Apple Classification Based on MRI Images Using VGG16 Convolutional Deep Learning Model

D. Vidya[1](✉), Shivanand Rumma[2], and Mallikarjun Hangargi[3]

[1] Department of Computer Science, Govt Women's First Grade College, Kalaburagi, Karnataka, India
vidyasarvottam80@gmail.com

[2] Department of Computer Science, Gulbarga University, Kalaburagi, Karnataka, India

[3] Department of Computer Science, Karnataka Arts, Science, and Commerce College, Bidar, Karnataka, India

Abstract. Apples are considered one of the healthiest fruits worldwide. With the increase in demand for apple, internal quality checking is a most challenging task. In Digital Image Processing different computer vision technologies are used to identify external defects like color, shape, and texture. MRI of apple fruit is the most effective non-destructive and non-invasive method to identify internal defects. In our present study, we have used our own dataset of 196 MRI images of apples. Further, these images are divided into 80:20 for training and testing. These images are classified by using the pre-trained deep learning model VGG16 and with this model, we got 66.21% of validation accuracy and 62.5% of testing accuracy.

Keywords: Apple · VGG16 · Magnetic Resonance Imaging (MRI) · Deep learning

1 Introduction

Apples are the most demanding fruits as health awareness increases around the world. Maintaining the quality parameters in apple is the most challenging task. The external defects like color, size, and texture can be identified using different computer vision technologies [1]. The most challenging task is to detect the internal defect of the apple without harming the fruit. There are different non-destructive technologies are available to detect internal defects in agricultural products like X-ray, sonography, MRI, etc. Whereas Magnetic Resonance Imaging methodology (MRI) is the most accurate and non-invasive and non-destructive technology used to identify internal defects in agricultural products. The analysis of these resulted images and data is carried out manually for a small number of samples. To overcome this issue there are many different robotic methodologies has been applied like Digital image processing for a large number of sample analysis.

In Digital image processing many machines vision-based technologies have been developed to detect defects in agricultural products. Most of the research has been

R. Manza et al. (Eds.): ACVAIT 2022, AISR 176, pp. 114–121, 2023.
https://doi.org/10.2991/978-94-6463-196-8_10

do developed in deep learning technology to identify defects and classify agricultural products most accurately.

Deep learning networking models made drastic growth in digital image processing for classification problems. Mainly Convolutional Neural Networks (CNNs) [2] are broadly used because of their capability to successfully share parameters among different layers inside the deep network model. Various CNN network models have been proposed. Whereas, VGG16 is the simplest network model used for fewer datasets for classification problems.

In our present work, we proposed a VGG16 model for the classification of good and defective apples using MRI images of apples by which we secured 66.2% of validation accuracy and 62.5% of testing accuracy.

2 Literature Survey

Many research has been carried to detect internal defects in agricultural products.

Boan Zion et al., (1995) [3] proposed a technique to identify bruises in apples using the magnetic resonance images (MRI) technique, the author used different sequences of pulse methods to investigate temporal changes in MRI images between bruised & unaffected areas of flesh. They also reported that there is a creased trend between the time contrast of bruised and non-bruised regions in flesh.

Ebrahimnejad Hamed et al. (2018) [4] reviewed the use of magnetic resonance imaging (MRI) in the quality control of food products. The author observed that MRI allows the structure of agricultural products to be imaged non-invasively & non-destructively. This review provides an overview of the most prominent applications of MRI in agriculture. Many advance technologies are available in digital image processing to detect defects in agricultural products. Cheng-Jin Du and Da-Wen Sun (2004) [5] reviewed new advances in digital image processing technology for food product quality evaluation. Anita Raghavendra et, al., (2021) [6] developed a non-destructive technology Near-Infrared spectroscopy (NIR). The author used the wavelength selection method to classify defective and good-quality mango fruits. Mango datasets are collected by using the NIR methodology with a range of wavelength 673 nm–1900 nm. The author used Euclidean distance measure to classify fruits. Different selective technologies are included in the study among which the experiment proved that Fisher criterion-based methods were found to be the good technology for better wavelength selection. With this method, they got 84% of accuracy.

Convolutional Neural Network (CNN) is considered the best network model to use in deep learning methodology to classify images. There are different CNN models used for better classification of images among which VGG models are considered the best models to classify fewer datasets.

Srikanth Tammina [7] developed a VGG16 deep convolutional model for the classification of images of Dogs and Cats. A small set of training samples are used to study the model. With fine-tuned VGG16 CNN model they got a training accuracy of 82% and validation accuracy of 95.40%.

