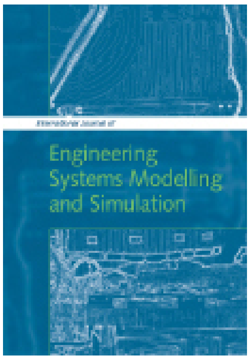

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An efficient fruit quality monitoring and classification using convolutional neural network and fuzzy system

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Abstract: Fruit quality monitoring in agro industries is carried out by people who may deviate from their responsibility due to tiredness, illness, or personal reasons. So, an automatic quality assessment system is proposed based on convolutional neural network (CNN) and Mamdani fuzzy logic that estimate quality of a Persian Lemon. The proposed CNN was trained with the transfer learning method and the results obtained were compared with previous works. The proposed CNN achieved 94.79% accuracy in the validation process which is 13% higher than the existing architecture. The proposed fuzzy logic classified each lemon in three ranges based on rules customised for the estimation of fruit quality standards.

Keywords: fuzzy systems; transfer learning; convolutional neural network; CNN.

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1 Introduction

The Automatic quality assessment process is currently gaining more importance in agro-industries (Albers et al., 2016; Chow et al., 2012; Markkandan et al., 2021). Present this quality assessment process is mostly conducted by people who, during the whole day, due to many reasons such as stress or tiredness may deviate from their work which in turn affect the quality of the product selected. This need arises to develop software that recognises the quality of the product obtained so that they are reliable and suitable for the customer. In quality control operation involving computer vision and logical classification, the combination of convolutional neural network (CNN) and fuzzy logic is ideal. CNNs (O'Shea and Nash, 2015) have found wide application in computer vision areas covering object detection and image classification. After the entry of AlexNet (Suresh et al., 2021), deep convolutional networks have become acceptable in many interesting applications. The diversification of similar networks with neural backgrounds has been substantial. From the Inception module to ResNet (Rajkumar et al., 2021), DenseNet (Perumal et al., 2021) and the ThinNet (Leonid and Jayaparvathy, 2021), the strides have been quite rapid.

The focus of this paper is to choose a suitable CNN to determine the physical state of the fruit (Zeiler and Fergus, 2014). Next, the physical characteristics are extracted by image processing techniques and sensors. Later the classification is done as per Mamdani Fuzzy logic with suitable inputs and outputs. Mexican standard NMX-FF-077-1996 (Banco Nacional de Comercio Exterior, 1996) is used to focus on the classification of the fruit in which classification parameters are given as in Table 1. Based on the size codes, the lemon quality is classified into three categories such as low, medium, and high based on weight and damage percentage on the surface of the fruit.

Table 1 Classification based on diameter

Size code	*Diameter range (mm)*	*Average interval (mm)*
1	58–67	62.5
2	53–62	57.5
3	48–57	52.5
4	46–52	49.5
5	43–46	44.5
6	38–43	40.5

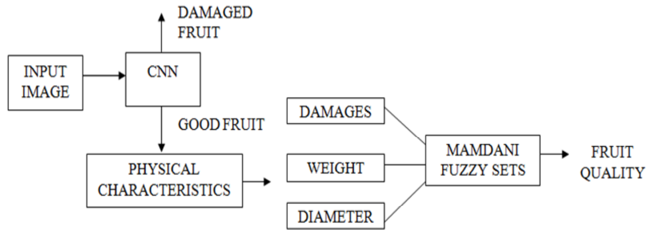
Source: Zeiler and Fergus (2014)

2 Methods

2.1 Quality assessment

There are three parts of the mechanism for the classification of fruits, among which the first part is a CNN which have four stages such as taking the database, adoption of architecture, training process, and verification with test images. The second part is for feature extraction by image processing to determine the damaged area on the exterior of the fruit, size, and weight by sensory devices (Kumarganesh and Suganthi, 2014). The third part is fuzzy systems for classification. Figure 1 shows the operation of the overall algorithm. This work is aimed at quality assessment of Persian lemons, but this algorithm can be applied to any fruits which need quality assessment for its sales.

