Muzzle Classification Using Neural Networks

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Abstract: *There are multiple techniques used in image classification such as Support Vector Machines (SVM), Artificial Neural Networks (ANN), Genetic Algorithms (GA), Fuzzy measures, and Fuzzy Support Vector Machines (FSVM). Classification of muzzle depending on one of this artificial technique has become widely known for guaranteeing the safety of cattle products and assisting in veterinary disease supervision and control. The aim of this paper is to focus on using neural network technique for image classification. First, the area of interest in the captured image of muzzle is detected then pre-processing operations such as histogram equalization and morphological filtering have been used for increasing the contrast and removing noise of the image. Then, using box-counting algorithm to extract the texture feature of each muzzle. This feature is used for learning and testing stage of the neural network for muzzle classification. The experimental result shows that after 15 input cases for each image in neural training step, the testing result is true and gives us the correct muzzle detection. Therefore, neural networks can be applied in classification of bovines for breeding and marketing systems registration.*

Keywords: *Muzzle classification, image processing, neural networks.*

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1. Introduction

Image classification is one of the most important tasks in image processing field in order to guarantee livestock products safety and help veterinarians in registration of beef cattle for marketing and breeding. Artificial techniques is useful in case of breeding and marketing systems registration because they help in tracing cattle, detecting diseases and reducing fraud that can occur in case of using ear tags. The distribution of ridges and valleys in cattle muzzles are responsible for the formation of a pattern that assists in recognition of the cattle. Baranov et al show that the cattle muzzle patterns are very asymmetric and hereditable between muzzle halves is significant [28]. The uniqueness of muzzle structure, leads to that the pattern can be considered as a biometric identifier [31]. Image classification is used for predicting the categories of the current input image (cattle muzzle) by using its features [10, 11, 12, 13]. In our study we used box-counting algorithm to calculate the texture feature.

The goal of image classification is to maximize the probability of classifiers to neural network classifiers. Several algorithms are developed to be used in digital image classification such as K-means, Artificial Neural Networks (ANN), Genetic Algorithms (GA), Support Vector Machine (SVM), K Nearest Neighbour (KNN), fuzzy measures and Adaptive boost (Adaboosted).

Statistical techniques for pattern recognition have been used before the revival of neural network. Before the widespread of neural network classification techniques of pattern recognition problems were solved by linear and quadratic discriminates [27] or the (non-parametric) KNN classifier and the Parzen density estimator [4]. In the mid-eighties, the Parallel Distributed Processing (PDP) group [5, 21] together with others introduced the back-propagation learning algorithm for neural networks. This algorithm made it possible to train a non-linear neural network equipped with layers that called hidden nodes [6].

Image classification is the most important challenge in livestock processing system because its depending on comparing texture feature of each image with the input vector and then giving decision that help veterinarians. ANN based on texture classification is a technique that providing rich information to muzzle image of interest. The current work deals with a task where an object of interest is to be captured and the area of interest are selected out, after that preprocessing techniques are used to remove noise and enhance muzzle contrast. Then, by using box-counting algorithm the texture feature vector for each muzzle is calculated and used as an input for neural network.

ANN, processes information like human brain because it takes the structure of biological neural systems. It has been used for many applications. Scientists have developed different ANN's structures suitable for their problem. After the network is trained using supervised learning technique, it can be used for image classification [26].

The rest of the paper is organized as follows. Image classification stages used in this paper are described in section 2. Neural networks structure is detailed introduced in section 3. In section 4 experimental result is presented. Conclusion and future work are reported in section 5.

2. Image Classification Stages

Image classification consists of the following steps that are illustrated in the following Figure 1:

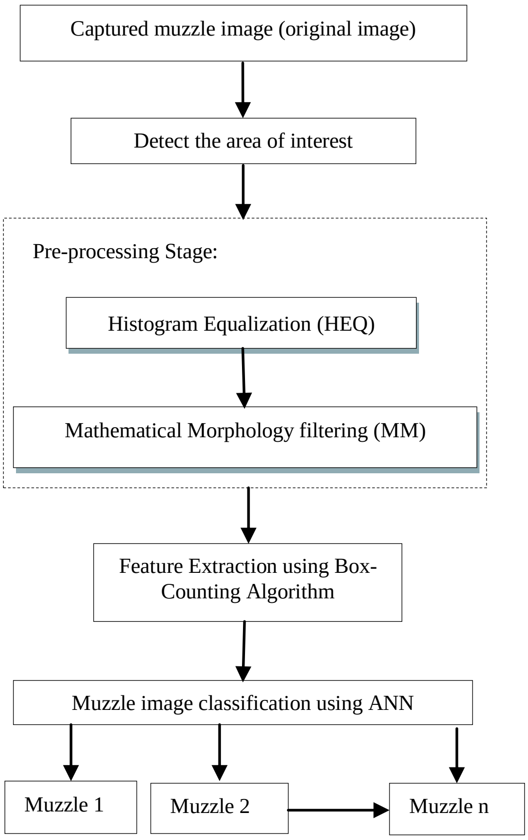

Figure 1. Block diagram of muzzle image classification.

