Smart-Log: A Deep-Learning based Automated Nutrition Monitoring System in the IoT

Prabha Sundaravadivel, *Member, IEEE*, Kavya Kesavan, *Student Member, IEEE*, Lokeshwar Kesavan, Saraju P. Mohanty, *Senior Member, IEEE*, and Elias Kougianos, *Senior Member, IEEE*

***Abstract*—A correct balance of nutrient intake is very important, particularly in infants. When the body is deprived of essential nutrients, it can lead to serious disease and organ deterioration which can cause serious health issues in adulthood. Automated monitoring of the nutritional content of food provided to infants, not only at home but also in daycare facilities, is essential for their healthy development. To address this challenge, this paper presents a new Internet of Things (IoT) based fully-automated nutrition monitoring system, called Smart-Log, to advance the state-of-art in smart healthcare. For the realization of Smart-Log, a novel 5-layer perceptron neural network and a Bayesian Network based accurate meal prediction algorithm are presented in this paper. Smart-Log is prototyped as a consumer electronics product which consists of WiFi enabled sensors for food nutrition quantification, and a smart phone application that collects nutritional facts of the food ingredients. The Smart-Log prototype uses an open IoT platform for data analytics and storage. Experimental results consisting of 8172 food items for 1000 meals show that the prediction accuracy of Smart-Log is 98.6%.**

***Index Terms*—Internet of Things (IoT), Consumer Electronics, Smart Healthcare, Smart Home, Food Monitoring, Nutrition Monitoring**

I. Introduction

Monitoring daily food intake is a relevant and important problem in health care. Wearables or monitoring systems in smart healthcare are designed to maintain a healthy lifestyle, focusing on calorie input and calorie output monitoring [1]. As important as it is to monitor the calorie output, it is equally important to monitor the calorie intake [2]. Though the focus of such monitoring systems might range from tracking weight loss to having a healthy balanced diet, the underlying motivation is to address nutrition imbalances. This condition can be caused by both undernourishment, in which not sufficient nutrients are consumed, as well as overeating, which results in excessive consumption of non-nutrient rich food, particularly in fats and salt. Overeating can lead to obesity which is a serious health concern in affluent societies today. Imbalance nutrition in infants and children can manifest in numerous modalities in adulthood including weak immune systems, cognitive disorders, weakened skeletal structure, thinning hairlines and bleeding gums, to mention just a few.

A conceptual view of the proposed Smart-Log system, which can be part of any household is presented in Fig. 1. The primary enabler for this research is the Internet of Things (IoT). The IoT is used as the link between sensor-derived data and cloud-based analytics [3]. The IoT is a network of physical devices where each device is recognizable within the network [3]. Each recognizable component in the IoT is a "thing" which can connect to the Internet. With the IoT covering a wide range of the business spectrum, it has helped researchers and developers to make intelligent systems [4]. The IoT is also the enabling technology of smart cities where diverse infrastructure components (e.g. vehicles, services, hospitals, traffic, buildings, and homes) are interconnected [5]. In the context of health care, the IoT has enabled remote assistance and has enriched peoples quality of life [6, 7].

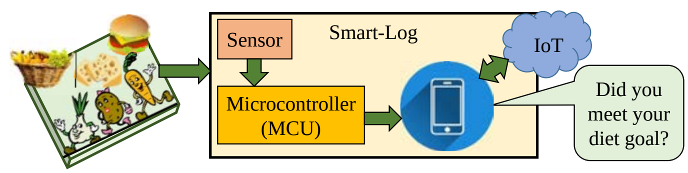

Fig. 1. Conceptual View of the Smart-Log System.

This paper is organized as follows: In Section II, the novel contributions of this work are presented. A detailed comparative overview of existing related prior research work is given in Section III. Section IV provides a broad overview of the proposed Smart-Log system. Section V gives a detailed explanation of methods involved in designing Smart-Log as a complete product suitable for the consumer electronics market. Section VI presents an experimental case study of the proposed Smart-Log system. Section VII concludes the paper.

II. Novel Contributions

This paper proposes a IoT-based system called Smart-Log with the following novel solutions:

- A novel 5-layer deep learning model based on a perceptron neural network with densely connected hidden layers for determining the nutritional balance after each meal is proposed.
- A novel algorithm based on Bayesian networks for determining nutrient features from food materials and for suggesting future meals or recipes, accordingly. This

P. Sundaravadivel is currently with the Dept. of Electrical Engineering, University of Texas at Tyler, (e-mail: PSundaravadivel@uttyler.edu).

Kavya Kesavan is with the Dept. of Computer Science and Engineering, University of Texas at Arlington, (e-mail: kavya.kesavan@mavs.uta.edu).

Lokeshwar Kesavan is with Versa Networks, San Jose, CA, (e-mail: lokeshwarkesavan@gmail.com).

S. P. Mohanty is with the Dept. of Computer Science and Engineering, University of North Texas, (e-mail: saraju.mohanty@unt.edu).

E. Kougianos is with the Dept. of Engineering Technology, University of North Texas, (e-mail: elias.kougianos@unt.edu).

algorithm is based on careful analysis of several Bayesian classifiers and provides superior performance.
- The proposed IoT based fully automated diet monitoring solution is the first solution to be built using Bayesian algorithms and 5 layer perceptron neural network method for diet monitoring.

III. Related Prior Research

Research in consumer electronics for the smart home has been focused on improving quality of life. The research in this discipline is multi-dimensional, including energy management in a home environment, lightweight middle-ware, efficient communication protocols [8], accurate remote monitoring, home automation [9], etc. An IoT based energy management system has been proposed by using big data approach in [10]. A system-on-chip based mobile platform is proposed that uses a wrist-wearable wireless sensor node and a mobile platform to form a remotely accessible body area network (BAN) in [11]. Home automation has been proposed through different components such as: a framework for controlling home appliances based on a TV set-top box [12]; a magic mirror to analyze social-emotion alleviation [13]; and, a human activity recognition framework based on depth-video [14]. The end product of the proposed Smart-Log system of the current paper is a consumer electronic system that will help in improving the quality of life through diet monitoring in smart homes.

