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Internal Defect Identification and Classification of Apple Using MRI Images Based on Convolutional Neural Network (CNN) Deep Learning Model

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***Abstract* - Apples are considered as most cultivated and consumed fruits worldwide. The quality evaluation is a highly challenging task. Presently, Digital Image Processing technology is used to detect external defects such as the shape, size, color, and texture of the apple fruit, whereas identifying the internal defect of an apple becomes a more tedious task. In this current study, an effort was made to detect the internal quality evaluation of apple fruits using the Magnetic Resonance Imaging (MRI) method. A total of 21 apples were subjected to MRI scanning by which we got 196 MRI images. Manually these MRI images are analyzed and classified as healthy and defective samples. Then, these MRI image datasets were divided into 60:40 as training and testing datasets respectively. The deep learning approach has been employed to classify apples. In our study, we developed Convolutional Neural Network (CNN) to classify healthy and defective apples and achieved 67% of accuracy.**

Index Terms - Apple, Digital Image Processing, Convolutional Neural Network (CNN), Magnetic Resonance Imaging (MRI).

INTRODUCTION

India is an agricultural-based country. Most of the economy of India is interdependent on the agricultural sector. Apple is considered as all seasonal fruit and the most demanding fruit because of its high nutritional value. In India Jammu and Kashmir, Himachal Pradesh is the state where apple is primarily cultivated. It grows around 1500-2700m above sea level in hill stations [1]. Apple fruit is exported to over 75 countries from India. The total volume of export in 2020-21 was around 30 thousand metric tons [1]. The quality of apples should be retained to increase its export, the defective apples should be spotted and removed before they are released in the market [2]. The external defect like texture, color, and size can be very effectively detected in digital image processing using biomolecular sensing technology, imaging hyperspectral techniques, imaging multispectral technology, and machine traditional vision technology [3]. Several studies in deep learning have been carried out to detect external defects in fruits using CNN, but there was less research has been done in digital image processing to detect internal defects in fruits. However, some imaging techniques arise after the 1980s to check the internal quality of agricultural products like X-rays, Sonography, etc. In the medical field to diagnose the severity of the disease in the patients MRI scanning was done because of its non-invasive and non-destructive nature. Whereas, in the field of agriculture digital image processing is not been applied on MRI images of fruits to detect internal defects. In our current study, a deep learning model CNN has been developed to detect an internal defect of apple and also to classify healthy and defective fruit using MR images of apple.

RELATED WORK

Author in [4] reviewed current advances in digital image processing methodology for evaluation of the quality of fruit. A survey in [5] is made on the availability of different non-destructive technologies such as X-ray, NIR, Sonic/ Ultrasonic methods to detect the internal defects of agricultural products. The author also discussed the advantages and disadvantages of these technologies.

The author in [6] proposed the finding of bruises in magnetic resonance images (MRI) of apples by using dissimilar pulse arrangement methods to examine chronological variations in MRI image dissimilarity in bruised & disinfected parts of the flesh. The author also stated that contrast between infected and dis-infected sections was found with time.

An application of MRI for Braeburn apple's tissue analysis is done in [7] . In this study, small samples of Braeburn apples were investigated with field MRI to identify the dissimilar tissue structures types. The author focused on MRI images for tissue classification using inner and outer cortex tissue and described the interior superiority faults such as holes, worms damage, or bruising & their alterations when time is passed.

A review of current challenges in the MRI methodology for agriculture products is made in [8]. MRI scanning is a significant technology to get a different variety of measurements to evaluate growth rate and quality constraints in agricultural and other food resources to improve the fundamental biological parameters. MRI scanning method is considered as the best method over last decades and Magnetic Resonance Imaging gives the structure of food to be imaged non-destructively, Since MRI does not produce any damaging radiation, it can be taken as an effective device for analysis of food products qualities [9].

Different computer vision technologies used to detect the internal quality of fruit are discussed in [10]. Color image of tomato fruit is taken for observation, defective skin is calculated using different image processing methods. If the value of the pixel is less than the threshold then it is considered a defective one otherwise it is taken as good quality fruit. Open CV/ Python application is used for implementation.

A combined CNN and LSTM deep learning model is applied in [11] and got 98.17% of classification accuracy after 50 epochs. The author used CNN classifier to classify a set of 6519 pomegranate fruits into normal and abnormal. of classification accuracy after 50 epochs.