Image classification is the process of identification that is used in pattern recognition techniques. In our study we used artificial neural network in order to classify muzzle pattern image into (Muzzle 1, Muzzle 2, ..., Muzzle n). Before this step we needed to extract the feature vector for each muzzle in order to use it in neural learning step. Texture feature extraction in calculated by using box-counting algorithm. The image that is used in feature extraction step is the original image after doing pre-processing steps on it such as Histogram Equalization (HEQ) and Mathematical Morphology filtering (MM) in order to increase the contrast of each muzzle image and remove image noise respectively.

2.1. Image Pre-Processing

Image pre-processing techniques are important, in order to find the direction of the muzzle image, to enhance image quality, increase image contrast and remove the noise from the image [3]. Before applying any image processing operations, pre-processing steps are very important in order to limit the search for exception such as noise without effect in muzzle image structure. In our study we used HEQ for increasing the contrast of image and using morphology filtering for noise removing from image [24].

2.1.1. Histogram Equalization

HEQ is responsible for redistribution of gray levels to obtain regular histogram. By implementing HEQ every pixel in the original image is replaced by integral of the histogram of image in that pixel [27]. HEQ is a technique that adjusts the image contrast using image's histogram. This adjustment makes better distributing of the intensity on the histogram. This allows the low contrast area to get better contrast by spreading out the most frequently intensity values [8].

2.1.2. HEQ Algorithm

- Consider a digital image with gray levels in the range [0, L-1], probability distribution function of the image can be computed by Equation 1:

$$P(r_k) = \frac{n_k}{N}, \; K=0, \ldots, L-1 \tag{1}$$

Where r_k is the k^{th} gray level and n_k is the number of pixels in the image having gray level r_k.

- Cumulative Distribution Function (CDF) can also be computed as follows:

$$C(n_k) = \sum_{i=0}^{i=k} P(r_i) \tag{2}$$

$$K=0, \ldots, L-1, \quad 0 \le C(n_k) \le 1$$

- HEQ appropriates gray level S_k to gray level r_k of the input image using Equation 2. So we have:

$$S_k = (L-1) \times C(r_k) \tag{3}$$

- Gray level S_k's changes can be computed by usual HEQ method:

$$\Delta S_k = (L-1) \times P(r_k) \tag{4}$$

Equation 4 means that distance between S_K and S_k+1 has direct relation with PDF of the input image at gray level r_k [14].

2.2. Mathematical Morphology Filtering

Morphology operations concept is based on shapes. In image processing, MM is used to determine the interaction between image using some morphology operations in our study we use opening operation and then do closing operation in the resulting image in order to remove noise. After comparing the corresponding pixels with their neighbours the resulting value of each pixel in the output muzzle image [8]. Opening and closing operation depends on erosion and dilation which are the two elementary operations in MM [16].

2.2.1. Mathematical Morphology Filtering Algorithm

- Dilation and erosion operations are not inverse operators. If X is eroded by B and then dilated by B, one may end up with a set smaller than the original set X. This set, denoted by $X \circ B$, is called the opening of X by B defined by by $X \circ B=(X \Theta B) \Phi B$. Likewise the closing of X by B is dilation of X followed by erosion, both with the same structuring element. The closing of X by B may return back a set larger than X; it is denoted by $X \bullet B$ and defined by $X \bullet B=(X \Theta B) \Phi B$.
- Dilations and erosions are closely related. This is expressed in the principle of duality [14] that states that

$$X \Theta B = (X^c \Phi \check{B})^c \text{ or } X \Phi B = (X^c \Phi \check{B})^c \tag{5}$$

Where the complement of X, denoted X^c, is defined as $X^c = \{p \in \varepsilon \mid p \notin X\}$, and the symmetric or transposed set of $B \subseteq \varepsilon$ is the set $\check{B}$ defined as $\check{B} = \{-b \mid b \in B\}$. Therefore, all statements concerning erosions and openings have a parallel statement for dilations and closings, and vice versa [7].

- The opening of A by B is obtained by the erosion of A by B, followed by dilation of the resulting image by B:

$$A \circ B=(A \Theta B) \Phi A \tag{6}$$

- The closing of A by B is obtained by the dilation of A by B, followed by erosion of the resulting structure by B:

$$A \bullet B=(X \Theta B) \Phi B \tag{7}$$

3. Feature Extraction using Box-Counting Algorithm

Texture feature extraction is the second step after pre-processing operations. It’s regarded as one of the most important factor in image classification step. Based on different features such as horizontal, vertical, diagonal and anti-diagonal transformations. This transformation should be chosen according to the characteristics of texture muzzle images. This transforms performance in the resulting image (closed image). There are several methods to calculate fractal dimension of muzzle image, but a lot of studies show that box counting algorithm is widely used in fractal dimensions calculations [1].

Box counting dimension algorithm D_b of any bounded subset of A in R n, which is a set in Euclidean space. Let $N_r(A)$ be the smallest number of the set of r that cover A. Then:

$$D_b(A) = -\lim_{r \to 0} \frac{\log(N_r(A))}{\log(1/r)} \tag{8}$$

Provided that the limit exists.

Subdividing R^n into a lattice of grid size $r \times r$ where r is continually reduced, it follows that $N'_r(A)$ is the number of grid elements that intersect A and $D_b(A)$is,

$$D_b(A) = -\lim_{r \to 0} \frac{\log(N'_r(A))}{\log(1/r)} \tag{9}$$

Provided that the limit exists.