Researchers have been constantly working towards identifying different techniques which can help in maintaining a healthy lifestyle [6, 15, 16]. Diet monitoring is one of the important components of smart healthcare and the smart home. Researchers have addressed this problem with an ingestive monitoring system to track ones eating frequency [17]. A smart dining table has been constructed using a weighing sensor and radio-frequency-identification (RFID), to measure the weight of food intake [18]. A hybrid eating behavior monitoring system involving a camera and microphone has been proposed to detect food portion size and consumption [19]. Features extracted from the images of food consumed, provide the advantage of comparing them with already existing or newly formed learning kernels [20–22]. Determining food or calorie intake based on physical activity can be approached in 2 ways: Monitoring activity of the arm or wrist when food is being placed in one's mouth (gesture recognition), or directly monitoring the chewing or swallowing of food. For gesture recognition, either sensors fused into a smart watch platform have been used [23] or custom sensors have been used for monitoring gestures [24]. An automated MEMS gyroscope based inertial monitoring system has been used to track the wrist activity [25]. An automatic chewing detection system has been proposed based on acoustic methods [26]. A neckband involving electrodes, amplifiers and analog-digital converters has been proposed to detect chewing and swallowing [27]. Another neckband based wearable solution has been proposed to identify vibrations related to different patterns of swallowing [28]. A piezoelectric based strain sensor is placed on the lower jaw for monitoring the chewing mechanism [29]. Another piezoelectric method has been proposed for detecting chewing and swallowing in [30]. In a preliminary version of this research [31], a piezo-based sensor board was proposed for automated food monitoring system.

IV. System-Level Description of Smart-Log

An overview of the proposed architecture for the smart food monitoring system is shown in Fig. 2. The system can be considered as a product which includes a smart sensor board along with a smart phone application. The sensor board contains a food weighing sensor. The weight of the food product or ingredient is sent via wireless to the cloud through the Internet under the coordination of a microcontroller integrated with a wireless module. Thus, the proposed system is converted to a "thing" in an IoT network. The corresponding nutritional facts of the food item are acquired with the help of a smart phone camera through the smart phone application. The system then provides a value of the total nutrients consumed. The calculated nutrient values and predictions are accessed by the user using the smart phone application. The data flow of the proposed Smart-Log system is shown in Fig. 3.

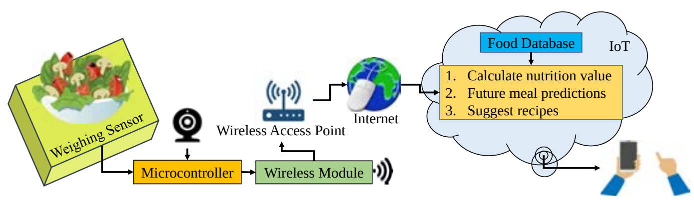

Fig. 2. Architecture of the Proposed IoT-Based Food Monitoring System.

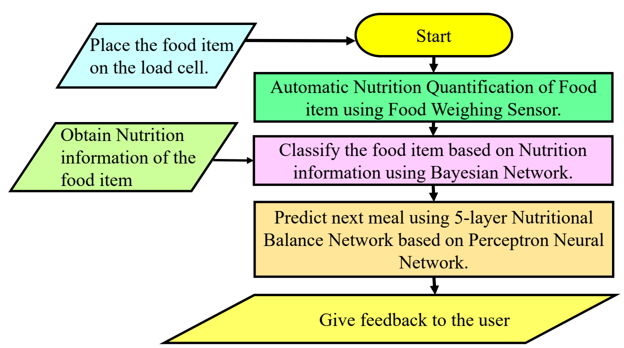

Fig. 3. Data flow of the proposed Smart-Log System.

The main objective of using the food weighing sensor in Smart-Log is to quantify the nutrients consumed by the user. The ideal output of this sensor should be the weight of the food ingredients placed on it, along with a time stamp. Logging the time stamp along with the fluctuations in food weight helps to determine the meal in which the food was consumed. The schematic of the food weighing sensor, which consists of load cells paired with a microcontroller is shown in Fig. 4.

V. Proposed Methods for the Automated Nutrition Monitoring System

The design of the proposed Smart-Log system can be broadly categorized into four significant methods: A method

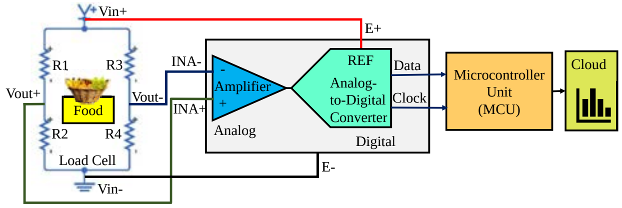

Fig. 4. Schematic Representation of the Food Weighing Sensor in Smart-Log.

for quantifying nutritional values, a method for data acquisition which details the different ways of acquiring nutrition facts from the product, a method for predicting future meals based on the leftover food, and a proposed machine learning method for food classification. A detailed explanation of these methods is discussed in this Section.

A. Method for Automatic Nutrition Quantification

The very first step in Smart-Log is to quantify the nutrient values, and is initiated immediately after the food is placed on the smart sensor board. Fig. 5 shows the method of automatic nutrition quantification used in the Smart-Log system. The food weight is calculated with the help of the load cells.

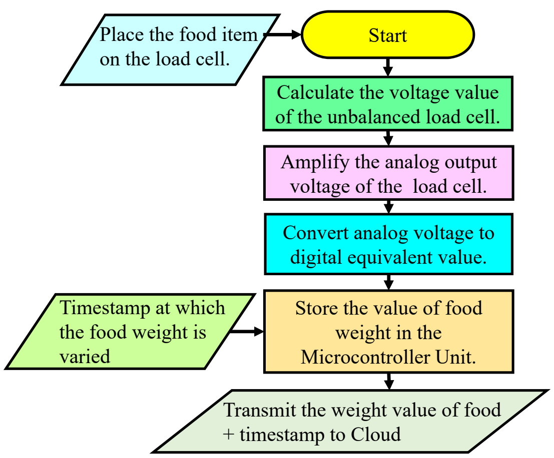

Fig. 5. Method for Automatic Nutrition Quantification.

