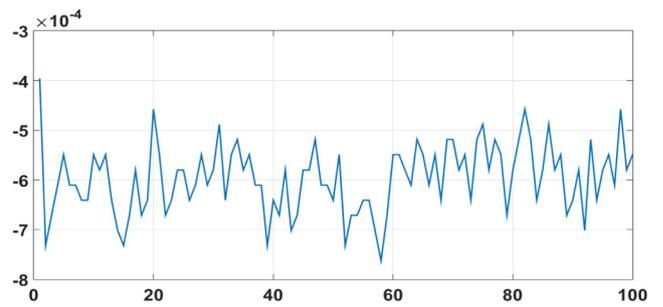


Fig. 14 Signal of 10 g food size, with chewing of 10 s and swallow

The food swallows completely without mastication shown in Fig. 8. Furthermore, the acoustic signal arises during swallow of food without chewing. In addition, the deep learning weights of convolution neural network for food size, chewing and swallowing in the non-linear fashion as shown in Fig. 9a-c. In Fig. 9a-c, the layer1 of deep learning signal for the input signal shown in Fig. 8, and similarly layer 2 and layer 3 of

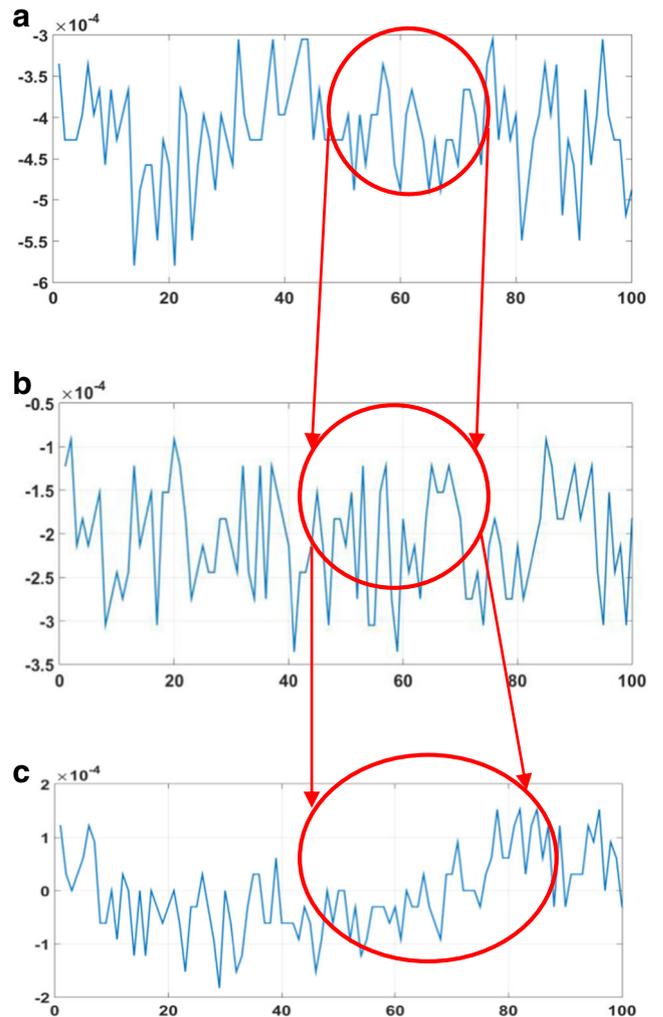


Fig. 15 a Layer 1 output for signal of with chewing of 10 s and swallow. b Layer 2 output for signal of with chewing of 10 s and swallow. c Layer 3 output for signal of with chewing of 10 s and swallow

Table 3 Statistical parameters for different layers and different signals for SCS

	Mean	Variance	Standard deviation	Kurtosis
Food swallow without chewing				
Input	0.0313	8.9649	9.4683	39.5518
Layer1	0.0195	7.9790	2.8247	1.8575
Layer2	0.0115	3.0928	1.7586	2.1118
Layer3	0.0070	1.7648	1.3285	2.6812
Food swallow with chewing				
Input	5.9662	4.8236	6.9452	2.8947
Layer1	4.1748	3.7418	6.1171	3.2084
Layer2	2.0599	3.7888	6.1553	2.0876
Layer3	6.1035	5.7196	7.5628	2.6835
Fast food consumption				
Input	1.5656	3.7752	6.1443	3.3379
Layer1	1.9836	3.4501	5.8738	3.2487
Layer2	2.1057	5.9961	7.7435	3.0714
Layer3	1.8921	3.9281	6.2675	2.2779
Saliva swallow without food				
Input	0.0024	2.6436	1.6259	5.4923
Layer1	0.0038	2.1612	1.4701	2.2400
Layer2	0.0013	9.4911	9.7422	2.8450
Layer3	1.6876	4.6558	6.8233	3.4431

deep learning shown in Fig. 9a–c. From the figures of layers shows the typical variations of food intake in size and chewing very precisely and the same marked in the figures. The layers and their statistical parameters discussed in the next section.

