Comparison of Machine Learning Algorithms in Classifying Segmented Photographs of Food for Food Logging

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Obesity is increasing globally and is a major cause for concern (WHO, 2016). The main cause of obesity is a result of a high calorie/ fat diet and when the energy is not burned off through exercise, then much of the excess energy will be stored as fat around the body. Obesity is a serious threat to an individual's health as it can contribute to a range of major chronic conditions such as heart disease, diabetes, and some cancers (National Institutes of Health, 1998). Food logging is a popular dietary management method that has been used by individuals to monitor food intake. Food logging can include the use of text or images to document intake and research has shown that food intake monitoring can promote weight loss (Wing, 2001).

There has been much research in using computer vision algorithms to classify images of food for food logging. Computer vision methods can offer a convenient way for the user to document energy intake. The motivation for this work is to inform the development of an application that would allow users to use a polygonal tool to draw around the food item for classification. This work explores the efficacy classifying segmented items of food instead of entire food images.

This work explores machine learning (ML) techniques and feature extraction methods to classify 27 food categories with each category containing 100 segmented images. The image dataset used for this work comprises of 27 distinct food categories gathered from other research. (Jontou et al, 2009; Bossard et al, 2014). Non-food items contained in the images were removed to promote accurate feature selection (Figure 1).

Figure 1. Example of segmented food image.

Global and local feature types were extracted from the food image dataset; BoF with Speeded-Up-Robust-Features (SURF), BoF with colour features, and LBP (local binary pattern). SURF and colour features were extracted using bag of features (BoF) method to compute features for each image. A number of ML classifiers were used in this work; Sequential Minimal Optimisation (SMO, PolyKernel), Naïve Bayes (Multinomial), Neural Network (single layer, 100 nodes, 1000 epochs), and Random Forest (300 trees). Combinations of local and global features were used with ML algorithms.

Ten-fold cross validation was used to evaluate each experiment. Percentage accuracy was used to initially assess the performance of each ML algorithm. Matlab (vR2016a) was used to import and extract features from the image dataset and to export feature vectors as a CSV file. Weka (3.7.13) was used to import feature vectors and to apply ML algorithms on the feature sets. A series of classification experiments were completed using BoF with SURF and BoF with colour. The visual vocabulary used in each BoF model was changed (500 visual word increments) in each experiment to record changes in accuracy.

Table 1 and table 2 lists the results of these experiments. Further experiments were completed combining SURF and colour features. SURF and colour feature visual word sizes that achieved the highest accuracy in the previous experiments were concatenated e.g. feature length 500 achieved highest accuracy for neural network classification using colour features, and 500 for SURF, these were combined. Table 3 lists the combination percentage accuracy results.

Visual Words	Naïve Bayes (MN)	SMO	Neural Network	Random Forest
500	32.85*	42.15*	46.70*	43.33*
1000	32.07	41.07	45.48	42.26
1500	31.67	41.22	43.74	39.30
2000	31.67	41.78	43.11	38.96
2500	31.11	41.67	42.96	37.85
3000	30.89	40.89	41.56	37.22
3500	30.85	40.96	42.52	36.67
4000	30.63	40.52	39.78	35.93
4500	30.30	40.63	41.22	35.41
5000	29.85	41.70	42.04	35.41

Table 1. Percentage accuracy results of BoF with Colour features using 10-Fold cross validation.

Visual Words	Naïve Bayes (MN)	SMO	Neural Network	Random Forest
500	44.44	56.22	59.67*	46.11*
1000	45.19*	55.93	57.70	42.81
1500	45.04	56.07	57.00	42.07
2000	44.63	55.85	57.41	41.96
2500	44.33	57.15*	56.19	40.74
3000	44.48	55.89	55.81	40.07
3500	44.26	56.44	56.26	40.22
4000	43.37	56.74	56.44	39.81
4500	43.56	56.22	55.15	40.41
5000	42.96	55.51	55.74	39.00

Table 2. Percentage accuracy results of BoF with SURF features using 10-Fold cross validation.

Feature Combination	Naïve Bayes	SMO	Neural Network	Random Forest
BoF-SURF +BoF- Colour + LBP	50.48	68.29	71.77*	56.77

Table 3. Percentage accuracy results combing BoF colour and SURF features with LBP features.

The experiments focused on using an image dataset that was manually segmented to remove non-item foods or irrelevant food items from the images. Results show that using a Neural Network achieved the highest accuracy with 71.77% accuracy when combining BoF-SURF and BoF-colour features with LBP. Future work will include using other feature selection methods such as segmentation fractal texture analysis (SFTA) (Costa, 2012) gray level co-occurrence matrix (GLCM), and also exploring the use of other ML algorithms such as convolutional neural networks feature extraction and classification, and also multiclass classification methods (one vs one, one vs rest). Attribute selection methods will also be incorporated to select strongest features for classification. As well as using other ML algorithms, more food categories will be added to the food dataset.

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