B. Method for Nutrient Data Acquisition in Smart-Log

Once the weight and time stamp of the food are obtained through the food weighing sensor board, the next important step is gathering nutrient information. In prior research, the emphasis has been placed on computer vision approaches and using already existing information. In this research, two different methods to obtain relevant nutrient values are used. In one approach, Optical Character Recognition (OCR) is used: the on-phone camera captures the FDA-mandated Nutritional Facts Label, when available, and the extracted information is then added in the local database. In the other approach, the barcode of the food is scanned, and nutritional information is retrieved from the Internet using open APIs. Both approaches are indicated in Fig. 6. Once the nutritional content of the food is obtained, the food weight and timestamp values are used to calculate the nutritional value of the food item. Similarly, the nutritional information of all the food items that are used to prepare the meal, are calculated. In order to compute the nutrient values for future meals, the nutrient information along with the weight and timestamp are stored under respective meal IDs. The timestamp is recorded to decide the type of meal i.e., breakfast, lunch or dinner.

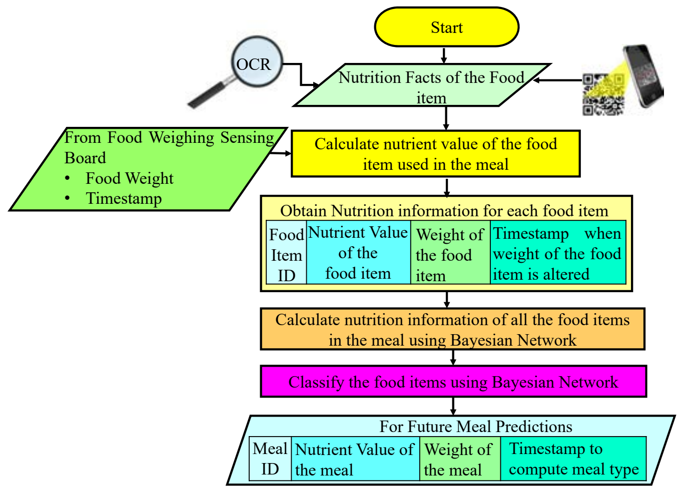

Fig. 6. Proposed Data Acquisition Approaches of Smart-Log.

C. Proposed Method for Future Meal Predictions

Fig. 7 shows the proposed steps to predict the next meal based on user feedback and measured food wastage. After consuming a meal, the weight of the leftover meal is calculated to quantify the wasted nutrients of each meal. This leftover nutrient information is combined with user input to check if the goal of a meal is fulfilled. User feedback is used to determine the purpose of the meal, i.e. whether the meal is a high-fiber, carbohydrate-rich breakfast, a low-carbohydrate, high-protein lunch, etc. The weight of wasted food is used to calculate the amount of nutrients not absorbed during the meal. In order to achieve a fully balanced diet, the nutrient values for the upcoming meals are computed, using the calculated deficient nutrients. Based on these inputs, future meals are predicted and suggested as feedback to the user.

D. Proposed Machine Learning based Method for Food Classification

The proposed algorithm is responsible for 3 main functions: (1) To extract the features of food nutrients and categorize the food based on highest nutrient value, (2) to identify the relationship between the consumed food and deficient nutrition, and (3) to identify the deficient nutrients and suggest replacements. To achieve these objectives, the proposed algorithm is built based on a Bayesian or belief network (BN). A BN structure can be built based on two approaches: the score-and-search method, which uses a scoring function to search, and the constraint-based method, where judgments are made based on conditional dependencies. For this application, a constraint-based method is considered. The joint probability

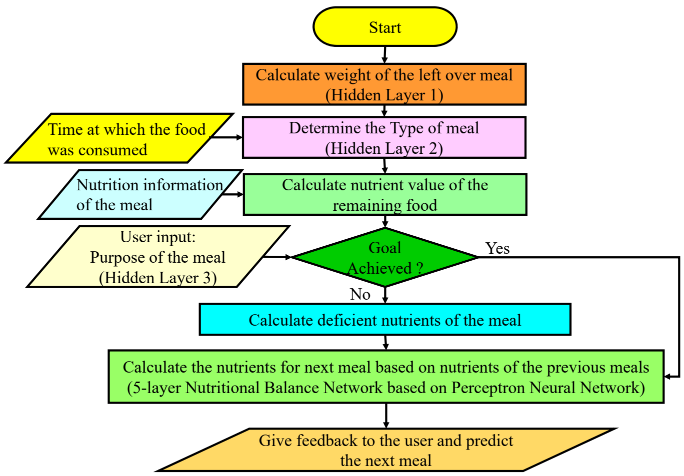

Fig. 7. Proposed Method for Next Meal Prediction.

of the two events, A and B is noted as $P(A \cap B)$ and their conditional probability, that is the probability of occurrence of A, depending upon the occurrence of a fixed event B, is noted as $P(A|B)$. The relationship between the two probabilities is given by Bayes theorem:

$$P(A|B) = \frac{P(A \cap B)}{P(B)}, \qquad \text{if} \quad P(B) \neq 0, \tag{1}$$

Bayes' theorem represents the joint distribution of a set of discrete variables and conditional probabilities such that each variable X in the Bayesian network has an associated hypothesis given by:

$$P(\theta|X) = \frac{P(X|\theta)}{P(X)} P(\theta), \tag{2}$$

where $P(\theta)$ is the hypothesis whose probability would be depended on the evidence or occurrence of data, $P(X)$. This probability given as, $P(\theta|X)$, is called the belief update or the posterior probability and the probability of the hypothesis, $P(\theta)$, is called the prior probability. The factor that connects these two probabilities is called the likelihood ratio. A Bayesian-based 5-layer perceptron neural network is built by using the prior distribution to determine the key parameters, which are then given as input to build the neural network. Neural networks are built in layers, which are interconnected nodes with an activation function. The input and output of the neural networks are connected through hidden layers, also known as "weighted connections". Equation (3) gives the mathematical representation of the interval activity of the neuron in a neural network as:

$$S_i = \sum_{i=1}^{n} W_{Ki} X_i, \tag{3}$$

where X_i is the input, W_{Ki} are the associated weights of the connected nodes and S_i represents the sum of all the weights. The final output Y_j is linked to the sum of weights through the activation function f which can be represented as:

