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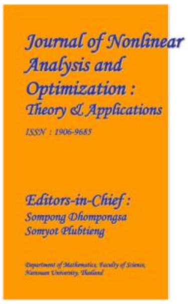

CALORIE ESTIMATION OF FOOD AND BEVERAGES THROUGH DEEP LEARNING

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ABSTRACT:
The worldwide prevalence of diabetes is rising. The challenge of accurately accessing their nutrients has slowed the development of this technology. Chronic diabetes causes high blood glucose levels. Three diabetes types have been identified by experts. Diabetics have frequent urination, thirst, hunger, weight fluctuations, unhealed wounds and bruises, sexual dysfunction, and hand, leg, and foot numbness/tingling. Early identification and treatment of at-risk individuals may prevent 70%–80% of Type 2 diabetes complications, according to recent studies. Various data mining and machine learning methods have been presented for diabetes diagnosis and management. This research offers meal suggestions. This method classifies food by size, shape, colour, and texture. The food image-based approach measures calorie content using a nutritional information table. Characteristics are extracted using three methods. SVMs have been effective in this field, and this study suggests that utilising them as a "second opinion" improves diagnostics. The severity of the sickness must be predicted and food suggestions made.

Diabetes is diagnosed by identifying at-risk individuals for Type 2 Diabetes Mellitus. The recommended system contains User Interface, Image Database Manager, Diabetic Analyser, Food Recommender, Agent Subsystem, Decision Manager, and Fuzzy Rule Manager modules. This project used food, diabetes, and picture databases. Decision managers supervise this proposed system's complete procedure. The decision manager uses rule base rules for food analysis, illness prediction, and recommendations. Multiclass SVM classifies food images after feature extraction. Calculating calories requires sample area and volume. Multiclass SVM approaches are compared to food samples using binary SVM.

Key words: Support Vector Machines (SVMs), Type 2 diabetes, Decision Manager.

1. INTRODUCTION

Given twice day by injection. Youth are more likely to have this diabetes. Primary drivers of illness initiation and progression include autoimmune, genetic, and environmental factors. Another term for T2DM is non-insulin-dependent diabetes. The body cannot use its insulin effectively, causing this disease. It usually affects those over 30. This variation affects 90-95% of diabetics. Overweight and elderly people with a family history of diabetes are more likely to develop this condition. About 30–80% of T2DM patients are undiagnosed. Gestational diabetes usually goes away after pregnancy. Women with gestational diabetes are more likely to acquire type 2 diabetes later in life. Diabetes affects 8.3% of adults worldwide, rising from 366 million in 2011 to 552 million by 2030. Prevention or delay of diabetes needs intervention [1].

A food image system that effectively documents daily meals is in great demand due to the increased interest in food-related health care. Multiple studies have shown that eating a healthy diet with enough calories reduces the risk of several diseases. Dietary intake monitoring tracks a person's daily food intake and calories. Methodically monitoring and assessing an individual's nutritional intake is required. Food consumption details are difficult to provide. Dietitians must undertake complex lab tests to assess dietary intake [2]. Quantifying daily calorie intake is a major healthcare research area. This thesis presents revolutionary food type diagnosis, diabetes prediction, and diabetes diet recommendations. These approaches will help diabetics control their condition and eat well. Since the calorie chart is a guide, this research focusses on effective food classification and calorie counting methods. It focusses on diabetes prediction. Food suggestions were based on expected diabetes and calorie needs.

This research's three main goals are to use intelligent algorithms to detect diabetes illness and prescribe foods with enough calories to reduce its severity. Intelligent methods for detecting food kinds and determining calories are also suggested. This study uses data mining algorithms to propose meals using relevant decision-making principles [3].

Medical data mining analyses medical data and its applications for human use to determine how it changes over time and across people. This information is used to create unique designs to forecast patient health and prescribe medical treatment [4].

Mining and working with human medical data is the hardest. The text discusses medical data heterogeneity, ethical and social issues, statistical philosophy, and medicine's particular position. Diagnostic and severity representation of sickness are increasingly dependent on medical data analysis. Analysis of knowledge representation model data is also useful. [5] proposed a feature extraction model for decision support system prediction.

1.1. Methods of identification

Classification is the most used data mining method in healthcare. It incorporates instance categorisation. The procedure has two phases.

A model is built using training data and instances belonging to a predetermined class. The model produces a tree structure, rules, or mathematical equations.

Model application: Based on the model, new instances are categorised. Classification divides data samples into target groups and predicts data point classes [6]. A classification technique will identify diabetes risk variables by assessing illness trends. This approach uses predetermined class groups and supervised learning.

