Stress-Log: An IoT-based Smart System to Monitor Stress-Eating

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***Abstract*—Stress eating, i.e., overeating due to stress, is one of the reasons for obesity. Chronic stress releases the hormone cortisol which increases the appetite levels of a person. Initial onset of stress causes a temporary loss of appetite but chronic stress leads to the development of addiction and/or cravings for 'comfort foods' that are calorific values. Chronic stress, uncontrolled or unmonitored food consumption, and obesity are intricately connected, even involving certain neurological adaptations. We propose a system which helps in identifying stress eating compared to normal eating. It allows the users to make a choice between two proposed methods for monitoring food intake: wearable and non-wearable. These methods take the log of food consumed by the user, calculate the calorie counts and notify the user about the eating behavior with an accuracy of 97%.**

***Index terms*—** Smart Healthcare, Smart Living, Smart Home, Stress-Eating, Stress-Level Analysis, Internet of Things (IoT), TensorFlow

I. Introduction

Chronic stress is one of the factors that may contribute to the development of obesity [1] [2]. Chronic stress releases a hormone called cortisol which increases the appetite of a person [3]. If the stress persists chronically, the appetite levels along with the cortisol levels remain unchanged. Additionally, when a person is stressed, the gut microbiota in the stomach secrete hormones which increase cravings for sugar-rich foods [4]. When uncontrolled, such cravings tend to lead to weight gain. Individuals with high-cortisol levels tend to gain more weight when compared with humans with low-cortisol levels [5]. A prolonged exposure to stress may lead to an increased risk for not only obesity, but also metabolic diseases, cardiovascular diseases, type 2 diabetes and also polycystic ovarian syndrome (PCOS) [6]. Owing to unhealthy eating habits, the basis for which can be due to chronic stress (where an individual is not self-aware stress-eating versus normal eating), or due to other factors such as busy life style, calorie-rich fast food consumption, as well as other genetic and environmental factors, obesity has now become an epidemic with more than 1 in 3 adults being obese [7]. Thus, tools for an individual to track and thereby gain control of their calorie intake, have been of substantial interest in the community (e.g. weightwatchers, myfitnesspal).

Internet of Medical Things (IoMT) is a collection of multiple medical devices independently connected to the Internet through wireless communication, with capability to exchange data with cloud based servers. Simple sensors or medical devices are the basic elements of IoMT [8]. IoMT is the backbone of smart healthcare which in turn is an important component in smart city architectures [9].

A sensor-based system to monitor the food intake and eating habits of a person could help to him/her to differentiate between stress eating and normal eating. Figure 1 shows a basic overview of this "Stress-Log" system. In a previous research, we have presented an IoT-enabled system that considered current food intake and predicted future food intake to maintain healthy diet [10], [11].

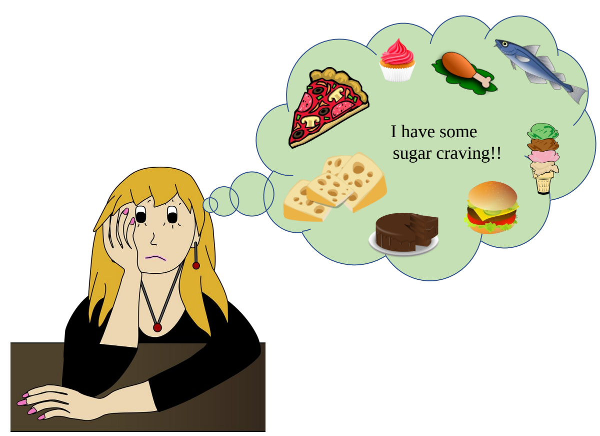

Fig. 1: Conceptual Overview of the Stress-Log.

The organization of the paper is as follows: Section II discusses the novel contributions of this paper. Section III provides a broad overview of the proposed food monitoring system. Section IV discusses existing related research. Section V gives a system-level description of the monitoring system. Section VI implements and validates the model of the proposed system. The paper concludes in Section VII.