$$Y_j = f(S_i), \tag{4}$$

A neural network is considered as a multilayer perceptron when it has a linear activation function f to map the weighed inputs to the final output. The perceptron updates the new weight based on the old weight, the target output and the actual output as:

$$W(n) = W(n+1) + \eta(d(n) - y(n)) * x(n), \tag{5}$$

where $W(n)$ and $W(n+1)$ are the old and new weight vectors respectively, $x(n)$ is the input for the corresponding output $y(n)$, $d(n)$ is the target vector and η is the user defined learning step. The node weights need to be updated after each training example such that the error is minimal and they must quickly converge to a response. To train such a perceptron neural network for determining the nutritional balance, the gradient descent algorithm is used. The algorithm for training the nutritional balance network is demonstrated in Algorithm 1. In this nutritional balance network, the stochastic gradient descent (SGD), the true gradient is approximated by the gradient for a point. The main advantage of SGD is that it trains the network to make predictions on the new data and processes the neurons with one row of data at a time. The multilayer perceptron nutrition network for the input (x_m) and output (y_m) is iteratively updated, to minimize the mean squared error (MSE), $[E(X)]$ which is defined as:

$$[E(X)] = \frac{1}{2N} \sum_{i=1}^{N} (output_m - y_m)^2), \tag{6}$$

where $output_m$ is the output of the hidden layer for the input x_m and N is the total number of input-output pairs. The delta equations obtained using gradient descent to compute the weight (W^p_{mn}) of the perceptron n in layer p for node m, based on the error function can be given as:

$$\Delta w^p_{mn} = -\alpha \frac{\partial E(X)}{\partial w^p_{mn}}, \tag{7}$$

where α is the learning rate. The delta equation to compute the bias for the perceptron m in layer p is given as:

$$\Delta b^p_m = -\alpha \frac{\partial E(X)}{\partial b^p_m}. \tag{8}$$

The Bayesian based multilayer perceptron neural network exploits the benefits of both the probabilistic model and function approximation. Figure 8 gives an example of building the BN structure for classifying food items and further determining the nutritional balance of the meals consumed with the help of the multilayer perceptron neural network. The relationships between the features are given by a directed edge, i.e. the likelihood of meeting a food goal (protein) is dependent on consuming a food item (boiled egg). For example, the likelihood of classifying bread as a carbohydrate-rich food (Carb-rich) can be determined using the conditional probability:

$$P(\text{Carb-rich}|\text{bread}) = \frac{P(\text{bread}|\text{Carb-rich})}{P(\text{bread})} P(\text{Carb-rich}), \tag{9}$$

where P(Carb-rich|bread), the posterior probability, is determined using the probability of carb-rich food. In similar fashion, a Bayesian network is built based on the hypothesis and

Algorithm 1 Nutritional Balance Network Algorithm for building a multilayer perceptron neural network using Stochastic Gradient Descent

Initialize the input layer (Type of Meal).
Initialize the connection weights W with small random numbers.
Randomize the order of input training examples for hidden layer (Weight of the meal, time at which the meal was consumer and intended nutritional goal) X.
while Not converged **do**
  for layer l_1 to l_{p-1} **do**
    Feed Forward Network: Compute output of each hidden layer by using the weights and bias for each meal.
    Back Propagation Network: Update the weights w^p_{mn} and biases b^p_m computed based on gradient descent.
    Compute the output layer, nutritional balance of the meal based on the hidden layers.
  end for
end while
Return Nutritional balance network.

Algorithm 2 Food classification algorithm for building Bayesian Network using hill-climbing search

Initialize the edges of the Bayesian network: $E \leftarrow 0$
Update the variables for nutrient values of the food product under consideration.
For the given dataset D, using the nutrient values, estimate the parameters P for local probability tables: $P \leftarrow$ Probability Tables (E, D).
Build a Bayesian Network $B \leftarrow$ Total set of variables, Edge, Parameters
Update the Posterior Probability Score (S).
while Posterior Probability Score (S) $>$ Maximum score (M). **do**
  Update Maximum score (M): $M \leftarrow S$.
  for an attribute pair (Food Category, Food Product) **do**
    for Each new edge ($E*$) **do**
      Calculate the dependencies of Food Product and Food Category.
      Calculate new Probability Table ($P*$), Bayesian Network ($B*$).
      Update the value new Posterior Probability Score ($S*$).
      if $S* > S$ **then**
        Update Bayesian Network: $B \leftarrow B*$.
        Update Posterior Probability Score: $S \leftarrow S*$.
      end if
    end for
  end for
end while
Return Bayesian Network (B).

experimental evidence. Algorithm 2 shows the steps involved in classification of food items using the Bayesian network. Each edge in this network is added or updated using the hill-climbing search algorithm, which assigns a probability score for the edges. Based on the updated probability score, the food item is categorized. After obtaining different food categories, the 5-layer perceptron neural network for Smart-Log is built by considering 3 hidden layers. There are certain criteria to be considered before building the hidden layers in the multilayer perceptron neural network. The first hidden layer should be represented by linearly separable functions; the second layer should help in approximating the function; the third layer should further improve the accuracy with the help of rational activation functions. In the proposed neural network model for computing nutritional balance, the 3 hidden layers are: time at which the meal was consumed, weight of the meal to determine the total nutrient values and the intended nutritional goal for each meal. The proposed learning model helps in developing a fully automated dietary monitoring solution.

VI. Experimental Case Study of the Proposed Smart-Log System

Implementation of the proposed Smart-Log system was divided into two interconnected phases: nutrient value data acquisition along with the weight, and analysis of the data acquired.

A. Data Acquisition for the Smart-Log System

Data acquisition for Smart-Log involves the hardware design of the food weighing sensor and nutrient feature extraction as described in the following sections.