CNN model was used in [12] for the classification of three varieties of fruits Apple, Banana, and Orange. The dataset contains a total of 443 images of apples, 363 images of oranges, and 231 images of bananas. CNN model was trained using Tensorflow with Mobilenet V2 implementation provided by Keras and succeeded with 95% of accuracy.

A CNN model was proposed in [13] to classify fresh and rotten fruits. The author used bananas, orange, and apple fruits for experimental purposes. The model was built with 16 convolutional filters of size 3 x 3. The total dataset is divided into three groups for training 60% and for validation 10% and for testing 30%. This model uses the Adam optimizer got 97.82% accuracy and with RMS prop got 85.64% of accuracy.

It has been observed that a lot of research has been done in biological science to detect internal defects without destructing fruits using MRI images because of its non-destructive and noninvasive nature. In digital image processing CNN model was used to detect external defects of fruits. In our proposed methodology, internal quality analysis was done using MRI images of apple fruits, and the CNN model is developed to classify healthy and defective apple fruits.

MATERIALS AND METHODS:

I. Dataset Preparation:

21 Delicia apples were brought from the local market. Firstly photographic pictures of each apple are taken in all angles Front, Back, Bottom, and Arial (Fig 1). Individual Apples were subjected to vertical and horizontal MRI scanning (Fig 2 & 3). MR images were obtained using 1.5 Tesla Sieman's Magnetom Spectro MR machine with T2- weighted MR images with a recurrence period (TR) of 8980 and Spin echo period (TE, the period during which sample magnetization dephases and then rephrases) of 100.2 with slice diameter of 116.7mm and interslice gap of 8.0mm. The total number of slices for all channels ranges from 9 to 33, leading to 145 images. The pixel size of each image was 512 X 512 (Table 1). The images are grayscale. MR image production period depends on the resolution, the higher the needed resolution the more acquisition are mandatory for image production and the lengthier it acquires to get an image. MRI images were analyzed using RadiAnt DICOM Viewer (64-bit) software.

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

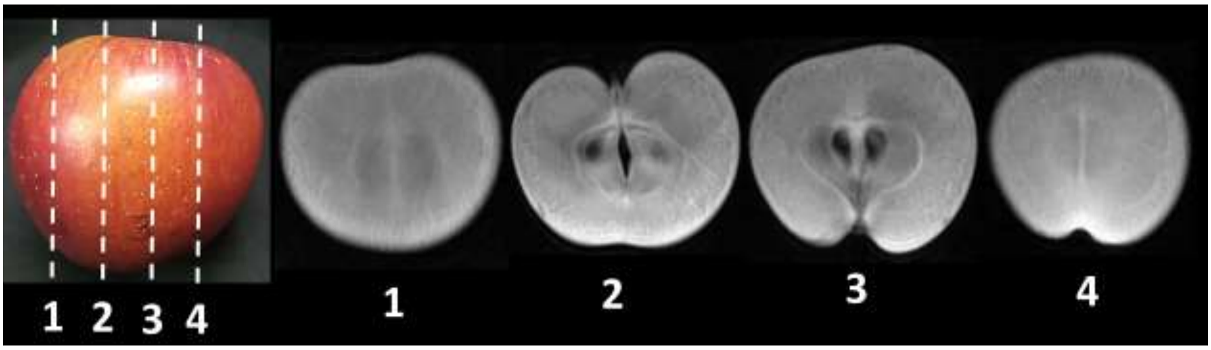


Fig 2: Apple's vertical slices of MRI images.

