International Journal of Innovative Technology and Exploring Engineering (IJITEE)
ISSN: 2278-3075 (Online), Volume-8 Issue-11, September 2019

Nutrition Monitoring and Calorie Estimation using Internet of Things (IoT)

P. Kamakshi Priyaa, S. Sathyapriya, L. Arockiam

Abstract: ***Diet observation is one of the principal aspect in precautionary health care that aims to cut back varied health risks. The various recent advancements in smartphone and wearable sensing element technologies have paved way to a proliferation of food observation applications that are based on automated image processing and intake detection, with an aim to beat drawbacks of the standard manual food journaling that's time overwhelming, inaccurate, underreporting, and low adherent. The currently developed food logging methods are very much time consuming and inconvenient that limits their effectiveness. The proposed work presents an Internet of Things (IoT) based mobile-controlled calorie estimation system to make technical advancements in healthcare industry. The proposed system operates on mobile environment, which allow the user to acquire the food image and quantify the calorie intake mechanically. The Mqtt protocol based MyMqtt broker is used to connect the application and the edge device and also to store the data in the Thingspeak cloud. A deep convolutional network is employed to classify the food accurately within the system. The volume estimation is done using sensors and the calorie approximation is done using formula.***

Keywords: ***Calorie Estimation, Convolutional Neural Network, , Deep Learning, IoT.***

I. INTRODUCTION

A well-balanced healthy diet is a vital goal for several individuals. A technique to attain this is by manually recording the quantity of calories consumed. This pursuit method, however, is often terribly tedious because it needs the user to have a food journal and to try and do complex calculations to be able to estimate the quantity of calories consumed in each food item. In fact, it has been conjointly shown that individuals tend to underestimate the amount of calories most of the time [1]. Nutritional imbalance will occur either because of under-nourishment or over-nourishment. Under-nutrition is a condition where the sufficient nutrients are not consumed. Malnourishment will result in organic process disorders which may be characterised by symptoms like anxiety, mood swings, tender bones, injury gums, and skinny hairline etc. Similarly, over-nutrition is a condition where multiple varieties of imbalanced food are consumed. Over-nutrition will increase the chance of obesity that is primarily caused by the intake of food that is high in salt and fat. The Internet of Things (IoT) aids in connecting real world sensing information to predominantly cloud based elucidations.

Manuscript published on 30 September 2019.
***Correspondence Author(s)**
S. Sathyapriya, Ph.D. Department of Computer Science, St. Joseph's College (Autonomous), Tiruchirappalli, Tamil Nadu, India
Dr. L. Arockiam, Associate Professor Department of Computer Science, St. Joseph's College (Autonomous), Tiruchirappalli, Tamil Nadu, India

It is an associate internetwork of sensors deployed within the physical world and helps in swapping data between these sensors and also the cloud [2]. In the current years, there are a number of measures supported by computer vision to estimate calories [3, 4]. For these strategies, the accuracy of estimation results are determined by two main factors namely: object detection algorithms and volume estimation methodology. Within the side of object detection, classification algorithm like Support Vector Machine (SVM) is used to recognise the generic food items. With the aspect of volume estimation, the standardisation of food and also the volume calculation are the key problems. The appliance of deep learning for food classification and recognition is extremely recommendable. Deep learning is associate rising approach from machine learning, and has been projected in recent years to switch the machine learning systems towards the discovery of multiple levels of illustration. The recent advancements in this area was surveyed in a detailed manner in [5]. The proposed system uses a robust deep learning based neural network model as a way of improving the reliability of food image classification and calorie estimation systems. The model integrates the mobile calorie activity application to the deep neural network. The Convolutional Neural Network (CNN) is a pillar that handles the training and testing requests at the upper layers without affecting the central layers.