II. Novel Contributions of this Paper

In this work, we approach this problem by analyzing the differences between regular eating and stress eating. The relationship between the amount of food consumed with the stress level is proposed by this system. This is done by:

- Continuous analysis of stress levels based on Table III in a person by using a wearable which captures the food, analyzes the calorie content of the food and sends the information to a cloud server from where the notification of stress eating is sent to the person using a mobile phone as an interface.
- A non-wearable manual input of the foods consumed and analysis of stress eating is done at the same time.
- If stress eating is detected, techniques to resolve stress are proposed.
- Allowing the user to access his/her own predicted stress levels from the previous days are provided with access to database storage.
- A mobile application is built which acts as an interface indicating the total number of calories consumed to the person along with the awareness of stress-eating and normal eating.

III. Stress-Log: A broad perspective of an IoT based approach to recognize and monitor stress-eating

Figure 2 presents a complete overview of the approach. A wearable for instance a camera capturers the food intake of the person and sends it to a cloud server via Internet where the information is processed to recognize the items whose calorie value can then be computed from a database. This processed information is sent to the mobile application to inform or alert the user.

Considering today's lifestyle [12], the growth of obesity [13] and stress levels of people [14], a remote non-wearable, IoT based solution will help in keeping people continuously monitored and notified about food intake and recognize stress levels. This study can be a major contribution to the field of smart healthcare, owing to the general difficulty in adhering to manual-logging of food intake. It is also of moderate cost, is adaptable to use and does not consume too much time for charging as this will be a software based solution. This study could have the potential to improve overall quality of life.

IV. Related Prior Research

The relationship of stress with the food intake is explained and discussed through many perspectives. Considering the various factors like the type of eating, metabolism rate, role of insulin, addictions towards eating, the behavioral relationship between stress and over eating is defined as compulsive [15]. Similarly, when a person under stress is likely to have a tendency to eat high calorie 'comfort' food which could lead to obesity [16]. Chronic stress affects not only quantity or timing of food intake but also the choice of foods, which may even lead to depression and inflammation and influence metabolic responses a human body undergoes in stress [3].

There are a number of mobile or web applications and electronic gadgets that attempt to help users to monitor their daily food intake [17]. However, there are no methods to-date that provide continuous monitoring through wearable devices in order to recognize the stress-eating event and to monitor it. Some previously proposed methods for food monitoring systems with automatic approaches are shown in Table I. Pressure sensors are embedded in a tablecloth or underneath a table to weigh and assess the amount of food taken by the user [18]. The correctness to measure the weight of the food placed is approximately 80%. This is not a wearable approach and it fails to identify the type of food consumed (e.g. dough-nut versus fresh fruits). In another approach, an external camera is used to detect the chewing patterns when a person is eating food [19]. This is a good approach to detect when and how often a person is eating but does not classify the food and relate it to the nutrition quality. In a similar approach, Doppler effect has been employed to monitor the vertical jaw movements of a person while eating food, which while identify frequency, timing and duration of food intake, does not recognize types of food and does not relate the consumed food to stress [20].

TABLE I: Automatic Approaches for Food Monitoring.

Work	Approach	Healthcare Problem	Drawback
Chang, et al. [18]	Pressure Method	Food Intake Monitoring	Food classification and weight estimation is not possible
Cadavid, et al. [19]	Surveillance-Video Method	Food Intake Detection	Needs external camera and a steady place while eating food
Tanigawa, et al. [20]	Doppler Sensor Method	Food Intake Monitoring	Non wearable approach

The state of the art of wearables which are currently available for detecting and monitoring food intake, is presented in Table II. Depending on the methodologies of the sensors used, a classification is provided and the drawbacks of each approach are indicated.

It is clear that the current state of research does not concentrate towards the detection of stress through automatic food monitoring, collecting the type and nutritional values of food and usage of cloud in order to access data in future.

V. Proposed Approaches for Smart Food Eating Monitoring System

Stress-Log addresses the open challenges described in previous sections problems by designing a wearable to detect the stress level of a person by considering food intake as a factor using IoT. This section defines the system level modeling of

