ISSN PRINT 2319 1775 Online 2320 7876

Research paper UGC CARE Listed (Group -I) Journal Volume 10, Iss 4, 2021

Food Image Classification using Deep Pretrained Lightweight Model

Hemalatha Eedi[1]
Assistant Professor, Department of CSE, JNTUH College of Engineering Hyderabad, Hyderabad, Telangana, India
hemamorarjee@jntuh.ac.in

Morarjee Kolla[2*]
Associate Professor, Department of CSE, Chaitanya Bharathi Institute of Technology, Hyderabad, Telangana, India
morarjeek_cse@cbit.ac.in

Abstract

Globally health consciousness is increasing among people nowadays leading to taking a balanced diet with nutritious food. People are showing interest in selecting required nutritious food from various food applications. Classifying food images is a challenging area in smart nutrition and kitchen-based applications. Food Image Classification models using Deep Learning produce prominent results with high computational resources. Most of the existing applications in this area are mobile applications to interact with common people. Hence deploying current Deep Learning models into mobile kind of devices grab the attention of researchers. To address this issue, we propose a Lightweight model using Binary Convolutional Neural Network (BCNN) for classifying food images. Our experimental results show a significant improvement compared to the competitive models.

Keywords: Binary Convolutional Neural Networks, Deep Learning, Food Image Classification, Lightweight Model, Nutritious Food.

1. Introduction

Humans living in this world are categorized as vegetarians and non-vegetarians. Some of them are eating both categories of food. Due to taking imbalanced diet and shortage of nutritious food intake, many diseases are attacking nowadays. This leads to diabetes, hypertension, cancer, heart disease, and other dangerous diseases[1]. To overcome these difficulties people are showing interest in precautionary measures with proper dietary management systems. Taking junk food and poor quality food leads to the spoiling of human health. Now people are showing interest in selecting nutritious food from available food repositories. Most of the commercial applications in

ISSN PRINT 2319 1775 Online 2320 7876

Research paper UGC CARE Listed (Group -I) Journal Volume 10, Iss 4, 2021

this area are concentrating on showcasing the food ingredients and Calories to gain kind of details about each category of food [2]. Identifying and selecting such categories of food from the food images is a daunting task. Several image processing applications developed for image classification using conventional features are still in the infancy stage. Recent Deep learning-based approaches with deep features are giving better results than conventional features [3]. Several researchers proposed different approaches for classifying food images as per user requirements to satisfy their quality food needs.

Advanced approaches in the area of deep learning with proper fine-tuning of their hyperparameters tuning delivering quality applications in the area of food engineering. Several food engineering applications like food categorization, Caption generation of ingredients, food clustering, food processing, food quality checking, and Nutrition identification in the area of food engineering need segmentation of food images [4]. This segmentation process recently followed a semantic extraction process for quality improvement. Further based on these segments classification of the image results in their performance. Food image repositories nowadays are available in larger volumes in quantity. Day-to-day dynamic improvement in this area producing varieties of foods with different categories are adding to these datasets increasing their size rapidly. Handling these heterogeneous real-time food datasets to extract semantic results is a challenging task. These food images are not available in equal size and some of the images are included with noise. Handling these issues with pre-processing and extracting analytical information with knowledge interpretation is required for many applications.

Deep Learning models require the highest computational resources to handle complex problems. Memory and speed are the bottlenecks for most deep-learning applications. Deep Parameter optimization techniques or model optimization techniques resolve these issues with advanced approaches [5]. Several compression techniques are proposed with deep features without degrading the performance. Some quantization techniques with these features are successful in reducing memory consumption and increasing computational speed with lower-end computing devices like mobiles. Lightweight models are developed to deploy into this kind of device with nearly equivalent to its original model performance. In this paper, we proposed a novel lightweight model using Binary CNN [6].

2. Related Work

Several researchers proposed classification techniques for food images using traditional image processing approaches. Some of them are proposed with superpixels to improve the performance of the models [5]. Some researchers proposed pre-trained deep-learning models for classification [7]. Few researchers proposed their customized models for classification [8]. Some researchers proposed lightweight models using MoblieNet [9], and EfficientNet[10] with promising results with real-time datasets. Food images with their nutrition-related classification works proposed by

ISSN PRINT 2319 1775 Online 2320 7876

Research paper **© 2012 IJFANS. All Rights Reserved, UGC CARE Listed (Group -I) Journal Volume 10, Iss 4, 2021**

some researchers [11]. Finding real-time datasets with sufficient images with grading is the major problem in this food classification model. Sufficient data is not available to train a classification model with limited train images. These issues are addressed with data augmentation and deep feature-based training to overcome the problem of underfitting the model [12]. Some researchers proposed quantized models to reduce memory occupancy [13]