II. RELATED WORKS

An innumerable amount of techniques have been applied to measure the calorie within the food. One amongst the primary clinical works in the domain is the 24 Hour Dietary Recall (24HR) [6], [7]. This method records the daily calorie intake limited to a duration of twenty four hours. The user is anticipated to recall the food items that have been consumed in the previous twenty four hours prior to the interview. In this technique, the estimation of food portion size is done using standardized cups and spoons. Based on the measure of food, the nutrient consumed is estimated using the food composition tables. Food Frequency Questionnaire (FFQ) is a technique [8] that focuses on elaborating the dietary patterns or food habits, however not the calorie intake. The major limitation of the 24HR and FFQ are namely the delay time in outlining the food consumed, the under-reporting of the food portion size, human memory dependency, requirement of qualified interviewers who can predict the quantity of calories and nutrients and the requirement of performing complicated calculations to estimate the frequencies. The process of automatically predicting the quantity of calories in food using their images has been receiving some attention within the domain of computer vision.

In [9] a food image recognition system was presented which was further enhanced to restaurant specific food logging system in [10]. A mobile phone based food classification system which assess the nutrient intake has been presented in [11]. The wearable sensor based automated methods could be a potential solution as they require minimal user intervention. These sensors adopt various detection techniques that are primarily based on the user activities [12]. An automated nutrition prediction monitoring system was proposed using machine learning techniques in [13] which was further improvised as a deep learning based model in the subsequent research [14]. There are numerous research works that have been performed to adopt the sensors to monitor food intake, but most of them are suited only for laboratory conditions along with limited participants. The average accuracy of the systems engineered using these sensors is about 90% [15]. So, it is a challenge to find an efficient solution to monitor the nutritional consumption with greater accuracy in the real-world context.

III. PROPOSED APPROACH

The proposed work aims to build an IoT Based Automated Nutrition Monitoring and Calorie Estimation System in mobile environment. The users of the system have the mobile interface through which the demographic information and physical measurement data are collected. The application is used to activate the microcontroller module through the MyMqtt broker. The microcontroller triggers the USB camera to capture a photo of the food item placed on the load sensor and the weight of the timestamped food item is also estimated. The collected data are stored in the Thingspeak cloud server. The subsequent data analytics is done using the collected data. Initially, a deep learning based Convolutional Neural Network model is built based on the classification of food items. The developed model is then used to predict the type of food. Based on the volume estimated by the load sensor and the prediction of the food item, the USDA (US Department of Agriculture) standardized data repository is utilized for collecting the nutritional facts which in turn determines the amount of calorie that was consumed by an individual. The architecture of the proposed system has been depicted pictorially in Fig. 1 and there is a subsequent elaborated view of all the activities in the system.

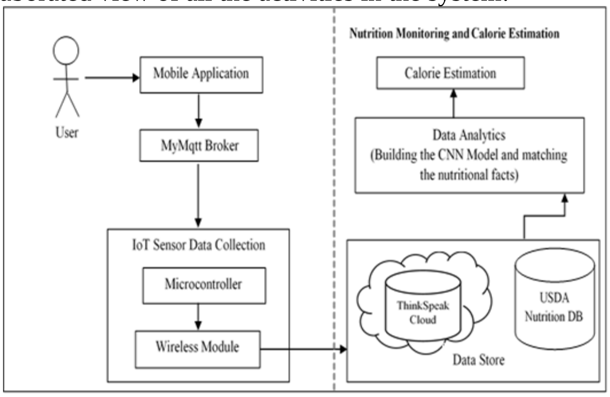

Fig. 1. Proposed Architecture

A. IoT Sensor Data Collection

This is the interface between the user and the system which collects the data using the data collection points. The user display the food item to the sensing element system and authenticate it via a mobile app. The mobile application publishes the request to activate the sensor system by the MyMqtt Broker. The microcontroller receives the request as it has subscribed to the mutual topic. The microcontroller activates the USB camera which captures the photo of the food item. The activated load sensor estimates the weight of the food placed on the weighing sensor along with the timestamp. The working procedure is represented in Fig. 2.

