

Research Article

Food Nutrition Detection System using Deep Learning and Fuzzy Logic

Garima Koushik and Prof. Dr. K. Rajeswari

Department of Computer Engineering Pimpri Chinchwad College of Engineering Pune, India

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Abstract

Food is one of the most essential requirements for the survival of any living being on this earth. Nutrients present in the food provide chemical energy required for the proper functioning of various organs and for performing various physical activities which in turn keeps the body fit and active. To achieve this, proper intake of fresh, pure, nutrient-enriched and standard quality food is very essential. Poor quality food not only impacts the health and wellbeing of the person but also increased the risk of chronic diseases such as obesity, diabetes, heart failure, etc. Proper monitoring of food intake is one of the most effective ways of keeping track of the dietary habit of an individual. Existing methods especially sensor-based are however able to detect the nutritional value of the food but those systems are quite difficult to use in day to day life. In this paper, we are developing and designing an efficient food nutrition detection system that is built using deep learning and fuzzy logic. An android application will be designed as a user interface for displaying the results to the user. The proposed system gives an advantage of the least user efforts over the other report based/questionnaire system where the user is required to manually give input about their food intake habits regularly.

Keywords: Deep Learning, Fuzzy Logic, Food Nutrition Detection System.

Introduction

In the past few decades, there has been a sudden increase in the health consciousness of the urban community. To maintain a healthy life, proper intake of energy and nutrient is very essential which comes from healthy eating habits only. Healthy eating not only maintains the lifestyle quality but also prevents chronic diseases like diabetes, high blood pressure, mental illness, asthma and so on. Obesity is one of the most common diseases caused by overeating. In obesity, excess body fat is accumulated to the extent that it harms the health of a person [1]. A person with a body mass index higher than 30kg/m² is considered to be obese. Similarly, disturbance in eating habits or weight control behavior of an individual is an eating disorder which is a very serious mental disorder[3]. Eating disorders like Anorexia nervosa, bulimia nervosa, binge eating are the most common eating disorder in the United States with lifetime prevalence ranging from 0.6 % to 4.5% [4]. In anorexia nervosa, individuals limited their food intake due to the fear of gaining weight. People suffering from bulimia nervosa increase their food intake which leads to the feeling of guilt that results in different ways to compensate food intake. Binge eating is similar to bulimia nervosa, but it does not include external compensatory reactions as bulimia.

According to the Institute for health and evaluation (IHME), dietary risks were the major cause of disease in Australia and it results in various health-related problems. For the early cognitive development in children and young people, the adoption of healthy dietary intake has also been proved to be beneficial [2]. Food provides the chemical energy needed for the proper functioning of vital organs and performing various physical activities where excessive energy is stored in glycogen and is utilized for future use. A proper diet can only come from nutrient-rich food. Nutrient-rich food is the requirement for the proper functioning of the body. It provides the most nutrients for fewer calories. These foods have less amount of sugars, sodium, and bad fats which nourish our body by providing a lot of vitamins, minerals thus reduce the risk of chronic diseases.

Due to the increasing rise in various health-related problems, people are forced to record and analyze their estimated nutrient intake in their bodies. Self-monitoring of food intake is one such way to keep track of the dietary habits of an individual. It is important for identifying, understanding and correcting food intake patterns of an individual. These methods provide accurate detection and classification of food intake with minimum efforts. Wearable sensors present one of the possibilities for monitoring food intake which can capture the duration, timing, the microstructure of food, characterization of rate of ingestion and its

nutritional content [5]. But there are many challenges associated with wearable sensors. The first challenge is the various variety of food consumed by individuals. Food is composed of multiple ingredients, each having its nutritional value. Modification in one of the ingredients can change the nutritional properties of food. The second challenge is the variations in the ingestive behavior of humans. We may eat single food items or eat the number of different food items. We eat food with hands, spoon, chopsticks, or drink our food. Some eat fast while others eat slowly. Some eat during the night or some during the day. Most of us consume a meal while sitting, some while lying down or walking. So ingestive behavior is completely variable and unpredictable. Self-monitoring of food intake can also be done using paper-based, mobile-based self-reporting methods, but this is also not convenient as users have to put extra effort to reports their food intake daily basis.

