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A Deep Convolutional Neural Network Model for Multi-Class Fruits Classification

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Abstract. Fruits classification is a challenging task due to the several types of fruits. To classify fruits more effectively, we propose a new deep convolutional neural network model to classify 118 fruits classes. The proposed model combines two aspects of convolutional neural networks, which are traditional and parallel convolutional layers. The parallel convolutional layers have been employed with different filter sizes to have better feature extraction. It also helps with backpropagation since the error can backpropagate from multiple paths. To avoid gradient vanishing problem and to have better feature representation, we have used residual connections. We have trained and tested our model on Fruits-360 dataset. Our model achieved an accuracy of 100% on a divided image set from the training set and achieved 99.6% on the test set, which outperformed previous methods.

Keywords: Fruits Classification, Convolutional Neural Network, Deep learning**.**

1 Introduction

In the field of academic research, fruit classification is still considered as an excitable issue. For instance, identifying the class of a single fruit helps the workers in the supermarket to determine its price rapidly [1]. In addition, it is useful to present nutritional instructions to assist customers in selecting their appropriate food types that meet their nutrient and well-being needs [2, 3]. For automatic packaging, fruit classification techniques are widely used in all food factories, as well.

Manual fruit classification remains a challenging topic since the fruit types and subtypes differ from region to another. This wide difference focuses on the availability of the fruit of population-dependent and region-dependent, as well as, the necessary ingredients in the fruits [3].

The great progression in computer vision and machine learning, mainly in the last decade, brings the attention of several researchers for employing the developed techniques in the automated fruit classification. Researchers commonly used some features related to the external quality descriptors, like shape, size, texture, and color in their work [3-15]. In general, most of the proposed classifiers were either restricted to a specific type, or their performance has not acceptable accuracy.

In previous work, some methods have utilized deep learning techniques to classify fruits [16, 17] which have shown a great performance. This motivated us to employ a deep learning model for fruits classification task which considers a very challenging task due to a large number of classes.

2 Related Work

In recent years, specialists introduced several automated fruit classification techniques. The first group of scientists used clustering technique for classifying fruits and vegetables is Pennington and Fisher in 2009 [3]. Pholpho et al. [4], employed visible spectroscopy technique for recognizing the damaged/undamaged fruits. While Yang et al. [5], introduced an estimation system, employing multispectral imaging analysis for blueberry fruit application. In contrast, classifying various types of fruit with 88.2% accuracy is achieved using computer vision and multi-class Support Vector Machine (SVM) [6]. Later, eight different citrus fruits are recognized utilizing Raman spectroscopy as a fast and undamaging tool, and two analysis techniques (hierarchical cluster and principal component) [7]. Fadhel, M., et al. have used color segmentation to recognize the unripe strawberry [21].

In 2013, Marchal et al. [8], employed computer vision and machine learning for developing an expert system, which aims to estimate the impurity content inside an individual sample of olive oil. While Breijo et al. [9], utilized an electronic nose (so-called an odor sampling system) for classifying Diospyros kaki aroma. The working parameters of the system have the ability to influence the variable configurations to make the system adaptable.

On the other hand, the artificial neural network with two hidden layers is applied for predicting the characteristics of the texture extracted from the food-surface image [10]. The backpropagation algorithm is used for training the network. Moreover, Omid et al. [11], introduced an expert system, using machine vision and fuzzy logic, for extracting size and defect features. Another automated fruit classification system was proposed based on fitness-scaled chaotic artificial bee colony algorithm [12]. In addition, the texture-based technique, which includes descriptor computation and interest-point feature extraction, was suggested for detecting green fruits on palms [14]. Lastly, data fruits were classified based on Weber local descriptor and local binary pattern techniques with SVM for classifier and Fisher discrimination ratio for selecting features [15].

Most of the previous works have the following drawbacks. a) They need high-priced sensors like weight, dew, heat, chemical, gas-sensitive, and invisible light sensors. b) The classifiers have the ability to recognize limited classes of fruits. c) The performance of the systems is not high enough, mainly with closely similar texture, color, and shape features. d) The accuracy of the classification does not achieve the requirements for typical applications.

3 Methodology

3.1 Dataset

We have used Fruits-360 dataset to train and test our model [16]. The dataset has been downloaded from the Kaggle website (link to the dataset: https://www.kaggle.com/moltean/fruits). It has 80653 as the total number of images, which represent 118 classes of fruits. The dataset divided into 60318 images for the training set and 20232 for the testing set. Each image of the dataset has the size of 100x100 pixels.

