JFBE 2(2): 155-162, 2019

Journal of Food and Bioprocess Engineering

Journal homepage: https://jfabe.ut.ac.ir

Original research

Combining image processing technique and three artificial intelligence methods to recognize the freshness of freshwater shrimp

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A B S T R A C T

Since seafood is highly susceptible to corruption, it is important to check their storage and shelf-life time. In this research, image processing technology was used to recognize the freshness (time lasted of catching) of shrimps. Shrimp samples were randomly selected from shrimp farming pools and stored in three storage conditions: freezer, refrigerator, and cool environments. Images were taken from the samples at intervals of two hours in a controlled environment for more than a month. Finally, 482 properties were extracted from each image. Three effective parameters for modeling were selected by sensitivity analysis. The time that lasted from catching was the output of the models. Modeling was performed using ANFIS, ANN, and RSM algorithms. In the modeling, the R^2 values of the ANN algorithm with 0.987006, 0.987009, 0.984484, and 0.976001 were the best model for storing conditions: freezer, refrigerator, cooler environments and the total of storage conditions, respectively. All three modeling methods can estimate the catching time with high accuracy. But the ANN model was recognized as the best one according to the remaining diagram and the values of R^2 and MSE.

Keywords: Recognizing algorithms, Machine vision, Modeling, Artificial intelligence, Controlled storage

Received 7 August 2019; Received 27 October 2019; Accepted 2 November 2019

1. Introduction

Nowadays, the usability of quality assessment systems and the determination of the freshness of fishery products are increasing due to the increasing market demand, shortage and high cost of labor in some countries, higher speed of machine systems and so on (Nollet & Toldrá, 2010; Cheng et al., 2014). Shrimp is one of the most important seafoods in the world market. On the other hand, its consumption in developed, industrialized, and rich countries is high (Hosseinpour et al., 2013; Mohebbi et al., 2009). Recognizing freshness of the shrimps is very important and necessary for shrimp's proper use in the consumer market. Image processing and artificial intelligence are considered significant in this domain for benefits such as non-destructiveness, low cost, accuracy and high speed for grading (Hosseinpour et al., 2011).

Shrimp processing is the most important factor in its marketing. Selection of processing technology for export is important. In this regard, market demand and food health should be considered and also be accepted by food safety organizations. Therefore, the most suitable technology can be selected for its processing. For groups of people, such as the elderly, who have trouble in chewing and digesting food, shrimp is a good option to supply their daily protein. After catching marine animals and their death, complex changes occur in them due to enzymatic, chemical and microbial activities (Alimelli, et al., 2007). These changes, because of the death of aquatics and the weakening of their immunity system, culminate in the multiplication of the bacteria, their attack on the tissues and growth of rotting bacteria using self-digestion phases (Gram & Dalgaard, 2002). Hence, the time spent from the point of catching shrimp is very important and affects the quality of the product. Research has been done to determine the quality of shrimp based on image processing, neural networks, and quality indicators (Hosseinpour et al., 2011). For example, Dowlati et al. (2013) have studied the freshness of fish (Sparus aurata) by eye and gill changes using machine vision system. They found that the machine vision system could be used as a quick and inexpensive way to determine the fish freshness. Freshness of the shrimp can be detected through

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its smell. The use of electronic nose to evaluate the freshness of the shrimp has been studied. The smell of shrimp, stored at 5 °C, was electronically sensed by an electronic nose (Du et al., 2015). In another research, durability, quality and shelf-life of white leg of Pacific shrimp (Vannamei) -which have been newly caught and stored on the ice- were studied (Okpala et al., 2014). Machine vision technique is one of the initial methods for assessing agricultural products and its wide use has been accentuated because of image processing hardware systems progress. Machine vision is currently used extensively in farming and product assessing. In sum, it can be said that the most application of this technique is in grading agricultural products, and recognition of color, apparent defects and texture. Therefore, it is very important to obtain optimal conditions for using this method (Omid et al., 2010). An important method for colorimetry of food products is the use of a machine vision that provides quick and inexpensive color assessment for food products- little research has been done on the use of this technique in the food industry. While major evaluations are performed using image processing in RGB space, it is also used in colorimetry of L a b space which is most similar to the human eye system (Abdullah et al., 2004; Goyache et al., 2001; Paulus et al., 1997; Sun & Brosnan, 2003).