This arises a strong need for designing a system that can monitor the food habits of individuals with the least user efforts. The proposed system is able to achieve this aim. The proposed system "Food Nutrition Detection System Using Deep Learning and Fuzzy Logic" requires the user to only capture the food image, the rest part is done by the system itself. The captured image is segmented, compressed and then the food

inception model for food image recognition. detection model is built to identify the food type using transfer learning with CNN. We are using Keras' pre-trained Nutrients present in the food are fetched by using Food API. After extracting the nutrient content of the food, the concept of fuzzy logic will be applied to consider the recommended dietary allowance to predict whether the given food intake is healthy or not. Fuzzy logic compares the nutrient content present in the food with the recommended dietary allowance to check if the food being intake is healthy enough or not. Before getting into the depth of the further sections, it is important to understand the basic concept of the below-mentioned terminologies.

A. Deep Learning

Deep learning can be defined as a subset of machine learning which takes the help of the artificial neural network to mimic the behavior of human thinking and learning. It learns on its own using computer algorithms. It works similarly as a biological neuron.

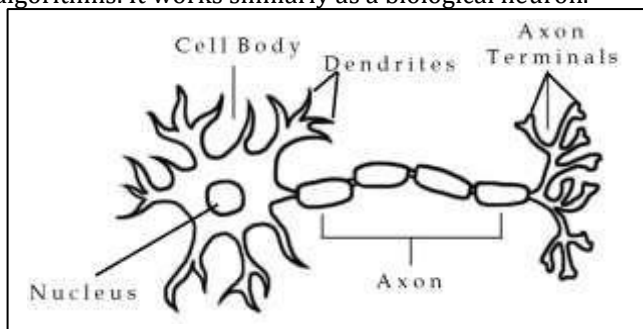


Fig.1. Structure of a biological neuron

Fig. 1. Shows the structure of a biological neuron. As can be seen from fig 1, a biological neuron have dendrites for receiving the input, the received input is summed into the cell body and then transferred to the next biological neuron using axons.

An artificial network works similarly: a neuron receives input from different sources, applies some computation, transformation, and function on this input and generates output. The computation performed on the neuron is generally an activation function.

A neural network consists of several connected neurons in the brain. Similarly, deep neural networks consist of layers. A layer is the collection of neurons which takes an input and produces the output. An activation function process the input to each of these neurons.

The deep neural network is made up of three types of layers:

- One Input Layer
- Number of Hidden Layer
- One Output Layer

The first layer of a deep neural network is the important layer for receiving all input and the last layer is called an output layer which provides the desired output.

One of the most popular and effective neural network N number of layer between the input and output layer are called the hidden layer. Depending upon the requirement of the application, the number of hidden layers and the number of neurons in each layer are decided.

B. Convolutional Neural Network

architecture is the convolutional neural network which is widely used in the computer vision domain.

The hidden layer of CNN consists of three layers:

- Convolutional layer
- Pooling layer
- Fully connected layer

Convolutional layer: This layer acts as a first layer for extracting features from the input image. In this layer, A filter is passed over an image and scans a few pixels at a time and then predicts the class of each feature by creating a feature map.

Convolution is a mathematical operation that takes two inputs: an image pixel and a filter.

For an input image ($h*w*d$) and filter (f_h*f_w*d), the generated output is $(h-f_h+1)*(w-f_w+1)*1$.

The output of convolution operation is a feature matrix, which is also called a feature map. It takes several hyperparameters like the number of filters, size of the filter, padding, activation function, strides.

Strides: The number of pixels to be move over the input matrix is called stride. For stride equal to N, the filter is moved to N pixels at a time.

Padding: It is used when the filter does not fit perfectly over the image. Padding can be applied in one of two ways:

- Pad the image with zeros so that the filter can fit properly over it. This type of padding is called zero paddings.
- Another type is valid padding where the part of the image is removed where the filter can not fit.

Activation Functions: For this work ReLU activation function is used. ReLU stands for rectified Linear unit. Its output is given in the form: $f(x) = \max(0, x)$.

In the Convolutional layer, generalized output dimension for the next layer is given as:

For an input $n \times n \times n_c$, filter $f \times f \times n_c$, padding p , and stride S , the output is given as:

$$output = \frac{(n+2p-f)}{s} + \frac{(n+2p-f)}{s} + 1 * F \tag{1}$$

Where, n_c = number of channels in input and filter,

F = number of filters

Number of channels increases as we go deeper into the network whereas the size of the image shrinks.

