# iLog: An Intelligent Device for Automatic Food Intake Monitoring and Stress Detection in the IoMT

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***Abstract*—Not knowing when to stop eating or how much food is too much can lead to many health issues. In iLog, we propose a system which can not only monitor but also create awareness for the user of how much food is too much. iLog provides information on the emotional state of a person along with the classification of eating behaviors to Normal-Eating or Stress-Eating. Chronic stress, uncontrolled or unmonitored food consumption, and obesity are intricately connected, even involving certain neurological adaptations. We propose a deep learning model for edge computing platforms which can automatically detect, classify and quantify the objects from the plate of the user. Three different paradigms where the idea of iLog can be performed are explored in this research. Two different edge platforms have been implemented in iLog. The platforms include mobile, as it is widely used, and a single board computer which can easily be a part of network for executing experiments with iLog-Glasses being the main wearable. The iLog model has produced an overall accuracy of 98% with an average precision of 85.8%.**

***Index terms*—** Smart Home, Smart Healthcare, Smart Living, Food Intake Monitoring, Stress-Eating, Stress-Level Analysis, Internet of Medical Things (IoMT), Machine Learning

## I. Introduction

Food intake monitoring applications which allow an individual to track the consumption of food have been of substantial interest in the technology community [1]. Long term effects of overeating on humans include obesity and polycystic ovary syndrome (PCOS). Obesity occurs due to caloric imbalance in one's diet. i.e., the amount of calories consumed exceeds the amount of calories burned. It is a condition where a person's weight is higher than the normal weight in regards to their height [2]. One of the main reasons for this excess calorie intake is overeating or not timing the food intake with proper intervals during the day.

Indirect factors of overeating include depression, imbalance in emotions and many other psychological dysfunctions such as stress. When a person is stressed, the human body releases a hormone called cortisol which will increase the appetite of the person. This hormone creates cravings for sugar rich foods and comfort foods [3]. Uncontrollable over consumption of high caloric foods is termed as Stress-Eating in iLog.

The Internet of Medical Things (IoMT) or Internet of Health Things (IoHT) is a collection of multiple medical devices independently connected to the Internet through wireless communication, with capability to exchange data with cloud based servers. IoMT which has simple sensors or medical devices as the basic elements, is the backbone of smart healthcare. An automatic IoT Edge level system to help a person differentiate between Stress-Eating and Normal-Eating is presented in iLog. The basic overview of the iLog system is shown in Fig. 1.

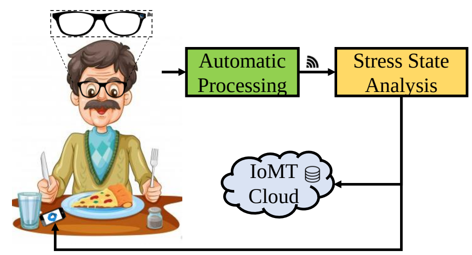


Fig. 1. System Level Overview of iLog.

iLog provides an automated stress level detection methodology, as explained in Section IV, that considers food habits, thereby helping users stay healthy. The main objectives of iLog are the following:

1) User's Convenience: There are many applications which help in monitoring direct food intake, as mentioned in Section II-A. However, there are very few options that have the user's convenience as the main motivation.
2) No User Input: The state-of-art in this area addresses semi-automated methods of monitoring food, as explained in Section II-A but the quantity of the consumed food must be always provided by the user. Proposing a no user input system was our second objective.
3) User Education: Educating the user on when to eat, what to eat, and how much to eat is our next objective. Helping the user understand is important because this helps in the reduction of consumption for high caloric foods.
4) Comprehend the Phrase "Stress-Eating": Chronic stress is one of the factors that may contribute to the development of obesity [2], [4]. 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 [5]. Food consumption under such uncontrollable cravings is referred to as "Stress-Eating." Helping the user comprehend the difference between Stress-Eating and Normal-Eating is

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the main objective.

The organization of the paper is as follows: Section II discusses existing related research and the novel contributions of the current for its advancement. Section III provides a broad overview of the proposed food monitoring system. Section IV outlines the learning algorithm and automatic processing of iLog. Section V provides the automatic stress state analysis and the data considered in iLog. Section VI presents the implementation of the model of the proposed system. Section VII is used to validate the individual results and also provide a comparative analysis. The paper concludes in Section VIII.

## II. Related Prior Research and Contributions of the Current Paper

### A. Related Prior Research

There are a number of mobile or web applications and electronic gadgets that attempt to help users to monitor their daily food intake [6]. Some are presented in Table I. A semi-automatic IoT-enabled system that considered current food intake and predicted future food intake to maintain healthy diet is proposed in [7]. However, the automatic quantification along with the stress state relationship is not observed.