Zabit Hameed et al.,[8] made a study on the classification of non-carcinoma and carcinoma breast cancer histopathology images. The author developed VGG16 and VGG19

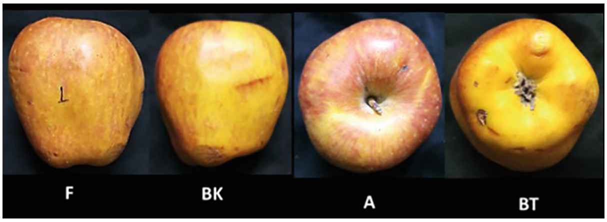

Fig. 1. Apple photography in different directions. (F: Front, BK: Back, A: Arial, BT: Bottom)

deep neural network models. Four trained models are used based on VGG16 and VGG19 pre-trained architectures. Initially, an operation called 5-fold cross-validation is used, namely, fully-trained and fine-tuned VGG16 models. They use an ensemble strategy with an average value of predicted values of probabilities. The author proved that fine-tuned VGG16 and VGG19 ensemble strategies performed good classification. By using VGG16 and VGG19 models, an overall accuracy of 95.29% was obtained.

Edmer Rezende et al.,[9] used the VGG16 deep network model for the classification of thousands of images occurring in malicious software. ImageNet dataset is used for pre-trained VGG16 neural network feature extraction. For experimental purposes, the author used a dataset of 10,136 image samples comprising 20 different families. The author showed that the model can be effectively used to classify malware families got an accuracy of 92.97%.

Shazzadul Islam et al.,[10] used the VGG16 model for feature extraction in Bird species. For experimental purposes collected 1600 images of 27 species of birds from Bangladesh. VGG16 model is used for feature extraction in bird species and then different classifiers like SVM, KNN, and Random Forest algorithms are used to classify bird species.

3 Materials and Methods

3.1 Dataset

21 Apples were collected from the local supermarket. All apples are numerically numbered. Depending on morphological appearance color photographic images are taken from different angles front, back, arial, and bottom (Fig. 1). Then apples were subjected to MR scanning. MR images were obtained using 1.5 T Sieman's Magnetom Spectro MR machine with T2- weighted MR images with a repetition time (TR) of 8980 and Spin echo time of 100.2 with slice diameter of 116.7mm and interslice gap of 8.0mm, which leads to a total of 196 MR images. MRI images were analyzed using RadiAnt DICOM Viewer (64-bit) software. After MR scanning apples were cut into two halves vertically and color photographic images were taken and a manual comparison study was carried out between colored and MRI images (Figs. 2 & 3).

3.2 VGG Model

VGG architecture was proposed by "Simonyan and Zisserman in a Visual Geometry Group of Oxford University" [11]. VGG16 model is having 16 layers containing tuneable

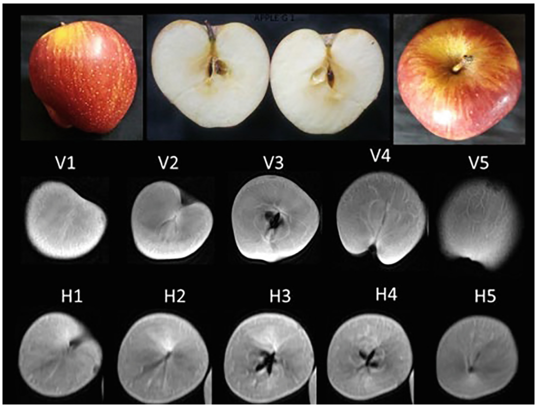

Fig. 2. Photographic images and MR images of good apples

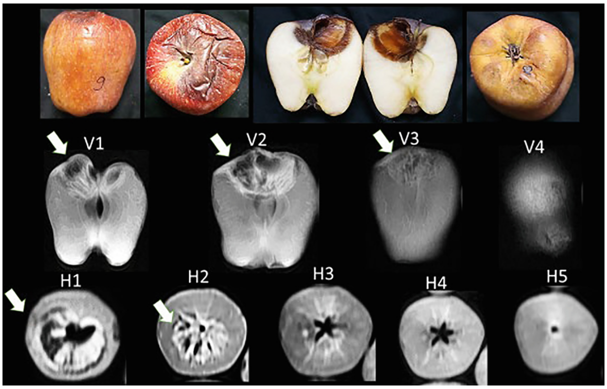

Fig. 3. Photographic images and MR images of defective apples.

parameters. The network model of the VGG16 model is shown in Fig. 4. It contains 13 Convolutional layers used to extract only relevant features from the image. This layer uses a mathematical formula to extract high-level features like color, edges, gradient orientation, etc. Each convolution is followed by one Maxpooling layer used to reduce the dimensionality of the image. The model contains three fully connected layers at the end. The size of the image is fixed to 224 × 224 which passes through the stack of the convolutional layer. Every convolutional filter has a small receptive field 3x3, stride 1. Max pooling layers use 2 × 2 kernels with a stride of 2 followed by the Softmax layer and the output layer (Sixteenth layer) containing 1000 units. The hidden layer in the Convolution layer has Relu as an activation function.