In a research the effect of cold storage on the quality (organoleptic properties, total microbial count, pH, total volatile base nitrogen and peroxide value) of cultured and sea shrimp from Persian Gulf was investigated for 120 days. The Results indicated that taste, smell, flavour, and colour of sea and cultured shrimps remained natural for 30 and 90 days, respectively (Moini & Pazira, 2004). In a study, shrimp freshness was classified and predicted by image processing and computational expert approaches including LDA, KNN, QDA, D-PLS. The best result was achieved with a combination of classification trees and LDA (Ghasemi-Varnamkhasti et al., 2016). In this research, we have been trying to estimate the time passed by the catching of the shrimps stored in the refrigerator by using image processing and combining it with artificial intelligence techniques. In this research, Artificial Neural Network (ANN), Adaptive Neuro Fuzzy Inference System (ANFIS) and Response Surface Methodology (RSM) modeling techniques have been used, their results compared and eventually the best method introduced.

2. Material and Methods

2.1. Imaging conditions

The machine vision system for image taking and processing included exposure box, camera and computer (laptop) and MATLAB software (MathWorks Co. V. 2015a). In the present study, taking image of shrimp samples requires a special imaging box that can match the imaging conditions of all specimens at all times. For this purpose, a chamber of white and non-shining MDF with dimensions of 16 cm × 16 cm and 11 cm height, was made. The chamber has been designed in such a way that its height for placing shrimps and also their space from the camera is adjustable. After examining different distances, the appropriate distance for placing the shrimp was determined as was 11 cm. On the top of the box designated for shrimp storage, a lid was placed. There was a hole in the middle of the lid which had a diameter of the same size of the camera lens. Having these preparations made the camera fixed in its place and therefore the angles of all taken pictures are the same.

The Nikon Coolpix S2800 camera (20.1 MP, 5X Optical Zoom) was used in this study. The highest quality was used for imaging. Low-power LED lamps, which had been symmetrically placed around the camera's position, were used for this purpose. In other words, lighting was done from above the shrimps.

2.2. Preparation of samples

In this research, 27 shrimps were selected randomly and purchased from shrimp breeding pool. The specimens were numbered and for each shrimp, a recording table was considered in order to accurately record the relevant parameters. Meanwhile, their catching time was recorded carefully.

The shrimps were numbered and placed inside the chamber. Then it was taken a photograph of all samples in the same direction. Each image was immediately recorded in a laptop. Then the samples were placed in the three storage environments: a refrigerator at a temperature of 3-5°C, freezer at a temperature of -18°C and cool environment at a temperature of 20°C. The shrimps were taking image nearly in each two hours for one and half a month (approximately 45 days). Meanwhile, the time passed from catching was recorded at the moment of images taking and finally 531 images were obtained.

2.3. Shrimp image processing

After imaging samples, the images should be processed in order to extract useful data. The image processing algorithm used is in accordance with Fig. 1.

2.4. Image size reduction

Given that the size of the images taken was 4222 × 2322 pixels, this magnitude created a very large matrix and greatly reduced the processing speed. As a result, the image size needed to be reduced without breaking the length and width ratios. First, crop command was used to focus on the images and then the image size was reduced to 763 by 543 pixels. In addition, the final image was converted to different colorful environments and each individual environment was examined separately. The colorful environments studied in this study were RGB, CMY, Gray, BW, HSV, I1I2I3, Lab, NrNgNb, YCbCr, YCrCgCb, YIQ and YUV. A sample of these images are shown in Fig. 2. Finally, 10 color channels were studied, each of which consisted of three monochrome channels. Considering the Gray monochrome channel, totally, 31 monochrome channels were evaluated.

2.5. Separating shrimp image from the background

It is necessary to separate the shrimp image from the background to perform image processing operations. For this purpose, the histogram of all 31 monochromatic channels were used. After careful screening of the shrimp image from the background, Y histogram of the CMY channel was used. According to the histogram of the mentioned channel and after repeated experiments, the threshold for separating was set at 130. Finally, the background image and shrimp's one was separated from each other, as shown in Fig. 3. To obtain some parameters related to shrimp image, such as texture and skin roughness, it is necessary to have image of the edges of shrimp's body. After examining of all the edge finding filters, the best results were obtained by the Cany filter with a coefficient of 0 as Fig. 3 shows this fact.