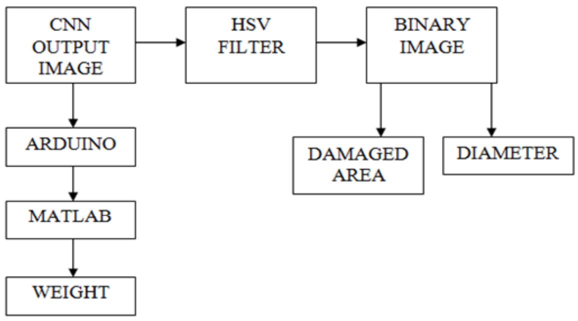
Figure 1 Block diagram of algorithm



To evaluate input images a CNN architecture known as ThinNet has been used because of its high accuracy. The transfer learning algorithm is used to train the CNN and final fully connected layers (Basha et al., 2019) with 2-classifier and softmax layer (Ijomah et al., 2018) were connected for fruit classification. Originally fully connected layer consists of a maximum of 1,000 classifier but in this case, it requires only two to evaluate spoil or good fruits.

The Parsian Lemon dataset has a total number of 320 images, out of which 50% belongs to good lemon and the rest of the 50% were damaged. Each category consists of 160 images out of 110 is for training 30 images are for network testing 20 are for validation to avoid overfitting of the network. The total number of images is divided into five groups to define the size. There were 30 epochs to perform the training of CNN. Overall, 150 iterations had five validations out of which every 30 iterations will be checked to avoid overfitting.

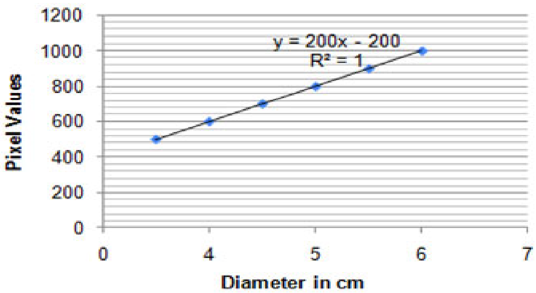
Figure 2 Physical parameters extraction



The block diagram of the second stage of the algorithm is shown in Figure 2. In this stage, the physical parameters of the fruit can be determined in four steps. In the first step, hue, saturation, value (HSV) filter was used with filter configurations of 0.125–0.399 for H, 0.2–1 for S, and 0–1 for V. After the binarised image is generated an area filter is applied to eliminate noise in the image. In the second step, the binary image from the HSV filter is inverted and based on the total number of pixels and small areas which represent defects, the percentage of the defected area can be obtained from equation (1). In the third step, the diameter of the fruit can be identified by formulae which calculate 13 specimens with a certain number of pixels and this must be considered for all the images. These results were tabulated and a graph is drawn between the number of pixels and diameter as shown in Figure 3. To find the weight of the fruit, An Arduino card, which gets an analogue voltage from the battery, is used. The weight obtained by this process is sent to MATLAB for further processing. Once all the above processes were completed the final stage, which is fuzzy classification can be applied to assess the quality of the fruit.

$$\% \text{ of Defects} = \sum \frac{\text{Total Area of Defects}(i) * 100}{\text{Total Surface Area of the Lemon}} \quad (1)$$

Figure 3 Determination of diameter of the fruit based on pixel values (see online version for colours)



2.1.1 CNN architecture

In this work, the CNN used to extract physical characteristics of the fruit is ThinNet. ThinNet is based on YOLOv2 (Redmon and Farhadi, 2017). It frames object detection into a regression problem that separated bounding boxes and class probabilities. As the detection pipeline is a single network, end-to-end optimisation is possible for detection. The operation of ThinNet can be explained in three stages such as,

a resizing of input images to dimensions 416 × 416.

b process ThinNet on the image and predict the probability and sum of multiple bounding boxes and related boxes

c the test result is selected according to the confidence level.

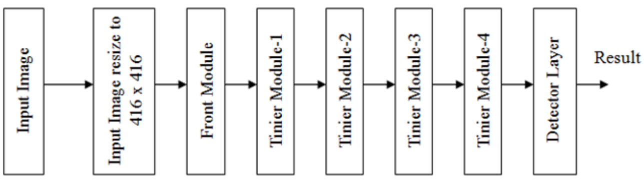
The basic architecture of ThinNet comprises of

1 front module

2 tinier module

3 detector layer as shown in Figure 4.

