

Personalized Dietary Self-Management using Mobile Vision-based Assistance

Georg Waltner¹, Michael Schwarz², Stefan Ladstätter², Anna Weber², Patrick Luley²,
 Meinrad Lindschinger³, Irene Schmid³, Walter Scheitz⁴, Horst Bischof¹ and Lucas Paletta²

¹ Graz University of Technology, Graz, Austria, {waltner,bischof}@icg.tugraz.at

² JOANNEUM RESEARCH Forschungsgesellschaft mbH, Graz, Austria,

{michael.schwarz,stefan.ladstaetter,anna.weber,patrick.luley,lucas.paletta}@joanneum.at

³ Institute for Nutritional and Metabolic Diseases, Schwarzl Outpatient Clinic, Lassnitzhöhe, Austria, office@lindschinger.at

⁴ FH Joanneum University for Applied Sciences, Graz, Austria, walter.scheitz@fh-joanneum.at

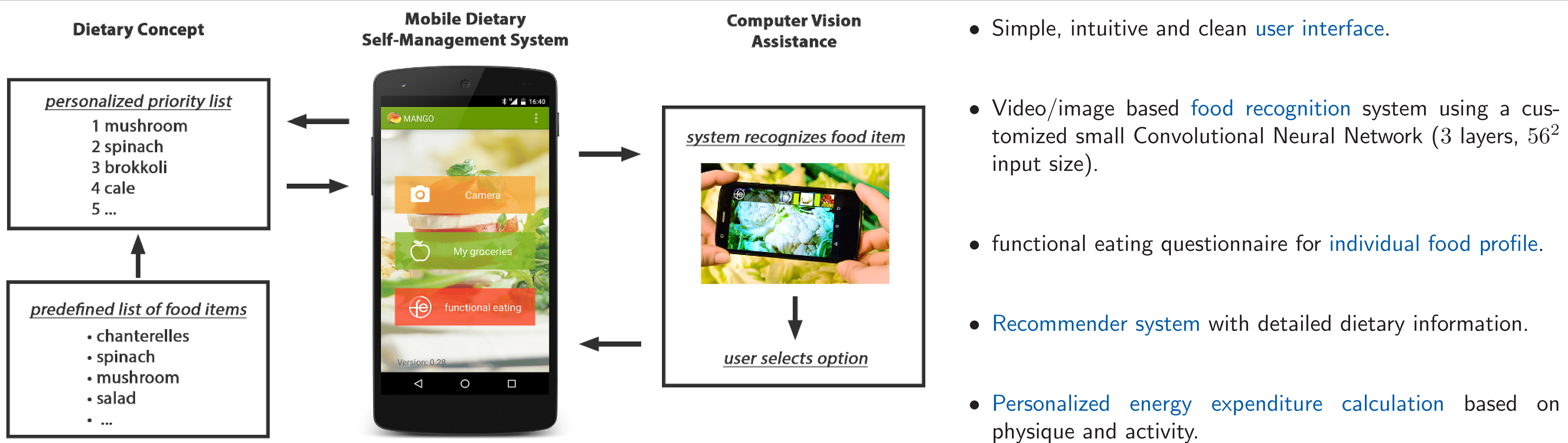
Motivation and Contribution

- Daily nutritional decisions happen in grocery stores. A big user variance exists in terms of physique and activity, resulting in a need for personalization. Sufficient mobile dietary assistance technology is not available.
- We present a mobile application as a take along personalized nutrition recommender system. The system uses image recognition for fast retrieval of detailed information from a medical supervised database. Users can provide personal detail to get customized energy expenditure information.

Requirements for Dietary Self-Management

- Dietary self-management must be ubiquitous available → mobile application
- Dietary self-management must be adapted to needs → personalization
- Dietary decision making starts in grocery stores → raw food recognition
- Dietary applications must work reliable → real-time, high accuracy, usability

System Overview



Dataset



Dataset overview: FruitVeg-81 dataset

- 15737 images, each annotated with 3 hierarchical labels
- 5 different android smart phones (Samsung Galaxy S3, Samsung Galaxy S5, HTC Three, HTC One, Motorola G)
- hierarchical labeling structure:
 - 53 coarse classes: general sort of food (apples, bananas, tomatoes,...)
 - 81 fine classes: cultivars with similar visual appearance (green apples, red apples,..)
- 125 cultivar classes: sort specific division (Golden Delicious, Granny Smith,...)
- can be used for classification, retrieval, fine-grained recognition,...



Results

- Results are evaluated on the 81 fine classes.
- Two experimental settings:
 - baseline**: classification of food items only
 - non-food**: classification of food items and an additional class for non-food detection (sampled from ImageNet)
- 1-vs-rest evaluation: train with data from 4 phones, evaluate on remaining phone
- reported top-k scores, as the application displays k best results to choose
- usability study with eyetracking (16 persons, mean age 26.3y): SUS score of 80%, UEQ score of 72% (±5%, 90% confidence interval)

Model	baseline/non-food				
	top-1	top-2	top-3	top-4	top-5
gxs3	72.99/64.45	84.34/80.72	88.93/87.55	92.27/91.15	94.58/93.35
gxs5	76.14/71.74	86.66/84.30	90.82/89.11	92.46/92.69	93.82/94.52
htc3	71.99/60.17	84.06/77.89	87.86/84.49	89.77/89.00	91.03/91.77
htco	65.28/52.30	76.95/71.32	82.84/80.41	85.65/85.50	88.40/88.14
motog	62.43/53.70	73.72/68.54	78.22/75.17	81.00/79.98	82.94/84.21
avg	69.77/60.47	81.15/76.53	85.72/83.35	88.23/87.66	90.16/90.41

Table 1: Results for baseline and integration of a non-food class. The mean top-k accuracy ranges from 69.77% to 90.19% for the baseline and from 60.47% to 90.41% for non-food integration (best top-1 accuracy is 76.14% and 71.74%). With non-food integration the top-1 mean accuracy drops by roughly 9%, while the top-5 mean accuracy remains the same.

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