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Deep Learning Model Based on ResNet-50 for Beef Quality Classification

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Abstract: Food quality measurement is one of the most essential topics in agriculture and industrial fields. To classify healthy food using computer visual inspection, a new architecture was proposed to classify beef images to specify the rancid and healthy ones. In traditional measurements, the specialists are not able to classify such images, due to the huge number of beef images required to build a deep learning model. In the present study, different images of beef including healthy and rancid cases were collected according to the analysis done by the Laboratory of Food Technology, Faculty of Agriculture, Kafrelsheikh University in January of 2020. The texture analysis of the beef surface of the enrolled images makes it difficult to distinguish between the rancid and healthy images. Moreover, a deep learning approach based on ResNet-50 was presented as a promising classifier to grade and classify the beef images. In this work, a limited number of images were used to present the research problem of image resource limitation; eight healthy images and ten rancid beef images. This number of images is not sufficient to be retrained using deep learning approaches. Thus, Generative Adversarial Network (GAN) was proposed to augment the enrolled images to produce one hundred eighty images. The results obtained based on ResNet-50 classification achieve accuracy of 96.03%, 91.67%, and 88.89% in the training, testing, and validation phases, respectively. Furthermore, a comparison of the current model (ResNet-50) with the classical and deep learning architecture is made to demonstrate the efficiency of ResNet-50, in image classification.

Keywords: Beef classification, diet and food quality, ResNet50, deep learning, generative adversarial network.

1 Introduction

Beef classification is one of the most important and difficult processes in the food production stages in factories. This is due to the measurements of beef quality that is more recommended and required to search for new methods to classify and determine the healthy and non-healthy food [1]. Consequently, the ancient human-based methods became imprecise and unsuitable in beef factories. Therefore, the progress in scientific methods, whether they are laboratory methods, which are represented in the development of analytical chemistry, has led to the knowledge of food components such as protein analysis, acidity number, and fats, but despite the accuracy of these methods, they are destructive methods and require time, effort and costs [2]. Reliance on those traditional methods is no longer appropriate in beef classification because there are two major challenges in beef classification methodologies. The first one is the colors on the beef surface that are difficult to be recognized using human eyes. The second challenge is the huge number of enrolled images that are required to be classified accurately with minimum elapsed time. Thus, the utilization of computer vision has increased, consisting of several disciplines. The most important of which are image processing, pattern recognition, and Machine Learning (ML).

Practically, computer vision is executed automatically to process images to perform specific tasks, such as detecting and identifying objects in the image [3]. Afterward, the extracted features are enrolled in ML such as Deep Learning (DL) which is performed like human thinking in using and processing data to reach the required decisions [4,5,6,7,8]. More

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especially, the machine has been developed to learn by itself, such as by stimulating the human mind by employing deep learning theories and algorithms [9,10,11,12,13].

Deep learning processes a large amount of data using Deep Neural Networks (DNNs) to obtain information from this data [14,15,16]. It consists of the input layer, hidden layer, an output layer, and a group of neurons, and each neuron has weight. The most common deep neural network is the Convolutional Neural Network (CNN) which is often used to classify images [17]. In recent work, reliance has increased on machine learning models in the field of agriculture in general and identifying food quality in particular, due to the ability of machine learning in the classification process, which is one of the latest developments in computer vision [18,19].

A Residual Neural Network (ResNet) is a type of deep learning network, which is an Artificial Neural Network (ANN) that mimics the biological network and the pyramidal cells in the human cortex [20,21,22,23]. ResNet is more widespread in the field of computer vision, especially after it proved its superiority over Alexnet in terms of image recognition. The researchers developed the residual network by increasing the number of layers to 152 layers, which led to a reduction of the error rate to 3.75 in image classification [24,25,25,27]. Deep learning includes different types of deep learning networks such as the residual network that is used in classification images, the recursive neural network, which processes data such as speech, text, and video, and the convolutional neural network, which is one of the neural networks with a front-feed that is used in image classification [28,29]. Data augmentation technology is a method to enable researchers to diversify new data without actually obtaining data. The data from actual images is the most common methodology used for increasing the accuracy of deep networks for image recognition and classification using optimization algorithms [30,31].