Pooling Layer: For reducing the size of the input and speeding up the communication, the pooling layer is used.

Pooling layers are of three types: \square max pooling

- avg pooling
- sum pooling

Max pooling picks the large pixel value from the rectified feature map. Avg pooling takes the average of all pixels from the rectified feature map. Sum pooling takes the sum of all elements in the feature map. Hyperparameters for the pooling layer are the size of the filter, stride, Max /avg pooling layer. For the input $h \times w \times c$ of pooling layer, the output will be:

$$output = \left\{ \left\{ \frac{(h-f)}{s} + 1 \right\} * \left\{ \frac{(w-f)}{s} + 1 \right\} * c \right\} \tag{2}$$

Where f is the number of filters.

Fully Connected Layer: After collecting the output from the convolution and pooling layer, the feature map matrix is flattened into a vector using a fully connected layer. This vector is then fed as an input to the next fully connected layer.

To create a model, a fully connected layer combines the feature by using an activation function such as a sigmoid function or softmax.

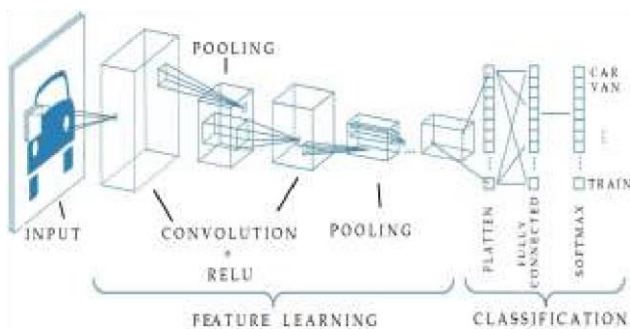


Fig.2 Convolutional Neural Network. Retrieved from <https://towardsdatascience.com/traffic-sign->

detection-usingconvolutional-neural-network-660fb32fe90e

Fig 2 shows the architecture of a convolutional neural network.

C. Fuzzy Logic

Fuzzy refers to the set of things that are not very clear. Zadeh introduced the concept of fuzzy logic in 1965. Fuzzy logic provides the solution for the logic of situations where it is difficult to determine if the given input is true or false. It uses the concept of intermediate value i.e. partially true or partially false instead of absolute true or absolute false.

Fuzzy logics are very flexible and one of the easiest to implement machine learning technique that helps in mimicking the behavior of human thinking.

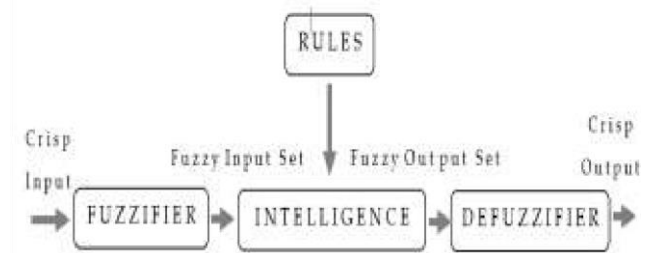


Fig.3. The architecture of the fuzzy logic system

Fig 3 shows the architecture of the fuzzy logic system which consists of four main parts:

- Rule-base: Rule base refers to the set rule and IFTHEN condition provided by an expert for controlling the decision-making system.
- Fuzzification: It is the process of converting input that is a crisp number into a fuzzy set. These crisp inputs are the output of sensors which are passed into the control system for further processing. example temperature, calorie value, pressure, etc.
- Inference engine: It determines the degree of match between fuzzy input with rules. Based on the degree of a match it makes decisions which rule needs to be implemented according to the input field.
- Defuzzification: It is the process of converting fuzzy sets into crisp value.

Literature Survey

Lifestyle quality is greatly impacted by healthy eating and it can prevent diet-related problems like diabetes, obesity, and heart-related problems, etc. The capability of managing food and nutrition is very important for a healthy and productive society. The nutrient content of the food is not the only important thing to consider, the quality of food is also very important. Much research work has been done in the area of dietary intake of an individual.

Liang et al. [1] proposed a “Calorie estimation method” which was designed for obese patients to check their food intake per day. This method is based on computer vision technique which requires the top and side view

of food to estimate calorie from it. For the detection of food items, one yuan coin is taken as a calibration object. The Faster R-CNN algorithm is used and the contour of each food is detected using grab cut algorithm whereas the volume of food is estimated using volume estimation formulas and at last calories of each food are estimated as the output.