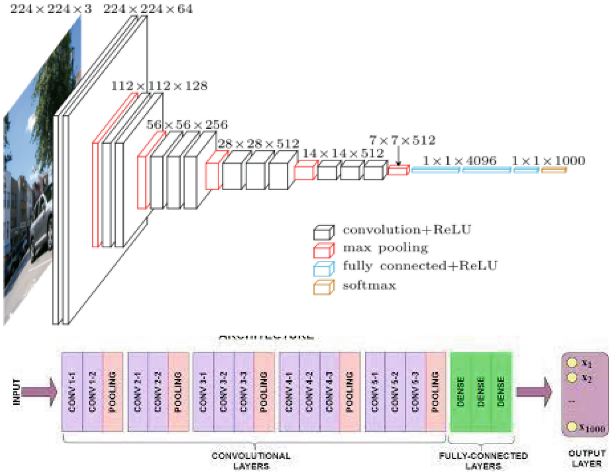

Fig. 4. VGG16 Convolutional network architecture. Source: https://towardsdatascience.com/step-by-step-vgg16-implementation-in-keras-for-beginners-a833c686ae6c"

4 Results and Discussion

For experimental purposes total of 196 MR images are divided into 80% for training and 20% for testing. VGG16 model was built using the python toolbox in the google colab platform. The model is tuned with better hyperparameters like the number of epochs, learning rate, and dropout rate to get better results (Table 1). The model summary is shown in Fig. 5. The first two input layers contain 2 convolutional layers and 1 Maxpooling layer followed by the next 3 convolutional layers and 1 Maxpooling layer and so on. The overall model consists of 13 convolutional layers and 5 Maxpooling layers and 3 activation layers.

$$\text{Total of 13 Convolutional layer} + 3\ \text{Activation layer} = 16\ \text{layers}$$

The resulting history of the model is shown in Fig. 6. After building the model, Modelcheckpoint methods are called from Keras. The Modelcheckpoint method helps to monitor the model with specific parameters. In our model validation accuracy is monitored using the Modelcheck point method and a prediction of apples are made after

Table 1. Hyperparameters for VGG16 model

Hyperparameters	Value
Epochs	72
Batch size	10
Activation function	ReLu
Learning Rate	0.5

building the model (Fig. 7). With this VGG16 deep network, we got 66.2% of validation accuracy and 62.5% of testing accuracy.

Layer (type)	Output Shape	Param #
input_1 (InputLayer)	[(None, 224, 224, 3)]	0
block1_conv1 (Conv2D)	(None, 224, 224, 64)	1792
block1_conv2 (Conv2D)	(None, 224, 224, 64)	36928
block1_pool (MaxPooling2D)	(None, 112, 112, 64)	0
block2_conv1 (Conv2D)	(None, 112, 112, 128)	73856
block2_conv2 (Conv2D)	(None, 112, 112, 128)	147584
block2_pool (MaxPooling2D)	(None, 56, 56, 128)	0
block3_conv1 (Conv2D)	(None, 56, 56, 256)	295168
block3_conv2 (Conv2D)	(None, 56, 56, 256)	590080
block3_conv3 (Conv2D)	(None, 56, 56, 256)	590080
block3_pool (MaxPooling2D)	(None, 28, 28, 256)	0
block4_conv1 (Conv2D)	(None, 28, 28, 512)	1180160
block4_conv2 (Conv2D)	(None, 28, 28, 512)	2359808
block4_conv3 (Conv2D)	(None, 28, 28, 512)	2359808
block4_pool (MaxPooling2D)	(None, 14, 14, 512)	0
block5_conv1 (Conv2D)	(None, 14, 14, 512)	2359808
block5_conv2 (Conv2D)	(None, 14, 14, 512)	2359808
block5_conv3 (Conv2D)	(None, 14, 14, 512)	2359808
block5_pool (MaxPooling2D)	(None, 7, 7, 512)	0
dropout_3 (Dropout)	(None, 7, 7, 512)	0
flatten (Flatten)	(None, 25088)	0
dropout_4 (Dropout)	(None, 25088)	0
dense_2 (Dense)	(None, 1)	25089

Total params: 14,739,777
Trainable params: 25,089
Non-trainable params: 14,714,688