The major Contributions of this paper are as follows

- To address the underfitting problem with data augmentation of train data.
- To effectively handle noisy data and large-scale benchmarked datasets of food images.
- To find an effective classification model with real-time food images.
- To produce an optimized model by Fine-tuning hyperparameters with Binary CNN.
- To utilize resources effectively with local features and crucial regions in building a model.
- To test the model with real-time large-scale food image datasets.
- To deploy and maintain a lightweight model for food image classification

3. Food Image Classification using BCNN

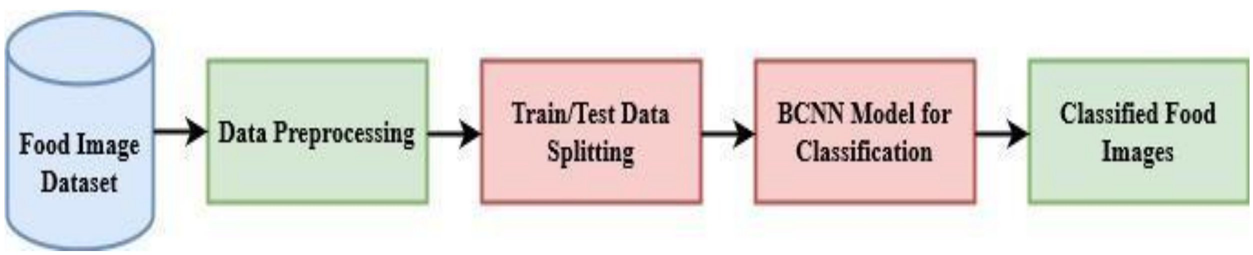

Figure 1. The architecture of Food Image Classification using the BCNN Model

The above Figure 1 depicts the flow of our proposed model with BCNN for food classification. Initially, the Food 101 data set [14] is given as input to the model. This dataset is preprocessed to remove the noise and inconsistencies and then splits this dataset as a train and test dataset. With the trained dataset our proposed BCNN model is developed with proper hyperparameter training. After getting convergence of the problem with optimizations in certain iterations used it for testing. This trained model is given for testing with a test dataset to produce the results. Data augmentation was also performed in our work to overcome the problem of underfitting.

4. Implementation Details

We conducted experiments on GPU based system with NVIDIA GPU memory of 12GB. Our implementation is based on Python, TensorFlow, and Keras.

ISSN PRINT 2319 1775 Online 2320 7876

Research paper UGC CARE Listed (Group -I) Journal Volume 10, Iss 4, 2021

4.1 Dataset Description

We conducted experiments on the Food 101 dataset [14] consisting of 1,01,000 food images of 101 categories. These images are scaled and normalized with benchmarked train and test images. In this work, we considered 75% of train images and 25% of test images.

4.2 Comparative Methods

We showed the efficacy of our system by comparing our model BCNN with six competitive models. The performance of our model has compared also with similar lightweight models.

4.3 Parameter Tuning

BCNN model considers the learning rate of 0.05, update interval of 300, convergence threshold of 0.1%, and mini-batch size of 256. We achieve an optimal solution with 1000 epochs. We consider the accuracy, memory consumption, and execution time for various pre-trained models and lightweight models.

4.4 Performance Evaluation Metrics

We consider classification execution time for 1000 epochs in seconds and memory consumption in Megabytes to prove our proposed memory-efficient classification's scaling factor.

5. Result Analysis

We compare the performance of our model BCNN with other models of AlexNet, VGGNet, Inception V3, Resnet 50, MobileNet, and EfficientNet, as shown in Table 1. Classification speed increases and memory consumption reduces in BCNN compared to other models.

Table 1. Comparison of Classification performance with various models

S. No	Classification Model	Accuracy	Memory Consumption in MB	Execution Time in Sec.
1	AlexNet	67.23	113.34	16346,4
2	VGGNet	72.84	173.45	18373.7
3	Inception v3	83.28	225.93	23722.9
4	ResNet 50	94.37	296.43	28837.5
5	MobileNet	90.34	162.34	18374.8
6	EfficientNet	91.67	152.36	17938.4
7	**Our Model with BCNN**	**93.69**	**134.23**	**15327.2**

6. Conclusion

This paper proposes the BCNN lightweight model for food image classification, which performs memory-efficient classification in a shorter execution time. Our model is suitable for mobile applications for effectively classifying food images. It reduces memory occupancy with binary weights and activations. Experiments conducted on Food 101 image dataset proved the improvement in performance without degrading the classification accuracy. This model achieves better memory consumption and speed than competitive models. In Future experiments conducted in a distributed environment with federated learning. In the future, experiments will be conducted on real-time datasets with encoder and decoder models with attention mechanisms that may improve the performance of the model.