This implies that the box counting dimension $D_b(A)$ and $N_r(A)$ are related by the following power law relation:

$$N_r(A) = \frac{1}{r_b^D(A)} \tag{10}$$

Proof of this relation can be obtained by taking logs of both sides of Equation 10 and rearranging to form Equation 11.

$$\log N_r(A) = D_b(A) \log(1/r) \tag{11}$$

From the Equation 11 it is possible to make an analogy to the equation of a straight line, $y=mx \pm c$, where m is the slope of the line and c is the y intersect. The box-counting dimension is implemented by placing a bounded set A, in the form of a muzzle image, on to a grid formed from boxes of size $r \times r$. Grid boxes containing some of the structure, which in the case of a muzzle image is represented by the grey-levels within a certain range, are next counted. The total number of boxes in the grid that contains some of the structure is $N_r(A)$. The algorithm continues by altering r to progressively smaller sizes and *count*$N_r(A)$. The slope of the line fitted through the plot of $\log(1/r)$ against $\log N_r(A)$is the fractal, or box-counting, dimension of the bovine muzzle image region under investigation.

3.1. ANN Classification Algorithm

During the training process in the learning algorithms the neural network becomes more adequate to data. We can use neural net algorithms because it focuses on supervised learning technique. The characteristics of this algorithm are to use the given output and compare it to the predicted output and adapted all parameters according to this comparison. The network parameters are its weights. Weight initial value is usually random value calculated from a standard normal distribution.

The following steps are repeated during the network training process [18]:

- First for the given inputs x and current random weights the neural network calculates an output $O(x)$.
- Check if the training process has not completed yet, the predicted output O will differ from the observed output y.
- Using the following equation to calculate an error function E, as the Sum of Squared Errors (SSE).

$$E = \frac{1}{2}\sum_{i=1}^{L}\sum_{h=1}^{H}(O_{1h} - y_{1h})^2 \qquad (12)$$

- Or the cross-entropy.

$$E = -\sum_{l=1}^{L}\sum_{h=1}^{H}(y_{1h}\log(O_{1h}) + (1-y_{1h})\log(1-O_{1h})) \qquad (13)$$

- The difference between predicted and observed output measures.
- Where l= 1, ..., L indexes the observations, i.e., given input-output pairs, and h= 1, ..., H the output nodes.
- According to the rule of a learning algorithm, all network weights are adapted.
- If a pre-specified criterion is fulfilled the process is terminated. e.g., if the error function with respect to weights $(\vartheta E/\vartheta W)$ are smaller than a given threshold.

3.2. Neural Networks Structure

The biological human brain consists of billions of connected processing elements called (neurons), which transfer information when the brain learns. ANN is an artificial presentation of the human brain that simulates its learning process [9]. ANN indicate the computational networks which simulate, in a gross case, the networks of nerve cell (neurons) of biological (human or animal) central nervous system. This simulation is a gross cell-by-cell (neuron-by-neuron, element-by-element) simulation [17].

Neural networks include a set of nodes (neurons) and edges which forms a network. Input nodes forms network first layer. In most neural networks, each input node is mapped to one input attribute that forms the muzzle texture feature. Output nodes usually represent the predictable attributes. The result of the output node is often a floating number between 0 and 1 [22].

In our study we use a supervised learning technique. The essential factor in supervised technique is the ability of an external teacher (Target), in which the network can be provided with the required target response. The network parameters are adjusted under the combined effect of the error signal and the training vector as shown in Figure 2.

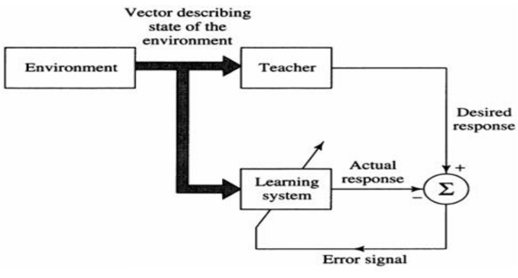

Figure 2. Supervised learning technique.

4. Experimental Results

4.1. Database

Muzzle database is the first challenge that we faced when we stated this research because of insufficiency muzzle printed database. Our muzzle database consists of 53 different cattle muzzle, each cattle has twenty capered image. A sample of three muzzle captured image is shown in Figure 3.

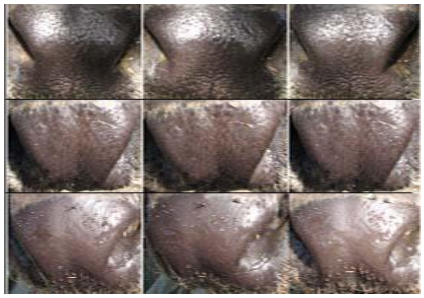

Figure 3. A sample of muzzle printed images from live animals. This figure represents muzzle print images taken from three different animals.

4.2. Pre-Processing Operations

Image preprocessing is the critical initial step before texture feature extraction. There are many preprocessing algorithms. In this paper, we present HEQ and MM filtering techniques, in order to enhance the image contrast and remove image noise.

4.2.1. Histogram Equalization

The contrast enhancement of image refers to the amount of color or gray differentiation that exists between various features in digital images. It is the range of the brightness present in the image. The images having a higher contrast level usually display a larger degree of color or gray scale difference as compared to lower contrast level. The contrast enhancement is a process that allows image features to show up more visibly by making best use of the color presented on the display devices [21].