Bahman et al. [6] proposed a smart nutrition monitoring system based on the internet of things that collects nutrition present in the food using various types of sensors. This system uses a concept of fog computing in which data collection points can do preprocessing and analytics before sending data to the cloud. Various sensors including camera (to generate 3D images for food volume estimation) are used to build system prototype. This system consists of a kiosk where sensors are installed to collect weight, volume, and structure of the food.

Edward et al. [7] presented a system that can detect a period of food intake by monitoring chewing using sensors, signal processing, and pattern recognition methodologies. The system uses a piezoelectric strain gauge sensor to capture movements of the lower jaw, these signals are then segmented and the most relevant feature was selected using forward feature selection. To create a food intake detection model, the SVM classifier is used which gives an accuracy of 80.98% using 20 fold cross-validation.

Podutwas et al. [8] proposed a system named "food portion recognition system" which measures the calorie and nutrition values by taking the picture of food and then detect and classify the food portion using SVM. Segmentation and food portion recognition are done using skull stripping and classification using SVM to calculate calorie and energy.

Wirsam et al. [9] in their article demonstrated how nutrient intake can be evaluated using fuzzy decision making. It also examines if fuzzy decision making can simplify nutrition education by making a small individual improvement in food selection. The recommended systems were presented using fuzzy sets. It helps in evaluating the intake of nutrient intake using an objective fuzzy value. The paper also shows how fuzzy logic can be used with fuzzy decision making for the optimization of the meals based upon individual food preference. This will help in nutritional counseling to improve nutrition intake by making a small change in food selection behaviour.

Chiun et al. [10] presented a 'personal diet and calorie intake monitoring system' that can be used in a smartphone. The system is built upon the concept of a fuzzy inference system that uses the QR code for saving the information about the nutrients. It then calculates the total nutritional intake from the individual session. Then it checks if the nutrition intake exceeds the daily recommended allowance. The system took advantage of G-sensors available on most smartphones to calculate the calorie burned during exercise. The fuzzy inference system then calculates the number of

calories burned. The system achieves 90% accuracy in terms of the calculation for calorie burn.

Hebden et al. [11] developed four smartphone applications which aids in modifying key lifestyle behavior of an individual associated with increasing body weight. This includes fast food consumption, vegetables, fruits, sugarsweetened drinks and physical activity. The development process of applications include 4 phases:

- Making decision on the behavior change strategies, data collection, and relevant guidelines.
- Selection of platform
- Deciding user interface, database architecture, and programming language.
- Prototype testing

The apps were developed in 18 months, involving the marketing, nutrition, physical activity and information technology field.

Fallaize et al. [12] created online Food4Me food frequency questionnaire (FFQ) which collects nutrient intake data. The validity and reproducibility of FFQ was accessed against 4-day weighed food record (WFR) using test-retest methodology.

Fontana et al. [13] focused on detection and characterization of food intake using wearable sensors. The paper explains the different types of wearable sensors which helps in monitoring food intake behavior. This includes two types of devices which includes wearable sensors: handheld devices and body-attached sensors. Second part of paper describes various signal processing and pattern-recognition algorithms for the automatic detection of food intake. These algorithms are: food intake detection using chewing and swallowing, hand gesture detection, and food intake detection from imagery.

Priyono et al. [15] developed a system which uses the concept of fuzzy logic for the recommendation nutritional need of a body. TSK inference model was used in this paper for the assessment of daily calorie needs and T sukamoto model for the assessment of calorie present in the food when the current/ existing calorie information is inconsistent.

All the existing sensor (including biosensor) based, selfreporting based food nutrients detection systems designed and proposed till date do have certain limitations such as selfreporting of dietary habits manually on papers, mobile phone, etc which is quite frustrating as user may find it difficult to manage on daily basis in the busy life, wearable sensor-based systems do also have certain challenges like various variety of food consumed by individuals. Food is composed of many multiple ingredients, each having its nutritional value. Modification is one of the ingredients that can change the nutritional properties of food. The second challenge is the variations in the ingestive behavior of humans. We may eat a single food item or eat several different food items. We eat food with hands, spoon, chopsticks, or drink our food. some

eat fast while others eat slowly. Some eat during the night or some during the day. Most of us consume a meal while sitting, some while lying down or walking. So, ingestive behavior is completely variable and predictable. Such challenges create a need for a smart way of monitoring food habits and nutrient intake in the body.