There are few visual approaches which use external camera captures and processes the food volume and food weight estimation [8], [9]. However, these approaches do not use the IoT and also fail to explain the relationship between stress and food consumed. Though [10] uses a visual approach, the automatic food quantification is not provided. Another semi-automatic system is proposed in [11], which allows users to obtain nutritional information before consuming the food. This requires manual input and no information about stress and food already consumed is provided.

A vibration-based detecting system using a microphone embedded in an ear pad for food classification is provided in [12], [13] which however, is not accurate and there is no correlation to stress.

Gyroscope and accelerometers have been used in [14] and [15]. However, the precision of the project is not high, and the classification and weight of the food consumed are not accurate. This also did not correlate with stress levels. The swallowing signal of the food is recorded and evaluated by the acoustic method [16], [17]. This is not accurate in calculating the food weight. Also, the classification of food, relationship with stress and food is not present.

The jaw movements of the person is detected, the force used by the jaw is sent to a piezoelectric film sensor and the amount of food consumed is detected [18]. By swallowing detection, the motion of throat skin is captured [19]. However, this does not classify the type of food consumed and the relationship with the stress is missing.

The major issues that are not properly addressed in most of the current research are:

- Users are not educated regarding the relationship between Stress-Eating vs Normal-Eating.
- Automatic food classification and quantification methods were not provided. For example, in classification, even after the related food was listed, the user is required to manually select the item from a list of items.
- Analysis of the variations of stress level with the food consumption habits is not presented.
- Techniques to control the variations of stress levels of the user are not provided.
- A convenient food monitoring wearable was not proposed.
- Automatic leftover food consideration is not provided.
- Fully-automated systems were not proposed by any of the articles cited above.

### B. Proposed Solutions of the Current Paper

iLog provides solutions to the research objectives stated by providing:

- Automatic continuous monitoring of food detection, classification and quantification consumed with no user input.
- A method which educates the users on the difference between Stress-Eating and Normal-Eating.
- Techniques to control the variations of stress.
- An interface representing the stress state analysis of the user by showing the time of last meal, total number of calories consumed, and the number of calories that could be consumed for that day.
- Different approaches where a mobile application is used as a front end for user access to the data, while the processing is done in the edge device.
- Allowing the user to access his/her own predicted stress levels from the previous days are provided with access to database storage.

### C. Novelty and Significance of the Proposed Solutions

The novelty and significance of the proposed solutions are:

- An automated food logging method without the user's manual entry by proposing iLog-Glasses which capture the images of food throughout the course of the meal. This is convenient by not having to take pictures of the food for every meal, for which there is high chance of genuine forgetfulness.
- Automatic food quantification without the user having to enter the quantity of food consumed for every meal.
- Providing a stress state analysis by considering the fact that the user may or may not have completed the food on the plate, i.e. the leftover food is also quantified to produce accurate analyses.
- Allowing the user to fully analyze and comprehend his/her stress levels based on previous logged data through an interface.
- Providing a fully-automated edge level device to monitor stress behavioral variations with no user input will help in promoting a healthy life style.

A detailed representation of iLog is provided in Fig. 2. The camera with which the images of food are taken can be placed anywhere according to the comfort of user.

TABLE I
MOBILE APPLICATIONS FOR FOOD INTAKE MONITORING.

| App Name | Manual Image Entry | Manual Data Entry | Bar-code Scanning | Calories Consumed | Drawbacks | Stress-Eating Classification |
|---|---|---|---|---|---|---|
| See How You Eat | Yes | Yes | No | Yes | No automatic classification and requires manual entry of portion size | No |
| Lose it | Yes | Yes | Yes | Yes | Requires manual food portion size and no automatic classification | No |
| YouAte | Yes | No | No | No | Automatic Food classification and manual entry of portion size | No |
| MealLogger | Yes | Yes | No | Yes | Needs manual entry of portion size and lacks automatic classification | No |
| BiteSnap | Yes | No | No | Yes | Automatic Food classification is not provided and manual entry of portion size is needed | No |
| **iLog (Proposed)** | No | No | No | Yes | None | Yes |

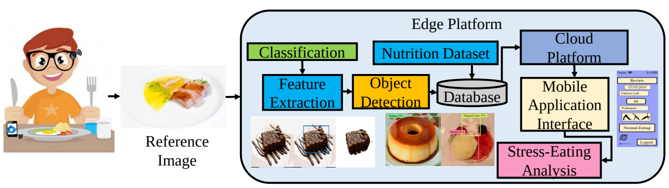



Fig. 2. A Detailed Representation of iLog.

## III. iLOG: A SYSTEM LEVEL OVERVIEW OF AN IOMT-BASED APPROACH TO RECOGNIZE AND MONITOR STRESS-EATING

The system level overview of the concept proposed in iLog is shown in Fig. 1. The camera which is attached to the glasses, and takes continuous images once the power supply is enabled. These captured images are sent to a platform where the automatic processing of the images will be done. After the processing, the stress state analysis of the person takes place. The analyzed outcome is sent to the mobile phone where the processing is done. This analyzed data is also sent to the cloud server for storage. The architecture of the iLog platform is shown in Fig. 3. The processing of iLog can be performed not only on high computing devices such as In-Cloud units [10] but can also be performed on edge level devices as discussed in Section III-B and in very low performance computing paradigms like sensors and single board computers.