Figure 4 Architecture of existing ThinNet



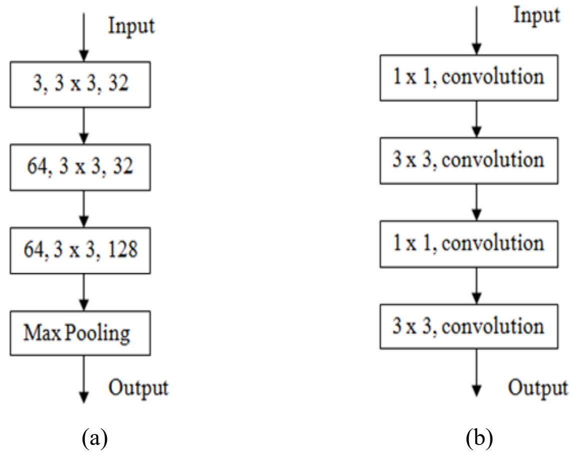
Source: Redmon and Farhadi (2017)

The details of ThinNet architecture with one front and four tinier modules were given in Table 2. In the final detection, a 1 × 1 convolutional layer is used with linear activation. After each Tinier module with the last module, the maximum pooling is performed with stride of 2. For the first Tinier module strength of filters is two 3 × 3 convolution layers of 64 channels. It may be noted that the number of channels is doubling after each pooling. By trial and error in an experimental activity, the number of 1 × 1 filter has 'μ = 0.25' (Leonid and Jayaparvathy, 2021) from the output channels of the preceding module per each Tinier module, where μ is the parameter introduced in ThinNet to reduce the number of convolution parameters.

2.1.2 Front module and tinier module

The state-of-the-art networks have repeated building blocks on a module with identical characteristics. Usually, better-designed blocks attain higher performance with relativity less theoretical complexity. For taking advantage of modular design, the Tinier module and Front module have been designed. Figure 5 shows a Tinier model which consists of two 1 × 1 convolution layers coupled with two 3 × 3 conventional layers. Convenient usage of 1 × 1 layer helps in reducing the dimensions. It may be noted that every convolution layer is linked to batch normalisation and ReLu (rectified linear unit) operations in successive stages. As in many current models, batch normalisation results in substantial improvement in convergence and this obviates what's the need for other regularisation.

Figure 5 Front module and tinier module, (a) front module (b) tinier module



Following patterns of inspectionv3 (Narmatha et al., 2020) and inseptionv4 (Szegedy et al., 2016) front module as shown in Figure 5, can be defined as a stair of three 3 × 3 convolution layers after which 2 × 2 layers of max-pooling are placed. For the 1st convolution layer the stride = 2 whereas for the next two the stride = 1. The single front module improves the performance of detection. This can be explained by the fact that in comparison with the DenseNet with 7 × 7 structure followed by 3 × 3 max pooling, at the end of the front module down sampling is applied and so the layers of evolution can have huge feature maps. It is pertinent to note that due to delayed down sampling larger feature maps can improve the performance as the data loss from the raw input image is reduced.

2.1.3 Modified ThinNet architecture

We modified the existing ThinNet architecture by replacing detector layer with a fully connected layer (Basha et al., 2019) with 2-Classifier and a Softmax layer (Ijomah et al., 2018) as exposed in Figure 6, to classify the fruit as good or damaged.

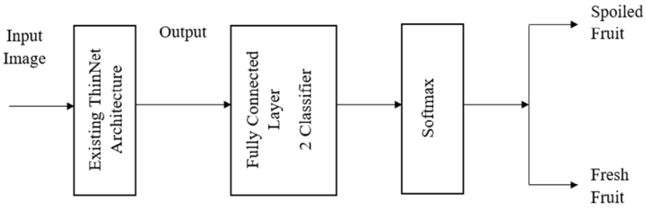
Table 2 Architecture information of existing ThinNet

Type	*Output size*	*Filter size/stride*	$N_{1\times1}$	$N_{3\times3}$
Input image	416 × 416 × 3	$\begin{pmatrix} 3\times3, 32, 2 \\ 3\times3, 32, 1 \\ 3\times3, 64, 1 \end{pmatrix}\times2$		
Front module	104 × 104 × 128		-	-
Tinier1	104 × 104 × 64	$\begin{pmatrix} 1\times1/1 \\ 3\times3/1 \end{pmatrix}\times2$	16	128
Tinier2	52 × 52 × 128	$\begin{pmatrix} 1\times1/1 \\ 3\times3/1 \end{pmatrix}\times2$	32	256
Tinier3	26 × 26 × 256	$\begin{pmatrix} 1\times1/1 \\ 3\times3/1 \end{pmatrix}\times2$	64	512
Tinier4	13 × 13 × 1,024	$\begin{pmatrix} 1\times1/1 \\ 3\times3/1 \end{pmatrix}\times2$	128	1,024
Detector layer	13 × 13 × 125	1 × 1, 125, 1	-	-

Note: $N_{1\times1}$ and $N_{3\times3}$ represents number of 1 × 1 and 3 × 3 filters.

