Global Journal of Animal Scientific Research. 3(2): 321-328. 2015

G.J.A.S.R

Global Journal of Animal Scientific Research

Journal homepage: www.gjasr.com

Print ISSN:2345-4377 Online ISSN:2345-4385

Original Article

Pelt Pattern Classification of New Born Lambs Using Image Processing and Artificial Neural Network

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ARTICLE INFO

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How to Cite this Article:
Khojastehkey, M., A.A. Aslaminejad, M.M. Shariati, R. Dianat. 2015. Pelt Pattern Classification of New Born Lambs Using Image Processing and Artificial Neural Network. *Global Journal of Animal Scientific Research.* 3(2): 321-328.

Article History:
Received: 6 December 2014
Accepted: 28 December 2014

ABSTRACT

In this study a method to determine the pelt pattern of Zandi sheep lambs using image processing and neural network is presented. Data were collected from Zandi sheep breeding center located in the North East of Tehran (Khojir). In the lambing season, pelt pattern (including regular and irregular patterns) of 300 newborn lambs along with other important characteristics were determined by qualified appraisers. Simultaneously, some photos were taken from each lamb pelt using digital camera. Due to the difference in image resolution and variety of pelt patterns, a total of 170 high quality pictures of lambs were selected and used for final assessment. Two independent image processing scenarios were developed in MATLAB GUI environment. In both scenarios, after the necessary image transformation and segmentation the relevant features were extracted from each image. In the first scenario, some morphological and texture features were extracted from images to classify the pelt pattern of lambs. In the second scenario, the original image firstly was divided into four equal sub-images, and in addition to the texture and morphological features which were extracted in the first scenario, variances and correlations between four sub-images were calculated and added to the features vector. The selected features were used as an input data to the artificial neural network to classify pelt pattern quality of lambs. Input data to the neural network in the first scenario included 21 morphological and texture features, while in the second scenario included 44 features. In both scenarios a three layers Percepteron artificial neural network with feed forward back-propagation algorithms were used. The regular and irregular pattern of lamb pelts were detected by the neural network with accuracy of 92 % and 100% in the first and second scenarios, respectively. The results showed that determination of pelt pattern of lambs based on proposed image processing method is feasible, and substitution of this new method instead of human appraisal method is achievable.

Keywords: Artificial neural networks, Image processing, Pelt quality, Zandi sheep.

INTRODUCTION

Production of luxurious karakul pelts in many countries as a profitable trade is widespread. Karakul pelts is used mainly in production of clothes, boots and overcoat. Usually, the pelt quality of karakul lambs is determined by the experienced assessors in the few days after birth, and this information is used to select the superior animals in order to producing beautiful and luxurious pelts (Schoeman and Albertin, 1993).

The pelt pattern is one of three important characteristics which determine the cost of karakul pelt. The curls (shape and twist of wool fibers on the pelt) are different in type, size and direction on karakul pelts. Whatever the type, size and direction of curls on the pelt are more similar and more uniform, the pelt appearance looks more beautiful, and pelt pattern is regular (Schoeman and Albertin, 1993).

Due to the differences in experience and skill of evaluators, appraisal time limitation, the lack of precise measurement tools, and the possibility of evaluator replacement in different years, the incidence of human errors in the appraisal process is inevitable. If the portion of human errors in the phenotypic variance is increased, the accuracy of breeding value estimations and genetic improvement in a population are decreased (Vilarrasa, 2010). A good solution to reduce in the human recording errors may possibly is employment of automated measuring tools such as image processing methods and artificial intelligence techniques (Goyal, 2013; Onder *et al*., 2010). Artificial neural networks are efficient tools in data mining process and its design is inspired by biological neural networks (Prevolnik, 2011). The structure of an artificial neural network consists of a number of neurons which in relation to each other have ability to make decisions, prediction and diagnosis. Each neuron in artificial neural network is a data processing unit and acts like a neuron in the human brain. Each neuron receives a set of input data. In the next step, he input data is processed using mathematical functions of each neuron, and finally an output signal is produced. Due to the communication of neurons with each other an artificial neural network is built with variety of conditional functions. The neural network can get the raw data and categorizes them into two or more distinct groups or predicts new data after a series of multi-step processing operations (Goyal, 2013).