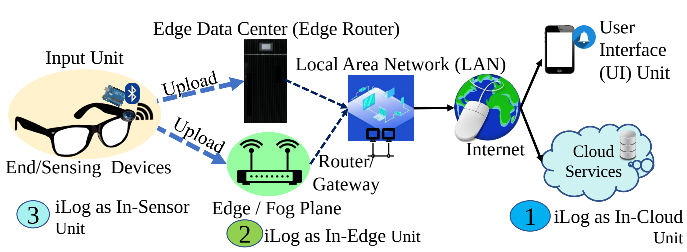



Fig. 3. An Architectural Overview of iLog Showing 3 Computing Paradigms: (1) Cloud-based, (2) Edge-based, and (3) Sensor-based.

### A. Relation between Stress and Food Consumption

The behavioral relationship between stress and food consumption is compulsive by considering various factors like the type of eating, metabolic rate, role of insulin, and food addictions [20]. Similarly, when a person is under stress it is likely to have a tendency to eat high calorie “comfort” foods [21]. Chronic stress affects not only the quantity and 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 [22]. The quantities and nutrition facts with which the analysis of Stress-Eating is done is explained in Section V-A.

### B. Edge Platform based Approach for Automatic Processing in iLog

The In-Edge based approach for stress state analysis of the person considering the eating habits is done by analyzing the image data from the camera through Wi-Fi. The received data is automatically processed inside the edge level device. The computations are all performed in the device and the stress state analysis is performed 4. The analyzed data is sent to the Internet cloud for storing and the user is also notified through the notification in mobile application. The daily statistics of food intake along with their respective nutritional facts considered in analyzing (see Sec V) are presented in the mobile application as an interface for the user’s convenience.

### C. Edge platform based Board Approach for Automatic Processing in iLog

The In-edge board approach works with the data from the camera which is considered as an input. The images are sent to the wireless embedded platform where automatic processing is done. Subsequently, the stress state analysis of the person is performed and is sent to the user’s mobile as a text message, as represented in Fig. 4.

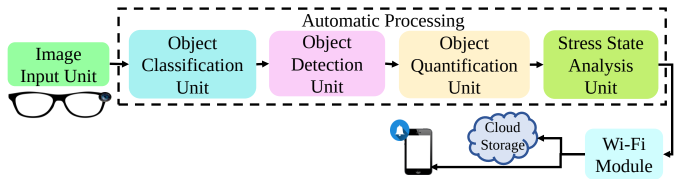



Fig. 4. Automatic Processing in iLog.

Fig. 6. Automatic Classification of Targeted Images Using Graphical Annotation Tools for Stress Analysis in iLog. Top Row: Single Object Classification; Bottom Row: Multiple Object Classification.

## IV. The Proposed Training Methodology for Machine Learning Models of iLog

### A. Design of the Learning Model

The design of the learning model that is used in iLog is represented in Fig. 5. The package printed nutritional facts of the food to be consumed can be considered as inputs through Optical Character Recognition (OCR) or bar-code scanning. These detected images are classified and then quantified using the same model. After the quantification of food is done, the calorific information that is consumed is calculated along with the time of the meal.

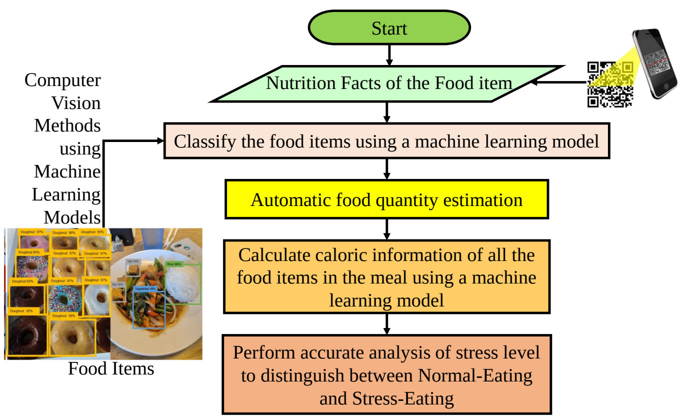



Fig. 5. Proposed food intake identification and quantification flow in iLog.

### B. Automatic Classification of Food from the Plate

Once the images are obtained, the next important stage is to classify the objects in the images. For this, graphical annotation tools are used with which the detected objects are labeled to certain food items. The classification using this tool is shown in Fig. 6. For some images where the object is interest is being covered by another random subject, suppressing the initial errors and image subtraction techniques are used. Thus, the background object is segmented. From that, the mapping function is used to restore the image.