HEQ [23] is based on distributing the intensities of pixels so the range of intensities is considered. This method increases the contrast of images when the used data is represented by close contrast values. This adjustment allows the areas of lower local contrast to gain a higher contrast [2]. Before implementing any process in image we calculate the gray scale for each image as follows Figure 4.

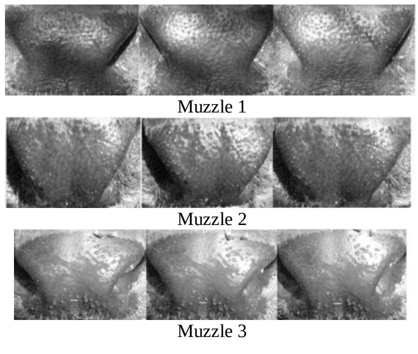

Figure 4. Gray scale level for three different cattle each with different captured image.

After implementing HEQ on the three cases above the resulting histogram for each muzzle is shown in the following Figure 5.

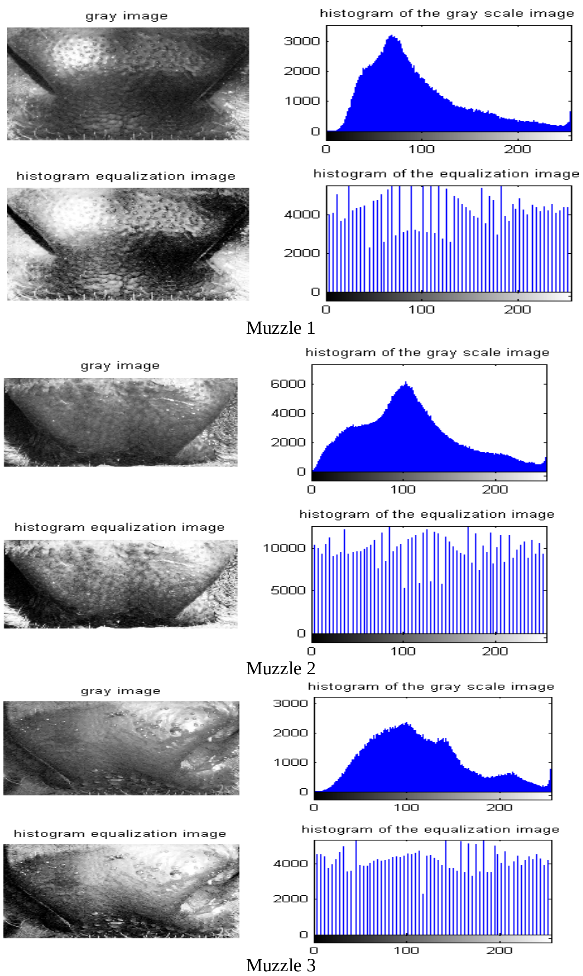

Figure 5. The HEQ for three different cattle's.

Also we can see that the image's contrast has been improved. The original histogram has been stretched along the full range of gray values, as we can see that in the HEQ resulting statistical graph. This is a simple result of the twenty resulting histograms for each muzzle.

By comparing HEQ to different images of the same cattle we found that histogram is symmetric as shown in the following Figure 6.

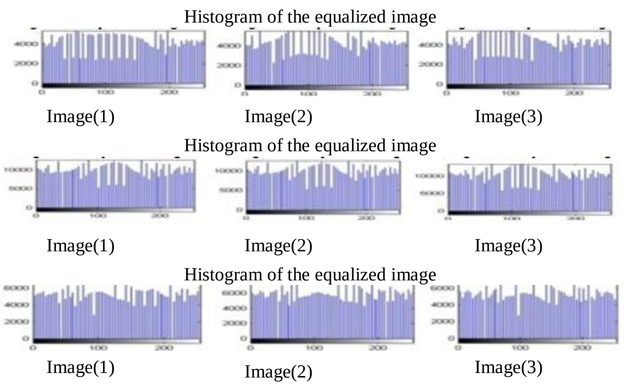

Figure 6. A sample of HEQ for cattle muzzle each with three different cases.

In image processing the HEQ is the process which shows the appearance of each intensity value in muzzle image. Histogram F [graph shows a number of pixels at each different intensity value. For example if the image has 9-bit grayscale this means that there are 512 different intensities values, so the histogram graph shows 512 numbers which show pixels distribution among each grayscale values [15]. HEQ increases image contrast because it specify the intensity value of the input image pixels, so histogram aim is that the output graph contain a uniform distribution of intensities. HEQ method increases global image contrast [29].

4.3. MM Filtering

The basic Mathematical Morphological operators are dilation, erosion, opening, closing. Dilation usually used to maximize the value in the object. So the muzzle image after dilation operation will increase the intensity or be brighter than the image before dilation. Muzzle image after dilation become darker than the original one because it retroactivity or thinning the object. Dilation also is used to lead to expand the image and to fill the spaces. Erosion definition is opposite to dilation. It's usually used to minimize the value in the object. Opening and closing operations consists of dilation and erosion. In our algorithm after implementing the HEQ on muzzle image, the next step in preprocessing operation is to implement the MM filtering on image in order to remove noise form image. First we implement the opening operation on the image and the resulting image is closed as follows [30].

4.3.1. Opening Operation

In opening operation first the image will be eroded and will be followed by dilation. As shown in Figure 7.

