An AI Based Nutrient Supplement System

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Abstract- *In computer vision research, image classification is an important problem that is useful for applications such as content-based image retrieval and automatic detection systems. One such area that we examine in our proposed method is the classification of food imagery.*

The categorizing of food can help applications like nutritional intake calculators and waiter-free restaurants pictures. We study two uses of pre-trained Faster R-CNN to achieve this. Using transfer learning, we first retrain the Faster R-CNN on images pertaining to food. To improve food segmentation and identification accuracy, a method for picture segmentation and classification is developed. To determine whether a photo has to be pre-processed, we impose limitations that are based on the brightness and chrominance of the image. After calculating the meal's calories from the photograph, the system makes food recommendations depending on the user's gender and age. Low-calorie options will be recommended if the user is eating food high in calories, and vice versa.

Keywords- Image Classification, Faster R-CNN.

I. INTRODUCTION

The paper titled “An Artificial Intelligence-Based System for Food and Nutrient Nourishment for an Individual” explores the creation of a system leveraging image classification for applications such as automatic detection systems and content-based image retrieval. Utilizing the Faster R-CNN deep learning model, the system classifies food images and suggests dietary options tailored to the user’s age and gender. It also introduces a novel food image database that proposes an advanced method for image segmentation and classification to enhance food identification accuracy. Designed to offer healthier food alternatives when a user's diet is high in calories, the system aims to support personalized nutrition management.

Regular monitoring of hospitalized patients' dietary intake significantly reduces the risk of malnutrition due to illness. There remains a critical need for a more accurate and fully automated method for estimating nutrient intake, which could enhance data quality and reduce costs for both individuals and healthcare providers. This study presents an innovative artificial intelligence (AI)-based technique that swiftly estimates nutrient consumption using RGB Depth (RGB-D) photo pairs captured before and after meals. The system's components include an algorithm for generating 3D surfaces, a few-shot learning-based classifier for food recognition trained on a limited number of examples, and a novel multi-task contextual network for food segmentation. This sequential food segmentation enables the fully automated evaluation of nutrient intake for each meal. Dedicated resources will be allocated for the system's development and evaluation.

An innovative data annotation approach is employed to compile a database containing images and nutritional data for 322 meals. Experimental results indicate that the projected nutrient intake outperforms current recommended methods for nutrient intake evaluation, exhibiting very low mean relative errors (20%) and a high correlation (> 0.91) with the ground truth. This study details the design, implementation, and evaluation of an innovative AI-based automated system for estimating hospitalized patients' nutritional intake. It introduces several novel methods, including the newly proposed few-shot learning classifier for food recognition and a newly created multimedia-nutrient combination database collected in a real hospital environment. We demonstrated that, compared to the state-of-the-art methods, the proposed algorithms show improved viability and performance in all aspects.

ESTIMATION OF NUTRIENT INTAKE WITH ACCURATE SEGMENTATION MAE (SD) MRE (%) Calories: 46.05 (43.26) kcal Protein: 5.33 (5.24) g Salt: 2.30 (2.58) g Fiber: 2.69 (2.61) g ** p < 0.001

For daily food intake: Calories: 43.95 (42.24) kcal Protein: 5.05 (5.09) g Salt: 2.05 (2.53) g Fiber: 2.42 (2.44) g ** p < 0.001

MAE (SD) MRE (%) for daily meal: 14.64 18.09 17.93 16.16 17.27 17.56 14.06 16.64 15.65 14.59 15.41 14.23

Developing an accurate nutrient intake assessment system using sparse training data is known as nutrient intake estimation with accurate segmentation and recognition MAE (SD) MRE (%). The proposed system, although developed and tested with images from a PC-driven depth camera, can be easily adapted for use with a smartphone camera equipped with a depth sensor for maximum convenience.

II. LITERATURE SURVEY

Image Classification and Food Recognition

Image classification is a critical aspect of computer vision, particularly in applications such as content-based image retrieval and automatic detection systems. One significant area of focus is the classification of food imagery. Various approaches have been proposed to tackle this challenge, leveraging different machine learning and deep learning techniques.

W. Zhang, J. Wang, and W. Feng (2013) discussed the integration of latent factor models with location features for event-based group recommendation, highlighting the importance of contextual information in classification tasks . Similarly, Y. He et al. (2019) explored feature analysis and classification of food images, emphasizing the role of detailed image features in improving classification accuracy .

Q. Macedo, L. B. Marinho, and R. L. Santos (2015) proposed context-aware event recommendation systems, which can be analogously applied to food recommendation by considering user preferences and contextual data such as meal timing and location .