3.2 Deep Learning

Artificial neural networks can obtain the most successful results, mainly in the field of image classification and recognition [18, 19, 22, 23,24]. Deep learning models are based on these networks. Machine learning algorithms can be categorized into different classes, where deep learning is one of them. It utilizes multi-layers that composed of nonlinear processing units [20]. All layers learn to convert their input data into a complex representation and somewhat further abstract. Several machine-learning algorithms are failing to stand against deep neural networks (DNNs) that have well managed. In certain domains, DNNs achieved the first supreme pattern recognition. Moreover, DNNs are extra boosted, since deep learning represents a significant step in the direction of achieving Robust Artificial Intelligence. Currently, convolutional neural networks (CNNs), as a type of DNNs, have approved for obtaining valuable results, mainly in the image recognition field. Each CNN has several types of layers such as loss, fully connected, ReLU, pooling, as well as, convolutional layers [20]. Generally, its structure consists of a convolutional layer followed by ReLU layer, a pooling layer, one or more convolutional layer, and one or more fully connected layer, respectively. The key feature that characterized the CNN apart of the normal neural network is the image structure during its processing. It should be noted that normal neural network changes the image input into a 1D array (one-dimensional array), which reduces the sensitivity of the trained classifier to positional variations. Studying the structure of CNN is critical. In this paper, we focused on how to design a model with better feature extraction and deal with overfitting and gradient vanishing problems.

3.3 Proposed Model

A large number of fruit classes require good feature extraction to discriminate between classes. Our proposed model is very effective due to the structure designed. At first, the model starts with two tradition convolutional layers of 3*3, 5*5 sizes to reduce the input size. Each convolutional layer is followed by batch normalization and rectified linear unit layers to speed up the training process and avoid gradient vanishing problems. Using small filter size (such as 1*1)at the beginning of the model could lead to losing large features. For that reason, we avoided using a small filter size. After the traditional convolutional part, four blocks of parallel convolutional layers have been employed to extract the features. In the first block, four convolutional layers work in parallel then the output of four convolutional layers and the traditional convolutional layers using residual connection concatenates in the first concatenation layer.

Table 1. Our model architecture, C refers to Convolutional Layer, B refers to Batch Normalization Layer, R refers to Rectified Linear Unit layer, CN refers to Concatenation Layer, G refers to Average Pooling Layer, D refers to dropout layer, F refers to fully connected layer.

Name of layer	Filter Size (FS) and Stride (S)	Activations
Input Layer	-	100*100*3
C1, B1, R1	FS=3*3 ; S = 1	100*100*16
C2, B2, R2	FS=5*5 ; S = 2	50 * 50*16
C3, B3, R3	FS=3*3 ; S = 1	50 * 50*16
C4, B4, R4	FS=5*5 ; S = 1	50 * 50*16
C5, B5, R5	FS=7*7 ; S = 1	50 * 50*16
C6, B6, R6	FS=11*11 ; S = 1	50 * 50*16
CN1, B1x	Input CN1 = 5	50 * 50*80
C7, B7, R7	FS=3*3 ; S = 2	25 *25 *32
C8, B8, R8	FS=5*5 ; S = 2	25 *25 *32
C9, B9, R9	FS=7*7 ; S = 2	25 *25 *32
C10, B10, R10	FS=11*11 ; S = 2	25 *25 *32
CN2, B2x	Input CN2 = 4	25*25 * 128
C11, B11, R11	FS=3*3 ; S = 1	25 *25 *32
C12, B12, R12	FS=5*5 ; S = 1	25 *25 *32
C13, B13, R13	FS=7*7 ; S = 1	25 *25 *32
C14, B14, R14	FS=11*11 ; S = 1	25 *25 *32
CN3, B3x	Input CN3 = 5	25 *25 *256
C15, B15, R15	FS=3*3 ; S = 2	13*13*64
C16, B16, R16	FS=5*5 ; S = 2	13*13*64
C17, B17, R17	FS=7*7 ; S = 2	13*13*64
C18, B18, R18	FS=11*11 ; S = 2	13*13*64
C19, B19, R19	FS=7*7 ; S = 4	13*13*64
CN4, B4x	Input CN4 = 5	13*13*320
A1	FS=7*7 ; S = 2	4*4*320
F1 , D1	-	1*1*300
F2, D2	-	1*1*200
F3	-	1*1*118
O,Softmax	-	118 class