### C. Automatic Object Detection From Plate

Once the images have been obtained, they undergo segmentation where the pixels of the image are segmented to groups in order to better identify the object. After the segmentation phase is done, the pixels that belong to the same set of visual descriptors are arranged together by various methods. Principal Component Analysis (PCA), is one of the methods that is used to cluster the data set by finding a principal set of dimensions. Subsequently, the images are labeled and classified in the machine learning model used for system. For the process of automatic object detection, an object detection API is used. In the model, assessment of a classification program also known as training is done with a set of pre-labeled images. In general, a multi layer topology of nodes with weights and bias values are considered in the learning stage of the model. These weights, bias values and the activation functions involved at each node and layer, help in predicting the value at the next layer or node as shown in Eq. (1). Given a layer $i$ and its values $(x)_i$, the next layer $j$ with values $(h)_j$ can be derived as:

$$(h)_j = f((W)_j, i \cdot (x)_i + (b)_j, i), \tag{1}$$

where $f$ is the activation function, $(W)_j, i$ is the weight matrix and $(b)_j, i$ the bias. The selection of the activation function depends upon the type of application the model is being trained for. The process of object detection along with classification is presented in Algorithm 1.

### D. Automatic Calorie Quantification

The detected, classified and labeled images are assigned with a unique identification number. All the nutrition information regarding the food items being detected is stored in a database. Based on the repetition of the objects in the plate, the identification number is iterated. The calorie information of the consumed food is derived based on the identification number. If the identification number is repeated, the nutrition information is also iterated with respect to the identification number. Thus, the quantities of foods consumed can be processed without any manual inputs. The processed information is then analyzed according to Table II, as shown in Fig. 7. The method of quantification is also presented in Algorithm 2 under the assumption of a person eating a donut and a bagel in a meal.

### E. Metrics for Automatic Processing in iLog

The metrics considered for the model are its Precision, Recall, Accurate Precision (AP), and Confidence [23]. In order to understand these, basic concepts such as True Positive (TP),

**Algorithm 1** Process of Object Detection and Classification used in iLog Model

1: Images which are to be used for testing and training the model are collected.
2: The formats of the images are converted from JPEG to XML after creating bounding boxes by using any graphical image annotation tool.
3: Multiple bounding boxes in various images for the same feature, which are called priors are also created in the same annotation tool.
4: Using box-coder, the dimensions of priors are made equal.
5: By considering the concept of IOU (Intersection Over Union), the matched and unmatched thresholds for matching the ground truth boxes to priors are set. This is mandatory as the model will not be ready for training if the match hasn't been made.
6: Images in XML format are made equal in size either by using reshape or resize functions.
7: Using convolution and rectified linear functions, the feature maps are assigned to every image sent to the model.
8: Based on these features, the images are either sent to regression or classification where the objects are detected through boxes in the images.
9: *Repeat the above steps for all the images.*

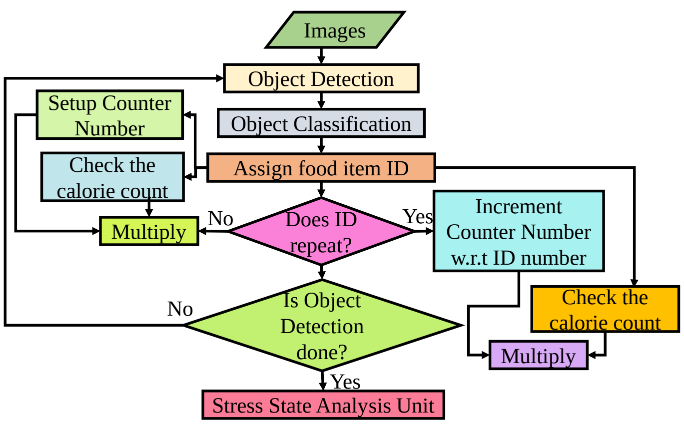



Fig. 7. Automatic Calorie Quantification of Classified Objects for Stress Analysis in iLog.

False Positive (FP), False Negative (FN) and True Negative (TN) need to be defined. In the following discussion, the intersection over union (IOU) is a measure that evaluates the overlap between two bounding boxes. It is given by the overlapping area between the predicted bounding box and the ground truth box divided by the area of union between them.

- True Positive (TP): A correct detection. This occurs when the detection with IOU is greater than or equal to the set threshold value.
- False Positive (FP): A wrong detection. This occurs when the IOU is less than the set threshold value.
- False Negative (FN): This occurs when a ground truth is not detected.
- True Negative (TN): This is the possible outcome where the model correctly predicts the ground false. This is not considered in object detection classifiers because there are many possible bounding boxes that should not be detected within an image.