In the recent two decades, use of artificial intelligence methods have been developed in military, medical, aerospace, identification, robotics and security systems for diagnosis (Burghardt, 2008). Some reports concerning the results of the application of artificial intelligence technology for categorization of objects are provided below. In one study, 5 kinds of fabric wrinkles were classified using digital image processing and support vector machine classifier with accuracy of 75% (Sun *et al*., 2011). Banumathi and Nasira (2012) used image processing and artificial neural network to detect fabric inspection, and their results showed that the proposed method was applicable in textile industries for defect detection and classification. Al-Hiary *et al*., (2011) could identify and classify plant diseases using image processing and neural network with accuracy between 83 to 94 %. Pazoki *et al*., (2014) classified 5 commercial rice types using artificial neural network with an accuracy of 99 %. According to Qian *et al*., (2011) using image processing and support vector machine classifier the amount of cashmere fibers in the sheep wool were determined with error of less than 5%. Wang *et al*., (2009) used digital image processing methods to detect the egg freshness in poultry, and reported that determination of egg freshness based on image features is possible.

As far as we know, as yet no study has been carried out on the use of artificial intelligence to determine the pattern quality of pelt sheep. In this study, for the first time, using image processing and artificial neural network a new method to determine pattern quality of pelt sheep is introduced. It is explained that this study is a part of my PhD thesis results entitled "Possibility of new trait definition in the breeding program of pelt sheep by means of artificial intelligence and computer simulation".

MATERIALS AND METHODS

Various steps of this study were as follow: determination of pelt quality in new born lambs by assessors, digital photography, image processing and feature extraction, and finally use of artificial neural network to classify and diagnose of pelt pattern quality.

Phenotypic Recording and Photography

This study was conducted in Zandi sheep breeding station (Khojier) at Tehran province. During the lambing period, 300 heads of new born lambs of Zandi sheep were registered and evaluated by trained appraisers for different pelt traits. The pelt pattern was classified in two ranks: regular and irregular. If the wool fibers on the pelt had a unique size and same direction, the pelt had attractive and uniform pattern, and otherwise had not. So, score 5 was considered for lambs with irregular pelt pattern, and 20 was considered for lambs with regular and uniform pelt pattern. Simultaneously, some images were taken from lambs using canon digital camera SX 150 IS in natural light conditions with size of 4320 × 3240 pixels considering a fixed distance of 40 cm. Due to the varying in the photos quality, 170 images of 300 were selected and used for final evaluation of pelt quality. To select appropriate photos, conserving of curl and pattern diversity of pelts were considered. In figures 1 and 2 both regular and irregular patterns of pels are shown.

Figure 1: Two pelts with regular pattern

Figure 2: Two pelts with irregular pattern

Image Processing

All images were processed using image processing tools (IPT) of MATLAB 7.8.0 software. Image processing steps involves taking photos, image pre-processing and editing, image segmentation, feature extraction and relevant feature selection. In Figure 3, different steps of image preparation and feature extraction have been shown.

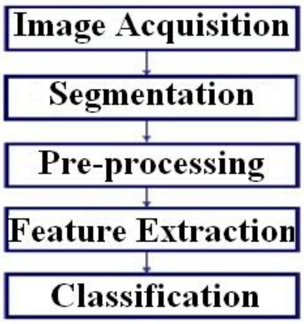

Figure 3: Steps of image processing

To improve the quality of digital images following pre-processing practices was carried out on each image: converting the color scale to the gray scale, brightness adjustment, segmentation, selecting the region of interest and using series of morphological operators to eliminate noise and unwarranted points.

Figure 4: Image preprocessing steps (a: color image taken from lateral side of lamb, b: image crop of lamb pelt in gray scale, c: image crop of lamb pelt in binary scale)

Feature Extraction

Two independent scenarios to extract relevant features were developed using MATLAB GUI environment. In the first scenario, 21 different morphological and texture features were extracted of each preprocessed image. Some of most important morphological features included area, perimeter, major axis length, minor axis length, diameter, distance, eccentricity, and solidity; either most important texture feature included energy, uniformity, homogeneity and correlation. In the second scenario, based on an innovative method, the original image firstly was divided into four equal sub-images which were complementary to each other (figure4). In this scenario, in addition to the 21 textural and morphological features, variances and correlations between four sub-images were added to the initial features, and total of 44 features were extracted from each original image.