Generative Adversarial Networks (GANs) are a type of machine learning network consisting of two neural networks (generator and discriminator), the purpose of which is to train to differentiate on fabricated similar to real data, which is difficult for a human or mechanical observer to distinguish between them [32]. GAN was used to identify different diseases of plants to improve model learning, which reduces the resulting bias and leads to a better classification process. An artificial image generator optimizes the Reactivation Reconstructive Loss (RRL) to obtain more information or features against natural images. Any object can be described in many different ways. For example, an image can be described on a vector basis of the brightness per pixel, or in an abstract manner based on the sum of the edges and regions that make up the image. Some of these techniques are better than others at simplifying machine learning, such as facial observation or expressive notation [33]. One of the motivations of this study is the utilization of deep learning to extract the beef features and classify the healthy and rancid from the enrolled images.

The Beef color is one of the most important features that is representing beef quality and attracts consumers. The color of beef reflects its quality from red to purple to brown, and the acidity number affects the color of beef, whereas the acidity number affects the growth of microorganisms that cause beef spoilage [34]. Therefore, the main contribution of this work is listed as follows:

- Building a deep learning model based on ResNet-50 to extract the features of the enrolled beef images.
- Classifying the beef images as healthy and rancid based on the extracted features of the ResNet-50.
- Utilization of GAN to expand the beef dataset to make the proposed methodology more reliable and robust.

The rest of the paper is organized as follows, the materials and methods are presented in section 2. The results and discussion are demonstrated in section 3. Finally, the conclusion and perspectives are shown in section 4.

2 Materials and Methods

2.1 Sample preparation

The beef piece was obtained four hours after the slaughtering process, and it was cut into forty samples with a thickness of 0.5mm. The beef samples were stored in a refrigerator at 4°C for ten storage days. The images of beef samples during the spoilage stages were also taken during the chemical laboratory analysis of beef, which represents the analysis of protein by the Keldahl method and estimation of the pH that controls the growth of microorganisms that cause beef spoilage. The chemical analyzes were carried out at the Laboratories of Food Technology Department, Faculty of Agriculture, Kafrelsheikh University, Egypt in January 2020.

Images were taken of eighteen beef samples in the two stages of validity and spoilage of beef with a Charge Coupled Device (CCD) camera (Kodak Easy Share M530). As shown in Figure 1, a camera with 12.2 Megapixels CCD, 3x (36-108 mm) Optical Zoom Lens, 2.7" LCD, ISO up to 1600, and Blur Reduction are utilized to capture the beef images. Video Recording with Audio was used to capture the image of the samples. The accuracy of the camera was calibrated for capturing the images. The samples were taken from ten reference white images where the reflection ratio was found to be 99% and 10 black reference images were taken with a reflection rate of 0%. The following equation (1) was used in calibrating the images [35] such that:

$$M = \frac{I_S - I_D}{I_W - I_D} \times 100\% \quad (1)$$

where M is the calibrated image, I_S is the raw image, I_D is the mean dark reference image, and I_W is the mean white reference image.

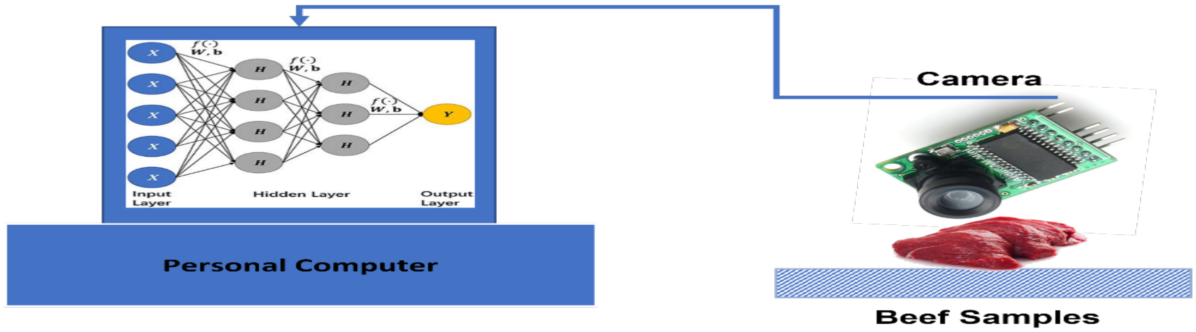

Fig. 1: Computer-Aided Beef Detection based Deep Learning Model.