The proposed system in this paper proposes a low cost, or we can say almost free of cost to the user, easily extensible, easy to use, highly accurate system with the least user efforts.

Proposed Methodology

A. System Architecture

The objective of this work is to not only identify the food present in the plate but also extract the nutrient content present in the food. The system also helps a user in regulating their dietary intake in case the particular nutrient intake exceeds the recommended dietary allowance, then the system will warn the user.



Fig.4. Workflow of the proposed system

Fig. 4 displays the workflow of the proposed system. The system consists of 5 different phases interconnected with each other. These phases are:

Phase 1: Collection of food image

Phase 2: Identification of food item

Phase 3: Detecting nutrients present in the food using Food API

Phase 4: Applying the fuzzy logic concept

Phase 5: Displaying result in an android application

The first step is an image data acquisition step. Image acquisition is the process of acquiring data from various sources to train a machine/deep learning model and learn from experience. In this work, we have used the ETHZ Food-101 dataset. Mislabelled images from the dataset have been removed which are not food. Training CNN on a large dataset can result in more skillful models, and image augmentation is one such technique that can be used to create variations in the image resulting in the improved ability of the fit models to generalize what they have learned to new images. Image data augmentation artificially increases the size of training data by creating a modified version

of images. The Keras deep learning neural network library provides the capability to fit models using image data augmentation via the ImageDataGenerator class. After performing the image augmentation, the machine learning model is built/ loaded using Keras. In this work pretrained GoogLeNet/Inception model has been used. Once the food category/ food type is identified by the model, this image is passed as an input to the food nutrition API which in turn extracts the nutrition content present in the food and passes this information to the fuzzy logic system. The fuzzy logic system checks the nutritional information with the recommended dietary allowance. If the nutrient content of a particular nutrient let's say calorie exceed the recommended dietary allowance, then the user will get the warning message in his/her mobile application to cut off the nutrition intake otherwise nutrition value of the food will be displayed to the user in an android application designed for this purpose.

B. Limitations of Other/ Traditional Deep Neural Network

There exist certain limitations in traditional network architecture-

- As we go deeper and deeper in the plain network, training error first decreases as we train deeper network and then start increasing rapidly.
- The deeper the network, the more chances of over-fitting (It can be noticed clearly when training data is small).
- The number of increase in parameter results in increasing computational resources and cost.
- It requires a very large amount of data to train CNN. Researchers do not always have enough datasets for domain-specific problems.
- Training of convolutional neural networks requires a week to month-long training time.

C. Inception Network

After considering sub-section B, it is important to design a model that can overcome the limitations of existing models. One way is to create a sparsely connected network i.e. increase in the layer of networks as well as the number of units at each layer. The proposed system is built using transfer learning. Transfer learning is one of the most popular methods in image processing. Transfer learning uses the pattern-based approach for learning instead of starting the learning from scratch. In the pattern-based approach, the patterns have been learned while solving a different problem. Using transfer learning an accurate model can be built in a time-consuming manner. The pre-trained model is used to express transfer learning in computer vision problems. These are the models that have been trained on a large benchmark data set. Using such models we applied the knowledge of the existing machine learning model to a new task.

This work is using Keras' pre-trained model named Inception model which is also known as GoogLeNet.

The inception model was the winner of the ILSVRC(ImageNet Large Scale Visual Recognition Competition) 2014 with a top 5 error rate of 6.7 % [10]. This model was developed by researchers at Google. Earlier models like AlexNet, VGC, etc have a simple stack module of convolution and max pooling. Generally while designing a convolutional neural network type of filter to be chosen is decided which is completely application-specific. This model contains a stack of 24 convolutions and a new module called Inception module. The module consists of parallel computation of convolution of different sizes (1*1 convolution layer, 3*3 convolutional layer, 5*5 convolutional layer) and max-pooling in the Inception layer. The output of these layers is connected into a single output vector which is considered as input to the next layer.