1) Food Weighing Sensor System: The hardware implementation of the food weighing sensor was done with the help of commercially available off the shelf (COTS) components. The main parameters to be considered in choosing the load cell are its sensitivity and resistance. Sensitivity (mV/V) of the load cell is the amount of output voltage when the input (excitation) voltage is 1 mV. In commercially available components, the sensitivity, resistance along with the offset values are given by the manufacturer. For the Smart-Log system, a load cell which has the capacity to weigh objects in the range of 0-5 Kg was considered. The output of the load cell was connected to a 24-bit Analog-to-Digital Converter (ADC), designed specifically for weighing applications. The architecture of the 24-bit ADC contains an on-chip programmable gain amplifier (PGA), analog power supply regulator and internal oscillator. The output of the ADC which is to be connected to the microcontroller for data retrieval, is the Serial Data Output (DOUT) and Serial clock (SCK). As per the design of the ADC for weighing applications, the output at DOUT remains high and SCK remains low, before the data are ready. When DOUT goes low, it indicates that the digital output is ready. Both the input and overall gain are controlled by the number of pulse shifts at SCK.

In prototyping the Smart-Log design, the overall efficiency of the system was analyzed based on its compatibility and ease of use which can be determined by the smaller size, low power dissipation and high processing speed. For this purpose, 2 microcontrollers were considered: one with a wireless module embedded along with the board and another

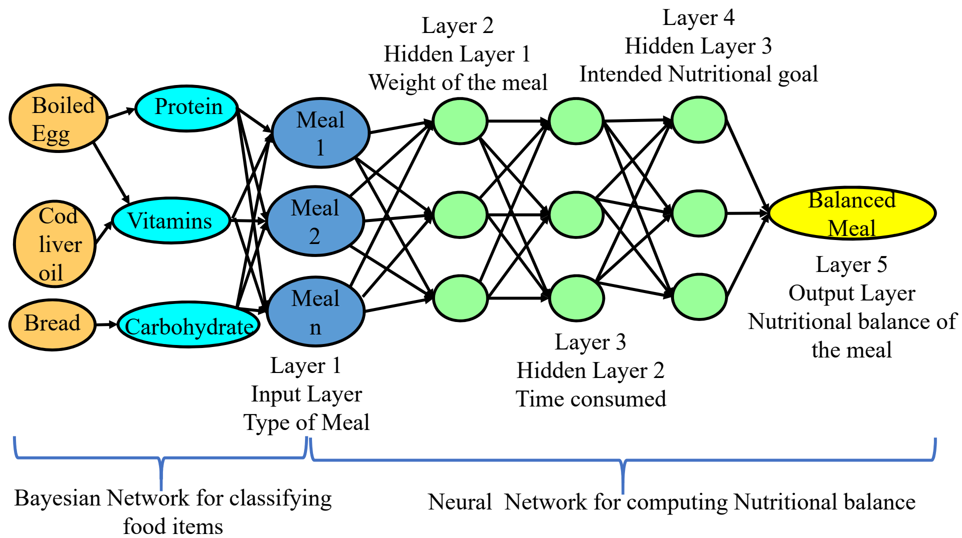

Fig. 8. Proposed Learning Model for Smart-Log using Bayesian Network for Classification of Food Items Based on Extracted Nutrient Features, and Neural Network for computing Nutritional Balance of the Food Consumed by the User.

one without a wireless module Table I gives a comparison of the two microcontrollers. Model 2 was considered for the final prototype as the main purpose of using a microcontroller in the Smart-Log design is to transmit data wirelessly to the cloud. In addition to this, considering the dimensions, Model 2 has a smaller form factor and can be easily used as a "Thing" in this IoT based solution.

TABLE I
COMPARISON OF HARDWARE PROTOTYPES FOR SMART-LOG SYSTEM BASED ON 2 MICROCONTROLLERS.

Characteristics	Model 1	Model 2
Operating Voltage	5 Volt	3.3 - 5 Volt
Dimensions of the board	101.52×53.3 mm^2	49×24.5 mm^2
Clock Speed	16MHz	80 MHz
Built-in Wi-Fi module	No	Yes
Digital I/O pins	54	11

2) Nutrition Acquisition: A JAVA application was developed to obtain nutritional values from the Internet. The USDA provides a freely accessible database of 8791 food items [32] and this was used for retrieving nutritional values. The US Department of Agriculture also maintains an API front end web site to its SR8 database which encodes foods based on a unique identifier, the NDB number. The user of Smart-Log is presented with a web page displaying a questionnaire regarding the name of the food item and the type of the meal based on a predefined characterization which includes: "breakfast", "brunch", "lunch", "snack", and "dinner". The main challenge in obtaining the nutrition information of each meal is calculating the nutrition value from each food item used in preparing the meal.From the food weight obtained by the sensor board and the nutritional information retrieved from the cloud, the overall nutritional content of the meal before ingestion is calculated. Following the meal, any leftover food is weighed again and the precise nutritional content of the meal is recalculated.

B. Data Analysis for the Smart-Log System

As mentioned in Section V, the Smart-Log system should autonomously monitor the food consumed by the user and provide efficient predictions. To achieve this, the data analytics were done using the Waikato Environment for Knowledge Analysis (WEKA) [33, 34] tool, which is used to classify each food item to various classes. The application generates an .arff (attribute-relation file format) entry which is passed on to WEKA. The response of the classifier is displayed on a web page by a custom JAVA application. Many data analytics algorithms are available in WEKA and these can be used for predictive modeling. The input to the system was an .arff file containing 1000 meal entries input by the Smart-Log UI. The Bayes-based classification algorithms and the multilayer perceptron neural network outperformed significantly the traditional decision table approach.

C. Experimental Prototype of the Smart-Log System

The overall compositional characteristics of the Smart-Log system are given in Table II. During the data acquisition phase the database, API and OCR approaches were used. OCR adds significant computational complexity to the system resulting in increased power consumption. For this reason, it was excluded from further consideration. Fig. 9 shows a photograph of the experimental setup for Smart-Log, implemented using off the shelf components.

TABLE II
CHARACTERIZATION OF SMART-LOG SYSTEM.