**Algorithm 2** Process of Automatic Calorie Quantification used in iLog Model

1: Initialize the random variables $D_1$ and $B_1$ to zero.
2: Obtain the detected, classified object and assign it to a variable or ID number $D_1$ (assumption that the object is a donut).
3: Assign value count of $D_1$, $vD_1$ to one.
4: Retrieve the nutrition fact information stored with ID $D_1$ from database. Therefore, calories associated with that ID, $D_1$ $(cD_1)$ are obtained.
5: Continue to the next object that is classified.
6: **if** object is already assigned to ID **then**
7:     iterate the variable $vD_1$ one time
8:     Multiply $vD_1$ with calorie information i.e., $cD_1$
9: **else**
10:     Assign new ID for the detected classified object $B_1$ (assumption that the new object is a bagel)
11:     Repeat step 4 with variable $B_1$ .
12: **end if**
13: Repeat the above steps for all the classified images.
14: Update the total calculated calorie $(tc)$ count for each individual ID along with the time of consumption in the database.

*1) Precision:* The ability of a model to identify only the relevant objects from an image is known as its precision ($P$):

$$P = \left( \frac{TP}{TP + FP} \times 100\% \right). \tag{2}$$

*2) Recall:* The ability of a model to identify all the relevant cases from the detected relevant objects is called recall ($R$):

$$R = \left( \frac{TP}{TP + FN} \times 100\% \right). \tag{3}$$

*3) Confidence:* Confidence is used to rank the predictions and quantify the relationship between prediction and recall as we consider increasing numbers of lower ranked predictions. Instead of presenting a single error code, a confidence interval $CI$ is calculated:

$$CI = z\sqrt{\left( \frac{\alpha \cdot (1-\alpha)}{N_{sample}} \right)}, \tag{4}$$

where $N_{sample}$ is the sample size, $z$ is a critical value from the Gaussian Distribution, and $\alpha$ is the accuracy obtained.

*4) Accuracy:* The accuracy of a model can be defined as the ratio of correct detections made by the model to all the detections made by the model:

$$\alpha = \left( \frac{TP + TN}{TP + TN + FN + FP} \right) \times 100\%. \tag{5}$$

*5) Precision-Recall Curve:* The performance of the object detector can be evaluated with the use of the precision-recall curve as the confidence is changed by plotting a curve for each object class. An object detector model is considered good if the precision and recall values remain high even after there is a change in the confidence threshold.

*6) Average Precision:* Average Precision ($AP$) is the precision averaged across all the recall values between 0 and 1. $AP$ helps in evaluating the performance of a model by calculating the area under the curve of the precision-recall curve. In order to obtain this, interpolation is performed, as discussed in [24]. $n$ point interpolation summarizes the shape of the precision-recall curve by averaging the precision at a set of 11 equally spaced recall levels $[0, 0.1, 0.2, ...., 1]$, as defined in Eq. (6) where $\rho(r')$ is the measured precision at recall $r'$:

$$AP = \left(\frac{1}{N_{sample}}\right) \sum_{r\epsilon 0,0.1,0.2,..,1} \rho_{interp(r)}. \quad (6)$$

$$= \left(\frac{1}{N_{sample}}\right) \sum_{r\epsilon 0,0.1,0.2,..,1} \max_{r'.r'>r} \rho_{(r')}. \quad (7)$$

## V. Automatic Stress Level Detection from Food-Intake Monitoring

Once the calorie quantification is derived, the data is compared with the threshold values for distinguishing between Stress-Eating and Normal-Eating, as shown in Fig. 8.

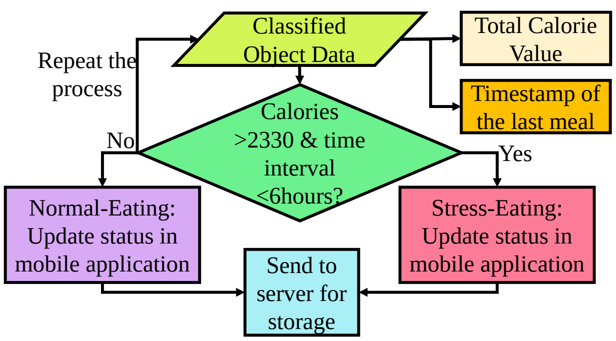



Fig. 8. An Example for Automatic Stress State Analysis of Classified Objects for Stress Analysis in iLog for Men.

### A. Factors Considered in the Analysis of Stress State Detection

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

1) The *type of foods* that are consumed during the awake period is very important as it defines the emotional state of the person. 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 [25].
2) The *amount of food* that is being consumed by the person is another important factor along with the type of food as uncontrollable eating behavior is not only considered as an abnormality but also as a symptom for stress-eating.
3) The *time* at which the food is being consumed is also important. Irregularity between meals can be used as a factor for Stress-Eating.
4) The *gender* of a person is also equally important to analyze Stress-Eating behaviors because the body requirements change accordingly.