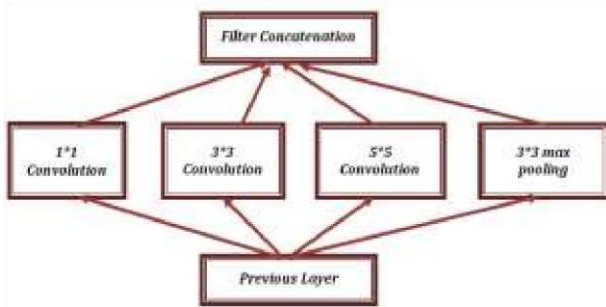


Fig.5. Inception module with naïve version
 Fig. 5 displays the naïve version of the inception module. The module consists of parallel computation of convolution of different sizes (1*1 convolution layer, 3*3 convolutional layer, 5*5 convolutional layer) and max-pooling in the Inception layer. The output of these layers is combined into a single output vector which acts as an input to the next player.

But given naïve version have few limitations: use of large size convolutions such as 5*5 increase the computational cost of a network and also increases the chances of over-fitting. Thus to reduce the computational cost 1*1 convolution is applied before large convolutions such as 3*3 and 5*5.

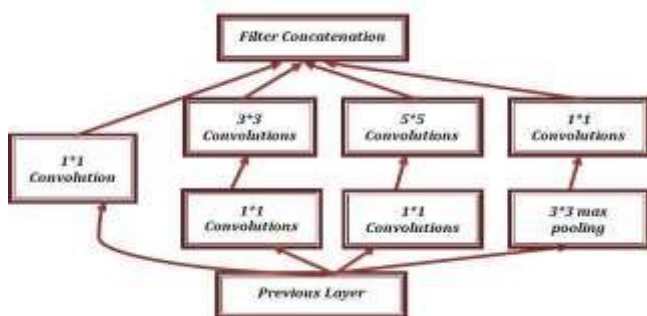


Fig.6. Inception module after adding 1*1 convolutions and max-pooling
 Fig.6 shows the advance version of the inception module with an additional layer of 1*1 convolutions and max-pooling layer.

D. Truswell Diagram

In literature, various work has been done in detecting nutrient content present in the food using fuzzy logic. In [9] a diagram has been presented by Truswell. This diagram shows the degree of health due to the variation in the intake of one nutrient while keeping the rest of the diet constant at the optimum level. Diagram consists of four different areas- an area of low intake, deficiency disease area, marginal and large optimal range area.

The low intake area is a very dangerous area (may lead to the death), recommended dietary intake/reference nutrient intake is presented at the top of the left-hand slope. The marginal area is the area of high intake, at the end again is a very dangerous area.

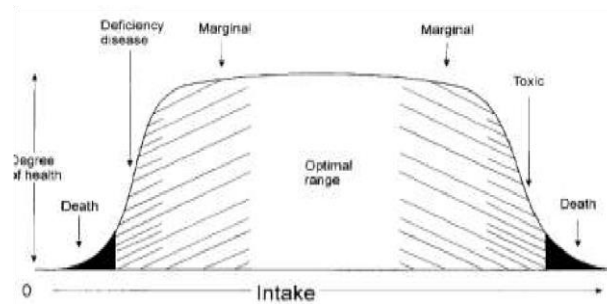


Fig.7. Degree of health when varying the intake of one nutrient and keeping the rest constant.

Truswell's diagram can also be interpreted as the 'optimal intake' curve that defines the fuzzy set.

In the case of a fuzzy set, optimal intake is given by $\mu(x_i)$ which is called a membership function. The membership function is a graph that shows how each input is mapped to membership value between 0 and 1. Input space is called the universe of discourse/universal set (u). 0 represent the death that is the worst status, 1 represent the absolute optimum value between 0 and 1 can be described using linguistic variables.

Five points have been considered for the construction of fuzzy sets:

The fuzzy value for zero intakes. This value is 0 for essential nutrients. The fuzzy value lies between 0 and 1, for semiessential nutrients like alcohol, cholesterol, sucrose. Optimal status reached for no intake. The fuzzy value is 1. Fuzzy value of 0.9 is the safe minimum limit. It is shown as a vertical line in the fuzzy set diagram (Fig. 7).

- Fuzzy value of 1 corresponds to the optimal intake.
- Fuzzy value of 0.9 corresponds to the safe upper limit. It is shown as a vertical line in the fuzzy set diagram.
- The toxic perilous area corresponds to the 0 fuzzy value.