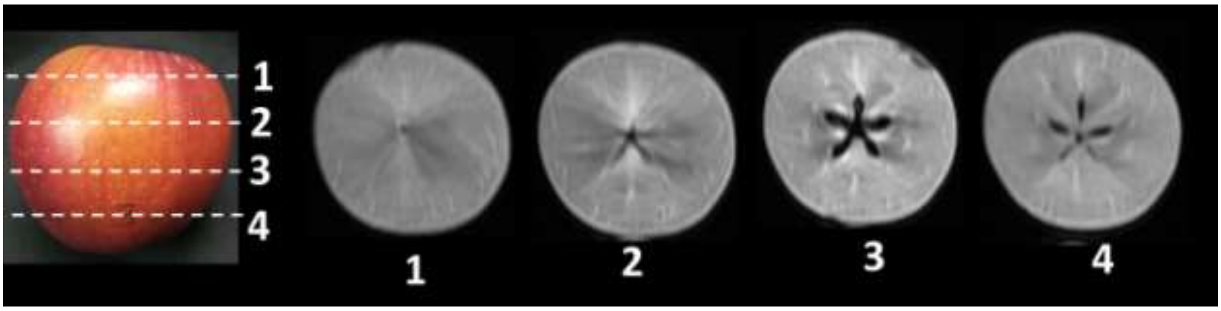


Fig 3: Apple's horizontal slices of MRI images.

Table 1: MRI scanning parameters.

Method	Parameters
Machine	1.5 Tesla Sieman's Magnetom Spectro
TR	8980
TE	100.2
Slice diameter	100.2
Slice gap	8.0mm
Image size	512 x 512

Convolutional Neural Network (CNN):

CNN is a category of neural network which mimics a biological neural network. It is considered as the subset of machine learning and the heart of deep learning neural networks. CNN is composed of a number of hidden layers each node connected to another node associated with weights and threshold [14]. CNN model is used for image classification, image recognition, etc. And an ideal model is composed of several layers such as Convolutional layer, Pooling layer, Fully connected layer, ReLu, Dropout layer, and Classification layer as shown in Figure 4.

Convolutional layer: This is the first layer, it takes input images and reduces the size of images by extracting various features from images. The convolution layer applies convolution operation to the input image and passes it to the next layer. It reduces the size of the image from the matrix into a vector bringing all information into a single pixel. Between the input image and filter of size M x M, a mathematical operation was performed [11] to extract features like edges and corners. The output of this layer contains information about the edges and corners of images. The mathematical operation convolution layer is:

$$F(i, j) = (I * K)(i, j) = \sum\sum (i+m, j+n) K(m,n) \quad (1)$$

Where I is input matrix K is 2D filter and F is the output of 2D feature map

Pooling layer: It is also called as downsampling layer and it is used for dimensionality reduction purposes. The working of the Pooling layer is the same as the convolutional layer only difference is that it does not contain weights. Pooling layers are further classified into two types:

Max pooling: As this filter is applied on the input image, It selects the maximum value pixel to send to the output array.

Average pooling: As this filter is applied across the input image, it computes the average value to send to the output array.

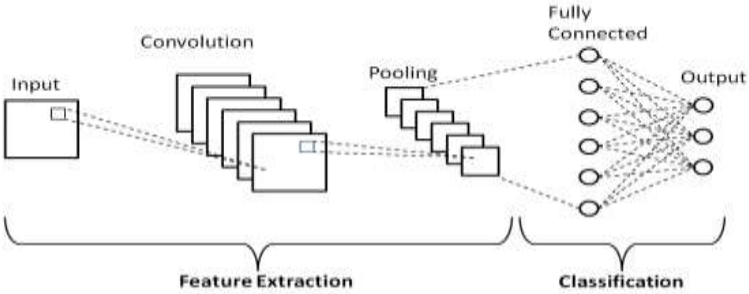
Fully connected layer (FC): In this layer, each node in the input layer is connected with each node of the previous layer[11]. In this layer feature extraction is performed from the previous layer and classification is done based on previous learning.

Rectified Linear Unit (ReLu): This layer exists after the convolutional layer. It consists activation function which takes positive input from the previous layer passes it to the next layer. If the input is negative then output is zero. The activation function of the ReLu layer

$$f(x) = max(0, x) \quad (2)$$

Dropout layer: Drop out layer exists after the FC layer, it removes the overfitting on the training data. Dropout deactivates some layers from the hidden layer as a result nullifies contribution to the output.

Classification layer: This is the layer where exact classification takes place, it comes after fully connected layer and it is the main layer where image identification takes place.