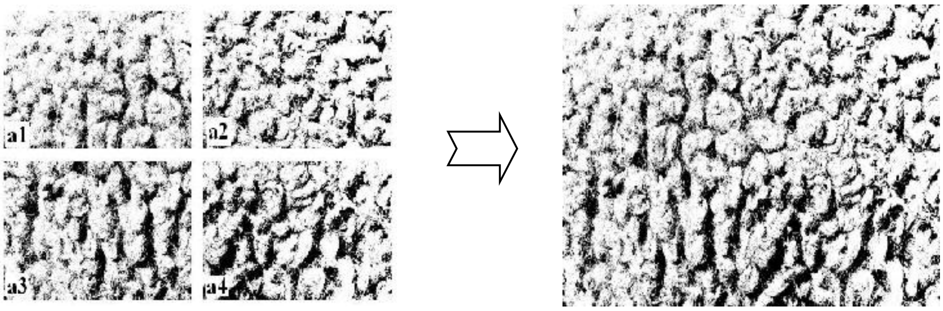

Figure 4: The original binary image is divided into 4 equal sub- images

Artificial Neural Network (ANN) Development

The Neural Pattern Recognition tools (NPRTool) of MATLAB was use to develop artificial neural networks. The developed ANNs in both first and second scenarios were multi-layer feed forward network which trained via back-propagation algorithm. In the first scenario, 21 neurons equal to the 21 features of input vector were considered in the input layer; 2 neurons for two regular and irregular types of pelt pattern were considered in the output layer, and 20 neurons were considered in the hidden layer using trial and error procedure. In the second scenario, the number of neurons considered in the input layer, hidden layer and output layer were 44, 22 and 2 respectively. In both scenarios the tangent sigmoid function was selected as a transfer function in the hidden and output layers. Figures5 and 6 shows two neural networks which designed to recognize pelt pattern in the first and second scenarios. 120 of 170 taken photos were used to develop ANN(80% for training, 10% for validation, and 10% for testing). Training was performed to minimize the mean square error (MSE) between targets and outputs. In each scenario, 50 additional pelt photos were introduced to the ANN to determine the classification accuracy of each developed model.

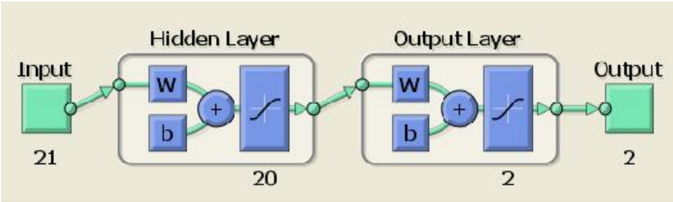

Figure 5: The structure of ANN in the first scenario

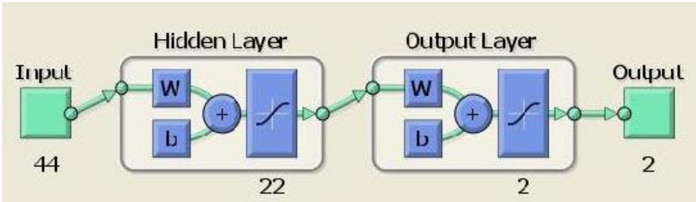

Figure 6: The structure of ANN in the second scenario

RESULTS AND DISCUSSION

Classification of the Pelt Pattern in the First Scenario

In the first scenario, the ANN was trained to identify 2 regular and irregular pelt patterns with an accuracy of 95.8 %(figure7). In the next step, 50 additional test data were introduced to the network and the pattern type of lamb pelts were classified by ANN with accuracy of 92 %(Table1).