The Deep belief network train with input data such as food swallow without mastication, Food swallow after mastication, saliva swallow and Fast food consumption.

The solid food consumes at a fast rate with abnormal mastication and the corresponding acoustic signal shown in Fig. 10.

During fast food consumption, saliva does not secrete during chewing. The non-secretion of saliva results in increased blood sugar level and verify with AccuChek Instant S Glucometer with Strip and tabulated in Table 2. The fast-food consumption and corresponding Deep belief nets hidden layers to train CNN is shown in Fig. 11a–c for the input signal as in Fig. 10.

The acoustic signal of saliva consumption train CNN to reduce saliva acoustic signal redundancies in masticated food consumption signal as shown in Fig. 12. The later

signal, hidden layer weights shown in Fig. 13a–c for the input as in Fig. 12.

The solid food of chewing of about 10 s induces saliva secretion and verify the same with 10 diabetic persons. The saliva with food chewing acoustic signal recorded and shown in Fig. 14. The later signal hidden layer weights shown in Fig. 15a–c for the input as in Fig. 14.

Table 2 shows the average blood glucose level measure with glucometer before and after food consumption for the different case, namely food swallow without mastication and food swallow after complete mastication from 30 diabetic persons.

Regression analysis

It is a statistical estimation of the relationship between one dependent variable and one or more independent variable. In linear regression, let the number of independent variables is one and denoted by x , β_0 and β_1 represents scalar and the dependent variable represented by y . In a simple regression analysis, the relationship represented by

$$y = \beta_0 + \beta_1 x \tag{11}$$

Let e represents the difference between the predicted value of y and actual value y

$$e = y - \hat{y} \tag{12}$$

Table 4 Blood glycemc level before and after SCS method

Average Blood glycemc level (mg/dL) from 10 cases with 15 days monitoring	Before SCS method	After SCS method
Before food	179	152
After food	204	170

The Least squares method is used to estimate y which minimizes the Sum of Squared Residuals (SSR) and it is given by

$$SSR = \sum_{k=1}^n e^k \quad (13)$$

In linear regression, the formulas for the least squares estimates are

$$\hat{\beta}_1 = \frac{\sum (x-\bar{x})(y-\bar{y})}{\sum (x-\bar{x})^2} \quad (14)$$

$$\hat{\beta}_0 = \bar{y} - \hat{\beta}_1 \bar{x}$$

where \bar{x} and \bar{y} are mean of the variables x and y . Table 3 shows the statistical parameters for different layers and different signals for SCS. The mean of the signal correlates highly with chewing due to continuous chewing, the amplitude of the signal is high. The amplitude of the signal correlates with diabetic value.

Hence, the mean value modelled with regression techniques of measured values and the equation of the regression as below.

$$Y = -2.8e3 * \text{Target} + 2.2e2 \quad (15)$$

The above equation validated for 10 unknown persons after chewing for 10 s and swallowing, for diabetic value measurement. Table 4 shows the average blood glycemic level before the SCS method and after following the SCS method of swallowing about 10 days for 10 diabetic persons who have diabetes for a duration of 4 years.

Conclusion

The MEMS acoustic sensor placed near the throat muscle region to monitor different SCS signal. The proposed method is non-invasive, easily powered by a battery of 9AAA size. The proposed method validates, blood sugar level varies for different types of south Indian food and their corresponding chewing level. The result shows that more chewing of solid food reduces blood glycemic index. Furthermore, the regression equation validated for 10 persons shows the result with measured values similar for 9 persons diabetic value, with an approximation of ± 15 of the measured diabetic. The SCS method optimize an average of 10 s for chewing considerably reduces the diabetic level due to saliva secretion, each south Indian food analyzed and apply through convolution neural network to determine an optimal chewing level of 10 s obtained from the average of 30 person measured diabetic value. Furthermore, the analysis can be extended to north Indian food and Chinese food. Since the north Indian food consists of non-vegetarian food items and could differ the SCS parameters.

Compliance with Ethical Standards

Conflict of Interest The authors have no conflict of interest.

Ethical Approval This article does not contain any studies with human participants or animals performed by any of the authors.

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