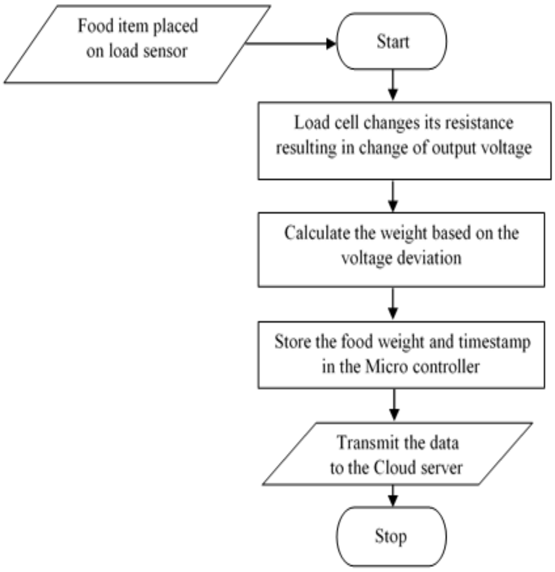

Fig. 2. IoT Data Flow

The experimental setup is shown in Fig. 3.

Fig. 3 Experimental Setup

B. Datastore

The data store contains both the raw data (sourced from the sensors and the mobile application) and the nutritional facts data (sourced from the USDA API).

C. Cloud Servers

The data received from the sensors and camera are temporarily stored in local SD card in the microcontroller and are later transmitted to the Thingspeak Cloud server.
The Thingspeak cloud server is employed for remote storage purpose. The data stored in the Thingspeak cloud is used for the analytics process.

Retrieval Number: K20720981119/19©BEIESP
DOI: 10.35940/ijitee.K2072.0981119
Journal Website: www.ijitee.org

Published By:
Blue Eyes Intelligence Engineering
and Sciences Publication (BEIESP)

D. Data Analytics

The Data Analytics module is responsible for statistical analysis and deep learning events in the system. It includes algorithms to detect objects, build a CNN model, estimate volume and associated nutritionary composition values and integrate the information. Fig. 4 displays a portion of the dataset used for model evaluation. Fig. 4 displays the portion of the image dataset.

Fig. 4. Sample Dataset

- **Building the model**

The process of building the deep neural network model is done when the data acquisition is done. The initial step for building the model is to produce a pre-trained model file using the CNN network. The model is built by collecting the images of a particular class (approximately 1000 images per class) and then using the object name-set they are labelled. The collected images are used to train the model. The model file thus generated is used to perform image recognition against the image captured by the user. The system predicts a list of probable class labels for the image and the class with the highest probability is assigned.

The various steps involved in building the CNN model is summarized as follows.

Step 1: The initial setup which comprises of importing the necessary packages namely Sequential, Convolution2D, MaxPooling2D, Flatten and Dense.

Step 2: The neural network is initialized using an object.

Step 3: The convolutional layers are added specifying the filter size, shape, dimensions and the activation function.

Step 4: Pooling is performed for feature map size reduction without losing the important image characteristics.

Step 5: Flattening is done by collecting all the pooled feature maps and putting them into a single vector.

Step 6: The full connection is created using the number of hidden layer nodes, relu function for hidden layer, softmax function for multiple outcomes and the output probabilities are randomly generated.

Step 7: The CNN model is compiled and image augmentation is done to train and test the model.

Step 8: The model is tested with unseen (new) image and the output is evaluated in terms of classification accuracy and Mean Square Error (MSE).

The constructed model's accuracy for 25 epochs is displayed in Fig. 5 and Fig. 6 shows the model's loss.