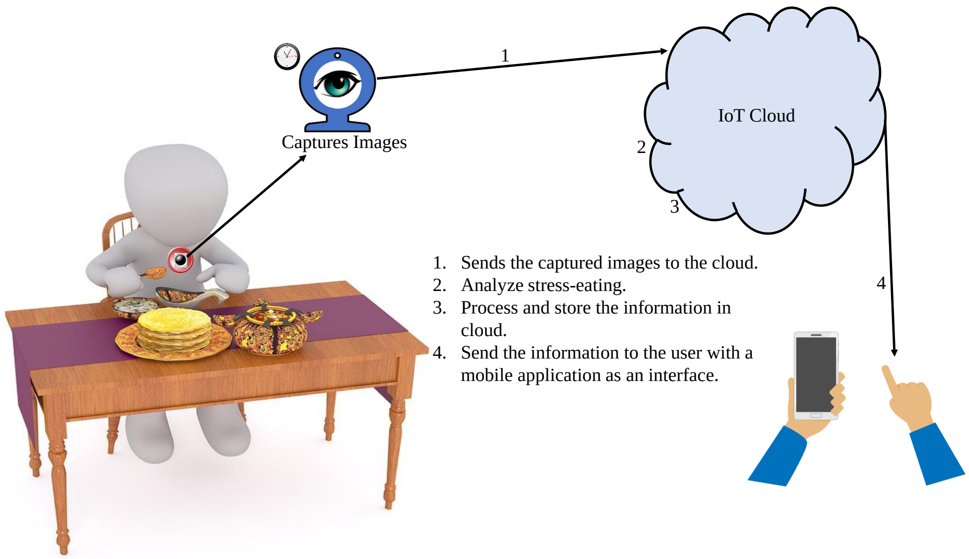

Fig. 2: An Overview of the Proposed Approach.

TABLE II: Wearable Approaches for Food Monitoring.

Approach	Body Position of Sensor	Application	Drawback
Acoustic Approach	Neck, inner ear towards ear drum and outer ear	Chewing: [21], [22]; Swallowing: [23]	Limited number of foods detected, no explanation of relationship with stress
Visual Approach	Upper body, external camera	Volume estimation, Food type classification [24], [25]	Needs a steady place while eating food and no explanation of relationship with stress
Inertial Approach	Wrist, hands, neck	Gesture detection-Gyroscope [26] ; bite events-Accelerometer [27]	Uncomfortable, no explanation of relationship with stress
Physiological Approach	Neck	EMG [28] and EGG [29]	Hard to detect signals , no explanation of relationship with stress
Piezoelectric Approach	Neck	Chewing [30] and Swallowing [31]	Limited number of foods detected , no explanation of relationship with stress

the setup that is required to analyze the stress-eating. The setup here has a camera as a wearable to capture images whenever a person is eating and uses TensorFlow to analyze the objects in the images.

A. Data Collection

In order to analyze the eating behavior of the person, the following data are considered:

- The type and amount food consumed.
- The time at which the food is consumed.
- The gender of the person.
- The mood of the person after every meal.

One of the reasons for obesity is because of the calories consumed. For a healthy lifestyle, the recommended calorie intake per day is in the range of 1600-2000 for women and 2000-3000 for men, respectively. This also includes calories which are generated from sugars, carbohydrates, proteins, etc. [32]. Each gram of sugar, carbohydrate and proteins yields 4 calories/gram and each gram of fat yields 9 calories/gram [33]. An excess of 20 calories/day leads to an increase of 1 kilo by the end of the year [34]. When analyzing the emotional behavior of the user with respect to food consumption, pleasuring foods such as sugar, salt and fat are instantly gratifying but have negative effect on mood and temper during the course of the day [35]. Also, the average time for the food to pass through the stomach, small and large intestine is 6-8 hours. So preferably a time gap of 6-8 hours is required for the digestive system to pass along the food [36]. Considering all these factors, the threshold values set to analyze stress-eating are represented in Table III.

TABLE III: Analyses of Stress-Eating

Recommended Calories/ day	Sugars (gm/day)	Total Calories	Time interval (hours)	Mood	Stress-Eating
Men: 2330	37.5grams of sugar or 150 calories	2500	6	Happy	Stress-Eating
Women: 1830	37.5grams of sugar or 150 calories	2000	5	Happy	Stress-Eating

A large variety of foods along with their nutritional values are taken from [37] for the analysis of stress-eating.