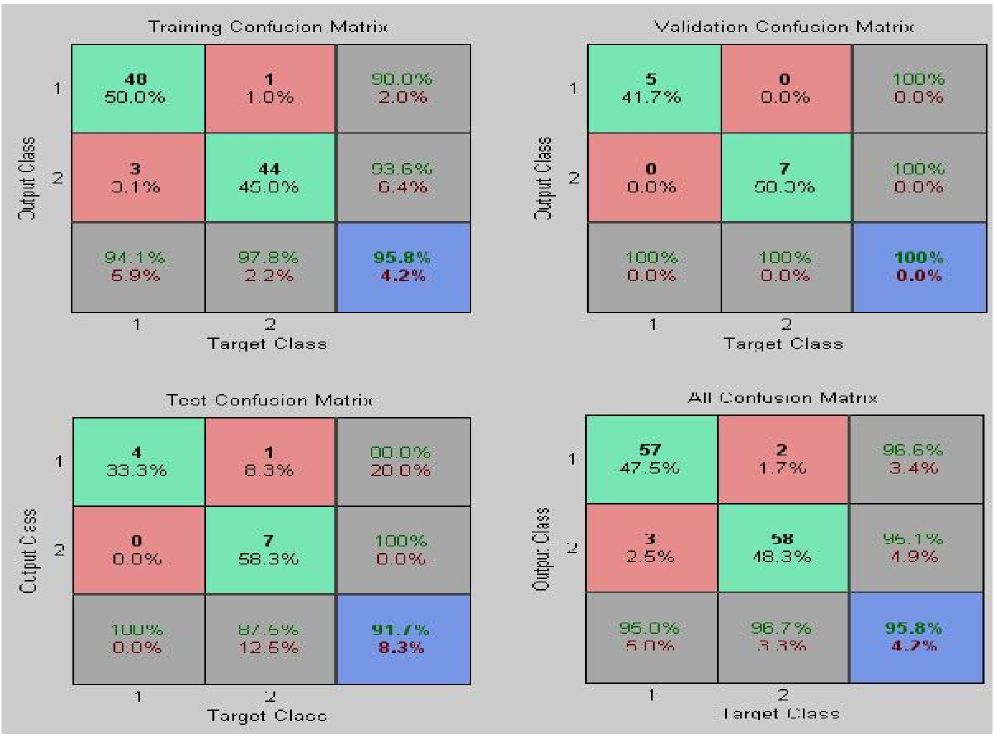

Figure 7: ANN performance matrixes to detect of pelt pattern in the first scenario

Table 1: Classifying the pelt pattern by ANN in the first scenario

Pelt pattern types	Number of images	Correct classification	Incorrect classification	Classification accuracy%
Regular	25	25	0	100
Irregular	25	21	4	84
Mean				92

As shown in table 1, all of 25 photos which represented regular pelt pattern were correctly classified by ANN, while 4 of 25 images which represented irregular pelt pattern were wrongly classified by the ANN.

Classification of the Pelt Pattern in the Second Scenario

In the second scenario, the ANN was trained to identify 2 regular and irregular pelt patterns with an accuracy of 99.2 %(figure8). As shown in figure 8, the error rate of the ANN was 1.6% to detect the regular pattern, and was zero to detect the irregular pattern. These results revenue the accuracy of the ANN to detect regular pelt patterns was less than the accuracy of irregular pattern detection. In the next step, 50 additional test data were introduced to the network and the pattern types of lamb pelts were classified by ANN with accuracy of 100 %(Table2).

