Muzzle Feature Extraction Based on gray level co-occurrence matrix

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Abstract— Nowadays veterinarians pay a numerous effort to save bovines' products because of its rapid growth. The critical point in this paper is to classify and distinguish between large different groups of bovines with high degree of accuracy. This paper presents two bovine's classification models depending on J48 decision tree and Naive Bayes classifier. These two models consist of three phases; pre-processing phase, texture feature extraction phase and classification phase. Pre-processing phase consists of average filter and median filter to remove noise from muzzle image. The second phase used gray level co-occurrence matrix (GLCM) algorithm to extract image features. Then the last phase used decision tree in the first model and used Naive Bayes the second model to classification muzzles and comparing the accuracy result. The used data base consists of fifty-two different bovine. The experimental result proves the advancement of decision tree classifier than Naive Bayes classifier. By comparing the result of decision tree with Naive Bayes the accuracy rate in case of using fifty-two different groups is 89.64% comparing with 75.38% in case of using Naive Bayes classification system.

Keywords:- bovine classification; average filter; Median filter; gray level co-occurrence matrix (GLCM)algorithm; Naive Bayes and Decision tree.

1. Introduction

Today, Veterinarians pay great effort to help the animal agriculture to save the bovine products. The rapid growth of the livestock products is the critical point. So veterinarians and Ministry of Animal Resources do their best to trace all animal especially bovine which has diseases infections. A lot of traditional techniques used to solve this critical problem but all cannot solve the deceitful farmers' problems. This paper aims to help the veterinarians and animal agriculture by build two models to know the deceitful farmer. A lot of farmers able to remove the bovines' ear tag easily after these bovine die and use this ear tag to another bovine. The proposed intelligent models can help is achieve justice. This paper help the end used to save the animal record and connect it with the bovine muzzle print. These models help veterinaries in tracing the non-healthy animals. The important point in this paper is to identify each bovine in this crowd. Bovine muzzle print plays a great role in bovine observation and monitoring especially in bovine diseases beginning, bovine ownership assignment and traceability, vaccination management and production management [1].

The traditional classification system such as muzzle ink printing, ear notching, ear tags, Electronic Identification and Radio Frequency Identification (RFID) [2], Freeze branding and hot iron branding, tattooing, Neck Chains and Barcode, blood test or hair sample (DNA) and Nose printing. These traditional techniques are not satisfied in case of classification and identification especially in cases such as bovine repetition and farmer fraudulent.

So, Ministry of Animal Resources forces no using more accurate and reliability systems to get rid of the disadvantages and defects of all the traditional tracing techniques. Fingerprint is the human identifier and in bovine muzzle print is its biological identifier. In human, hair cover skins except some parts of the body like fingerprint. In bovine muzzle consists of distribution of valleys and ridges over it. Researchers such as Baranov and his team discovered the muzzle print for the bovine is discovered the asymmetry between the two halves and hereditable [3]. Bovine muzzle print consider as a biometric identifier because the uniqueness [4]. The essential key to identify each animal or individual is the biometric depending on the behavioral features [5], [6].

Bovine classification models must have the following characteristics; reliability, acceptability, accuracy, uniquely identifies each bovine and solves the fraudulent problems [7]. Since 1921, the bovine muzzle is considered as a unique biological identifier like fingerprint in human case. The traditional techniques such as ink print that is paper based technique and it was the earlier technique for animal identifying by animal agriculture. The disadvantages of using ink print technique are holding the animal still, build up wetness on the bovine noses, and use a lot of ink which case in wasting time. From this point of view the animal agriculture starts to search for new intelligent techniques that solve the traditional techniques disadvantages. The new intelligent techniques based on the using digital image processing in bovine classification and identification systems. The new intelligent techniques use digital cameras instead of the ink print techniques. The advantages of these techniques depend on using different factors such as the growth of the availability of using workstations and microcomputers with large capability in saving livestock and working with large data base. These factors help in reducing the cost of computation and image acquisition and the rapid increasing in the image processing applications because they improve and increase the capabilities of image equipment and display devices [8].

So the first critical part in this paper is to collect a live bovine database based on different captured image for each bovine. The difference between what really automatically extracted from feature extracted technique and human observation is known scientifically by a Semantic Gap Problem [9]. The second critical part is the number of features in each feature vector that visually represents each captured bovine muzzle image contains. The feature vectors were used to solve the semantic gap problem [10]. The new researches in texture feature extraction field is used to increase the ability of differentiate between each bovine muzzle images [11]. The technique that used for image texture feature extraction is gray level co-occurrence matrix (GLCM), which is used in the second phase in the proposed two models in this paper [12].