### B. Food Data Collection for Stress State Detection

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. [26]. Each gram of sugar, carbohydrate and proteins yields 4 calories/gram and each gram of fat yields 9 calories/gram [27]. An excess of 20 calories/day leads to an increase of 1 kilo by the end of the year [28]. 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 [29]. Considering all these factors, the threshold values set to analyze Stress-Eating are represented in Table II.

TABLE II
Analyses of Stress-Eating

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

The data that is used to train the iLog model is taken from an online database [30]. The sample information that is being considered in iLog is described in Table III.

TABLE III
Nutrition Facts Considered to Analyze Stress-Eating

| Food Item | Food Type | Portion | Added Sugars | Calories |
|---|---|---|---|---|
| Jelly Donut | Dessert | 1 | 51.70 | 221 |
| Chocolate Cupcake | Dessert | 1 | 49.70 | 240.64 |
| French Toast | Dessert | 3.609” across | 15.45 | 157.95 |
| Muffin | Dessert | 1 | 3.714 | 136.30 |
| Pancake | Dessert | 1 medium 5” across | 0 | 183.20 |
| Waffle | Dessert | 1 round 4” across | 3.15 | 102.96 |
| Coffee Cake | Dessert | 1 slice | 29.20 | 159.80 |
| Chocolate Chip Cookies | Dessert | 1 2” across | 12.57 | 48.10 |
| Brownie | Dessert | 1 2” sq | 47.98 | 128.86 |
| Ice cream | Dessert | 1 cup | 95.20 | 267.30 |

## VI. Implementation of iLog using Edge Computing Platforms

The system level block diagram of iLog is shown in Fig. 9. The input JPEG format images will be captured at the iLog glasses and through Wi-Fi connectivity, the images are sent to the edge platform where the classification of features, and their extraction is done. Using the extracted features, objects from the images are detected. Once the object detection is performed, the data is sent and compared in the database with the nutrition dataset. From here, using cloud platform as base, the analyzed data is sent to the edge platform where in the stress-state analysis is done and the data are sent to the mobile application. A large variety of foods along with their nutritional values are taken from [30] for the analysis of Stress-Eating in this model. A total of 130 classes have been defined in order to classify the detected food objects. The model has been trained with 1000 images. These images were all license-free and are collected from websites which provide copyright-free images such as Pixabay and Freepik. Out of 1000 images, 800 images are used for training the model while the remaining 200 are used for testing.

The collected classified data is sent to the Firebase database where the analysis of the data is done according to Table II.

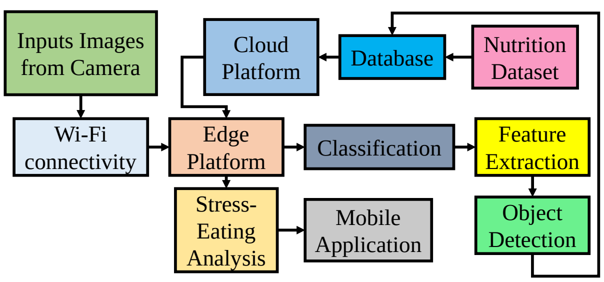



Fig. 9. System Level Representation of iLog.

### A. Mobile Computing Platform

As one of the edge computing platforms, a mobile phone is considered for availability and usability to the users. The images from iLog glasses are sent to the mobile phone through Wi-Fi connectivity where the model will be implemented. The detection and classification of objects from a plate along with their confidence rates are shown in Fig. 10.

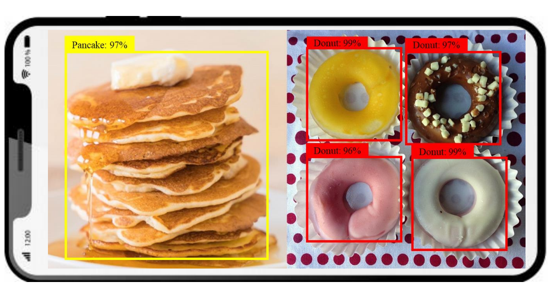



Fig. 10. Object Detection Result.

The gender of the user can be noted while setting-up the wearable. Based on the received information and analysis, the eating behaviors of the user are reported accordingly to the user using a mobile application as an interface. The log of the user's meals are provided along with the eating behaviors and suggested remedies if the user is experiencing Stress-Eating. The data is also stored in the cloud platform where the user can login to have an access to the previous data, as shown in Fig. 11.