Target classes might be binary or multiclass. Multilevel classification categorises data into more than two class labels, whereas binary classification categorises data into two classes. The bulk of illness diagnostic research trains data samples using categorisation methods. Decision trees and neural networks are common classification methods. Classification tree algorithms excel in classification and prediction tasks in data mining. A classification tree labels and classifies records. Additionally, it provides a confidence measure to verify categorisation correctness. Classification trees are built using binary recursive partitioning. This method partitions data iteratively and then on each branch [7].

1.2. Artificial Neural Network Classifier

ANNs are great for training large datasets with minimal inputs. Neural networks can handle incomplete, missing, and noisy data, making them useful for extracting meaningful information from large clinical datasets. They are useful for data mining since they can be updated with new data without system changes. Therefore, they are ideal for dynamic clinical datasets. Artificial neural networks help create statistical models and replace regression methods. Medical data mining has generally employed regression models to build predictive models. Neural networks implicitly recognise complicated nonlinear relationships between variables and need less training than statistical models. Multiple training strategies are beneficial. For several reasons, ANN is employed in medical diagnosis and image interpretation.

1.3. A Fuzzy Cognitive Map

A mathematical model that captures changing linkages and interactions to depict and understand complex systems. [9] presented neural network-based Fuzzy Cognitive Maps for causal reasoning and representation. Mathematical variables are typically numbered. Fuzzy logic applications use non-numeric variables to describe rules and facts. First-order logic is impracticable for ambiguity situations, hence fuzzy logic is utilised. Fuzziness and randomness are terms for events that lack clarity or accuracy.

Fuzzy sets represent uncertain notions using language factors, not quantitative data. Modelling complicated systems requires new methods that use existing knowledge and human experience. A fuzzy neural network, or neuro-fuzzy system, teaches computers to uncover complex rules and identify sets in a challenging way. It moves this using neural networks.

2. LITERATURE REVIEW

The 24-Hour Dietary Recall (24 HR) method records food consumption for 24 hours in a specified way [10]. Gender, age, education, and obesity might delay food consumption history reporting. Food models with visuals failed to report large portions. Several research have established a regular meal intake schedule to combat obesity.

However, several researches focused on calorie detection from food photos and data preservation for future reference. Two studies recommend taking images of food before and after eating it to identify and categorise it [20].

According to [11], the techniques for converting meal servings into pixels use a predetermined picture value measurement. All of these situations are difficult. A device that collects photos and transmits them for 30 computations or analysis to quantify meal calories has been proposed. This system extracts and analyses food. Due to its offline nature, results may take longer.

Dietary recommendation systems and image processing have been extensively studied [12]. A technique was presented to record SVM classifier-fed food items and compute calories and nutritional value. Systems use calibration cards to set value benchmarks. This card is put near the lunch plate to calculate its calorie content. Dependence on the card and inability to calculate food picture nutritional values are major constraints. A solution using a Light Emitting Diode (LED) parallel to the optical axis and a predetermined distance from the camera was presented [13]. Analysing the projected image's distortion and calculating the distance from the oblique angle to the object plane may reveal the highlight pattern. The algorithm only works effectively for estimating flat or almost flat meals and known forms, which is its biggest drawback.

The picture value is calculated by examining the pattern, focussing on the centre. [14] utilised contour method image segmentation and SVM classifier food identification. This device uses a tray for calibration before taking a shot. Patients may use a PDA to save and retrieve their regular meal nutritional information. The system takes longer to load and retrieve data. This technique lacks support vector machine categorisation, a key drawback. The feature extraction process only considered a few characteristics, and determining calorie value needs a tray technique that is not possible.

3. PROPOSED METHOD

A multi-class Support Vector Machine classifier is used to automate food recognition in this work. Food is classified by size, shape, colour, and texture. Previous studies only examined individual foods, while recent study covers combinations. The Region of Interest (ROI) method identifies mixed foods. This categorisation method uses four critical criteria for high accuracy.

The system reads food photos and calculates calories using a nutritional table. Characteristics are extracted using three ways. The Scale Invariant Feature Transformation approach extracts picture shapes. (2) Gabor method: texture feature retrieval. Image colour attributes are extracted using the colour histogram. Food picture classification uses a multiclass SVM after feature extraction. By measuring food's area and volume, calories may be calculated. Multiclass SVM methods like "one-against-one" and "one-against-all." are tested using binary SVM and food samples. The findings show that the techniques improve class size.