References

[1] Rajayogi, J. R., G. Manjunath, and G. Shobha. "Indian food image classification with transfer learning." In *2019 4th International Conference on Computational Systems and Information Technology for Sustainable Solution (CSITSS)*, pp. 1-4. IEEE, 2019.
[2] Şengür, Abdulkadir, Yaman Akbulut, and Ümit Budak. "Food image classification with deep features." In *2019 international artificial intelligence and data processing symposium (IDAP)*, pp. 1-6. Ieee, 2019.
[3] Zhang, Weishan, Dehai Zhao, Wenjuan Gong, Zhongwei Li, Qinghua Lu, and Su Yang. "Food image recognition with convolutional neural networks." In *2015 IEEE 12th Intl Conf on Ubiquitous Intelligence and Computing and 2015 IEEE 12th Intl Conf on Autonomic and Trusted Computing and 2015 IEEE 15th Intl Conf on Scalable Computing and Communications and Its Associated Workshops (UIC-ATC-ScalCom)*, pp. 690-693. IEEE, 2015.
[4] Xu, Bing, Xiaopei He, and Zhijian Qu. "Asian food image classification based on deep learning." *Journal of Computer and Communications* 9, no. 03 (2021): 10.
[5] Kiourt, Chairi, George Pavlidis, and Stella Markantonatou. "Deep learning approaches in food recognition." *Machine Learning Paradigms: Advances in Deep Learning-based Technological Applications* (2020): 83-108.
[6] Lin, Xiaofan, Cong Zhao, and Wei Pan. "Towards accurate binary convolutional neural network." *Advances in neural information processing systems* 30 (2017).
[7] Singla, Ashutosh, Lin Yuan, and Touradj Ebrahimi. "Food/non-food image classification and food categorization using pre-trained googlenet model." In *Proceedings of the 2nd International Workshop on Multimedia Assisted Dietary Management*, pp. 3-11. 2016.
[8] Islam, Kh Tohidul, Sudanthi Wijewickrema, Masud Pervez, and Stephen O'Leary. "An exploration of deep transfer learning for food image classification." In *2018 Digital Image Computing: Techniques and Applications (DICTA)*, pp. 1-5. IEEE, 2018.
[9] Phiphiphatphaisit, Sirawan, and Olarik Surinta. "Food image classification with improved MobileNet architecture and data augmentation." In *Proceedings of the 3rd International Conference on Information Science and Systems*, pp. 51-56. 2020.
[10] Atila, Ümit, Murat Uçar, Kemal Akyol, and Emine Uçar. "Plant leaf disease classification using EfficientNet deep learning model." *Ecological Informatics* 61 (2021): 101182.
[11] Sathish, Suriyakrishnan, S. Ashwin, Md Abdul Quadir, and L. K. Pavithra. "Analysis of Convolutional Neural Networks on Indian food detection and estimation of calories." *Materials Today: Proceedings* 62 (2022): 4665-4670.
[12] Pan, Lili, Jiaohua Qin, Hao Chen, Xuyu Xiang, Cong Li, and Ran Chen. "Image Augmentation-Based Food Recognition with Convolutional Neural Networks." *Computers, Materials & Continua* 59, no. 1 (2019).

ISSN PRINT 2319 1775 Online 2320 7876

Research paper **UGC CARE Listed (Group -I) Journal Volume 10, Iss 4, 2021**

[13] Redfern, Arthur J., Lijun Zhu, and Molly K. Newquist. "BCNN: A binary CNN with all matrix Ops Quantized to 1 bit precision." In *Proceedings of the IEEE/CVF conference on computer vision and pattern recognition*, pp. 4604-4612. 2021.
[14] Bossard, Lukas, Matthieu Guillaumin, and Luc Van Gool. "Food-101–mining discriminative components with random forests." In *Computer Vision–ECCV 2014: 13th European Conference, Zurich, Switzerland, September 6-12, 2014, Proceedings, Part VI 13*, pp. 446-461. Springer International Publishing, 2014.