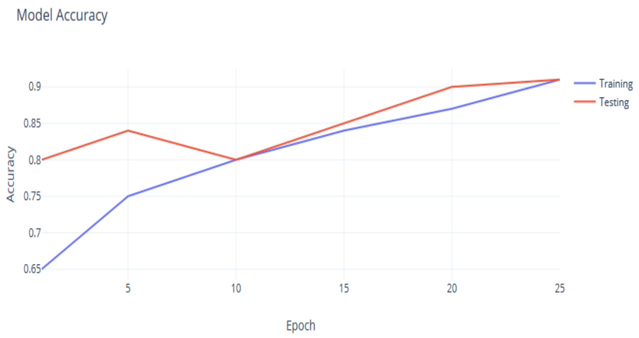

Fig. 5. The accuracy of the model with 25 epochs

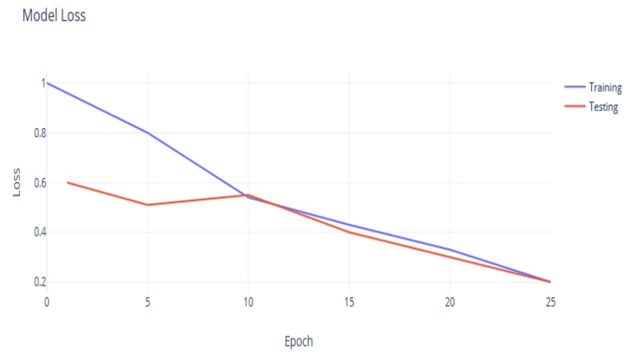

Fig. 6. The loss of the model with 25 epochs

E. Calorie Estimation

The prototype consists of the Weighing Load Cell Sensor (5kg) connected with a Raspberry Pi 3 microcontroller which can be efficiently programmed using Python. The data logging is achieved through the USB port. An approximate estimation of the weight is provided by the sensor (in gm). Once the weight is estimated and the food label is predicted, it can be utilized to calculate the calorific value using the formula. The SR Legacy database available at the US Department of Agriculture website is used to estimate the calorific value.

$$\text{Calorie Value} = \frac{\text{Calorific table value} * \text{Weight of the predicted food}}{\text{Mass in the Nutrition Table}}$$

Published By:
Blue Eyes Intelligence Engineering
and Sciences Publication (BEIESP)

A sample of the estimated calorie value using the prediction model is provided in Table-I.

Table- I: Calorie Estimation

Food item	Standard Calorie (100 gm)	Mass obtained (in gm)	Estimated Calorie
Samosa	262	107	280.34
Vegetable rice	129	256	330.24
Sandwich	243	308	748.44
Donuts	396	43	170.28
Chocolate cake	458	86	393.88
Apple	254	62	157.48
Aloo paratha	240	273	655.20
Vegetable salad	170	208	353.60
Pizza	269	363	976.47
Spaghetti	66.64	564	375.85

IV. CONCLUSION

In the proposed work, a food data logging system which estimates the calories using IoT has been developed. This system analyzes the average calorie intake of a person in a day and helps them by providing some insights about their diet. The study utilizes a cost effective sensor system and seamless data logging method, which makes the system more desirable. The deep learning model achieved an accuracy of 90.69% with a loss of 0.2324. The future work is to cover more food types from a variety of cuisines around the world. In addition, an obesity prediction system considering the daily calorific intake along with other relevant attributes is to be developed to analyze the correlation among obesity and the attributes.