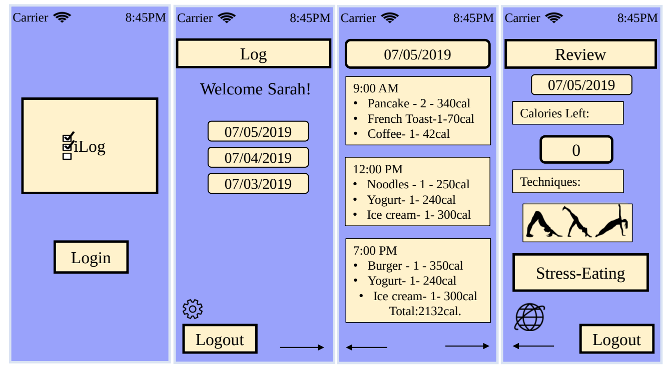



Fig. 11. In Edge Stress-Eating Demonstration for a Female User.

### B. Single Board Computer Platform

As one possible edge platform, single board computers (SBC) can be used. The camera is considered as the input source for images and the data is automatically processed in the SBC. The size of the processor used prevents it from being placed on the pair of glasses, but the glasses can be a part of the wearable network connected the with Internet, as represented in Fig. 1. The object detection result using an SBC is shown in Fig. 12

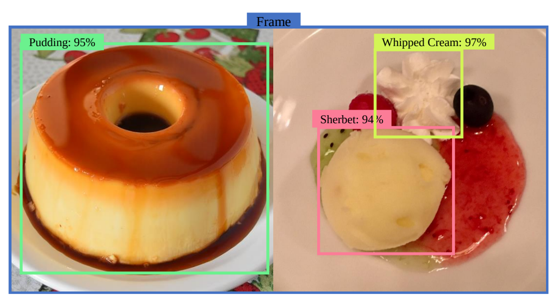



Fig. 12. Object Detection Result using SBC.

### C. Characteristics of iLog

The average measuring details of automatic processing is represented in Table IV.

## VII. Validation of iLog

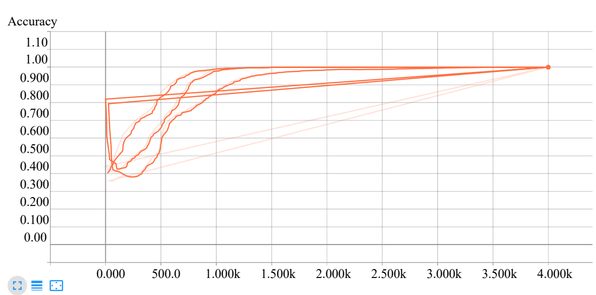
The TensorFlow Object Detection API is used for the training and testing the model. SSD (Single Shot MultiBox Detector) MobileNet is used as the classifier as the frame per second capability is very much higher than the Region-Convolutional Neural Network (RCNN) classifier. The total number of layers defined inside this model is 7 with a batch

TABLE IV
ACCURACY RESULTS OF ILOG

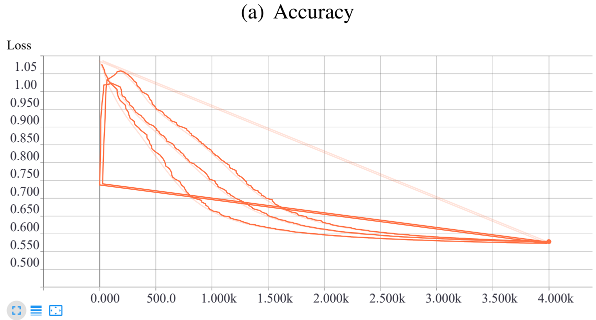
| Food Item | CI(%) for 5 fold cross validation with 15 epochs | CI for 5 Repeated 5 fold cross validation with 15 epochs |
|---|---|---|
| Pancake | 92 | 97 |
| Donut | 94 | 98 |
| French Toast | 89 | 95 |
| Ice Cream | 90 | 97 |
| Brownie | 91 | 95 |
| Waffle | 88 | 96 |
| Muffin | 90 | 98 |
| Cake | 92 | 96 |
| Chocolate | 91 | 95 |
| Cookies | 90 | 95 |

size of 24 images for every iteration of training at an initial learning rate of 0.004. The activation function used at each layer is ReLu i.e., Rectified Linear Unit function.

The total accuracy of iLog is obtained as 97% approximately. The pattern of maintaining the accuracy and tracking the loss in detecting the images is shown in Fig. 13. Loss is representing the rate at which the system is optimized. The accuracy curve shows the pattern in which the system is trained and has reached the highest level of detecting the images.




(a) Accuracy




(b) Loss

Fig. 13. Accuracy and Loss of iLog.

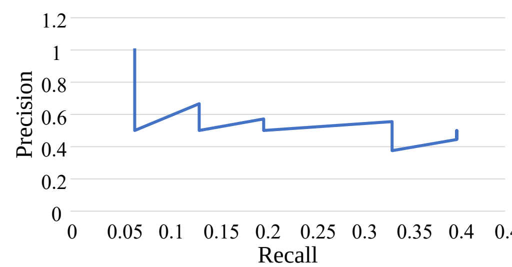
## A. *Validation of In-Edge based Approach using Mobile Phone*

In-Edge implementation of the iLog is presented here. With a total of 1000 images, 800 images are used for training while the remaining are used for testing the model. With 300 objects being detected from 200 testing images, the precisions and recalls are calculated within the model, while the precision-recall curve for In-Edge implementation is provided in Fig. 14.