Characteristics	Specifics
Sensor system	Food Weighing Sensor
Data acquisition	API and Database approach
Data Analysis Tool	WEKA
Input Dataset	8791 instances
Classifier	Bayesian Network
Accuracy (worst case)	98.6 %

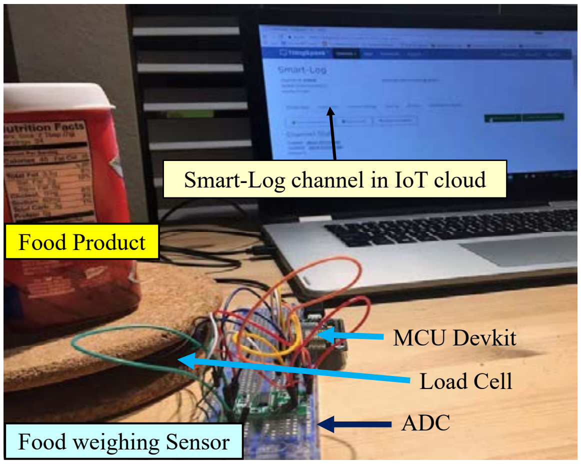

Fig. 9. Experimental Setup of the Smart-Log implementation.

D. Comparative Perspective with Prior research in Consumer Electronics

A comparison of existing research in developing smart consumer electronic systems based on Bayesian modeling is given in Table III. It can be observed that Bayesian modeling has been widely used for building a belief network in use cases such as image processing, intelligent environment, and speech recognition. This paper proposes a novel Bayesian based 5-layer perceptron neural network for developing a fully automated diet monitoring consumer electronic product. A thorough literature survey shows that direct comparison of this research with consumer electronic products is not possible. The authors envision that the end product of this research will be a consumer electronic product in a smart home environment.

TABLE III
BAYESIAN MODELING FOR CONSUMER ELECTRONICS PRODUCT.

Proposed Consumer Electronic Systems	Category	Method
Mandarin Speech Recognition System [35]	Speech Recognition	Bayesian neural network based language model
An adaptable environment (curtain, music, and light control) based on user's input [36]	Intelligent Environment	Multilevel Bayesian network to model user's preference and priority
An online speaker segmentation approach for spoken document retrieval [37]	Information Retrieval	Bayesian information criterion built using Gaussian Mixture Model (GMM)
Skin color detection under rapidly changing illumination conditions [38]	Image Processing	Bayesian based decision framework
Multiple object detection and tracking framework for video surveillance [39]	Image Processing	Bayesian tracking model with multimodal distributions
An Automated Nutrition Monitoring System **(the current paper)**	Diet Monitoring	Bayesian based 5-layer perceptron neural network for monitoring nutritional intake

The efficiency of this research is evaluated based on the accuracy of classification of food items and meal prediction. In this research, the pattern analysis follows the meal information provided by the user to provide additional feedback regarding achievement of the meal goals. The number of main classes to be predicted by the food classification algorithm are 4, i.e. protein-rich, carbohydrate-rich, fiber-rich and vitamin-rich. The classification is done with help of the Bayesian based classification algorithm by taking 15 attributes from the nutrition facts of the food item. The activation function used in hidden layer 1 and 2 is logistic sigmoid as the inputs are non-negative. The activation function of the hidden layer 3 is linear function as the final output is a classification to understand if the nutritional goal is achieved or not. Hidden layer h_1 contains 10 neurons, hidden layers h_2 and h_3 contain 4 neurons each. The input to the multilayer perceptron based 5-layer Nutritional Balance Network is the type of meal classified using the Bayesian Network. The output is the nutritional balance of the meal. The weights, number of hidden layers and number of neurons were selected after carefully analyzing the sample dataset for several iterations using the algorithm. In this work, 8172 sample meals were considered as input to the custom Bayesian network and 5-layer perceptron neural network developed after consideration of the WEKA results. 60% of the data set was used for training and 40% was used for prediction. The final results of this analysis provided a worst-case accuracy of 98.6%.

VII. Conclusions

An autonomous food data logging system is presented in this work. The implemented design is cost efficient with high accuracy in diet monitoring. The algorithm for nutrient feature extraction based on a Bayesian network and an algorithm based on a 5 layer perceptron neural network for determining the nutritional balance after each meal, was proposed after a thorough analysis of various classifiers using WEKA. Since an open food database was used, the input dataset contained certain products logged multiple times. To overcome this, the user is presented with additional options to correct a data entry in case of redundancy with corresponding increase in the final accuracy. In addition to an analysis of the meal nutritional content, suggestions are made by the system to decrease the risk of imbalanced diet. This system can become an essential product for household or child care usage. Even though the scope of Smart-Log is demonstrated in the context of food habits of infants in the current paper, the Smart-Log can be used for adults as well by expanding the food databased in its cloud storage. As future research, Smart-Log will be integrated with physiological monitoring mechanisms to keep track of user activities for accurate automated prediction of diet for adults.

References

[1] J. Wang, Z. Zhang, B. Li, S. Lee, and R. Sherratt, "An Enhanced Fall Detection System for Elderly Person Monitoring using Consumer Home Networks," *IEEE Trans. Consum. Electron.*, vol. 60, no. 1, pp. 23–29, Feb 2014.

[2] J. Wei and A. D. Cheok, "Foodie: Play with Your Food Promote Interaction and Fun with Edible Interface," *IEEE Trans. Consum. Electron.*, vol. 58, no. 2, pp. 178–183, May 2012.

[3] S. M. R. Islam, M. N. Uddin, and K. S. Kwak, "The IoT: Exciting Possibilities for Bettering Lives," *IEEE Consum. Electron. Mag.*, vol. 5, no. 2, pp. 49–57, April 2016.

[4] B. K. Kang, S. H. Park, T. L. Lee, and S. H. Park, "IoT-based Monitoring System using Tri-Level Context Making Model for Smart Home Services," in *Proc. IEEE Int. Conf. Consum. Electron.*, no. 198-199, 2015.

[5] S. P. Mohanty, U. Choppali, and E. Kougianos, "Everything You wanted to Know about Smart Cities," *IEEE Consum. Electron. Mag.*, vol. 5, no. 3, pp. 60–70, July 2016.

[6] P. Sundaravadivel, E. Kougianos, S. P. Mohanty, and M. Ganapathiraju, "Everything You Wanted to Know about Smart Healthcare," *IEEE Consum. Electron. Mag.*, vol. 8, no. 1, pp. 18–28, January 2018.