All these points were plotted point to point by parabolas to get smooth curves.

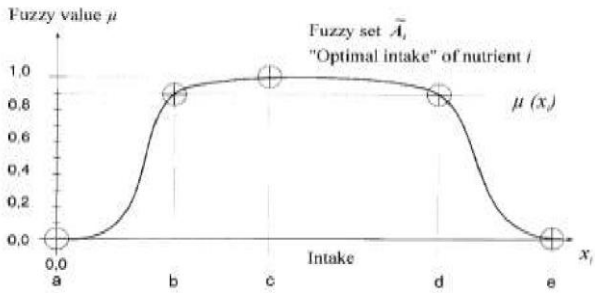


Fig.8. Fuzzy set 'optimal intake' of nutrients

After extracting the nutrient content from the food, Fuzzy logic takes this nutrient value as an input and then based on the recommended dietary allowance it will show the user recommendation whether the food is healthy or not.

E. Dataset

For this work, the inception model is trained using the ETHZ Food-101 dataset. The dataset consists of 101 different food categories. Each food category has 1000 food images resulting in a total of 101,000 images with the size of each image as 512 pixels. The dataset is already divided into train and test data consisting of 750 and 250 images respectively and contains some amount of noise usually in the form of intense colors, wrong labels.

Implementation Till Date And Performance Matrix

Phase 1 and 2 have been implemented in project dissertation-I. Phase 1 corresponds to data acquisition. Image data used for this purpose is ETHZ Food-101. Image augmentation has been applied to the data to increase its size to increase the accuracy of the model while performing the classification. In phase 2 the image data is used for training Keras' pre-trained inception model. Once trained, the model was used directly for getting a list of probabilities that an image belonging to a class. We have tried to visualize the history of training and validation data using the graphs and evaluated the accuracy and loss score on validation data.

For the assessment of the performance of the food detection model. Two performance measures have been taken into consideration: confusion matrix and classification report.

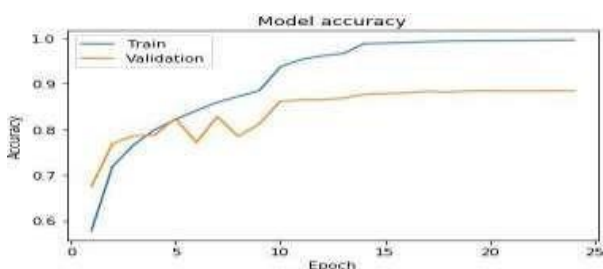


Fig. 9. Model accuracy history for training and validation data

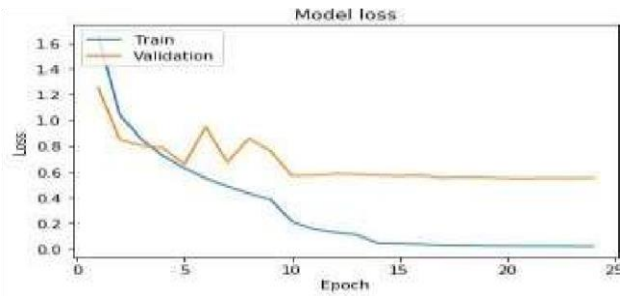


Fig. 10. Model loss history for training and validation data

We have used the line graph for the visualization model accuracy and loss history or training and validation data as can be seen in Fig.8 and Fig. 9. After training the model on a given dataset, loss and accuracy achieved on validation data were equals to 54.74 %, 88.36%. For the assessment of the performance of the model. Two performance measures have been taken into consideration: confusion matrix and classification report.

Confusion Matrix: Confusion matrix is one of the most widely used performance measure measurements for most of the classification algorithms. The confusion matrix gives a summary of the predicted result for a given classification problem. The confusion matrix tells the way in which the classifier made a mistake while making the prediction of data. It can be understood in terms of true positive, true negative, false positive, false negative.

True Positive: These are the correctly predicted positive values by machine learning classifiers. It can be understood as the actual values are true and classifier predicted them as true.

True Negative: These are the correctly predicted negative values by classifier means actual values are false and classifier predicted them as false values.

False Positive: These are the actual negative values that are predicted as true by the classifier.

False Negative: These are the actual positive values that are predicted as false by the classifier.