Source: Leonid and Jayaparvathy (2021)

Figure 6 Modified ThinNet architecture for fruit classification



2.1.4 Fuzzy system interfacing

The fuzzy interface system (FIS) is an important unit of fuzzy logic (Kumarganesh and Suganthi, 2018). We used Mamdani fuzzy interface (shown in Figure 8) as it is more spontaneous and easier to realise. This fuzzy system works based on obtained inputs and a series of IF-THEN rules as shown in Table 3 and Figure 7. Membership Functions for input variables damages, weight, and diameter are shown in Figure 9. We assigned triangular membership function (trimf) for input and output variables. Figure 10 shows the response surfaces of the fuzzy system (Thiyaneswaran et al., 2020).

Table 3 If-then rules for fuzzy system

Surface defects	*Weight*	*Diameter*	*Output quality*
Low	High	High	Good
Low	High	Medium	Good
Low	High	Low	Medium
Low	Medium	High	Medium
Low	Medium	Medium	Medium
Low	Medium	Low	Low
Low	Low	High	Medium
Low	Low	Medium	Low
Low	Low	Low	Low
Medium	High	High	Good
Medium	High	Medium	Medium
Medium	High	Low	Low
Medium	Medium	High	Medium
Medium	Medium	Medium	Medium
Medium	Medium	Low	Low
Medium	Low	High	Medium
Medium	Low	Medium	Low
Medium	Low	Low	Low
High	High	High	Good
High	High	Low	Medium
High	High	Medium	Medium
High	Medium	High	Medium
High	Medium	Medium	Low
High	Medium	Low	Low
High	Low	High	Medium
High	Low	Medium	Low
High	Low	Low	Low

Figure 7 If-then rules for fuzzy system (see online version for colours)

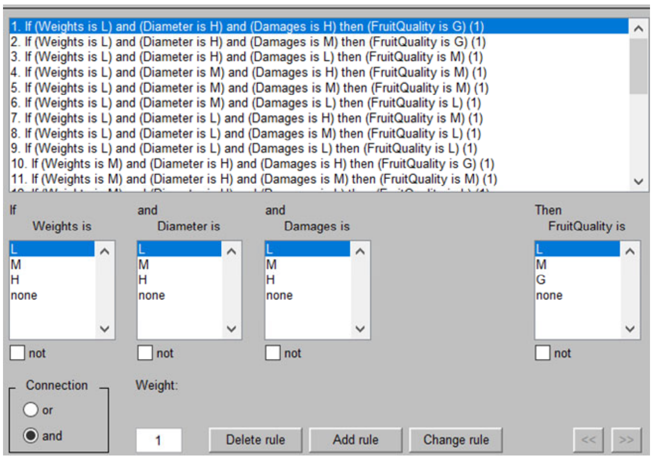


Figure 8 Mamdani FIS (see online version for colours)

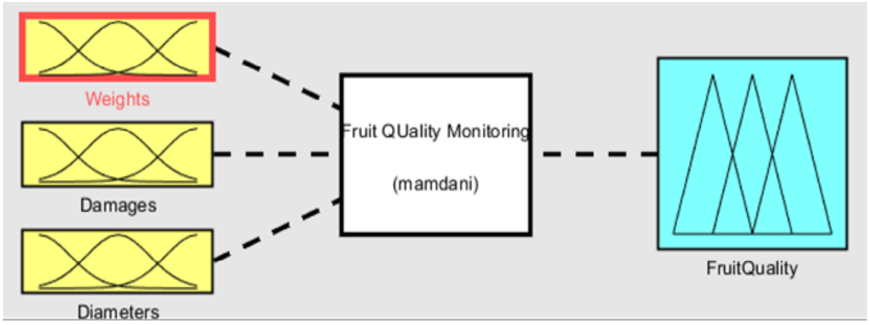


Figure 9 Membership function for input variables damage, weight, diameter and output variable fruit quality (see online version for colours)