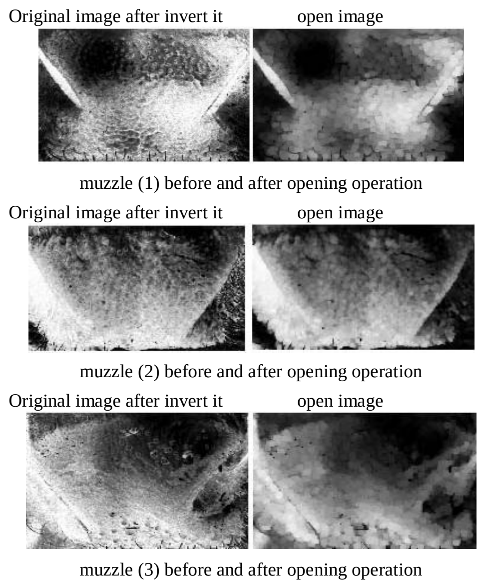

Figure 7. A sample of applying the opening operation on the cattle images for three different cases.

4.3.2. Closing Operation

In closing operation first the image will be dilated and the result will be erosion as shown in Figure 8.

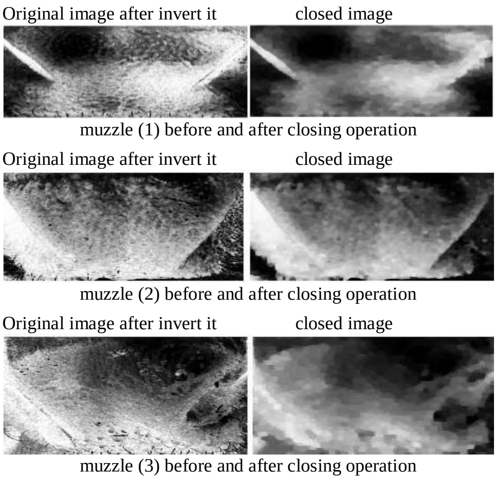

Figure 8. A sample of applying the closing operation on the cattle images for three different cases.

After image preprocessing operations HEQ and MM filtering low contrast muzzle are transformed into high contrast and noise is removed respectively. Now the muzzle image becomes ready to the second step that is texture feature extraction.

4.3.3. Texture Feature Extraction Algorithm

Feature extraction is a critical step in image processing field. To extract features that reflect the content of the images it is still a challenging problem [28]. We use box-counting algorithm to extract texture feature. By implementing box-counting in different muzzle on the same cattle the resulting feature vector is approximately the same.

By implementing box-counting we also get a feature vector which consists of nine different features for each muzzle. The above figure shows a sample of resulting texture feature extracted from box counting algorithm. As shown each statistical chart represents texture feature for one muzzle in some group. Figure 9 shows the result of three different cattle with six different captured muzzles to each. It also illustrates the high similarity between each group (i.e., all muzzles for one cattle result is the same).