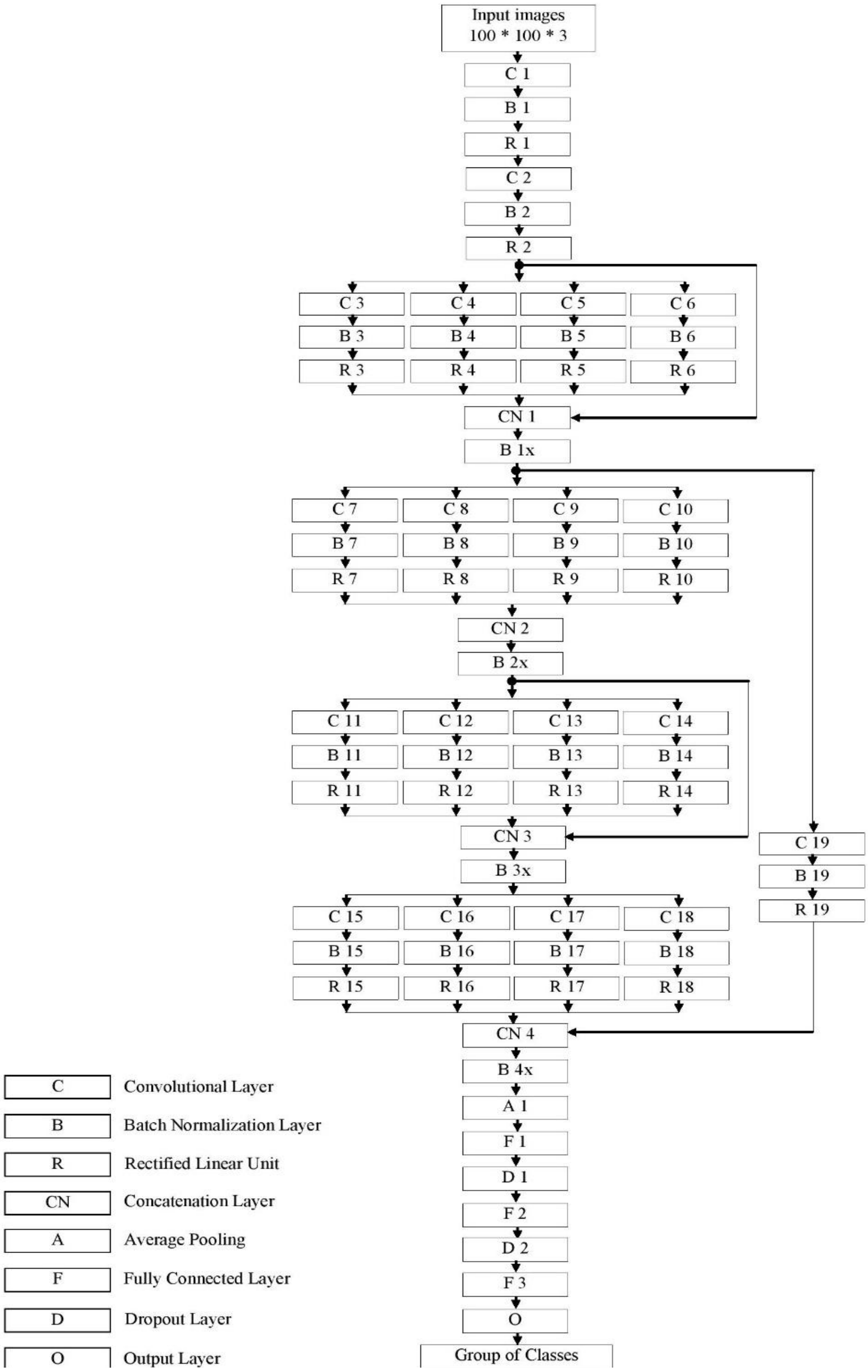

Fig. 1. Our model architecture

The convolutional layers have different filter sizes (3*3,5*5,7*7,11*11) and followed by batch normalization and rectified linear unit layers which applied to all four blocks. The second block followed the same structure of block one except for the residual connection part. The output of block two and block three concatenates in the third concatenation layer. Furthermore, the output of block one passed through a single convolutional layer and concatenates with the output of block four in fourth concatenation layer. On top of that, the average pooling layer has been employed to perform the huge dimensional reduction which helps to void overfitting problem.
Then, three fully connected layers have been utilized and two dropout layers employed between the three fully connected layers to prevent the overfitting problem. Lastly, the softmax function used to classify 118 fruit classes. The total number of layers of our model is 74 as described in Tablel1 and Fig1.
We have trained out model for 3700 iterations until the learning stopped as shown in Fig2.