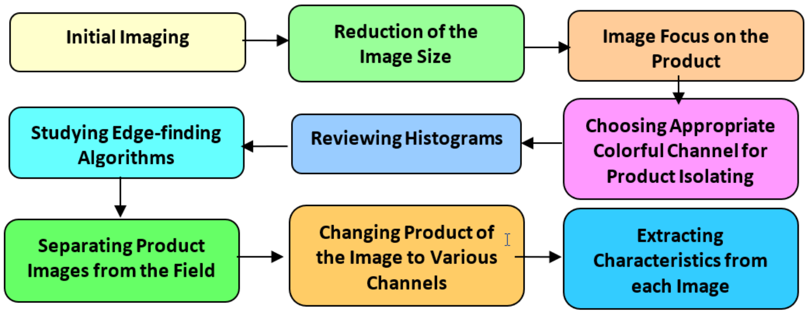

Fig. 1. Used image processing algorithm.

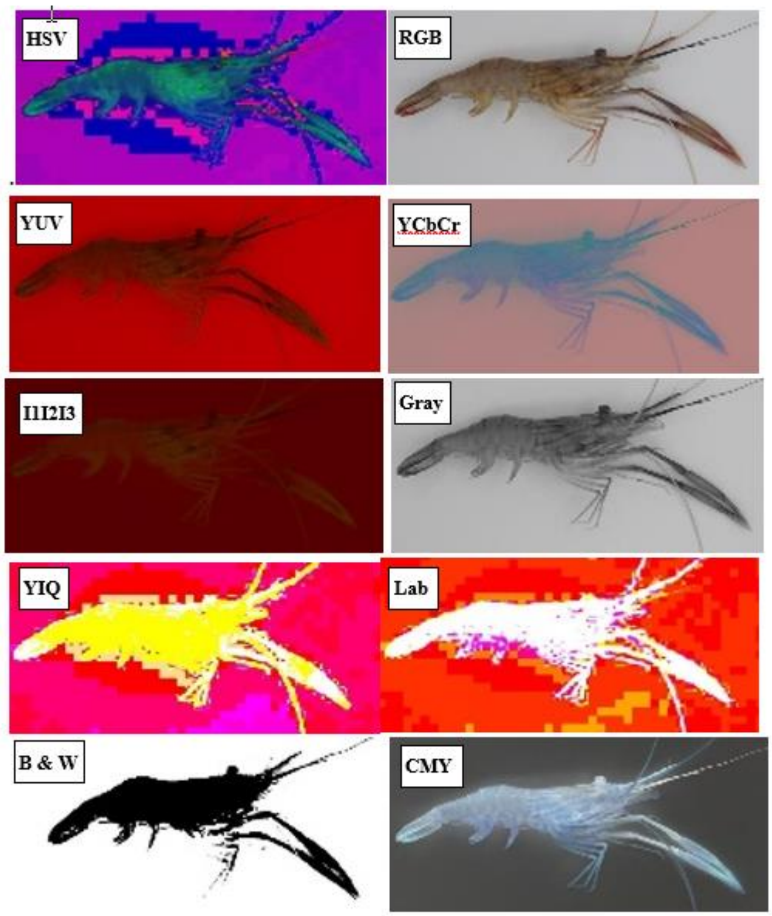

Fig. 2. Shrimp images in selected different colored environments.

2.6. *Data extraction*

In general, as mentioned earlier, 10 channels were examined. Considering the single-colored Gray channel and the number of three monochrome channels for each of the 10 color channels, it can be said that 31 monochrome channels were examined. In each monochrome channel, 15 parameters were measured: minimum, mean, maximum, standard deviation, mode, and correlation coefficient, range of variations, skewness, Kurtosis, entropy, variance, mean, harmonic mean, covariance and contrast. In other words, 31 × 15 parameters or 465 inputs for the models were extracted from the images. A total of 11 general parameters were also measured, including skin roughness, length, width, circumference, outermost center, surface center, texture, surface, width to length ratio, width ratio to surface and length ratio to surface. In general, 482 parameters were extracted from each image. In other words, for 27 shrimp samples, the extracted data will include an 1836*482 matrix.