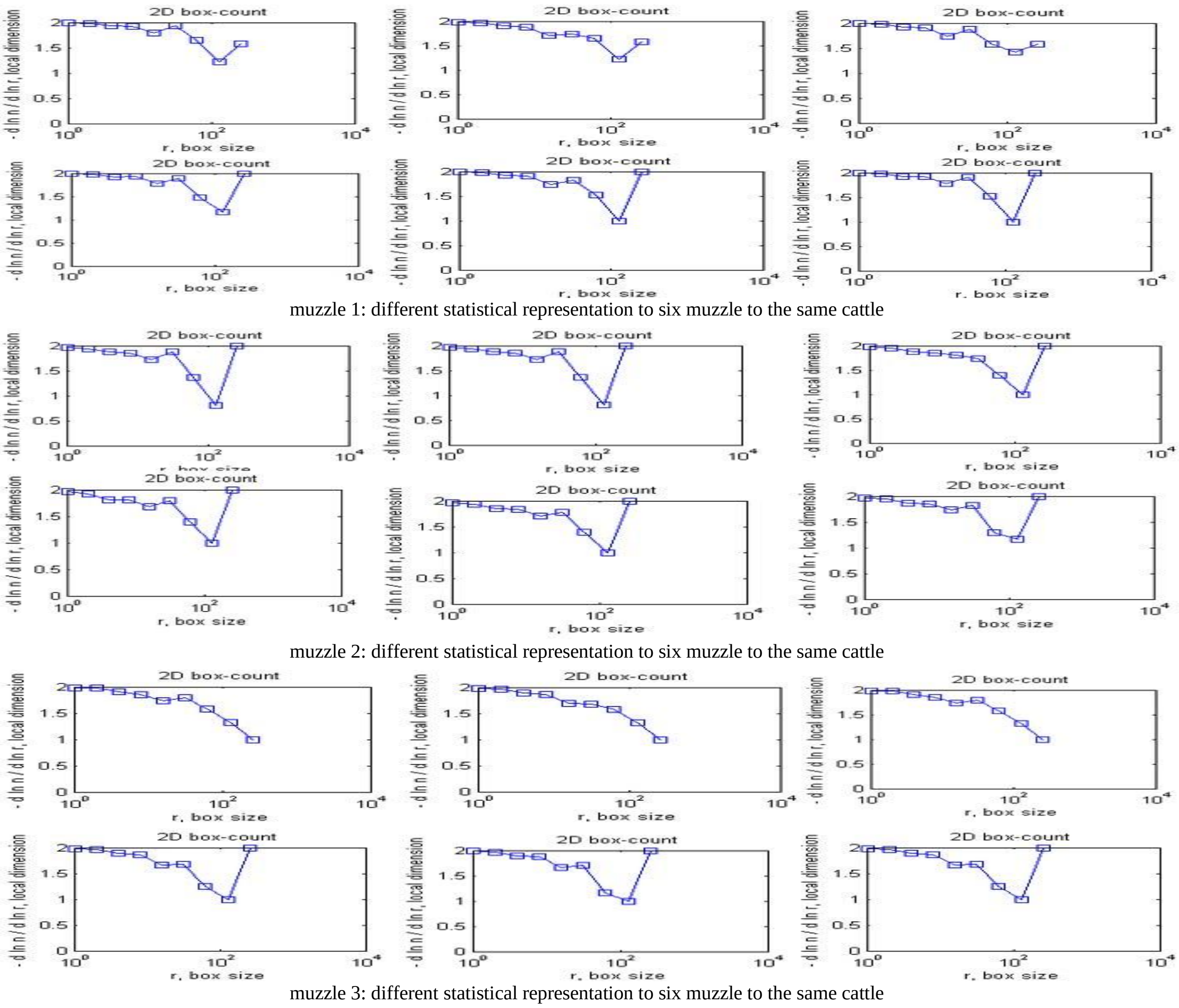

Figure 9. A sample of applying box-counting algorithm in three different cases, each case has six different images for the cattle.

As we can see in the resulting statistical graph that represents feature vector to the sample that consists of three different images to the same muzzle. But our sample consists of twenty muzzles for each cattle as shown in Figure 10. As we know that the statistical representation is not accuracy in distinguishing between large numbers of data, so we used one of the artificial techniques that is used in classification i.e., neural network. To use artificial neural network we use the resulting feature vector that is shown above as an input to the network.

1.584963	1.222392	1.652077	1.932886	1.792558	1.924955	1.93627	1.977827	1.988653
2	1.169925	1.473931	1.895303	1.782769	1.9331	1.926434	1.980535	1.990228
1.584963	1.222392	1.652077	1.730393	1.711042	1.883768	1.900114	1.969664	1.985578
1.584963	1.222392	1.584963	1.817136	1.721284	1.902153	1.911523	1.972299	1.981613
2	1	1.523562	1.902703	1.783189	1.91983	1.927355	1.976785	1.98901
1.584963	1.415037	1.584963	1.874469	1.735325	1.91246	1.926206	1.976581	1.986779
2	1.169925	1.473931	1.895303	1.68966	1.931053	1.917612	1.980255	1.989535
1.584963	1.415037	1.584963	1.906891	1.802768	1.922125	1.919284	1.973556	1.98647
1	1.321928	1.378512	1.884523	1.849666	1.929506	1.939646	1.987534	1.992353
2	1.169925	1.473931	1.847997	1.77961	1.942856	1.934475	1.985552	1.992157
2	1	1.523562	1.816288	1.731612	1.904386	1.914416	1.974115	1.986515
1.584963	1.415037	1.523562	1.724366	1.694587	1.896689	1.890417	1.968107	1.984636
2	1.169925	1.473931	1.695994	1.726239	1.898252	1.91371	1.968713	1.985286
2	1.169925	1.473931	1.659925	1.746068	1.889731	1.895287	1.967448	1.984108
2	1.169925	1.078003	1.68281	1.577057	1.851955	1.837467	1.958708	1.9779
2	1	1.523562	1.816288	1.731612	1.904386	1.914416	1.974115	1.986515
1.584963	1.415037	1.523562	1.724366	1.694587	1.896689	1.890417	1.968107	1.984636
2	1.169925	1.473931	1.695994	1.726239	1.898252	1.91371	1.968713	1.985286

Figure 10. A sample of the texture feature that extracted from box-counting algorithm.

4.3.4. Image Classification using Neural Network Algorithm

ANN is used in solving complex problems because it's able to learn more complex nonlinear (input-output) relations. Network adapts itself by using sequential training algorithm. Feed-forward network, is the most known technique in pattern recognition and classification [19]. Self-Organization Map (SOM) and Kohonen network is another popular network techniques but it is used in feature mapping and clustering techniques [20]. We use feed-forward in our research and it gives us a very accurate result. The network adapts itself by updating its architecture and its connected weights [25].

In our implementation method we use matlab (R2009a) on laptop with processor Intel(R) Core(TM) Duo CPU T2350 @ 1.86GHz 1.87 GHz. Running at 3.00 GB of RAM.

The procedures followed when implementing neural networks are:

1. Use the input feature vector data set as network input layer. In our research we use tree different vector set and compare the result to prove that the artificial network learn as human brain. The more the network learns, the more accurate result we get. And target in our sample is three-element target vector.
2. Create a network. We use a pattern recognition network, which is a feed-forward network with tan-sigmoid transfer functions in both the hidden layer and the output layer. As in the function-fitting example, use 20 neurons in one hidden layer:
   - The network has three output neurons, because there is the muzzle categories associated with each input vector.
   - Each output neuron represents one muzzle category.
   - When an input vector of the appropriate category is applied to the network, the corresponding neuron should produce a 1, and the other neurons should output a 0.
3. Train the network. The pattern recognition network uses the default Scaled Conjugate Gradient Algorithm for training. The application randomly divides the input vectors and target vectors into three sets:
   - 60% are used for training.
   - 20% are used to validate that the network is generalized and to stop training before over fitting.
   - The last 20% are used as a completely independent test of network generalization.
4. Test the network with cases as input vector without target and test the network. We use eleven cases to test the network in the three different cases with different vectors.
5. Our result after comparing is shown in the following Table 1.