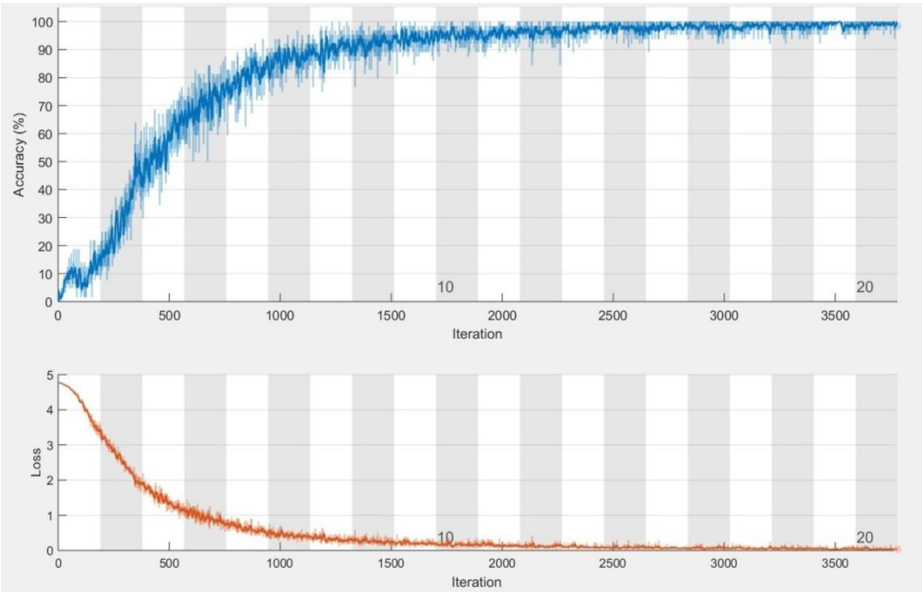

Fig. 2**.** Our model training progress

4 Experimental Results

We have evaluated our model in term of accuracy. Accuracy is measured as a key indicator of model effectiveness. Accuracy is defined as the ratio of the number of correct predictions to the total number of predictions. Our model achieved an accuracy of 100% on a divided set from the training set and achieved an accuracy of 99.6% on the testing set. It is superior to all methods that employed in Ref [16] which is the same source of the Fruits-360 dataset. It is worth mentioning that the Ref [16] classified 101 classes while our model used to classify 118 classes. Table3 shows some test samples with correct predictions.

Table 2. Comparison of previous methods and our method on Fruits-360 dataset.

Method	Accuracy on the training set (%)	Accuracy on the testing set (%)
Method 1 [16]	99.60	96.13
Method 2 [16]	99.37	95.85
Method 3 [16]	99.61	95.53
Method 4 [16]	98.95	93.13
Method 5 [16]	99.62	96.03
Method 6 [16]	96.03	92.30
Method 7 [16]	99.57	95.95
Method 8 [16]	99.47	95.80
Method 9 [16]	98.70	93.26
Method 10 [16]	99.44	94.16
Our Model	100	99.60

Table 3. Test samples with correct predictions

 Avocado: 99.1%	 Apple Red3: 98.5%	 Tomato1: 97.7%	 Potato White: 96.1%
 Plum 3: 95.1%	 Pineapple: 99.2%	 Banana: 100%	 Dates: 98.1%

			
Cocos: 98.9%	AppleGolden2: 98.7%	Kiwi: 99.3%	Lemon: 100%

5 Conclusion

We proposed a deep convolutional neural network model for fruits classification which is a challenging task due to the many types of fruits. Our model used to classify 118 types of fruits. The proposed model aggregated two modes of convolutional neural networks which are traditional and parallel convolutional layers. Our model has proved to be very helpful for the backpropagation process since the error can backpropagate from multiple paths. For the sake of preventing gradient vanishing problem and to have better feature representation, we have utilized residual connections. The fruits-360 dataset has been used to train and test our model on. Our model achieved an accuracy of 100% on divided images set from the training set and achieved 99.6% on test set which outperformed previous methods.