2.2 Residual Neural Network

The ResNet contains different types, the most important of which are ResNet-18 and ResNet-50, which are the most advanced and common in classifying images. ResNet-50 model consists of 48 coiled layers, 1 MaxPool, an intermediate pool layer, and the ReLU activation method, Figure 2. ResNet is characterized by its ability to overcome the problem of overfitting, in which the front-fed neural network contains a hidden layer, that contains several specific neurons sufficient to fill in the data in linear methods and this hidden layer may contain a huge number of parameters, so the network training becomes linked to a specified number of data. The overfitting problem led to a decrease in the accuracy of ResNet to classify images [36,37]. ResNet also managed to overcome the vanishing gradient problem, which is the iterative multiplication of the derivative value of the first layers, so the derivative value decreases, and as a result, the network accuracy decreases for deep learning. The researchers tried to find a solution to these problems before the appearance of the residual network by adding loss to the middle layer, but the ResNet proved to be highly efficient in solving this problem [38,39]. The idea of ResNet is to reduce the accumulation of layers by adding a shortcut link, which bypasses one or more layers in the network structure that reduces errors during data training. Equations (2 and 3) of the original residual unit, are as follows:

$$y_l = h(x_l) + f(x_l, w_l) \quad (2)$$

$$x_{l+1} = f(y_l) \quad (3)$$

where x_l is the input feature, w_l is a set of weights (and biases), and f denotes the residual function of a stack of two 3×3 convolutional layers. The function f is the operation after element-wise addition, and f is ReLU. The function h is set as an identity mapping such that the features are computed as in Equation (4).

$$x_L = x_l + \sum_{i=l}^{L-1} F(x_i, w_i) \quad (4)$$

The feature x_L is a series of matrix-vector products; L is the summation of the outputs of all preceding residual functions. The loss equation functions as E, from the chain rule of backpropagation as in Equation (5).

$$\frac{\delta E}{\delta x_l} = \frac{\delta E}{\delta x_L}\frac{\delta x_L}{\delta x_l} = \frac{\delta E}{\delta x_L}\left(1 + \frac{\delta}{\delta x_l}\sum_{i=l}^{L-1} F(x_i, w_i)\right) \quad \mathbf{(5)}$$

Equation 5, indicates that the gradient $\frac{\delta E}{\delta x_l}$ can be decomposed into two additive terms: a term of $\frac{\delta E}{\delta x_L}$ that spreads information directly without concerning any weight layers and another term of $\frac{\delta E}{\delta x_L}\left(\frac{\delta}{\delta x_l}\sum_{i=l}^{L-1} F(x_i, w_i)\right)$ that propagates through the weight layers. The additive term of $\frac{\delta}{\delta x_L}$ ensures that information is directly propagated back to any shallower. Equation 5 also suggests that it is unlikely for the gradient $\frac{\delta E}{\delta x_l}$ to be canceled out for a mini-batch because in general, the term $\frac{\delta}{\delta x_l}\sum_{i=l}^{L-1}F(x_i,w_i)$ cannot always be equal to -1 for all samples in a mini-batch. This implies that the gradient of a layer does not vanish even when the weights are arbitrarily small.

2.3 Data augmentation

In data augmentation, techniques are used to increase the amount of data by image processing such as adding cropping, rotating, and flipping from each image. The resolution of the images can be changed by using the contrast between pixels and sharpening [40]. In this paper, augmentation was made for the input images to generate a large-scale dataset that is used for enhancing the accuracy of the proposal ResNet-50 architecture. This may be helpful to ensure the reliability and robustness of the architecture. Generative Adversarial Network (GAN) is an artificial intelligence technology, and one of the types of artificial neural networks. In it, two neural networks work together, or rather: they work in opposite directions, Figure 3. The importance of GAN is to start with feeding both networks a large amount of training data and giving each of them an independent task. Where the first network - known as the generator - produces an artificial output, such as handwriting, videos, or sounds, by studying the training data and trying to imitate it. The other network - known as the umpire - determines whether the output is real by comparing it each time with the same training data [6].