B. *Design of the Learning Model*

1) Wearable Approach: A wearable for instance a camera or any other device which captures images of food whenever it experiences a action is considered in this approach. In order to analyze the data from the collected images to detect stress-eating behavior, the machine learning based smart system TensorFlow is used. To test this approach, we collected 1,000 images from the open access repository Pixabay by searching for images with food-specific keywords such as doughnuts, vegetables, noodles, rice, etc. The images are labeled manually by an individual using TensorFlow application labelimg.exe, to mark the image regions with specific food items. There were overall 130 varieties of foods labeled in the images. Of these images, 800 images were used for training and 200 images were used for testing. We have used TensorFlow version 1.9.0 and have utilized the object detection application programming interface. This enables the system to train only the required areas which enables to detect the specified objects in the plate of food. The objects which are detected are sent to the Google cloud platform which can also be a platform for the user to access the information. From here, the data collected is sent to the Firebase Database in which the calorie count is generated. After this, the count of the calories left to consume by the person with respect to the threshold from Table III is provided to the user by the mobile application. Also, the mobile application suggests some general home remedies from Google in order to reduce stress levels. The data collected and the calorie count calculated will be stored in the database for future reference.

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2) Non-wearable Manual Approach: On par with the wearable approach this research also works on the non-wearable manual approach where the consumed food data will be entered by the user with the mobile application as an interface.

When the user enters the information in to the application, the data assigned to the information entered is collected from the Firebase Database. The calorie computations and analysis of the stress-eating is done and the information is presented to the user. The application was developed by using the XCode 8.3 development platform and used the Swift 3.0 programming language.

VI. Implementation and Validation of Stress-Log

A. *Implementation and Experimental Results*

1) Wearable Approach: In this approach, the wearable camera will detect the objects in the image when there is a hand movement detected in front of the camera and sends this to the cloud storage. This detection process is done using TensorFlow and the data is therefore sent to the Google cloud platform. Once the information is stored here, the information is sent to the Firebase database where the related information of the detected objects is stored. Here, computations such as the calories count for the detected images along with the calories that are acquired from the sugars are performed. The results from the performed operations are sent to the mobile application connected to Firebase.

Typical results of object detection in TensorFlow are presented in Fig. 3. This shows the food object detected along with the accuracy of the detected image to that of the original image. For instance, the system detected doughnuts with different accuracy percentages. The accuracy of the object detection system depends on the number of images the system has been trained with.

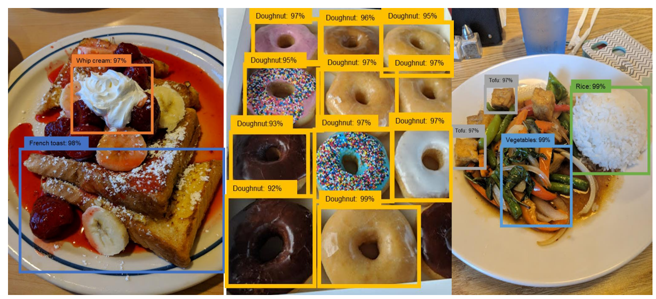

Fig. 3: Object Detection Results.

The pattern of maintaining the accuracy and tracking the loss in detecting the images is shown in Figure 4. Loss here is representing the rate at which the system is optimized. The lower the loss, the higher the system optimization. The accuracy curve shows the pattern in which the system is trained and has reached the highest level of detecting the images. The higher the accuracy, the higher the trueness of the system.

The results are sent to the Google cloud platform as it has the access to the Firebase database with which the mobile application is generated. From the Firebase connection to the mobile application, the details of foods are represented allowing the user to access them.

2) Non-wearable Approach: In order to protect the data, the application starts with the login page. The user inputs type of food, timing of meal, and mood after meal. The results of the experiment for normal eating is represented in Fig, 5. In this, the user enters time, the meals and the result is shown. The results page also has the calories left that can be consumed, calories consumed, overall mood. The results for stress-eating are shown in Fig. 6.

The above figures represent the application which takes human inputs and analyses the eating behaviors. Therefore, the analysis of stress in a person by monitoring the eating behaviors can be done using the wearable and a non-wearable method. Though the two methods have a same final goal, the

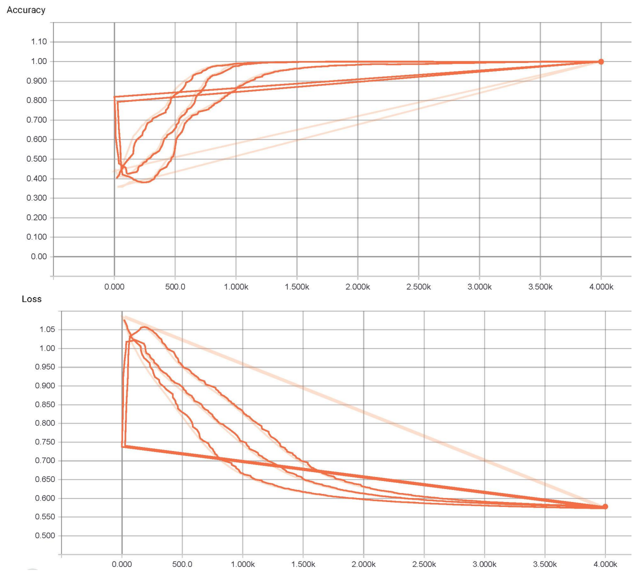

Fig. 4: Loss and Accuracy of Object Detection.