REFERENCES

1. Elbel B, "Consumer estimation of recommended and actual calories at fast food restaurants", Obesity, Vol. 19, Issue 10, 2011, pp. 1971 – 1978.
2. Kougianos E, Mohanty S P, Coelho G, Albalawi U and Sundaravadivel P, "Design of a High-Performance System for Secure Image Communication in the Internet of Things," IEEE Access, Vol. 4, 2016, pp. 1222 – 1242.
3. Jia W, Chen H C, Yue Y, Li Z, Fernstrom J, Bai Y, Li C and Sun M, "Accuracy of food portion size estimation from digital pictures acquired by a chest-worn camera", Public Health Nutrition, Vol. 17, Issue 8, 2014, pp. 1671 – 1681.
4. Pouladzadeh P, Kuhad P, Peddi S V B, Yassine A and Shirmohammadi S, "Mobile cloud based food calorie measurement", In Proceedings of the International Instrumentation and Measurement Technology, 2016, pp. 1 – 6.
5. Kamakshi Priyaa P, Arockiam L, "A Survey on Nutrition Monitoring and Dietary Management System", IJRAR- International Journal of Research and Analytical Reviews (IJRAR), Vol. 6, Issue 2, 2019, 329-334, DOI: http://doi.one/10.1729/Journal.21493.
6. Livingstone M B E, Robson P J and Wallace J M W, "Issues in dietary intake assessment of children and adolescents", British Journal of Nutrition, Vol. 92, Issue S2, 2004, pp. S213 – S222.
7. Bandini L, Must A, Cyr H, Anderson S, Spadano J and Dietz W, "Longitudinal changes in the accuracy of reported energy intake in girls 10-15 y of age", The American Journal of Clinical Nutrition, Vol. 78, Issue 3, 2003, pp. 480 – 484.
8. Luo W, Morrison H, de Groh M, Waters C, DesMeules M, Jones-McLean E, Ugnat A M, Desjardins S, Lim M and Mao Y, "The burden of adult obesity in Canada", Chronic Diseases in Canada, Vol. 27, Issue 4, 2007, pp. 135 – 144.
9. Chen M Y, Yang Y H, Ho C J, Wang S H, Liu S M, Chang E, Yeh C H and Ouhyoung M "Automatic Chinese Food Identification and Quantity Estimation," In SIGGRAPH Asia 2012 Technical Briefs, ACM, 2012.
10. Oscar Beijbom , Neel Joshi , Dan Morris , Scott Saponas and Siddharth Khullar, "Menu-Match: Restaurant-Specific Food Logging from Images", Proceedings of the 2015 IEEE Winter Conference on Applications of Computer Vision, 2015, pp. 844 – 851, [doi>10.1109/WACV.2015.117].
11. Kiran Abhore and Dawande N A, "Measuring Calories and Nutrition from Food Image", International Journal of Advanced Research in Computer and Communication Engineering, Vol. 5, Issue 6, 2016.
12. Niloofar Hezarjaribi, Cody A, Reynolds, Drew T. Miller, Naomi Chaytor and Hassan Ghasemzadeh, "S2NI: A mobile platform for nutrition monitoring from spoken data", 38th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC), 2016, pp. 1991 – 1994.
13. Prabha Sundaravadivel, Kavya Kesavan, Lokeshwar Kesavan, Saraju P. Mohanty, Elias Kougianos and Madhavi Ganapathiraju, "Smart-log: An automated, predictive nutrition monitoring system for infants through the IoT", IEEE International Conference on Consumer Electronics (ICCE), 2018.
14. Prabha Sundaravadivel, Kavya Kesavan, Lokeshwar Kesavan, Saraju P. Mohanty and Elias Kougianos, "Smart-Log: A Deep-Learning based Automated Nutrition Monitoring System in the IoT", IEEE Transactions on Consumer Electronics, Vol. 64, Issue 3, 2018, pp. 390 – 398.
15. Vu T, Lin F, Alshurafa N and Xu W, "Wearable food intake monitoring technologies: A comprehensive review", Computers, Vol. 6, Issue 1, 2017.

AUTHORS PROFILE

P. Kamakshi Priyaa is pursuing her M.Phil. in Computer Science at St .Joseph's College (Autonomous), Tiruchirappalli, Tamil Nadu, India. Her research area is IoT Data Analytics.

S. Sathyapriya is doing her Ph.D. in Computer Science at St. Joseph's College (Autonomous), Tiruchirappalli, Tamil Nadu, India. Her research area is IoT Data Analytics.

Dr. L. Arockiam is working as an Associate Professor in the Department of Computer Science, St. Joseph's College (Autonomous), Tiruchirappalli, Tamil Nadu, India. His research interests are: Software Measurement, Cognitive Aspects in Programming, Data Mining, Mobile Networks, IoT and Cloud Computing.