G. M. Farinella et al. (2014) introduced the concept of classifying food images using a bag of Textons approach, which serves as a precursor to more sophisticated deep learning models . Sundarramurthi et al. (2020) presented a personalized food classifier using deep learning, demonstrating the potential of convolutional neural networks (CNNs) in recognizing diverse food items .

Nutritional Monitoring and RGB-D Imaging

Eduardo Aguilar et al. (2018) discussed the use of semantic food detection in smart restaurants, showcasing the application of AI in enhancing customer experience and nutritional tracking . This approach utilizes RGB-D sensors for accurate food identification and nutrient estimation.

F. Sung et al. (2018) and S. Mezgec & B. K. Seljak (2017) introduced few-shot learning techniques and multitask contextual networks for food recognition, addressing the challenge of limited training data by leveraging transfer learning and multitask learning paradigms . These methods improve the generalization capability of food classification models, making them more robust in diverse real-world scenarios.

Gordana Ispirova et al. (2020) examined the bias in prediction tasks for food and nutrition, underscoring the importance of domain-specific knowledge in training deep learning models for dietary assessment . This work complements the efforts by M. Ahmed Subhi et al. (2018) who surveyed vision-based approaches for automatic food recognition and dietary assessment, highlighting the advancements and challenges in the field .

Kenji Iizuka and Masakazu Morimoto (2018) developed a nutrient content estimation system using RGB-D sensors, demonstrating the feasibility of accurate nutrient intake assessment in buffet settings .

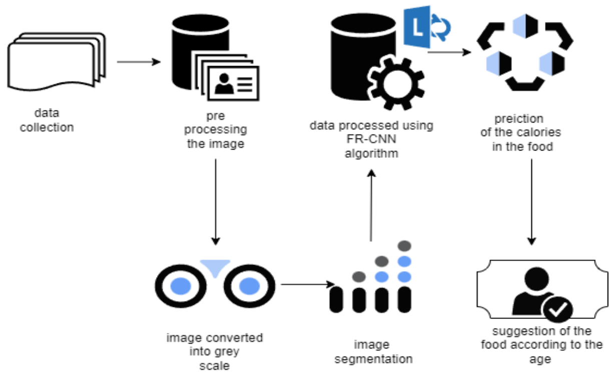
III. PROPOSED SYSTEM

Deep learning powers the most sophisticated photo classification algorithms in use today. Convolutional layers are necessary for photo identification, as opposed to several layers for deep learning. Utilizing the data that the convolutional layers were able to extract, the classifier, the final layer, is fully connected. After a while, the network generates a one-hot vector for each class it can identify as the class of the input image, with an output equal to 1. Features of the local region are mentioned for points of interest and/or local regions.

An invariant local area feature describes these points of interest in the same way across multiple images with different lighting, size, and perspectives. The idea functions similarly to enlarging the layer, a tried-and-true technique for expanding a neural network`s representational capacity while reducing the rising computing load.

Faster Region Convolutional Neural Network:

Faster R-CNN is an end-to-end trained single-stage model. In contrast to conventional algorithms like Selective Search, it generates area suggestions using a new region proposal network (RPN). From each area proposal, a fixed length feature vector is extracted using the ROI Pooling layer .



Architecture Diagram

IV. MODULES DESCSRIPTION

Data Collection

Data collection is the systematic process of gathering and analyzing information on relevant variables to address specific research questions, test hypotheses, and evaluate outcomes. Data can be categorized into four main types based on the methods of collection: produced, simulation, experimental, and observational. The type of data collected influences the data handling process. For this project, a dataset comprising images of various foods along with their calorie counts is being compiled from several websites, ensuring a diverse range of sources.

Data Pre-Processing

Data pre-processing is a crucial step aimed at minimizing the impact of minor errors in experimental computations. This involves creating intervals from samples and replacing categorical values. Order data is converted into Boolean values using index variables. For instance, if there are more than two values (n), n - 1 columns need to be created. Centering and scaling the data is done by subtracting the mean across all variables, followed by dividing by the standard deviation. Principal Component Analysis (PCA) is often employed to reduce the dimensionality of large datasets. PCA compresses a large number of variables into a smaller set while retaining most of the significant information. Although some precision is lost, the simplification enables machine learning algorithms to process the data more efficiently and effectively. In summary, PCA aims to reduce the number of variables while preserving the most critical information.