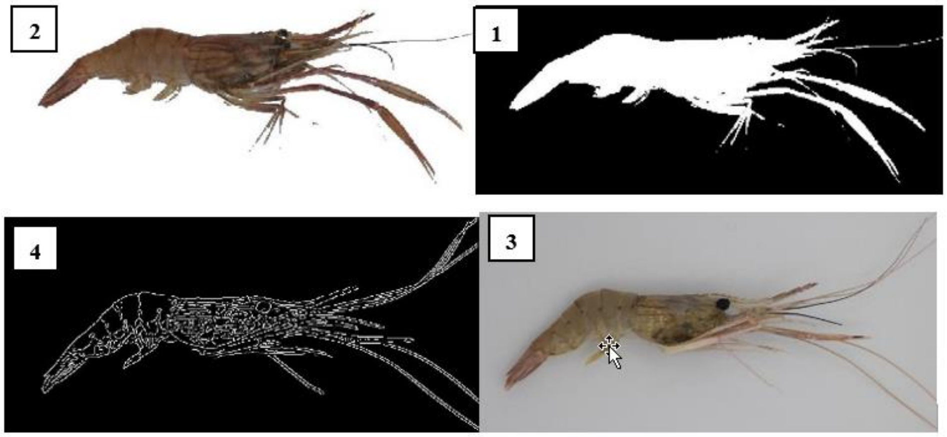

Fig. 3. Further image processing operations to separate the shrimp image from the background and finding the edge of image. 1) Separated background image of shrimp, 2) Image of shrimp separated from background, 3) Shrimp image in RGB environment and 4) Shrimp edges image by Cany filter.

Table 1. Sensitivity analysis of the nine selected parameters relative to the time passed from catching for three storage conditions.

Storage enviroments	Refrigerator	Freezer	Cool environments
1	Maximum value of S for HSV images	Average mean value of Y for CMY images	Average value of Y for CMY images
2	Maximum value of U in VUY images	Maximum value of S for HSV images	Maximum value of S for HSV images
3	Average value of Y for CMY images	Shrimp texture	Shrimp texture

Table 2. Characteristics of the best model of ANFIS for estimating the time passed from shrimp catching.

Number of inputs	Number of fuzzy sets of each input	Type of fuzzy set	Output type	Optimization method	Number of epochs
3	5	G Bell	Linear	Hybrid	100

2.7. *Estimating of time passed from catching*

Samples kept in the three storage conditions, were imaged every day and in each two hours hour and the time passed from catching time were recorded. Previous research indicated that taste, smell, flavour and colour of cultured shrimp remained natural for 90 days in freezer -18°C (Moini & Pazira, 2004). So, this work was done for 45 days for all storage conditions in order to compare the methods and it's modeling. The recorded period will be considered as the output of the models. All image processing and modeling operations were performed using MATLAB software. Three improved modeling technique including ANN, ANFIS and RSM have been used for estimate time passed from shrimp catching.

3. Results and Discussion

3.1. *Selecting effective inputs*

Due to the large number of parameters, it is necessary to select some of them that are more effective in modeling. Over the past years, researchers have proposed several feature selection methods, including principal components analysis (Omid et al., 2009), decision-making tree (Mollazade et al. 2012), Genetic algorithm and Backup vector machine (Yuan et al., 2007). Sensitivity analysis (Hill & Tiedeman, 2006) is also a powerful tool for selecting effective inputs. Because of the high number of extracted parameters from each image, 482, firstly and in order to attain a proper answer, those monochrome images of each channel were selected, which were deemed to be appropriate. Then, by limiting the extracted parameters from each selected image, the sensitivity analysis was used. In other words, the inputs were selected for sensitivity analysis of 9 inputs, including: 1- Shrimp texture 2. Maximum R value for RGB images 3. Maximum value of G for RGB images 4. Maximum amount of S for HSV images 5. Maximum Y value for YCbCr images 6. Maximum U value for YUV images 7. Minimum M value for CMY images 8. Average value of Y for CMY images 9- Maximum value for gray.

Table 3. Performance of the best model of ANFIS, ANN, and RSM for estimating the time passed from shrimp catching.