This paper used two different techniques in the classification phase; J48 decision tree and Naive Bayes Classification Algorithms then it used to compare between the accuracy rates depending on the number of features extracted in the second phase. The second phase in this paper is texture feature extraction using CLCM in content based for muzzle image retrieval. The two main concepts extract feature in spatial range or domain or extract it in transformed range (domain) [13]. Spatial domain feature extraction consists of CBIR algorithm that based on image histogram, VQ [14] [15] [16] and BTC [17] [18] [19]. Transform domain algorithm widely used in case of digital image compression because it result to the very high energy compression in case of the transformed digital images. So the best decision is to use transformed domain for image feature extraction in CBIR [20].

The final phase in this paper is the classification process using decision tree and Naive Bayes classifier techniques. Decision tree technique is a robust statistical technique for interpretation, prediction, data manipulation and classification which is used in many research fields. Decision tree technique commonly used in data mining in case of classification systems that depends on different attributes and to advanced prediction method for the target variable. Decision tree depends on classifies the problem in to branch such as segments that form the inverted tree with a root node, internal nodes and leaves nodes [21]. Naïve Bayes classifier is depending on probability. Naïve classification technique used as a supervised learning technique and statistical technique in classification phase. Naïve Bayes is the simplest probabilistic technique depending on Bayesian theorem and independence assumption. The proposed model in this research used gray level co-occurrence matrix (GLCM) algorithms in the feature extraction part and then compare between the accuracy rates of the classification process that depends on Naïve Bayes and J48 decision tree techniques. This is the continual contribution for the authors and this is the best accurate model if the authors compare between this model and the previous models accuracy rates.

The rest of the paper is organized as follows. Backgrounds are discussed in Section 2. Section 3 presents the proposed the bovine classification model in detail. Experimental results are discussed in Section 4. Conclusions and future work are discussed in Section 5.

2. Background

2.1 Average filter

The average filter is the widely common used filter. Essential because researchers found that average filter is the easiest filter for image filtering to use and easy to understand. Despite this filter is sample, it is the optimal choice for reducing noise which randomly distributed on the image detained a sharp step response. This property makes it the main used filter [22]. The average name implies that it operates by calculate the average number of points for the input image signal to produce the value of this point in the output image. Equation (1) that use for this processes is written in the following line.

$$y(i) = \frac{1}{n}\sum_{j=0}^{n-1} x[i+j] \quad (1)$$

Where the input pixel represent by x [ ], output pixel represent by y [ ], and n denotes number of points in the average. Average filter algorithm starts with Replace each pixel with the average of itself and its neighbors. Then calculates the kernel (W) contains only 1s, after that the result is divided by the sum of the weights, i.e., with 1/9. Fast operation for small neighborhoods, then differing pixel values will become more like their neighbors this means that noise is reduced and sharp edges are blurred. So the general representation for average filter for M* M binary image with weighted average filter of size m*m is given with equation (2).

$$g(x,y) = \frac{\sum_{s=-a}^{a}\sum_{t=-b}^{b} w(s,t)\, f(x+s, y+t)}{\sum_{s=-a}^{a}\sum_{t=-b}^{b} w(s,t)}$$

Where m=2a+1 and n=2b+1 (2)

2.1 Median filter

Median filter is a nonlinear filter used for removing noise from images. Its output depends on the rank of pixels value includes in filtered regions. Median filter best known because of its ability of decreasing certain noises types. It replaces the center value of required pixel with the median of pixel values under the filtered areas [23] [24].

Algorithm 1:- Proposed Algorithm. An algorithm for Preserving the edge in medical image

Input:

```
        [Img] :muzzle bovine Image; Mask Size: Size of
        Mask, threshold €
        Output: [O] :Enhanced Image
        1. compute [Rw Col] = size[Img] // No of Row
and Cols in Matrix
        2. Img[1,:] = Img; Img[Rw +1,:] =0; Img[:,1]
        =0;Img[:,Col+1]=0 // zero padding in First, Last
        row and First and Last Column of Img
        3. compute N = MaskSize/2;
        4. for each Row ∈ Rw //Scan the image from top
to bottom
        5. for each Column ∈ Col // Scan the image of
mask from left to right
                a. compute Mask = Img[Row – N : Row +
N; Column – N : Column + N] ;
                b. m= median[median[Mask[:]]]
                c. x1 =sum[sum[Iedge[i-1:i+1,j-1]]];
                d. x2 =sum[sum[Iedge[i-1:i+1,j+1]]];
                e. y1 =sum[sum[Iedge[i-1,j-1:j+1]]];
                f. y2 =sum[sum[Iedge[i-1,j-1:j+1]]];
                g. z1 =sum[sum[Iedge[i==j]]];
                h. Count= [x1 ~=0 | x2 ~=0 | y1 ~=0 | y2
~=0 | z1 ~=0]
                i. If Count <€
        6. Imed[Img,j] =mean[neighboring[Iedge[i,j]]]
           Else
           Imed[Img,j] = m
End
```

2.2 Gray level co-occurrence matrix (GLCM) feature extraction technique

Image texture is the most important property used in case of denoting and identifying the area of interest in the image. The earliest feature extraction technique consists of Grey Level Co-occurrence Matrices (GLCM) which is introduced in 1973 by Haralick et.al. [25]. Starting from this time the GLCM becomes the widely important technique used for extract image texture feature in different application areas and remain the most effective technique in the area of image texture feature extraction and analysis [26].