FR-CNN Model Creation

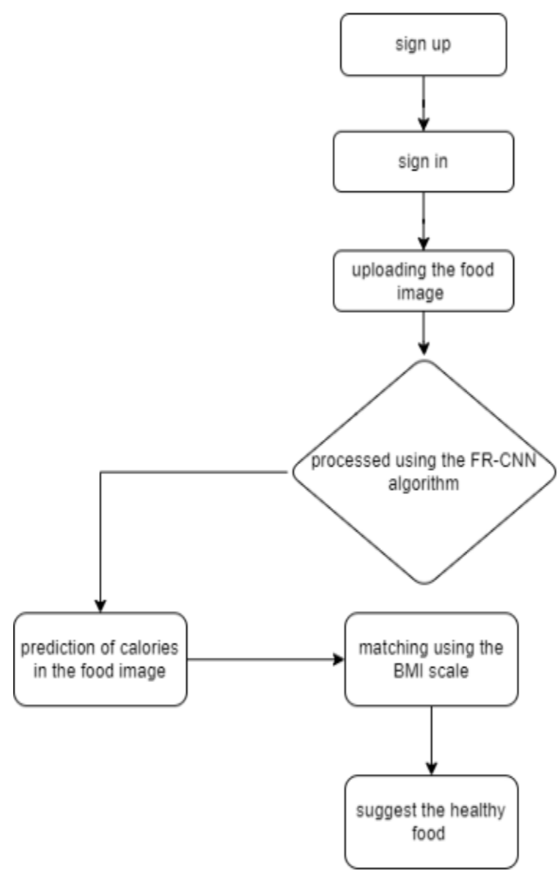
In this module, the FR-CNN algorithm is used to construct the model. Similar to the R-CNN detector, the Fast R-CNN detector employs an Edge Box-like algorithm to generate region proposals. However, unlike the R-CNN detector, which resizes and shrinks region proposals, the Fast R-CNN detector processes the entire image. The Fast R-CNN pools CNN features corresponding to each region proposal, eliminating the need to classify each region individually. This makes Fast R-CNN more efficient than R-CNN, as it shares computations for overlapping regions.

Calorie Estimation

To estimate the calorie content of food, users submit an image of their meal to this module. Using the FR-CNN technique, the image is processed, and the calorie count of the food item is displayed. This feature is particularly useful for individuals who are monitoring their dietary intake.

Food Recommendation

If the analyzed dish image is found to have a high-calorie content, this module will recommend a lower-calorie, healthier alternative based on the user's gender and BMI scale. This helps users make more informed dietary choices in line with their health goals.



Flow Diagram

V. RESULT

The system's capabilities extend beyond mere classification; it also performs image segmentation to improve accuracy in food identification. It assesses images based on brightness and chrominance to determine the need for pre-processing56. Once the food is recognized, the system calculates its caloric content and suggests alternative foods tailored to the user's age and gender, promoting healthier choices for those consuming high-calorie meals and vice versa.

METRIC	MEAN ABSOLUTE ERROR (MAE)	MEAN RELATIVE ERROR (MRE) (%)	STANDARD DEVIATION (SD)	CORRELATION GROUND TRUTH
CALORIES (PER MEAL)	46.05 kcal	20%	43.26 kcal	>0.91
PROTEIN (PER MEAL)	5.33 g	20%	5.24 g	>0.91
SALT (PER MEAL)	2.30 g	20%	2.58 g	>0.91
FIBER (PER MEAL)	2.69 g	20%	2.61 g	>0.91

This AI-based approach offers a significant advancement in nutritional monitoring, particularly for hospitalized patients, by automating nutrient intake estimation using RGB Depth (RGB-D) image pairs. The proposed multi-task contextual network and few-shot learning-based classifier demonstrate superior performance in nutrient intake assessment, with minimal mean relative errors, showcasing the potential for widespread application in health care and personal diet management.

In conclusion, the system represents a significant step forward in personalized nutrition, combining cutting-edge AI techniques with practical dietary recommendations to foster healthier eating habits. Bold elements are used to emphasize key aspects of the system and its benefits.

VI. CONCLUSION

In order to recognize food items in photographs and recommend food based on a person's age and gender, we described an image classification and food recommendation system.

We have shown a considerable improvement in food recognition accuracy over previous tests. Automatically identifying food items in a photo is challenging. We understand that we won't be able to recognize every kind of food. We are still investigating visual aspects in addition to contextual information to improve the accuracy and use of the system.

REFERENCES

[1] W. Zhang, J. Wang, and W. Feng, "Combining latent factor model with location features for event-based group recommendation," in Proceedings of the 19th ACM SIGKDD international conference on Knowledge discovery and data mining, 2013, pp.910–918.