Storage place	Modeling technique		Sample Number	SSE	MAE	MSE	R	P
Refrigerator	ANFIS	Training	371	0.880515	0.030983	0.002367	0.982196	8.8E-271
		Testing	160	0.723333	0.036072	0.004549	0.960305	5.88E-89
		Total	531	1.603848	0.032507	0.00302	0.976018	0
	ANN	Training	371	0.589655	0.020157	0.001585	0.987757	1.2E-300
		Testing	160	0.270997	0.025252	0.001704	0.984926	1.5E-121
		Total	531	0.860653	0.021683	0.001621	0.987009	0
	RSM	Training	371	3.488038	0.077979	0.009376	0.956748	1.7E-200
		Testing	160	1.807491	0.081851	0.011368	0.93667	1.96E-73
		Total	531	5.295529	0.079138	0.009973	0.950003	1.4E-269
freezer	ANFIS	Training	555	3.612599	0.071024	0.006509	0.972462	0
		Testing	237	1.453779	0.069031	0.006134	0.963379	2.5E-136
		Total	792	5.066378	0.070428	0.006397	0.970004	0
	ANN	Training	555	1.319292	0.040781	0.002377	0.987525	0
		Testing	237	0.562667	0.040805	0.002374	0.985319	2.1E-182
		Total	792	1.881959	0.040788	0.002376	0.987006	0
	RSM	Training	555	6.047748	0.071774	0.010897	0.964363	0
		Testing	237	3.227207	0.074796	0.013617	0.951176	5.8E-122
		Total	792	9.274955	0.072678	0.011711	0.960101	0
Cool environment	ANFIS	Training	359	0.576086	0.028476	0.0016	0.983106	4.2E-266
		Testing	154	0.245451	0.029756	0.001604	0.982252	1.2E-111
		Total	513	0.821537	0.028858	0.001601	0.982809	0
	ANN	Training	359	0.50209	0.026924	0.001395	0.985396	2.4E-277
		Testing	154	0.239782	0.030183	0.001567	0.981816	7.2E-111
		Total	513	0.741872	0.027896	0.001446	0.984484	0
	RSM	Training	359	1.502893	0.058432	0.004175	0.954845	8.8E-191
		Testing	154	0.689285	0.060263	0.004505	0.950301	2.04E-78
		Total	513	2.192178	0.058978	0.004273	0.953423	3.8E-268

Table 4. Characteristics of the best ANN model for the time passed from catching.

Storage places	Number of inputs	General Structure of the Network	Training Function	Transfer Functions
Refrigerator	3	15-15-1	Levenberg-Marquardt	Tansig - Tansig -Purelin
Freezer	3	12-13-1	Levenberg-Marquardt	Tansig - Tansig -Purelin
Cool environment	3	15-11-1	Levenberg-Marquardt	Tansig - Tansig -Purelin

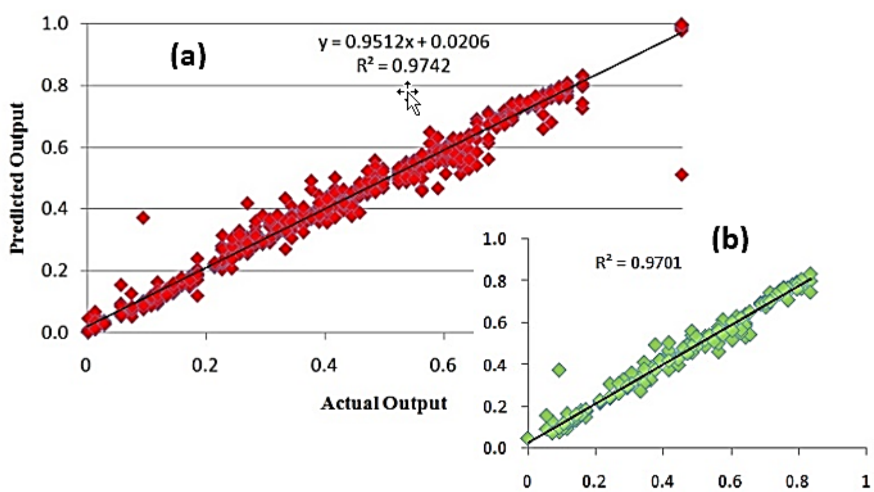

Fig. 4. Diagram of the Performance of the Models for Estimating time passed from catching (ANN an in refrigerator), (a): Total Data and (b): Test Data.