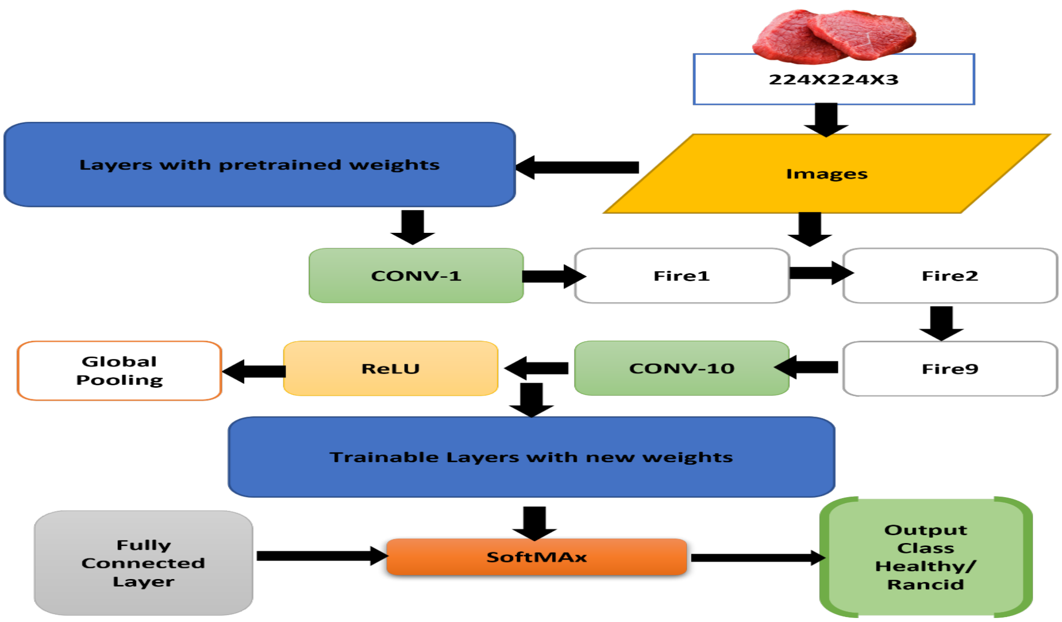

Fig. 2: The Proposed Architecture of the ResNet-50 model.

Every time the network succeeds in the judgment rejecting the generated network output, the generator network returns to try again. This technology allows computers to learn effectively from data that is not semantic and can be used to create realistic-looking images and videos [41].

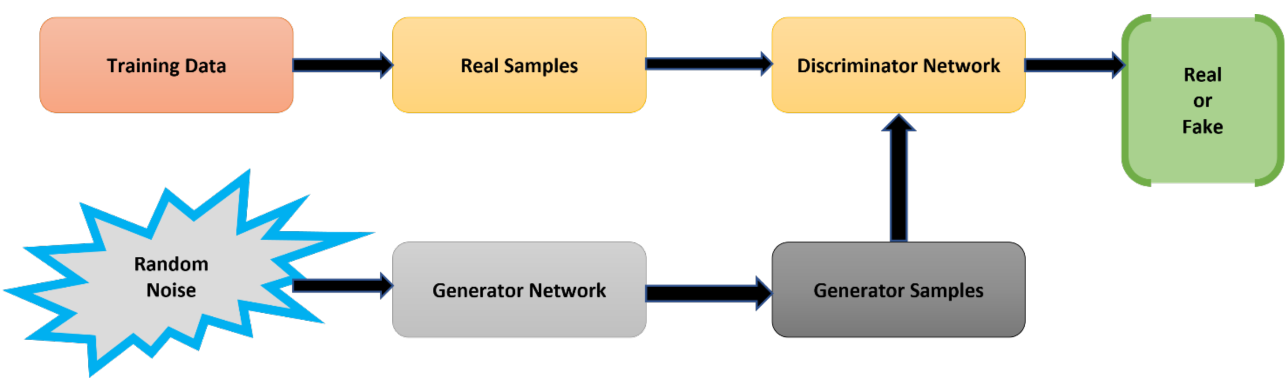

Fig. 3: A general framework of generative adversarial.

The generative adversarial network was trained as follows: First, a packet of fabricated data is created by the generative network. After that, this fabricated data is added to an identical number of real data and displayed on the discrimination network for training to strengthen its capabilities to differentiate between real and fabricated data [42]. In a third step, the generative network itself is trained to optimize the production of fabricated data to deceive the discriminating network. These three steps are then repeated for several periods: The ability of the discriminant network to differentiate between real and fabricated data improves in each era, and at the same time the generative network's ability to produce data similar to the real data that can deceive the discriminant network improves, Figure 4. From training periods until it becomes difficult for any human observer to distinguish between real and fabricated data by the network.