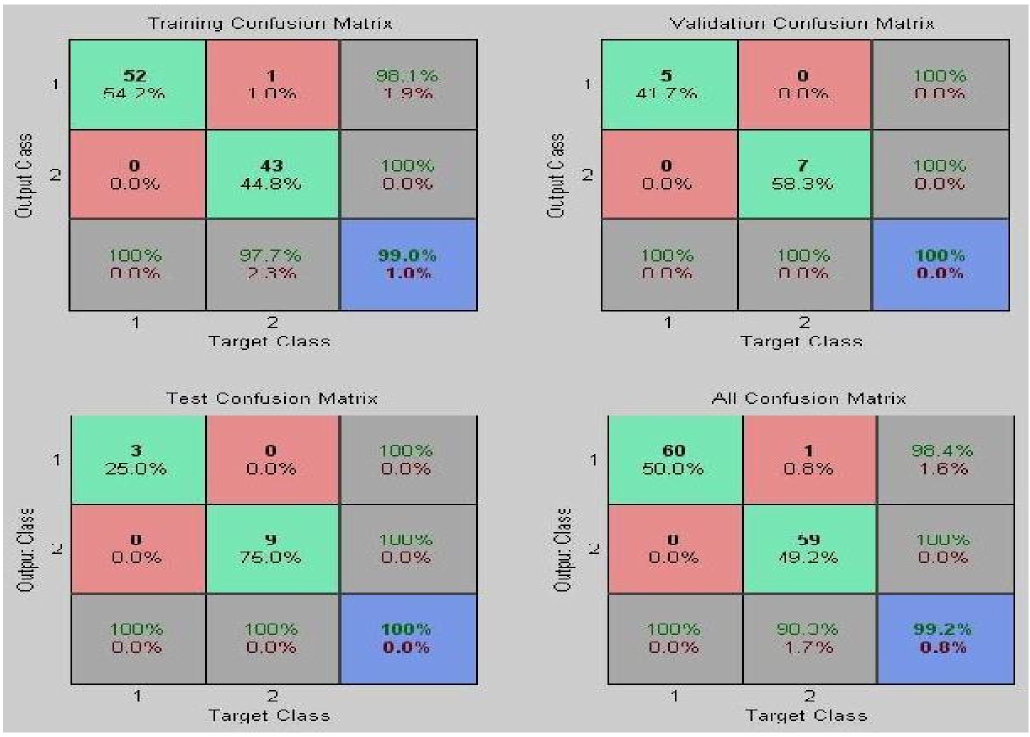

Figure 8: ANN performance matrixes to detect of pelt pattern in the second scenario

Table 2: Classifying the pelt pattern by ANN in the second scenario

Pelt pattern types	Number of images	Correct classification	Incorrect classification	Classification accuracy%
Regular	25	25	0	100
Irregular	25	25	0	100
Mean				100

DISCUSSION

Due to the differences in the evaluator experiences, the possibility of evaluator replacement and time limitation the human appraisal is not accurate and appropriate method (Vilarrasa, 2010). The results of present study showed that determination of pattern type of lamb pelts using image processing methods is feasible and substitution of this new method instead of human appraisal method is achievable.

However there are not any direct reports in use of artificial intelligence to detect the pelt pattern of new born lambs; but there are different reports in the field of using image processing and neural network to classify different subjects. For example, different plant diseases were classified by Al-Hiary *et al*., (2011) using image processing and neural network with accuracy between 83% and 94% in different scenarios. Alipasandi *et al*., (2013) presented a method using image processing and artificial neural network in which three genotypes of unripe and ripe peaches were classified with accuracy of 98.5% and 99.3%, respectively. In the other study, 17 plant species were recognized by Wijesingha and Marikar (2012) using image processing and neural network with accuracy of 85%. Also, 4 kinds of tea granoles were classified by Borah *et al* (2007) using image processing and neural network with accuracy of 80%. The 5 types of commercial rice were diagnosed by Pazoki *et al*., (2014) using artificial neural network with accuracy of 99 %.

According to the results mentioned above, the accuracy of the proposed method for classifying pattern type of lamb pelts in this study was in the range of accuracies reported by the other studies to classify different subjects. Also the results indicated that use of more relevant features as the input vector was led to increasing in the classification accuracy of ANN in the second scenario. This is in agreement with May *et al*., (2011) and Zien and Kramer (2009) who reported that in order to train the neural network , whatever more relevant features are used, the network accuracy will increase.

CONCLUSION

The results showed that the artificial intelligence is an appropriate tool for determining the pelt quality of new born lambs in the pelt sheep breeds. Thus it is hoped that by providing the required hardware and software, artificial intelligence will replace the human to determine the quality of lamb pelts.

ACKNOWLEDGMENT

Comments by staff of Khojir sheep breeding station especially Mr. Sharif and Mr. Hasani are gratefully appreciated.

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