Research shows that Support Vector Machine classifiers outperform other classification methods in recognition rates. The Support Vector Machine (SVM) was designed for binary decision-making problems. It is difficult to apply it to multiclass issues. Applying it to a multiclass situation remains a difficult research topic. However, Support Vector Machines (SVMs) may solve multiclass problems by dividing them into many two-class problems.

Diabetes prevalence is rising worldwide. The challenge of accurately retrieving their nourishment has slowed this technology's progress. Diabetes causes high blood glucose levels and is a chronic disease. have classified diabetics into three groups. Most children have type 1 diabetes, which is not inherited. The body doesn't produce enough insulin in this disease. About 10% are Type 1 diabetes. In Type 2 Diabetes, insulin synthesis is inadequate, impairing function. These folks comprise 90% of diabetics globally. Gestational Diabetes only affects pregnant women. Frequent urination, intense hunger, weight increase or loss, unhealed wounds and bruises, sexual dysfunction, and hand, leg, and foot numbness/tingling are diabetes symptoms.

A. Classification of Diabetes

Type 1 diabetes is caused by insulin deficiency.

Insulin production is low. Type 1 diabetes develops before 40, often in adolescence or early adulthood. These comprise 10% of diabetes cases. Regular blood tests and nutrition help manage insulin levels. Type 2 diabetes causes high blood sugar.

Up to 90% of diabetes patients globally have this kind. This condition may be managed by monitoring blood sugar levels, eating appropriately, and exercising as required. Type 1 Diabetes is hereditary and progressive, requiring insulin pills or injections for severe cases and declining health. Weighty people are more likely to develop Type 2 diabetes than lean people. Gestational diabetes arises throughout pregnancy. Women during pregnancy are affected by this illness. Some pregnant women have high blood glucose. You may not create enough insulin to transfer glucose into cells, raising blood glucose levels gradually. Multiple tests are done throughout pregnancy to detect gestational diabetes. Most gestational diabetes patients may control their disease with a healthy diet and frequent exercise. Drugs to regulate blood glucose are needed by 10% to 30% of patients.