Grey Level Co-occurrence Matrices (GLCM) extracted feature vector consist of feature such difference entropy, correlation, angular second moment, difference variance, contrast, inverse difference moment, variance, sum entropy, sum average, entropy, sum variance, maximal correlation coefficient, cluster prominence, information measures of correlation, local homogeneity, inertia, energy and cluster shade. These all feature are used widely in order to classify and analysis of digital images. These features goal is to accurately characterize the most stochastic characters distribution for the gray level digital images. The GLCM technique returns the accurate texture feature of the digital image by using only two pixels. Haralick introduce the GLCM technique to illustrate the texture feature using statistical sample how the image gray level represent with relating it to the other image gray levels. Also GLCM feature vector consists of a lot of the above features there are about seven effective features like correlation, entropy, local homogeneity, energy, contrast, cluster prominence and cluster shade addition to mean and stander deviation which are the first order mathematical and statistical texture feature [27].

2.3 Naïve Bayes Algorithm

One of the widely and fastest classification techniques in Naïve Bayes, which based on the probability of feature attributes contained in the required data base separately and after that it classify this data accurately [28]. Naïve Bayes classifier presented as a supervised learning technique and statistical based technique for image feature vector classification phase. Naïve Bayes encode the probability distributed function for set n variables, (X_1, X_2, X_3 …X_n) as directed cycle and set the conditional probability distributed values. Every nodes match to a variable and the conditional probability distributed CPD supported with it gives the probability of the case of the variable given every reasonable collection of cases of its parents.

Algorithm 2 :- fitting a Naïve Bayes classifier to binary features

INPUT: Training set (T),
Hold-out set (H),
Initial number of components (k_0), and
Convergence thresholds T_{EM} and T_{Add}
Initialize M with one component and $k = k_0$
Repeat
Add (k) new mixture components to (M),
Initialized using (k) random examples from (T).
Remove the (k) initialization examples from (T).
Repeat
E-step: Fractionally assign examples in T to mixture components, using (M).
M-step: Compute maximum likelihood parameters for (M), using the filled-in data.
If log P(H|M) is best so far, save (M) in M_{best}.
Every 5 cycles, prune low-weight components of M.
Until
Log P(H|M) fails to improve by ratio T_{EM}.
$M = M_{best}$
Prune low weight components of M.
k = 2k
Until
log P(H|M) fails to improve by ratio T_{Add}.
Execute E-step and M-step twice more on M_{best}, using examples from both H and T.
Return M_{best}.

2.4 Decision tree algorithm

Decision tree is widely used in expert systems to represent knowledge. Decision tree classifiers formed to classify the feature vector for each muzzle with Boolean or categorical class labels [29]. Breiman et al propose the classification and regression tree (CART) [30] structure which called as Hierarchical Optimal Discriminate Analysis (HODA). CART is not a parametric decision tree that produces either regression or classification trees based on the reliant variable is numeric or categorical. The term binary means that node in a decision tree can split into two groups only. CART depends on gini index which used as cheating measure for selecting bovine muzzle image patters attribute. The process of splitting the nodes depends on using the attributes with the large reduction in the population. CART uses categorical and numerical values and also solves the problem of missing values. It is useful to use cost complexity refinement and generate regression tree.

Algorithm 3 :- Decision tree induction algorithm

Tree(E, F)
If
1: stop-condition(E,F)=true, then
2: Set leaf🡸create-node ().
3: leaf-label🡸classify (E).
4: return leaf.
Else
5: Root🡸create-node ().
6: Root.test.condition= find.best-split(E,F).
7: Let V🡸{U|U is a possible outcome of Root.test.condition}.
8: For each U ε V do
9: E_U 🡸{e|Root.test.condition(e)=U and e ε E}.
10: child🡸Tree(E,F).
11: add child as descendent of root and label the edge (root🡺child) as U.
12: end for
13: end id
14: return root.