Table 1. Classification accuracy after using ANN classifier.

NO. Feature Vector	NO. Iterations	Time (sec)	Accuracy (%)
180	30	2 sec	75.27 %
240	82	2 sec	81%
300	95	3 sec	99.18%

6. Statistical representation to the accuracy result is shown in the following:
   a) In a case that contains 180 feature vectors the accuracy of performance is shown in Figure 11.

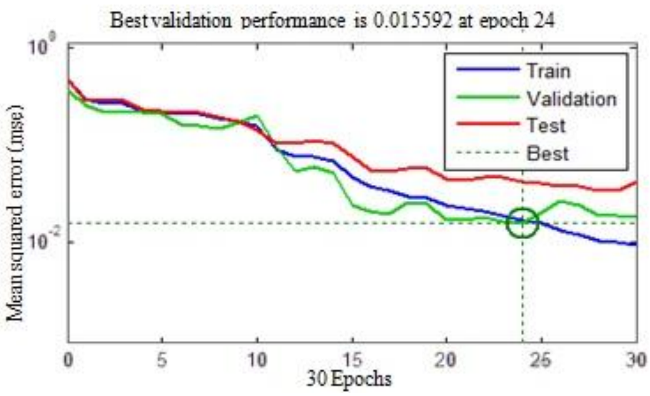

Figure 11. The accuracy rate performance in case of using 180 feature vector.

   b) In a case that contains 240 feature vector the accuracy of performance is shown in Figure 12.

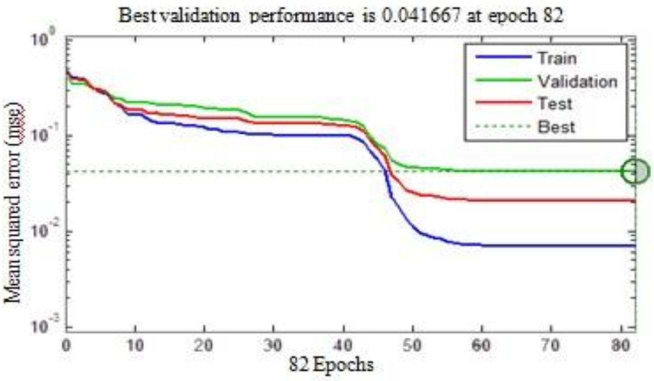

Figure 12. The accuracy rate performance in case of using 240 feature vector.

c) In a case that contains 300 feature vectors the accuracy of performance is shown in Figure 13.

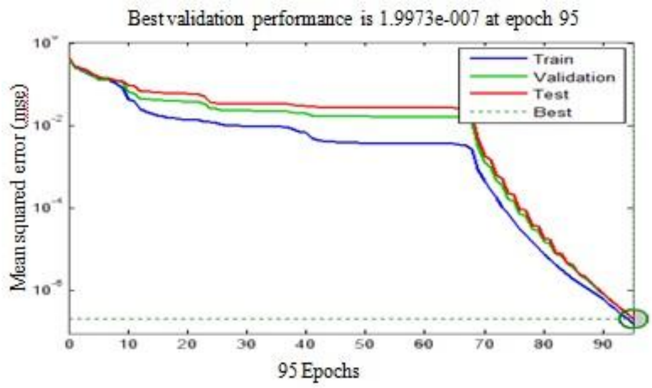

Figure 13. The accuracy rate performance in case of using 300 feature vector.

5. Conclusions and Future Work

It has been shown that the more the neural network is trained the more the network gives correct results. It has been shown that in the case which contains 180 feature vectors the accuracy was 75.27 %. When the number of input feature vectors has been increased in the second case to 240 the accuracy was 81%. For the third time, when the number of input vectors has been increased to 300 cases the result of accuracy was 99.18% and the time difference is not high. In the first two cases it has consumed 2 seconds and 3 seconds in the third case. In the future work the authors aim to use another softcomputing technique such as genetic algorithms and compare the results with neural networks.

References

[1] Anitha S. and Radha V., "Comparison of Image Preprocessing Techniques for Textile Texture Images," *International Journal of Engineering Science and Technology*, vol. 2, no. 12, pp. 7619-7625, 2010.

[2] Balan A., Traina A., Traina C., and Azevedo-Marques P., "Fractal Analysis of Image Textures for Indexing and Retrival by Content," *in Proceeding of 18th IEEE Symposium on Computer-Based Medical Systems*, Bangkok, pp. 581-586, 2005.

[3] Bandyopadhyay S., "Pre-Processing of Mammogram Images," *International Journal of Engineering Science and Technology*, vol. 2, no. 11, pp. 6753-6758, 2010.

[4] Baranov A., Graml R., Pirchner F., and Schmid D., "Breed Differences and Intra-Breed Genetic Variability of Dermatoglyphic Pattern of Cattle," *Journal of Animal Breeding and Genetics*, vol. 110, no. 1-6, pp. 385-392, 1993.