[7] S. Bounyong and S. Adachi and J. Ozawa and Y. Yamada and M. Kimura and Y. Watanabe and K. Yokoyama, "Fall Risk Estimation Based on Co-contraction of Lower Limb During Walking," in *Proc. IEEE Int. Conf. Consum. Electron.*, 2016, pp. 331–332.

[8] J. Byun, B. Jeon, J. Noh, Y. Kim, and S. Park, "An Intelligent Self-Adjusting Sensor for Smart Home Services based on ZigBee Communications," *IEEE Trans. Consum. Electron.*, vol. 58, no. 3, pp. 794–802, August 2012.

[9] I. A. Zualkernan, A. R. Al-ali, M. A. Jabbar, I. Zabalawi, and A. Wasfy, "InfoPods: Zigbee-based Remote Information Monitoring Devices for Smart-Homes ," *IEEE Trans. Consum. Electron.*, vol. 55, no. 3, pp. 1221–1226, August 2009.

[10] A. R. Al-Ali, I. A. Zualkernan, M. Rashid, R. Gupta, and M. Alikarar, "A Smart Home Energy Management System using IoT and Big Data Analytics Approach," *IEEE Trans. Consum. Electron.*, vol. 63, no. 4, pp. 426–434, November 2017.

[11] J. Winkley, P. Jiang, and W. Jiang, "Verity: An Ambient Assisted Living Platform," *IEEE Trans. Consum. Electron.*, vol. 58, no. 2, pp. 364–373, May 2012.

[12] J. Y. Son, J. H. Park, K. D. Moon, and Y. H. Lee, "Resource-aware Smart Home Management System by Constructing Resource Relation," *IEEE Trans. Consum. Electron.*, vol. 57, no. 3, pp. 1112–1119, August 2011.

[13] Y. C. Yu, S. D. You, and D. R. Tsai, "Magic Mirror Table for Social-Emotion Alleviation in the Smart Home," *IEEE Trans. Consum. Electron.*, vol. 58, no. 1, pp. 126–131, February 2012.

[14] A. Jalal, M. Z. Uddin, and T. S. Kim, "Depth Video-based Human Activity Recognition System using Translation and Scaling Invariant Freatures for Life Logging at Smart Home," *IEEE Trans. Consum. Electron.*, vol. 58, no. 3, pp. 863–871, August 2012.

[15] T. Vu, F. Lin, N. Alshurafa, and W. Xu, "Wearable Food Intake Moniroting Technologies: A Comprehensive Review," *Computers*, vol. 6, no. 4, 2017.

[16] H. Kalantarian, N. Alshurafa, and M. Sarrafzadeh, "A Survey of Diet Monitoring Technology," *IEEE Pervasive Comput.*, vol. 16, no. 1, pp. 57–65, January 2017.

[17] E. S. Sazonov, O. Makeyev, S. Schuckers, P. Lopez-Meyer, E. L. Melanson, and M. R. Neuman, "Automatic Detection of Swallowing Events by Acoustical Means for Applications of Monitoring of Ingestive Behavior," *IEEE Trans. Biomed. Eng.*, vol. 57, no. 3, pp. 626–633, March 2010.

[18] K.-h. Chang, S.-y. Liu, H.-h. Chu, J. Y.-j. Hsu, C. Chen, T.-y. Lin, C.-y. Chen, and P. Huang, "The Diet-Aware Dining Table: Observing Dietary Behaviors over a Tabletop Surface," in *Proc. Int. Conf. Pervasive Comput.*, 2006, pp. 366–382.

[19] J. Liu, E. Johns, L. Atallah, C. Pettitt, B. Lo, G. Frost, and G. Z. Yang, "An Intelligent Food-Intake Monitoring System Using Wearable Sensors," in *Proc. IEEE Int. Conf. Wear. Implant. BSN*, 2012, pp. 154–160.

[20] M. Y. Chen, Y. H. Yang, C. J. Ho, S. H. Wang, S. M. Liu, E. Chang, C. H. Yeh, and M. Ouhyoung, "Automatic Chinese Food Identification and Quantity Estimation," in *Proc. SIGGRAPH Asia*, 2012.

[21] O. Beijbom, N. Joshi, D. Morris, S. Saponas, and S. Khullar, "Menu-Match: Restaurant-Specific Food Logging from Images," in *Proc. IEEE Winter Conf. Appl. of Comput. Vis.*, 2015.

[22] T. Joutou and K. Yanai, "A food image recognition system with multiple kernel Learning," in *Proc. IEEE Int. Conf. Image Proc.*, 2009, pp. 285–288.

[23] M. Shoaib, S. Bosch, H. Scholten, P. J. M. Havinga, and O. D. Incel, "Towards Detection of Bad Habits by Fusing SmartSmart and SmartSmart Sensors," in *Proc. IEEE Int. Conf. Pervasive Comput. and Comm.*, 2015, pp. 591–596.

[24] O. Amft and G. Trster, "Recognition of dietary Activity Events using On-Body Sensors," *AI in Med.*, vol. 42, no. 2, pp. 121–136, February 2008.

[25] Y. Dong, A. Hoover, J. Scisco, and E. Muth, "A New Method for Measuring Meal Intake in Humans via Automated Wrist Motion Tracking," *Applied Psycho. and Biofeedback*, vol. 37, no. 3, pp. 205–215, 2012.

[26] K. Yatani and K. N. Truong, "BodyScope: A Werable Acoustic Sensor for Activity Recognition," in *Proc. ACM Conf. Ubiq. Comp.*, 2012, pp. 341–350.

[27] J. Cheng, O. Amft, and P. Lukowicz, "Active Capacitive Sensing: Exploring a New Wearable Sensing Modality for Activity Recognition," in *Proc. Int. Conf. Pervasive Comput.*, 2010, pp. 319–336.

[28] N. Alshurafa, H. Kalantarian, M. Pourhomayoun, J. J. Liu, S. Sarin, B. Shahbazi, and M. Sarrafzadeh, "Recognition of Nutrition Intake Using Time-Frequency Decomposition in a Wearable Necklace Using a Piezoelectric Sensor," *IEEE Sensors J.*, vol. 15, no. 7, pp. 3909–3916, July 2015.