(Figure 4: Network of CNN model)

EXPERIMENTAL RESULTS AND DISCUSSION

I. Dataset Acquisition:

only 21 apple fruits were able to scan and a total of 196 MRI slices were acquired by RadiAnt DICOM Viewer (64-bit) software. As observed manually from the MRI images fruits were categorized into two groups Group 1 is having fruits that are seen as healthy and no defect observed externally as well as internally (Fig 5) as compared with photographic as well as MRI images. Group 2 has fruits containing defects externally and internally when compared with photographic and MRI image slices (Fig 6). Defect severity is also being calculated based on the coverage area of the defect and color intensity in the MRI images.

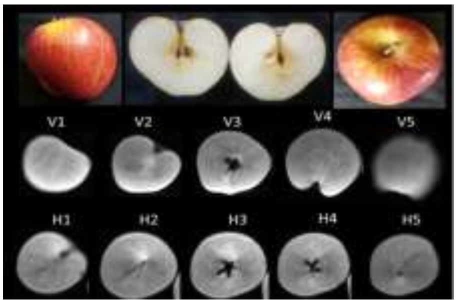


Fig 5: No defects found externally as well as internally.

Fig 6: Apple has defects externally as well as internally.

The dataset includes a total of 196 MR images including healthy and defective ones as given in Table 2.

Table 2: Dataset details

Name	No. of Images
Healthy	128
Defective	68

II. B. Experimental Setup:

For experimental purposes, among 196 MRI images, 60% were used for training purposes, and the remaining 40% were used for testing purposes. CNN model was built using python toolbox in the Google Colab platform. Hyperparameters of the model like the number of epochs, learning rate, and dropout are tuned to the best value to get better results .

III. The number of epochs:

An epoch represents the number of iterations taken by a machine to get the entire training dataset [23]. One epoch means when the entire dataset moves backward and forward through the network. The number of epochs needed to run the model depends on the number of the training dataset. In our model, we have used 20 epochs to run the model successfully.

IV. Batch size:

Batch size defines total amount of datasets fed into the model. The whole dataset cannot be passed into the model at once so datasets are divided into a number of batches. In our model, the batch size was 5 per epoch.

V. Activation function:

The activation function decides the output. This function is used to deactivate some hidden layers taken from the previous layer[13]. Activation functions can be used anywhere in the model. In our model, we used two activation functions ReLu and Sigmoid. ReLu (Rectified Linear unit) takes only positive inputs from the previous layer and passes into the next layer and in other cases it outputs zero. A sigmoid function is used after the dense layer. Sigmoid layer predicts the probability of output that exists between (0,1), since the probability of anything exists between (0,1) so sigmoid is the better choice.

VI. Dropout Rate:

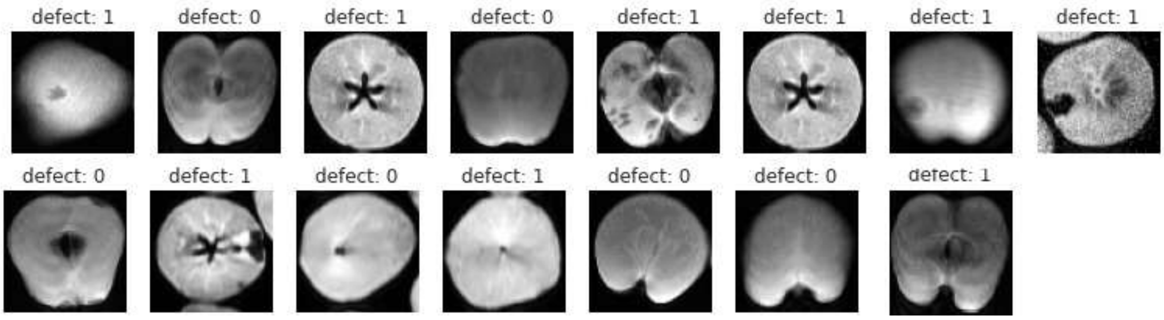
The model will drop out some nodes during the training to fit the model [9], it prevents the model from overfitting. The dropout rate that exists between (0,1), our model dropout rate was 0.5.

CNN model hyperparameters are summarized in Table 3.