[5] Basu J., Bhattacharyya D., and Kim T., "Use of Artificial Neural Network in Pattern Recognition," *International Journal of Software Engineering and its Applications*, vol. 4, no. 2, pp. 23-34, 2010.

[6] Devijver P. and Kittler J., *Pattern Recognition: A Statistical Approach*, Prentice Hall, 1982.

[7] Droogenbroeck M. and Buckley M., "Morphological Erosions and Openings: Fast Algorithms based on Anchors," *Journal of Mathematical Imaging and Vision*, vol. 22, no. 2, pp. 121-142, 2005.

[8] Dubey R., Hanmandlu M., and Gupta S., "A Comparison of Two Methods for the Segmentation of Masses in the Digital Mammograms," *Computerized Medical Imaging and Graphics*, vol. 34, no. 3, pp. 185-191, 2010.

[9] Egmont-Petersen M., Ridder D., and Handels H., "Image Processing with Neural Networks-a Review," *The Journal of the Pattern Recognition Society*, vol. 35, no. 10, pp. 2279-2301, 2002.

[10] El-Bakry H., El-Hennawy I., and El-Hadad H., "Bovines Muzzle Identification using Box-Counting," *International Journal of Computer Science and Information Security*, vol. 12, no. 5, pp. 29-34, 2014.

[11] El-Henawy I., El-Bakry H., and El-Hadad H., "Cattle Identification using Segmentation-based Fractal Texture Analysis and Artificial Neural Networks," *International Journal of Electronics and Information Engineering*, vol. 4, no. 2, pp. 82-93, 2016.

[12] El-Henawy I., El-Bakry H., El-Hadad H., and Mastorakis N., "Muzzle Feature Extraction Based on Gray Level Co-Occurrence Matrix," *International Journal of Veterinary Medicine*, vol. 1, pp.16-24, 2016.

[13] El-Henawy I., El-Bakry H., El-Hadad H., and Mastorakis N., "Bovines' Texture Feature Extraction Based on Discrete Wavelet Transform," *International Journal of Veterinary Medicine*, vol. 1, pp.5-15, 2016.

[14] Fukunaga K., *Introduction to Statistical Pattern Recognition*, Academic Press, 1990.

[15] Gonzalez R., Woods R., and Eddins S., *Digital Image Processing using MATLAB*, Pearson

Education, 2004.
[16] Gonzalez R. and Woods R., *Digital Image Processing*, Prentice-Hall, 2008.
[17] Graupe D., *Principles of Artificial Neural Networks*, World Scientific, 2007.
[18] Günther F. and Fritsch S., "Neuralnet: Training of Neural Networks," *The R Journal*, vol. 2/1, no. 1, pp. 30-38, 2010.
[19] Jain A., Mao J., and Mohiuddin K., "Artificial Neural Networks: A Tutorial," *Computer*, vol. 29, no. 3, pp. 31- 44, 1996.
[20] Kohonen T., *Self-Organizing Maps*, Springer-Verlage, 1995.
[21] Lal S. and Chandra M., "Efficient Algorithm for Contrast Enhancement of Natural Images," *The International Arab Journal of Information Technology*, vol. 11, no. 1, pp. 95-102, 2014.
[22] MacLennan J., Tang Z., and Crivat B., *Data Mining with Microsoft SQL Server*, Wiley, 2008.
[23] Mehena J., "Medical Images Edge Detection Based on Mathematical Morphology," *International Journal of Computer and Communication Technology*, vol. 2, no. 6, pp. 49-53, 2011.
[24] Ponraj D., Jenifer M., Poongodi P., and Manoharan J., "A Survey on the Preprocessing Techniques of *Mammogram for the Detection of Breast Cancer*," *Journal of Emerging Trends in Computing and Information Sciences*, vol. 2, no. 12, pp. 656-664, 2011.
[25] Rumelhart D. and McClelland J., *Parallel Distributed Processing: Explorations in the Microstructure of Cognition*, MIT Press, 1986.
[26] Thai L., Hai T., and Thuy N., "Image Classification using Support Vector Machine and Artificial Neural Network," *Information Technology and Computer Science*, vol. 4, no. 5, pp. 32-38, 2012.
[27] Thangavel K. and Roselin R., "Mammogram Mining with Genetic Optimization of Ant-Miner Parameters," *International Journal of Recent Trends in Engineering*, vol. 2, no. 3, pp. 67-69, 2009.
[28] Tian D., "A Review on Image Feature Extraction and Representation Techniques," *International Journal of Multimedia and Ubiquitous Engineering*, vol. 8, no. 4, pp. 385-396, 2013.
[29] Vatsa M., Chauhan D., and Singh S., "Image Contrast using Histogram Equalization," *in Proceeding of I-Society*, Punjab, pp. 1-7, 2012.
[30] Wang Y., Chen Q., and Zhang B., "Image Enhancement based on Equal Area Dualistic Sub-Image Histogram Equalization Method," *IEEE Transaction on Consumer Electronics*, vol. 45, no. 1, pp. 68-75, 1999.
[31] Yeganeh H., Ziaei A., and Rezaie A., "A Novel Approach for Contrast Enhancement Based on Histogram Equalization," *in Proceeding of the International Conference on Computer and Communication Engineering*, Coimbatore, pp. 256-260, 2008.

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