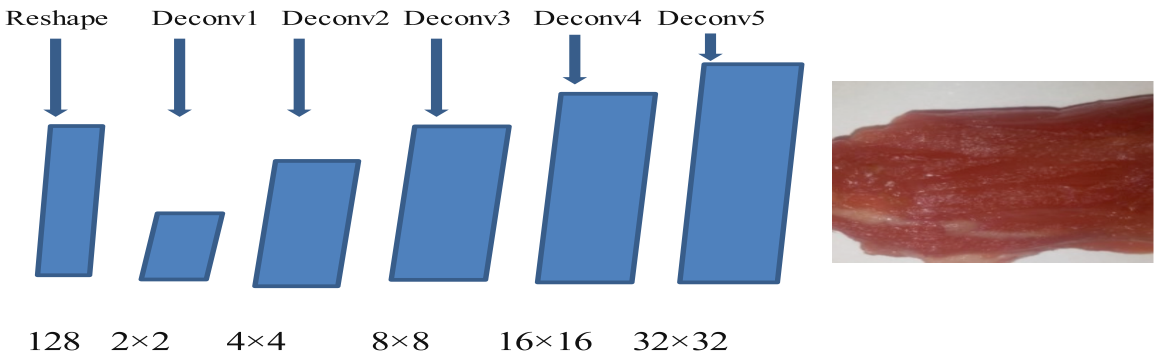

Fig. 4: The proposed generator architecture stage in GAN.

3 Results and Discussion

A beef dataset containing ten healthy images, and eight rancid beef images were collected. These collected images were taken randomly through the deterioration period of beef. The changes in beef surface were tracked and analyzed to extract features of beef images. The eighteen beef images are not sufficient for deep neural network classification and feature extraction. Therefore, as stated before GAN was used for image augmentation. Figure 5 shows samples of the collected beef images including the healthy (a) and rancid cases (b).

As ten images of healthy beef and eight images of rancid beef are available, this number of images is not sufficient to train the ResNet-50 deep network. Therefore, Generative adversarial networks through data augmentation were used to increase the images included in the ResNet-50 training. The augmentation process based on GAN produces one hundred eighty beef images, a hundred healthy, and eighty rancid images, which means all images are multiplied by ten to produce the total number of images that are entered into the Deep Convolutional Neural Network (DCNN) architecture.

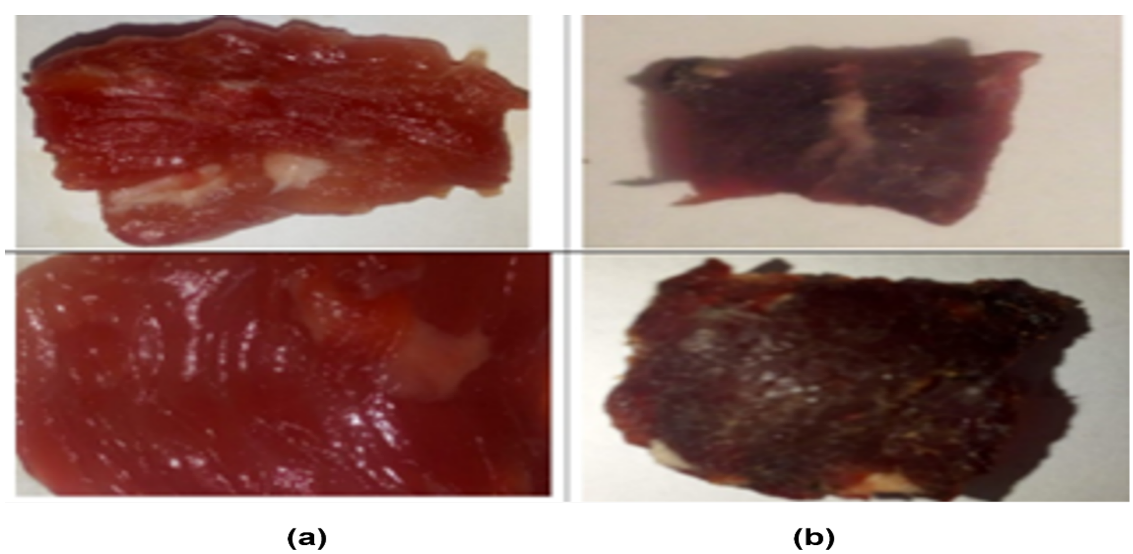

Fig. 5: The Collected Beef Images (a) Healthy beef (b) Rancid beef.