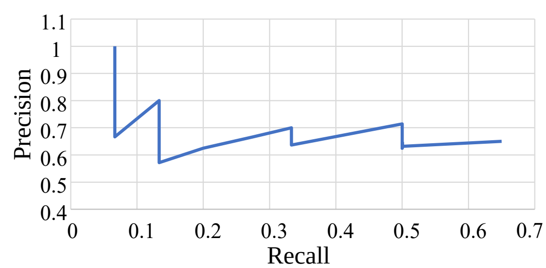
Using Eqn. (6), the average precision of the In-Edge implementation is 81.8%. The total accuracy of the model within Edge is 98% approximately.

## B. *Validation of Single Board Approach*

The SBC implementation of the iLog is represented here. With 300 objects being detected from 200 testing images, the precision and recalls are calculated within the model while the precision-recall curve for SBC implementation is provided in Fig. 14.




(a) Precision x Recall for In-Edge Implementation




(b) Precision x Recall for Single Board Implementation

Fig. 14. Precision x Recall for iLog.

Using Eqn. (6), the average precision of the In-Sensor implementation is 85.8%. The total accuracy of the model within Sensor is 97% approximately. While the accuracy of the model is independent of the precision of the model, the average precision and accuracy can be increased with an increased number of training and testing images or the dataset being used to train and test the model.

## C. *Comparison of the Approaches*

A brief comparison of the approaches proposed by iLog and Stress-Log [10] is presented in Table V. The Table presents the type of automation, processing capabilities and system characteristics.

## D. *Comparison with Existing Research*

Though there are several studies conducted to prove and verify the connection between eating behaviors to stress of a person, as explained in Section II-A, there are very few studies

TABLE V
SPECIFICATIONS OF ILOG FOR DIFFERENT PLATFORMS

| Characteristics | Mobile Platform | SBC-1 | SBC-2 |
|---|---|---|---|
| Camera | 16MP; 1080x2340 pixels | 5MP; 640x480 | 5MP; 640x480 |
| Accuracy | 98% | 97% | NA |
| Average Precision | 81.8% | 85.8% | NA |
| Object Detection | Yes | Yes | Yes |
| Object Classification | Yes | Yes | Yes |
| Object Quantification | Yes | Yes | Yes |
| Input Type | Image | Image | Image |
| Automation | Fully Automated | Fully Automated | Fully Automated |

which provide a continuously monitoring system in order to keep track of day-to-day stress. Some of these studies, along with this work are presented in Table VI.

TABLE VI
COMPARATIVE ANALYSIS OF SELF-MONITORING SYSTEMS

| Research | Inputs | Device Prototype | Self-Analysis | Fully Automated |
|---|---|---|---|---|
| Harrison, et.al [31] | Pictorial stroop task, Emotion recognition from images | No | Not possible | NA |
| Beijbo, et.al [32] | Images | No | Cannot be achieved completely | Semi-automatic |
| Jiang, et.al [11] | Images | No | Not much helpful | semi-automatic |
| Taichi, et.al [33] | Images | No | No nutrition Info. | No, requires manual input |
| Pouladzadeh, et.al [34] | Images | No | Not much helpful | Semi-automatic, no quantification |
| Rachakonda, et.al [10] | Images | Yes | Yes | Semi-automatic |
| **iLog** (Current Paper) | Food intake | Yes, iLog-glasses | Yes | Fully Automatic system |

## VIII. 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 well-being 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 behavior is Stress-Eating or Normal-Eating. The proposed idea of iLog is implemented using edge platforms, a mobile platform and an SBC platform. The foods from the images are automatically detected, classified and quantified. The quantified foods are then compared to the stored database of the nutrition in Firebase and the user is provided with feedback using a mobile application as an interface. The average precision and accuracy of the two fully automated approaches are 81.8%, 98% and 85.8%, 97%, respectively.

The use of glasses and the embedded platform friendly software allows an advancement in the state of the art. iLog could be the answer to the need for watching the food behaviors and their impact on overall physical and mental health. Also, the three different paradigms, In-Cloud, In-Edge and In-Sensor, based on computational capability and performance are explored in iLog. Further light weight machine learning models might be needed to implement iLog in micro-controllers with very less computing capabilities. In-Sensor processing of deep learning technologies could be considered as future work.

## IX. ACKNOWLEDGMENTS

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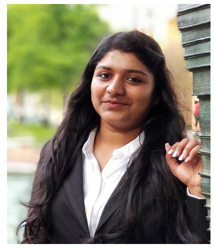

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