6 References

1. Zhang, B.H.; Huang, W.; Li, J.; Zhao, C.; Fan, S.; Wu, J.; Liu, C.: Principles, developments and applications of computer vision for external quality inspection of fruits and vege bles: A review. Food Res., 62, 326–343, (2014).
2. Zhang, Y.D.; Wu, L.; Wang, S.; Ji, G. Comment on: Principles, developments and applications of computer vision for external quality inspection of fruits and vegtables: A review (Food Research International; 2014, 62: 326–343)". Food Res., 70, 142–142, (2015).
3. Pennington, J.A.T.; Fisher, R.A.: Classification of fruits and vegetables. J. Food Compos. Anal., 22 (Suppl. 1), S23–S31, (2009).
4. Pholpho, T.; Pathaveerat, S.; Sirisomboon, P.: Classification of longan fruit bruising using visible spectroscopy. J. Food Eng, 104, 169–172, (2011).
5. Yang, C.; Lee, W.S.; Williamson, J.G.: Classification of blueberry fruit and leaves based on spectral signatures. Biosyst. Eng., 113, 351–362, (2012).
6. Wu, L.; Zhang, Y.: Classification of Fruits Using Computer Vision and a Multiclass Support Vector Machine. Sensors, 12, 12489–12505, (2012).
7. Feng, X.W.; Zhang, Q.H.; Zhu, Z.L.: Rapid Classification of Citrus Fruits Based on Raman Spectroscopy and Pattern Recognition Techniques. Food Sci. Technol. Res., 19, 1077–1084, (2013).
8. Cano Marchal, P.; Gila, D.M.; García, J.G.; Ortega, J.G.: Expert system based on computer vision to estimate the content of impurities in olive oil samples. J. Food Eng., 119, 220–228, (2013).

9. Breijo, E.G.; Guarrasi, V.; Peris, R.M.; Fillol, M.A.; Pinatti, C.O.: Odour sampling system with modifiable parameters applied to fruit classification. J. Food Eng., 116, 277–285, (2013).
10. Fan, F.H.; Ma, Q.; Ge, J.; Peng, Q.Y.; Riley, W.W.; Tang, S.Z.: Prediction of texture characteristics from extrusion food surface images using a computer vision system and artificial neural networks. J. Food Eng., 118, 426–433, (2013).
11. Omid, M.; Soltani, M.; Dehrouyeh, M.H.; Mohtasebi, S.S.; Ahmadi, H.: An expert egg grading system based on machine vision and artificial intelligence techniques. J. Food Eng., 118, 70–77, (2013).
12. Zhang, Y.; Wang, S.; Ji, G.; Phillips, P.: Fruit classification using computer vision and feedforward neural network. J. Food Eng., 143, 167–177, (2014).
13. Khanmohammadi, M.; Karami, F.; Mir-Marqués, A.; Garmarudi, A.B.; Ga rigues, S.; de la Guardia, M.: Classification of persimmon fruit origin by near infrared spectrometry and least squares-support vector machines. J. Food Eng., 142, 17–22, (2014).
14. Chaivivatrakul, S.; Dailey, M.N. Texture-based fruit detection. Precis. Agric., 15, 662–683, (2014).
15. Muhammad, G.: Date fruits classification using texture descriptors and shape size features. Eng. Appl. Artif. Intell., 37, 361–367, (2015).
16. Mureşan, Horea, and Mihai Oltean.: Fruit recognition from images using deep learning. Acta Universitatis Sapientiae, Informatica 10.1, 26-42, (2018).
17. Siddiqi, Raheel: Effectiveness of Transfer Learning and Fine Tuning in Automated Fruit Image Classification. Proceedings of the 2019 3rd International Conference on Deep Learning Technologies. ACM, (2019).
18. Alzubaidi, L., et al.: Deep learning models for classification of red blood cells in microscopy images to aid in sickle cell anemia diagnosis. Electronics **9**(3), 427 (2020).
19. Alzubaidi, L., Fadhel, M.A., Oleiwi, S.R., et al.: DFU_QUTNet: diabetic foot ulcer classification using novel deep convolutional neural network. Multimed. Tools Appl. **79**, 15655–15677 (2020). https://doi.org/10.1007/s11042-019-07820-w.
20. Schmidhuber, Jürgen: Deep learning in neural networks: An overview. Neural networks 61, 85-117, (2015).
21. Fadhel, M., et al. "Recognition of the unripe strawberry by using color segmentation techniques." International Journal of Engineering & Technology 7.4 (2018): 3383-3387.
22. Al-Shamma, O., et al.: Boosting convolutional neural networks performance based on FPGA accelerator. In: International Conference on Intelligent Systems Design and Applications. Springer, Cham (2018).
23. Alzubaidi, L., et al.: Optimizing the performance of breast cancer classification by employing the same domain transfer learning from hybrid deep convolutional neural network model. Electronics **9**(3), 445 (2020).
24. Alzubaidi, L., et al.: Towards a better understanding of transfer learning for medical imaging: a case study. Appl. Sci. **10**(13), 4523 (2020)