Fig. 5. Model summary

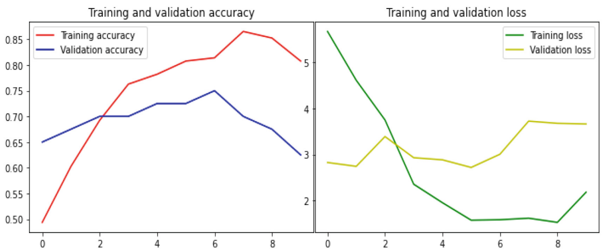

Fig. 6. Model history

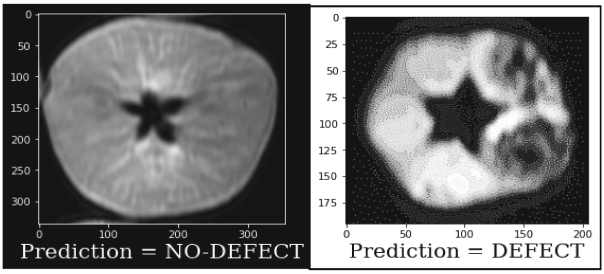

Fig. 7. Model Prediction of apples

5 Conclusion and Future Work

In this study, an experiment was carried out to find the internal defects in apples. A deep learning model VGG16 is used for the classification of defective and good-quality apples. By using the VGG16 network, we achieved 66.2% of validation accuracy and 62.5% of test accuracy. The proposed model is limited to only one fruit and the datasets gathered are fewer. Further, our aim is to improve the number of datasets and use different varieties of fruits and then apply different deep learning algorithms to get more percentage of accuracy.

Acknowledgments. We would like to thank Dr. Kiran Desai, Girish Scanning Center, Kalaburagi, Karnataka, India, for making MRI equipment available for this study.

We also would like to thank Dr. Babasaheb Ambedkar Marathwada University, Aurangabad (MS) India for providing the publication support.

Authors' Contributions. **Vidya D**- Conceptualization, Methodologies, Software writing, Draft preparation.

Dr. Mallikarjun Hangargi- Supervision, Validation, Draft-review, Editing.

Shivanand Rumma-Supervision.

References

1. Komal Sindhi, Jaymit Pandya, and Sudhir Vegad "Quality evaluation of apple fruit: A Survey" *International Journal of Computer Applications* (0975 – 8887) Volume 136 – No.1, February 2016.
2. Lecun, Y.; Bottou, L.; Bengio, Y.; Haffner, P. Gradient-based learning applied to document recognition. Proc. IEEE 1998, 86, 2278–2324. [CrossRef].
3. Boan Zion, Pictiaw Chen, Michael J, McCarthy, Detection of bruises in magnetic resonance images of apples, *Computers and Electronics in Agriculture* 13 (1995) 289-299.
4. Hamed Ebrahimnejad, Hadi Ebrahimnejad,2 A. Salajegheh,3 and H. Barghi. Use of Magnetic Resonance Imaging in Food Quality Control: A Review. *J Biomed Phys Eng*. 2018 Mar; 8(1): 127–132.

5. Cheng-Jin Du and Da-Wen Sun. Recent developments in the applications of image processing techniques for food quality evaluation. *Trends in Food Science & Technology* 15 (2004) 230–249.
6. Anitha Raghavendra, D.S. Guru, Mahesh K. Rao "Mango internal defect detection based on optimal wavelength selection method using NIR spectroscopy", Artificial Intelligence in Agriculture 5(2021) 43–5.
7. Srikanth Tammina," Transfer learning using VGG-16 with Deep Convolutional Neural Network for Classifying Images" , International Journal of Scientific and Research Publications, Volume 9, Issue 10, October 2019 143 ISSN 2250–3153.
8. Zabit Hameed , Sofia Zahia , Begonya Garcia-Zapirain , Jose Javier Aguirre and Ana Maria Vanegas, "Breast Cancer Histopathology Image Classification Using an Ensemble of Deep Learning Models", Sensors 2020, 20, 4373; doi:https://doi.org/10.3390/s20164373
9. Edmar Rezende, Guilherme Ruppert, Tiago Carvalho , Antonio Theophilo , Fabio Ramos and Paulo de Geus, " Malicious Software Classification using VGG16 Deep Neural Network's Bottleneck Features".
10. Shazzadul Islam, Sabit Ibn Ali Khan, Md. Minhazul Abedin, Khan Mohammad Habibullah, Amit Kumar Das, "Bird Species Classification from an Image Using VGG-16 Network", ICCCM 2019, July 27–29, 2019, Bangkok, Thailand © 2019 Association for Computing Machinery. ACM ISBN 978–1–4503–7195–7/19/07
11. K. Simonyan and A. Zisserman, "Very deep convolutional networks for large-scale image recognition,"arXiv preprint arXiv:1409.1556, 2014.