[29] H. Kalantarian, N. Alshurafa, and M. Sarrafzadeh, "A Wearable Nutrition Monitoring System," in *Proc. IEEE Int. Conf. Wear. Implant. BSN*, 2014, pp. 75–80.

[30] M. Farooq and E. Sazonov, "Comparative Testing of Piezoelectric and Printed Strain Sensors in Characterization of Chewing," in *Proc. Annual Int. Conf. IEEE Eng. in Med. and Bio. Soc.*, 2015, pp. 7538–7541.

[31] P. Sundaravadivel, K. Kesavan, L. Kesavan, S. P. Mohanty, E. Kougianos, and M. K. Ganapathiraju, "Smart-Log: An Automated, Predictive Nutrition Monitoring System for Infants Through IoT," in *Proc. IEEE Int. Conf. Consum. Electron.*, 2018.

[32] A. R. S. US Department of Agriculture and N. D. Laboratory, "USDA National Nutrient Database for Standard Reference," May 2016, release 28. [Online]. Available: https://ndb.nal.usda.gov/ndb/

[33] M. Hall, E. Frank, G. Holmes, B. Pfahringer, P. Reutemann, and I. H. Witten, "The weka data mining software: An update," *SIGKDD Explo.*, vol. 11, 2009.

[34] E. Frank, M. A. Hall, and I. H. Witten, *The WEKA Workbench. Online Appendix for "Data Mining: Practical Machine Learning Tools and Techniques"*, 4th ed., M. Kaufmann, Ed., 2016.

[35] C.-C. Huang, J.-F. Wang, and J.-Y. Lee, "A Mandarin Speech Dictation System based on Neural Network and Language Processing Model," *IEEE Trans. Consum. Electron.*, vol. 40, no. 3, pp. 437–445, August 1994.

[36] M. K. Hasan, K. A. P. Ngoc, Y. K. Lee, and S. Lee, "Preference Learning on an OSGi based Home Gateway," *IEEE Trans. Consum. Electron.*, vol. 55, no. 3, pp. 1322–1329, August 2009.

[37] K. Park, J. S. Park, and Y. H. Oh, "GMM Adaptation based Online Speaker Segmentation for Spoken Document Retrieval," *IEEE Trans. Consum. Electron.*, vol. 56, no. 2, pp. 1123–1129, May 2010.

[38] L. Liu, N. Sang, S. Yang, and R. Huang, "Real-time Skin Color Detection under rapidly changing Illumination Conditions," *IEEE Trans. Consum. Electron.*, vol. 57, no. 3, pp. 1295–1302, August 2011.

[39] C. R. del Blanco, F. Jaureguizar, and N. Garcia, "An Efficient Multiple Object Detection and Tracking Framework for Automatic Counting and Video Surveillance Applications," *IEEE Trans. Consum. Electron.*, vol. 58, no. 3, pp. 857–862, August 2012.

Prabha Sundaravadivel (S'15, M'18) is an Assistant Professor in the Department of Electrical Engineering, at the University of Texas at Tyler, Tyler, TX. She received her Ph.D. degree in Computer Science and Engineering at the University of North Texas, Denton, TX in 2018. Before joining the research group at Smart Electronic Systems Laboratory at UNT, she earned her Bachelors of Technology (B.Tech) in Electronics and Communication from SRM University, Chennai, India, in 2011 and Masters of Technology (M.Tech) in VLSI Design from VIT University, India, in 2015. Her research interests include application specific architectures for Consumer Electronic systems, mixed signal IC design, VLSI design and embedded system for Internet of Things. She has authored or co-authored a dozen of peer-reviewed research articles.

Kavya Kesavan (S'17) is currently pursuing her Masters in Computer Science and Engineering at University of Texas, Arlington, TX. She earned her integrated Masters in Software Engineering from Vellore Institute of Technology, Vellore, India, in 2015. Her research interests include Artificial Intelligence, Data Science and Machine Learning.

Lokeshwar Kesavan received a B. Tech in Electronics and Communication from SRM University, Chennai, India, in 2011 and Masters in Computer Science from the University of Texas, Dallas, TX, in 2016. He is currently working as a Systems Engineer with Versa Networks. His research interests include Software Defined Network, Virtual Network and Smart cities.

Saraju P. Mohanty (SM'08) is a Professor at the University of North Texas. Prof. Mohanty's research is in "Smart Electronic Systems" which has been funded by National Science Foundations, Semiconductor Corporation, US Air Force, and Indo-US Science & Technology Forum. He authored 280 research articles, 3 books, and invented 4 US patents. His Google Scholar h-index is 29 and i10-index is 89. He is the EiC of the IEEE Consumer Electronics Magazine. He has been recognized as a IEEE Distinguished Lecturer by the Consumer Electronics Society in 2017. He received IEEE-CS-TCVLSI Distinguished Leadership Award in 2018 for services to IEEE, and to the VLSI research community. He was conferred the Glorious India Award in 2017 for his exemplary contributions to the discipline. He was the recipient of 2016 PROSE Award for best Textbook in Physical Sciences & Mathematics from the Association of American Publishers for his Mixed-Signal System Design book published by McGraw-Hill in 2015. He was conferred 2016-17 UNT Toulouse Scholars Award for sustained excellent scholarship and teaching achievements.

Elias Kougianos (SM'07) is a Professor in the Department of Engineering Technology, at the University of North Texas (UNT), Denton, TX. He received a BSEE from the University of Patras, Greece in 1985 and an MSEE in 1987, an MS in Physics in 1988 and a Ph.D. in EE in 1997, all from Lousiana State University. From 1988 through 1997 he was with Texas Instruments, Inc. Initially he concentrated on process integration of flash memories and later as a researcher in the areas of Technology CAD and VLSI CAD development. In 1997 he joined Avant! Corp. (now Synopsys) in Phoenix, AZ as a Senior Applications engineer and in 2001 he joined Cadence Design Systems, Inc., in Dallas, TX as a Senior Architect in Analog/Mixed-Signal Custom IC design. He has been at UNT since 2004. His research interests are in the area of Analog/Mixed-Signal/RF IC design and simulation and in the development of VLSI architectures for multimedia and IoT applications. He is author or co-author of over 120 peer-reviewed journal and conference publications.