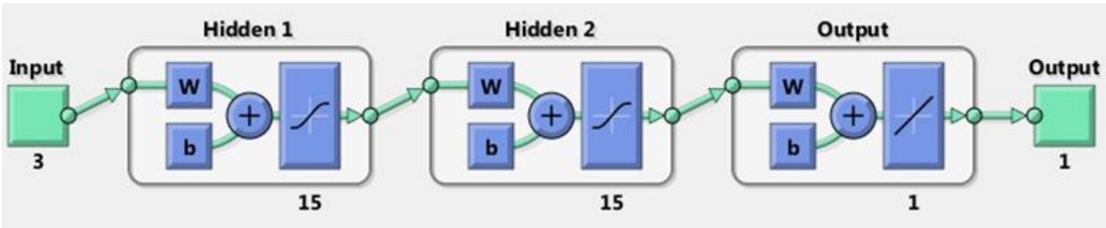

Fig. 4. An overview of the general structure of the ANN model for estimating the time passed from catching.

3.2. *Sensitivity analysis*

Nine selected inputs in addition to time passed from catching was investigated by the sensitivity analysis. The resulting is shown in Table 1. in the storage with freezer the three selected parameters for modeling are: 1- Shrimp texture 2. Maximum value of S for HSV images 3. Average mean value of Y for CMY images.

3.3. *Modeling the time passed from catching*

3.3.1. *ANFIS*

For every storage environment, three selected parameters from Table 1 was used as input of ANFIS model and the output of the time passed from catching was in hour. 30% of the data was used for testing and the rest for training. Characteristics of the best model are according to Table 2 and their performance have been reflected in Table 3. In the Modeling the Time Passed from Catching by ANFIS, the R^2 values were calculated in freezer, Refrigerator and Cool environment 0.970004, 0.976.18 and 0.982809, respectively. In every stage of modeling, the performance Diagrams of the model is drawn for the estimation of the time passed from catching (Fig. 4).

3.3.2. *ANN*

As ANFIS modeling, three selective parameters were also used as an input for the ANN model, and the output of the model was time passed from catching. 30% of the data was used for testing and the rest for training. Fig. 5 shows an overview of the overall structure of the ANN model to estimate time passed from catching. Characteristics of the best model are in accordance with Table 4 and the performance of the model is in accordance with Table 3. In the modeling the time passed from catching by ANN, the R^2 values were calculated in freezer, refrigerator and cool environment 0.987006, 0.987009, and 0.984484, respectively. The performance diagrams of the model in the estimation of the passed from catching are as shown in Fig. 4 for refrigerator. So that Fig. 4a refers to the total data and Fig. 4b is related to the test data.

3.3.3. *RSM*

For modeling by responding level method, Design Experts software was used. The best model was of quartic kind and its performance is in accordance with Table 3. In the Modeling the time passed from catching by RSM, the R^2 values were calculated in freezer, refrigerator and cool environment 0.960101, 0.950003 and 0.983423, respectively. Alike ANFIS and ANN performance diagrams of the model are drawn in the estimation of the time passed from real catching (Fig. 4).

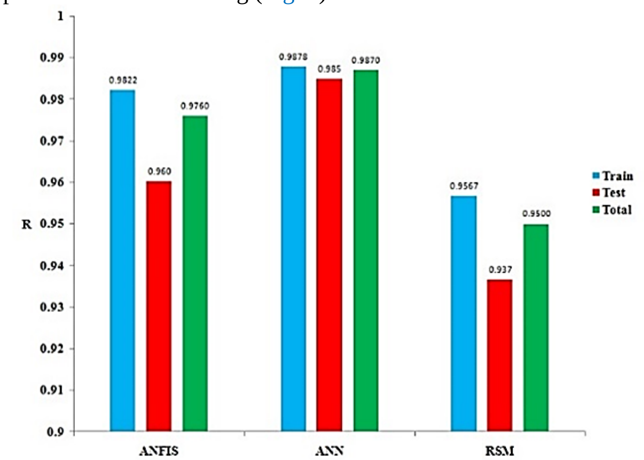

Fig. 6. R values of training, test, and total data for all models of estimation of the time passed from catching.