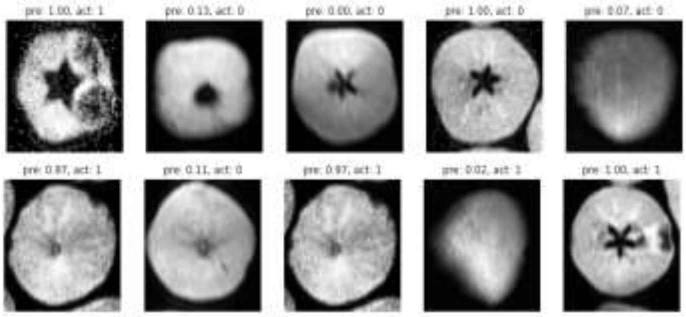
Table 3: Hyperparameters of CNN training model

Hyperparameters	**Value**
Epochs	20
Batch size	5
Activation function	ReLu, Sigmoid
Dropout rate	0.5

Initially, before building CNN model MRI images of healthy and defective apples were numbered as 1(healthy) and 0(defective) as shown in Figure 7. Then the model is built and fruits are classified and we got classification accuracy 67% and images are labeled with the prediction values range from 0 to 1 as shown in Figure 8. The model history is shown in figure 10.



(Fig 7: Fruits with defect=1 and without defect=0)



(Fig 8: predicted results after prediction values ranges from 0 to 1 actual 0 to 1)

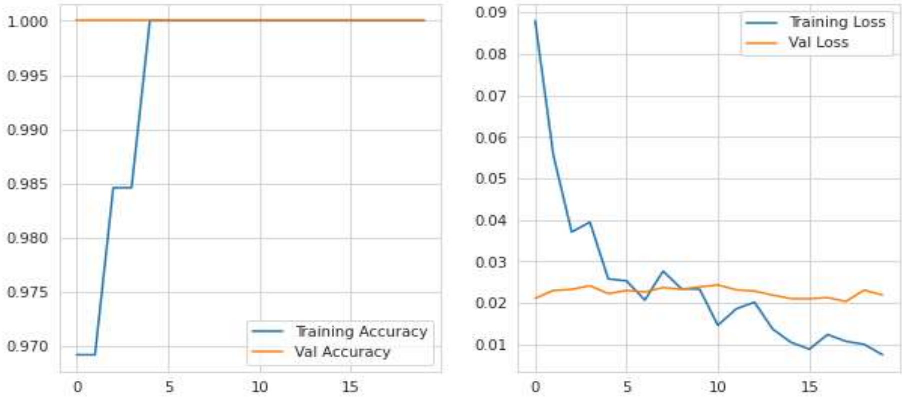


Fig 9: Model history

VII. . Evaluation of performance:

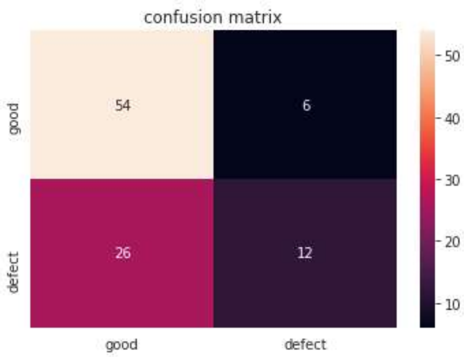
Confusion matrix is a 2 x 2 matrix used to evaluate the model [27] on test data. It consists of 4 different parameters used for the analysis correctly predicted and actual values. Accuracy of confusion matrix denotes the number of samples that are correctly classified. The model is evaluated using confusion matrix and we got 67% accuracy. The meaning of different parameters are confusion matrix is described below:

TP (True Positive) – "No of samples predicted positive and it was true".

TN (True Negative) – "No. of samples predicted negative and it was true".

FP (False Positive) – "No. of samples predicted positive and it was false".

FN (False Negative) – "No. of samples predicted negative and it was false".



$$\text{Accuracy} = \frac{\textit{Total number of images classified}}{\textit{Total number of images used for testing}} \times 100$$

$$\text{Accuracy} = \frac{TP+TN}{TP+TN+FP+FN} = \frac{54+12}{54+6+26+12} = 67\%$$

CONCLUSION AND FUTURE WORK

This entire study was carried out to find the internal quality of apples. A digital image processing technology is used for the classification of defective and good-quality apples. By using CNN methodology, we achieved only 67 percent of test accuracy. The proposed model is limited to only one fruit and datasets gathered are fewer. Further, our aim is to improve the number of datasets and to use different varieties of fruits then to apply different deep learning algorithms to get more percentage of accuracy.

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