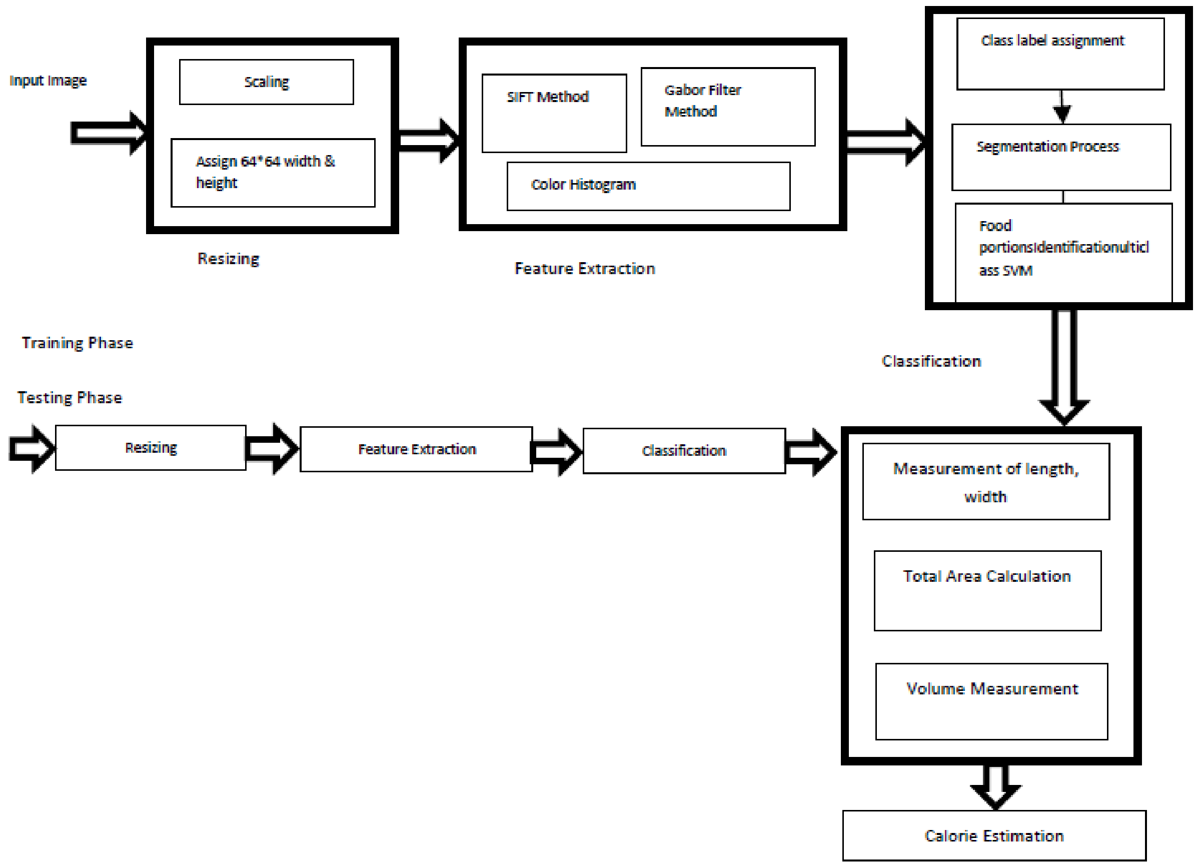


Figure 1. Proposed Model

B. Technical specifications and operational procedures

1. Altering the size:

The supplied food image is given through to the resizing stage first. This module adjusts the size of a picture according to its width and height. The image is resized to a dimension of 64 pixels. Next, photos are rescaled to 64*64 pixels to measure the size of food photographs.

2. Extraction of Features:

This module utilizes three techniques, namely SIFT, Gabor filter, and Color histogram approach, to extract various information from the provided image. The SIFT method, also known as Scale Invariant Feature Transform, is a technique used for achieving scale invariance. Characteristic The local features of an image can be found and described using the transform algorithm. The resized image is provided to the feature extraction module as input. This phase captures critical points and feature vectors from a dense grid on the image. The SIFT technique is utilised to extract important points and feature vectors. The algorithm comprises four distinct processes.

4. PERFROMANCE ANALYSIS

The datasets being used from the http://data.vision.ee.ethz.ch/cvl/food-101.tar.gz and it performs downloading and extracting the data from the datasets as given below,

```
def get_data_extract():
  if "food-101" in os.listdir():
    print("Dataset already exists")
  else:
    print("Downloading the data...")
    !wget http://data.vision.ee.ethz.ch/cvl/food-101.tar.gz
    print("Dataset downloaded!")
    print("Extracting data..")
    !tar xzvf food-101.tar.gz
    print("Extraction done!")
```

```
['macarons',
 'french_toast',
 'lobster_bisque',
 'prime_rib',
 'pork_chop',
 'guacamole',
 'baby_back_ribs',
 'mussels',
 'beef_carpaccio',
 'poutine',
 'hot_and_sour_soup',
 'seaweed_salad',
 'foie_gras',
 'dumplings',
 'peking_duck',
 'takoyaki',
```

Then the datasets are trained based on the Meta class in the form of txt.

```
 apple_pie
 baby_back_ribs
 baklava
 beef_carpaccio
 beef_tartare
 beet_salad
 beignets
 bibimbap
 bread_pudding
 breakfast_burrito
```

Visualize random image from each of the 101 classes

Rows = 17

Col = 6

Showing one random image from each class and helped me fix the suptitle overlapping with axes issue and returns the list of all files present in each food category. Picks one food item from the list as choice, takes a list and returns one random item

```
Creating train data...


Copying images into  apple_pie


Copying images into  baby_back_ribs


Copying images into  baklava


Copying images into  beef_carpaccio


Copying images into  beef_tartare


Copying images into  beet_salad
```

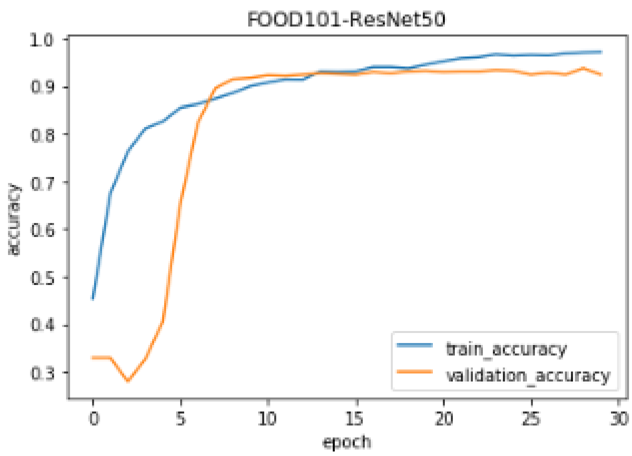
Prepare train dataset by copying images from food-101/images to food-101/train using the file train.txt and foods are sorted.