ResNet-50 was used in this experiment as one of the most promising DCNN approaches for feature extraction and classification. The ResNet-50 architecture consists of fifty layers and this network can classify images into different categories based on the pre-trained model. Image with a fixed size 224 × 224 × 3 is enrolled to ResNet-50 with one hundred and seventy-seven layers. The connection layers are one hundred ninety-two to produce a fully connected layer at the top of the network. Moreover, the weights are randomly initialized based on a pre-trained model on Image Net. Keras Tensor Flow (KTF) is utilized as an efficient tool for inputting images for the proposed model. Two classes were produced: the healthy, and the rancid beef at the final fully connected layer. The evaluation results of the proposed ResNet-50 are based on the confusion matrix that can be determined as in equations from six to ten. The confusion matrix details are listed in Table 1 as investigated I equations (6-10) by which it was investigated that seventy rancid beef images sixty-six correctly classified, whereas on the other hand fifty-five healthy beef images are correctly classified out of fifty-six healthy cases. Furthermore, the accuracy was determined, specificity, precision, sensitivity, and F1-score for training 70%, testing 20%, and validation 10%, respectively as investigated in Table 2 [43]. Here in the training phase, the accuracy achieved is 96.03%, which proves the ability of the proposed ResNet-50 model to identify and classify beef images.

$$Sensitivity = TP/ (TP+FN) \tag{6}$$

$$Specificity = TN/ (TN+FP) \tag{7}$$

$$Precision = TP/ (TP+FP) \tag{8}$$

$$Accuracy = (TP+TN)/ (TP+TN+FP+FN) \tag{9}$$

$$F1\text{-}score= 2TP/ (2TP+FP+FN) \tag{10}$$

where TN is a true negative, FP is a false positive, TP is a true positive, and FN is a false positive.

Table 1: The confusion matrix of the trained ResNet-50 architecture.

Rancid	66	4	94.29%
Healthy	1	55	98.21%
	98.51%	93.22%	96.03%
	Rancid	Healthy	

Table 2: Performance evaluation of the proposed ResNet-50 model.

ResNet-50	Training, %	Testing, %	Validation, %
Accuracy	96.03	91.67	88.89
Specificity	98.21	87.50	87.50
Precision	98.51	90.48	87.50
Sensitivity	94.29	95.00	90.00
F1-score	96.35	92.68	90.00

Twenty-five epochs were used to represent the number of iterations and the accuracy for training, testing, and validation sets in ResNet-50 for classifying images of beef, respectively achieved, as shown in Figure 6 as follows.

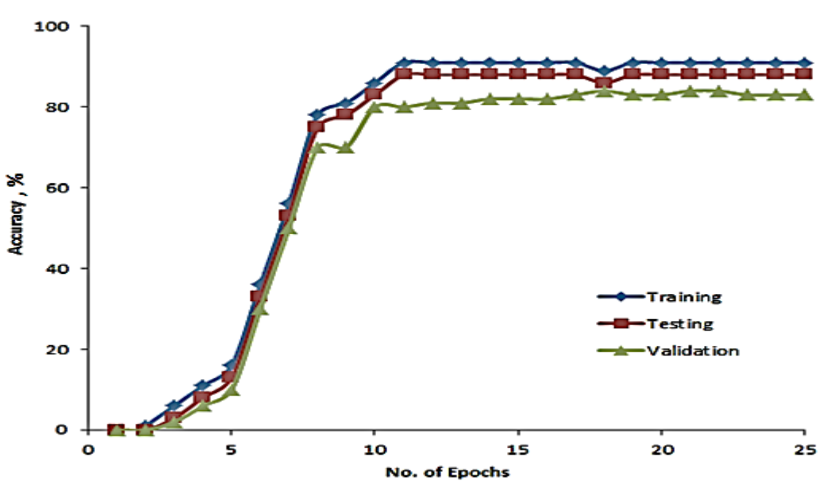

Fig.6: Number of epochs and accuracy for ResNet-50.

4 Conclusions and Perspectives

The Residual Network (ResNet) is considered the best in deep learning networks, for the following reasons; residual solved the overfitting problem and the vanishing gradient problem. The basic idea of the residual network is to add something called an "identity shortcut connection" that bypasses one or more layers, making it easier to train. The number of images of healthy and rancid beef samples was small and not suitable for training the ResNet-50 network. Therefore, a GAN was used to increase the number of images to one hundred eighty images. The performance of the ResNet-50 network in the training group was high, reaching 96.03%, indicating the ability of the network to classify beef images well. From our perspective, the utilization of texture analysis and pattern recognition of RGB color to grayscale is required to boost the results obtained. This further required to detect and classify more class labels and/or beef disease detection. Moreover, the researchers are attempting to optimize the residual network and propose a pre-activation variant of the residual network, so that the derivative value can pass through the identity shortcut connection to any previous layer without hindrance.

Conflict of interest

The authors declare that there is no conflict regarding the publication of this paper.

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