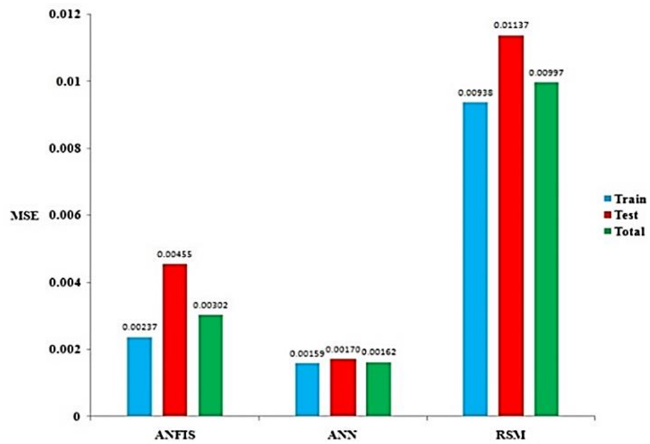

Fig. 7. MSE values of training, test, and total data for all models of estimation of the time passed from catching.

3.4. *Summing up of time passed from catching modelling*

The diagrams for R, MSE, and the remainder of all models are shown in Fig. 6 to 8, respectively. The more the R value is closer to one and the smaller the MSE value is, the better the model performs. The diagram relating to the remainder of the diagrams shows the fluctuations of the model's output estimate, that is, the past time of the catch. The smaller the fluctuations are, the better the model will perform. According to the figures, it can be said that the ANN model has shown better performance than the rest. Thus, an image processing device and Artificial Intelligence methods especially ANN Methods can be used to evaluate shrimp freshness. so that it has agreement with the previous study that showed (Ghasemi-Varnamkhasti et al., 2016) the computer vision system can be used to automate and online evaluate shrimp quality and freshness.

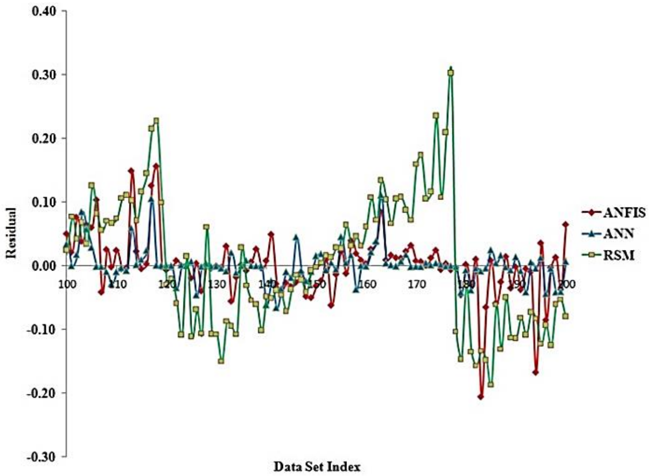

Fig. 8. Remaining diagram of all models for estimating time passed from catching.

4. Conclusion

In this study, the potential of image processing technique and artificial intelligence approaches was evaluated to predict time passed from shrimp catching. For this purpose, 27 shrimp samples were procured live. Their catching time was recorded and they were stored in common three storage environments. The image of samples was taken every two hours for 45 days and finally 531 images were obtained. A total of 482 data were extracted from each photo of shrimp during the stage of image processing. In total, the research set of data was a 482 × 531 matrix. 9 parameters were selected, from among these 482 ones, using proper methods of selecting images and comparing the change level of parameters. Then, three effective parameters were selected from among the 9 selected ones using sensitivity analysis., including: Maximum value of S for HSV images, mean value of Y for CMY images, and Shrimp texture (the parameter "Maximum value of U in VUY images" only in refrigerator treatment). In other words, the three parameters in every storage environment were considered as inputs of the model and the output of all models was the time passed from catching in terms of hour. For modeling, ANFIS, ANN and RSM methods were used. In all storage environments, overall the R^2 values for three models of ANFIS, ANN and RSM were 0.964, 0.976 and 0.958 respectively, and their MSE values were calculated to be 0.003, 0.001 and 0.010, respectively. However, the modeling results showed that the precision of the three modeling methods are very close together. But, according to the remaining chart and the values of R^2 and MSE, the model obtained through the neural network was recognized as the best one.

Acknowledgment

The authors are very thankful to the Biosystems Engineering Department of the Razi University and Shahid Chamran University of Ahvaz (SCUA) for their support.

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