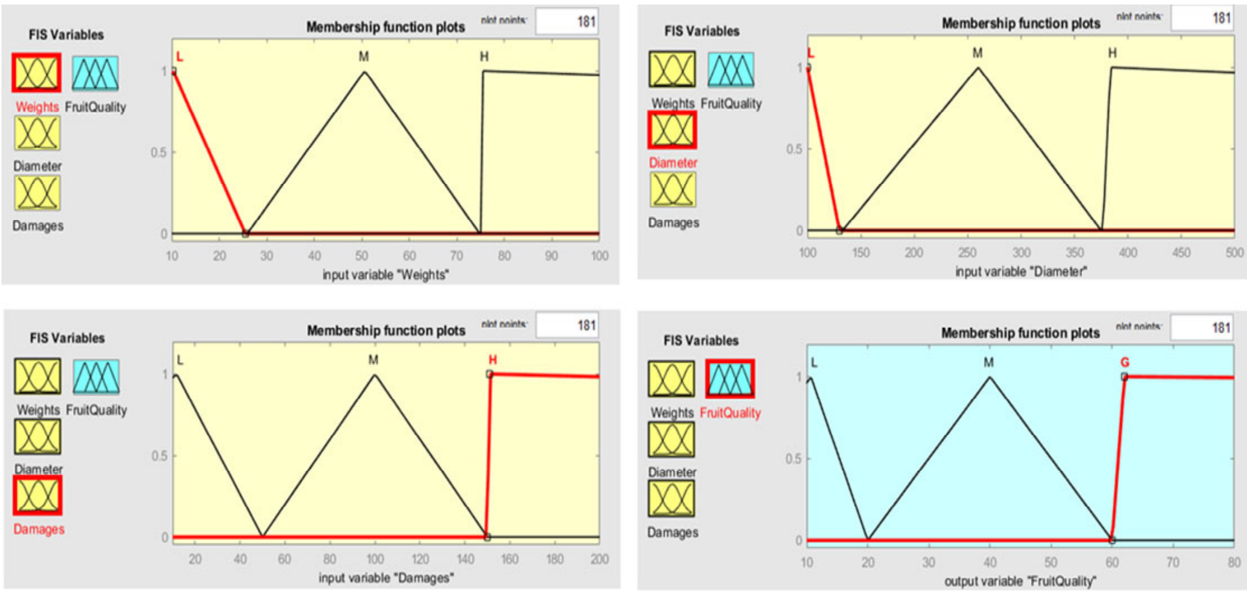
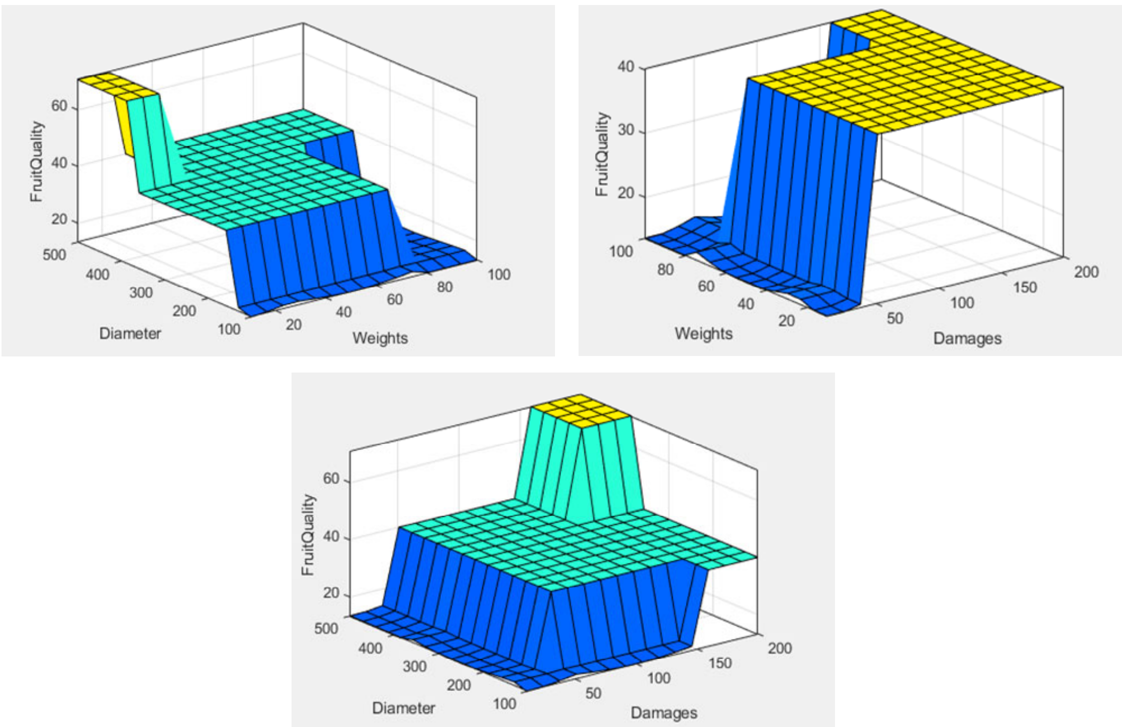