[2] Q. Macedo, L. B. Marinho, and R. L. Santos, "Context-aware event recommendation in eventbased social networks," in Proceedings of the 9th ACM Conference onRecommender Systems, 2015, pp. 123–130.

[3] Y. He, C. Xu, N. Khanna, C. J. Boushey, and E. J. Delp, ``Analysis of food images:Features and classification," in Proc. IEEE Int. Conf. Image Process. (ICIP), Oct. 2019,pp.2744-2748.

[4] G. M. Farinella, M. Moltisanti, and S. Battiato,``Classifying food images represented as bag of Textons," in Proc. IEEE Int. Conf. Image Pro- cess. (ICIP), Oct. 2014,pp. 5212-5216.

[5] M. Sundarramurthi, Nihar M, Anandi Giridharan," Personalised Food Classifier and Nutrition Interpreter Multimedia Tool Using Deep Learning", 2020 IEEE Region 10 conference (TENCON).

[6] Gordana Ispirova, Tome Eftimov, Barbara Koroušić Seljak," Exploring Knowledge Domain Bias on a Prediction Task for Food and Nutrition", 2020 IEEE International Conference on Big Data (Big Data).

[7] Charles N. C. Freitas, Filipe R. Cordeiro, Valmir Macario," My Food- A Food Segmentation and Classification System to Aid Nutritional Monitoring", 202033rd SIBGRAPI Conference on Graphics, Patterns andImages (SIBGRAPI).

[8] Raciel Yera Toledo, Ahmad A. Alzahrani, Luis Martínez," A Food Recommender System Considering Nutritional Information and User Preferences", IEEE Access,2019.

[9] G. Ciocca, P. Napoletano, and R. Schettini, ``IVLFood-WS: Recognizing food in the wild using deep learning," in Proc. IEEE 8th Int. Conf. Consum. Electron. -Berlin (ICCE-Berlin), Sep. 2018, pp. 1-6. 34

[10] W. Min, B.-K. Bao, S. Mei, Y. Zhu, Y. Rui, and S. Jiang, ``You are what you eat: Exploring rich recipe information for crossregion food analysis," IEEE Trans. Multimedia, vol. 20, no. 4, pp. 950-964, Apr. 2018.

[11] Eduardo Aguilar, Beatriz Remeseiro,Marc Bolaños,Petia Radeva," Grab, Pay and Eat: Semantic Food Detection for Smart Restaurants ",2018 IEEE Transactionson Multimedia.

[12] T. Ege et al., “Image-based estimation of real food size for accurate food calorie estimation,” in Proc. of IEEE Int. Conf. on Multimedia Info. Proce. and Retr., 2019.
[13] F. Sung et al., “Learning to compare: relation network for few-shot learning,” in Proc.of IEEE conf. Comput. Vis. Pattern Recognit., 2018.
[14] S. Kuanar, V. Athitsos, N. Pradhan, A. Mishra, and K. Rao, “Cognitive analysis of working memory load from eeg, by a deep recurrent neural network,” in Proc. of IEEEInt. Conf. on Acoustics Speech and Signal Processing, 2018.
[15] Shiba Kuanar,Vassilis Athitsos,Dwarikanath Mahapatra,K.R.Roa,Zahid Akhtar,Dipankar Dasgupta,“Low dose abdominal ct image reconstruction: An unsupervised learning based approach,” in Proc.of IEEE Int. Conf. on Image Processing, 2019.
[16] Tossawat Mokdara; Priyakorn Pusawiro; Jaturon Harnsomburana, “Personalized Food Recommendation Using Deep Neural Network”, 2018 Seventh ICT International Student Project Conference (ICT-ISPC).
[17] Kenji Iizuka; Masakazu Morimoto, ”A Nutrient Content Estimation System of Buffet Menu using RGB-D Sensor”, 2018 Joint 7th International Conference on Informatics, Electronics & Vision (ICIEV) and 2018 2ndInternational Conference on Imaging,Vision & PatternRecognition (icIVPR)
[18] Mohammed Ahmed Subhi; Sawal Hamid Ali; Mohammed Abulameer Mohammed,” Vision-Based Approaches for AutomaticFood Recognition and DietaryAssessment: A Survey”, IEEE Access. 35
[19] A. A. Fatehah, B. K. Poh, S. N. Shanita and J. E. Wong, "Feasibility of reviewing digital food images for dietary assessment among nutrition professionals", Nutrients, vol. 10, no. 8, pp. 984, 2018.
[20] S. Mezgec and B. Korousiˇ c Seljak, “Nutrient: A deep learning food ´ and drink image recognition system for dietary assessment,” Nutrients, vol. 9, no. 7, p. 657, 2017.