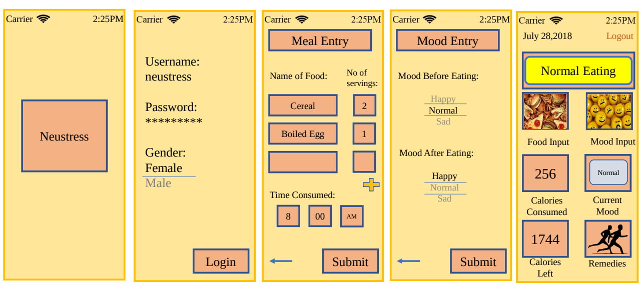

Fig. 5: Non-wearable Normal Eating Result.

process involved, human activity involved and price vary. It is completely dependable on the user to which method to follow.

B. Performance Evaluation

Though there are several studies conducted to prove and verify the connection between eating behaviors to stress of a person, as explained in Section IV, there are very few studies which provide a continuously monitoring system in order to

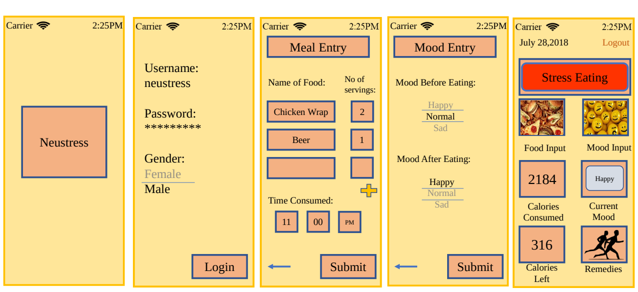

Fig. 6: Non-wearable Stress Eating Result.

keep track of day-to-day stress. Some of these studies, along with this work are presented in Table IV.

VII. Conclusions and Future Research

Stress monitoring is one of the most important aspects of smart healthcare for lifestyle management, considering the impact of stress on overall health and wellbeing of individuals. The approach presented here provides an extension to the monitoring systems by focusing on the eating behaviors of the users and analyzing if the eating is stressed eating or normal eating. This design provides two different approaches: the first, is a wearable method with which the objects can be detected, classified and the calorie count along with the eating behavior is notified to the user through a mobile application. The second, is a non-wearable mobile application which allows the users to enter the information and self analyze their eating behavior along with stress-relieving techniques. The accuracy of detecting food composition is found to be 97%, which strongly suggests this approach to be suitable for effectively logging nutritional and calorific value of daily food intake. Incorporating the camera to an actual wearable device, and designing the manual/automatic triggering of image capture are what we seek to address in future. This approach has the potential to enhance the state of the art of monitoring eating behaviors. It also presents opportunities for improvements using machine learning and community based improvement of quality of life. The approach could be answer a long time sought after need for watching the food behaviors and their impact on overall physical and mental health.

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TABLE IV: Comparative Analysis of Self-Monitoring Systems

Research	Stressors	Device Prototype	Self-Analysis	Cost
Vanstrien, et.al [38]	Sad and Joy news	No	Not possible	Moderately high
Vanstrien, et.al [39]	Statistics and Meditation	No	Not possible	Moderately high
Adam, et.al [40]	Challenge and Fear conditions	No	Not possible	Moderately high
Harrison, et.al [41]	Pictorial stroop task, emotion recognition in images, self responses for situations, clinical measures, adult reading tests, eating disorder test	No	Not possible	Moderately high
Ariga, et.al [42]	Structured interviews, self-rate questionnaire, statistical analysis	No	Not possible	Moderately high
Stress-Log (Current Paper)	Daily activity, human time isn't required	Yes, a mobile phone application and a wearable for instance a camera are presented	No need of heavy equipment; self monitoring is allowed	Moderately low

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