Classification Report: Classification report is another measure of the quality of prediction of the model. It tells the number of predictions that are true and false. Classification report metric is predicted using the true positive, true negative, false positive and false negative. And it measures the score of precision, recall, f1 score and support.

Precision: It can be defined as the ratio of correctly predicted positive outcomes to the total predicted positive observations. It is the ability of a model not to label a sample as 'positive' which is actually 'negative'.

$$precision = \frac{TP}{TP+FP} \tag{3}$$

Equation 3 gives the formula for calculating the precision for given true positive (TP), and false positive (FP) values which are calculated using a confusion matrix.

Recall: Recall is also known as sensitivity. It is the ratio of correctly predicted positive observation of all observations in actual class 'true'. It is the ability of a classifier to find all positive samples.

$$\text{recall} = \frac{TP}{TP+FN} \quad (4)$$

Equation 4 gives the formula for calculating the recall for given true positive (TP), and false negative (FN) values which are calculated using a confusion matrix.

F1-Score: It is the harmonic mean of precision and recall. It is good to measure for imbalanced data.

$$\text{F1 score} = \frac{2 * \text{precision} * \text{recall}}{\text{precision} + \text{recall}} \quad (5)$$

Equation 5 gives the formula for calculation of F1-score for given precision and recall.

Support: Support is used to tell the number of samples of true response lies in each class of target value.

Results And Discussion

As discussed in section IV, phase 1 and 2 of the project has been implemented till date i.e. image data acquisition and image identification. The performance of the model is assessed using the confusion matrix and classification report. Below fig 11 and 12 show the snap of a confusion matrix and classification report of the model.

Confusion Matrix

```

[[ 179  0  10 ...  1  0  2]
 [  0 216  0 ...  0  0  0]
 [  5  0 235 ...  0  0  0]
 ...
 [  2  0  2 ... 212  0  0]
 [  0  0  0 ...  0 202  0]
 [  1  0  0 ...  1  0 232]]

```

Fig. 11. A snap of a confusion matrix of the model

Classification Report

| | precision | recall | f1-score | support |
|-------------------|-----------|--------|----------|---------|
| apple_pie | 0.77 | 0.72 | 0.74 | 250 |
| baby_back_ribs | 0.86 | 0.86 | 0.86 | 250 |
| baklava | 0.90 | 0.94 | 0.92 | 250 |
| beef_carpaccio | 0.95 | 0.93 | 0.94 | 250 |
| beef_tartare | 0.89 | 0.82 | 0.85 | 250 |
| beet_salad | 0.81 | 0.82 | 0.82 | 249 |
| beignets | 0.89 | 0.90 | 0.89 | 249 |
| bibimbap | 0.98 | 0.93 | 0.96 | 250 |
| bread_pudding | 0.79 | 0.75 | 0.77 | 250 |
| breakfast_burrito | 0.87 | 0.82 | 0.84 | 249 |
| bruschetta | 0.86 | 0.84 | 0.85 | 250 |
| caesar_salad | 0.90 | 0.95 | 0.92 | 250 |
| cannoli | 0.97 | 0.92 | 0.94 | 249 |
| caprese_salad | 0.86 | 0.92 | 0.89 | 249 |
| carrot_cake | 0.86 | 0.85 | 0.85 | 248 |
| ceviche | 0.80 | 0.81 | 0.80 | 250 |

Fig. 12. A snap of a of a classification report of the model

Conclusion

This project work proposes a methodology for automatic food nutrition detection system which is capable of identifying the content of nutrients present in the food. To date, the system is able to classify the food into one of the hundreds of categories mentioned in the dataset. The classification has been performed

on the well-known benchmark food dataset namely 'ETHZ Food 101'. Keras's pre-trained inception module has been used for performing the classification. Future works include the detection of the nutrition value of the food using nutrition API. The results of the food detection model will be passed to the nutrition API in order to extract the nutritional value of the food. In order to give users the convenience of proper monitoring of nutritional intake and allows them to control their intake, concepts of fuzzy logic will be applied. Fuzzy logic checks the nutrient value of the food and then compares this value with the recommended dietary allowance and warn the user in case the nutritional intake of particular content for eg. a calorie is exceeding the recommended dietary allowance. The system will also develop an android application for displaying the nutrition value of the food to the user on their mobile application. The system will be designed by considering the minimal user efforts and providing them a better experience of self-monitoring of their food intake behavior.

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