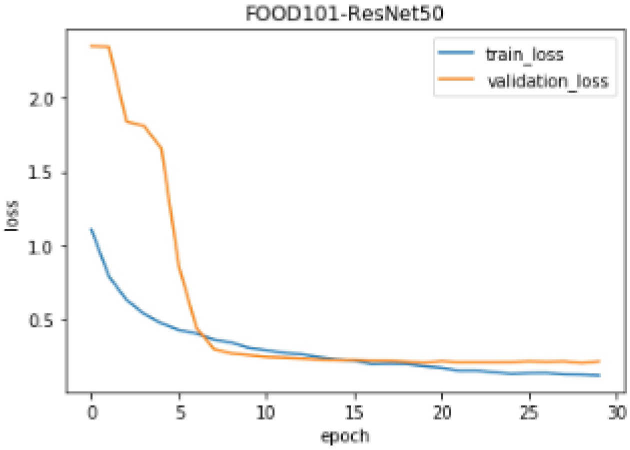
```
['apple_pie',
 'baby_back_ribs',
 'baklava',
 'beef_carpaccio',
 'beef_tartare',
 'beet_salad',
 'beignets',
 'bibimbap',
 'bread_pudding',
 'breakfast_burrito',
 'bruschetta',
 'caesar_salad',
 'cannoli',
 'caprese_salad',
 'carrot_cake',
 'ceviche',
 'cheese_plate',
 'cheesecake',
 'chicken_curry',
 'chicken_quesadilla',
```

```
Creating train data folder with new classes
Copying images into apple_pie
Copying images into pizza
Copying images into omelette
```

```
resnet50 = ResNet50(weights='imagenet', include_top=False)
x = resnet50.output
x = GlobalAveragePooling2D()(x)
x = Dense(128,activation='relu')(x)
x = Dropout(0.2)(x)

predictions = Dense(3,kernel_regularizer=regularizers.l2(0.005), activation='softmax')(x)

model = Model(inputs=resnet50.input, outputs=predictions)
model.compile(optimizer=SGD(lr=0.0001, momentum=0.9), loss='categorical_crossentropy', metrics=['accuracy'])
checkpointer = ModelCheckpoint(filepath='/kaggle/working/best_model_3class.hdf5', verbose=1, save_best_only=True)
csv_logger = CSVLogger('/kaggle/working/history_3class.log')

history = model.fit_generator(train_generator,
                    steps_per_epoch = nb_train_samples // batch_size,
                    validation_data=validation_generator,
                    validation_steps=nb_validation_samples // batch_size,
                    epochs=30,
                    verbose=1,
                    callbacks=[csv_logger, checkpointer])

model.save('/kaggle/working/model_trained_3class.hdf5')
```

```
Found 2250 images belonging to 3 classes.
Found 750 images belonging to 3 classes.

/opt/conda/lib/python3.6/site-packages/keras_applications/resnet50.py:265: UserWarning: The output shape of `ResNet50(include_top
=False)` has been changed since Keras 2.2.0.
  warnings.warn('The output shape of `ResNet50(include_top=False)` '

Downloading data from https://github.com/fchollet/deep-learning-models/releases/download/v0.2/resnet50_weights_tf_dim_ordering_tf
_kernels_notop.h5
94658560/94653016 [==============================] - 1s 0us/step
Epoch 1/30
139/140 [============================>.] - ETA: 0s - loss: 1.1083 - acc: 0.4540
Epoch 00001: val_loss improved from inf to 2.34971, saving model to /kaggle/working/best_model_3class.hdf5
140/140 [==============================] - 58s 414ms/step - loss: 1.1083 - acc: 0.4544 - val_loss: 2.3497 - val_acc: 0.3302
Epoch 2/30
139/140 [============================>.] - ETA: 0s - loss: 0.7917 - acc: 0.6757
Epoch 00002: val_loss improved from 2.34971 to 2.34536, saving model to /kaggle/working/best_model_3class.hdf5
140/140 [==============================] - 40s 283ms/step - loss: 0.7924 - acc: 0.6749 - val_loss: 2.3454 - val_acc: 0.3302
```






```python
# Make a list of downloaded images and test the trained model
images = []
images.append('applepie.jpg')
images.append('pizza.jpg')
images.append('omelette.jpg')
predict_class(model_best, images, True)
```

apple_pie

pizza

omelette

CONCLUSION

Novel picture classification and segmentation methods for every food photo. This helps create a portable software that automatically calculates meal calories for diabetics. This study measured calories in five stages. The investigations used a fresh dataset of 1200 fruit pictures from 6 dietary groups. Increased accuracy was found.

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