Figure 10 Fuzzy system response surface (see online version for colours)



3 Results

The merits of Modified ThinNet architecture (shown in Table 4) shows that our proposed architecture achieved better accuracy than previous works. The trained CNN provided an average of 67.9% accuracy by considering both Training and Validation. Figure 11 shows the accuracy and loss of CNN while trained for 150 iterations in five batches. Input and Output Images of CNN were shown in Figure 12. A confusion matrix (Figure 13) obtained from training process of CNN, evaluating 50 images shows the classification by the categories was 100% correct.

Table 4 Merits of modified ThinNet architecture

Architecture	*Output layer*	*Purpose*	*Accuracy*
Tiny YOLO	Detector layer	Object detection	63.4%
AlexNet [11]	fully connected layer	Image classification	80.3%
ThinNet	detector layer	Object detection	81.7%
Modified ThinNet (proposed work)	Fully connected layer with 2-classifier and softmax layer	Image classification	94.79%

Figure 11 Increment of accuracy and decrement of loss while training CNN (see online version for colours)

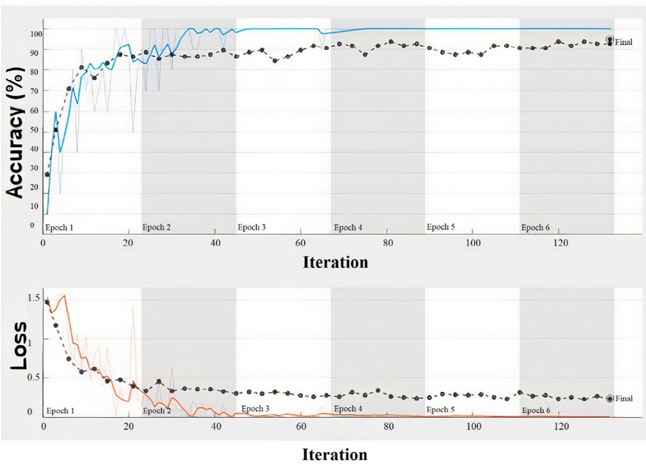


Figure 12 Input and output images of CNN (see online version for colours)

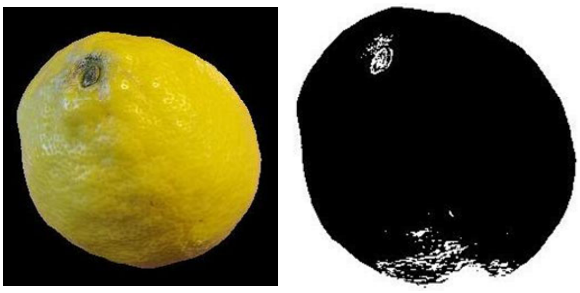
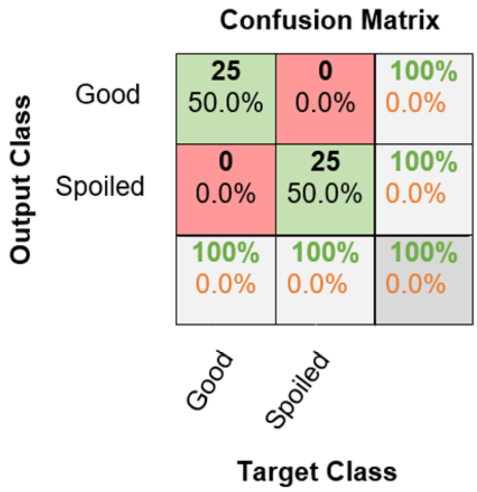


Figure 13 Confusion matrix obtained from CNN training (see online version for colours)



4 Conclusions

The proposed CNN designed with ThinNet architecture, trained with transfer learning method achieved an average of 94.79% of accuracy for the classification of good and damaged fruit. This accuracy can be improved by modifying feature extraction properties if CNN and with image enhancement techniques. The proposed system for physical characteristics extraction of fruit worked properly. The Mamdani FIS classified the fruits accurately by considering all the characteristics into account. This work concentrated on the Persian lemon data set, but, if necessary changes made in CNN, in the feature extraction and Fuzzy system then it can be applied to any kind of product to increase the quality standards of the products.

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