3. The Proposed Bovine Muzzle Identification Models

In this paper, the proposed two models consist of three phases: pre-processing phase that is the first and critical initial phase. The pre-processing part contains both average filter and median filter in order to remove noise form the bovine muzzle images. The texture feature extraction is the second phase of the proposed model in which we use Gray level co-occurrence matrix (GLCM) to extract the feature vector of each bovine muzzle image that reflects each image contents. The decision tree and Naïve Bayes are used the third and the last phase to classify bovine muzzles pattern image. These three phases are discussed in this section. The proposed models and phases are shown in Figure 1.

3.1 Pre-processing phase

Pre-processing phase is the first and critical phase. The proposed two models in this paper use average filter and median filter. Average filter usually is the first filter that used in case of facing problem in images. Even if the facing problem is solved, the need for average filter is still required. Average filter is used to remove noise from image with keep the details of the image. Average filter is linear filter and median filter is nonlinear filter. The corner stone in the digital image processing is median filtering. Median filter is widely used for filtering and smoothing images. Figure 2 show the flow chart for noise removing phase.

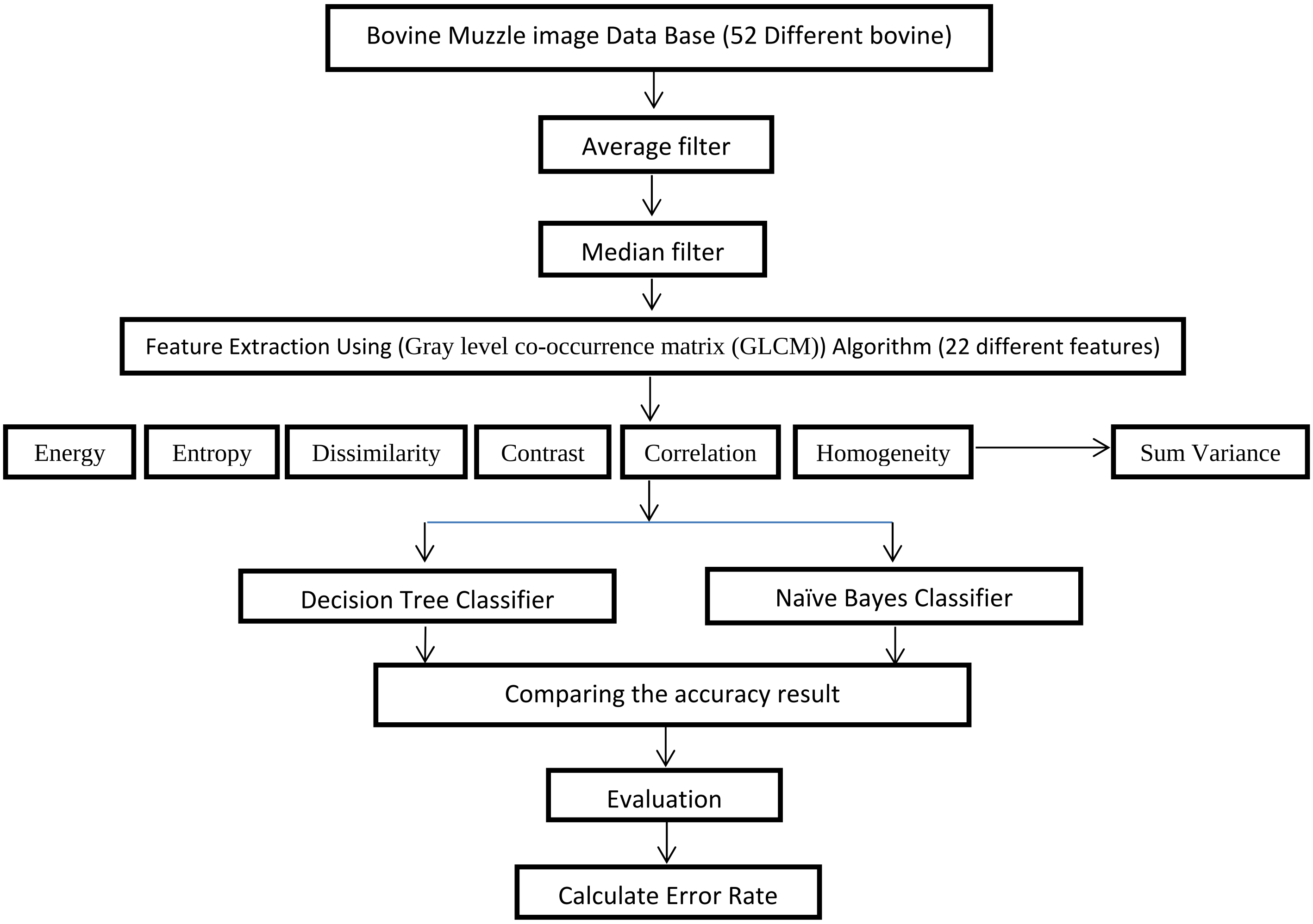

Figure 1. The Proposed bovine Classification Models

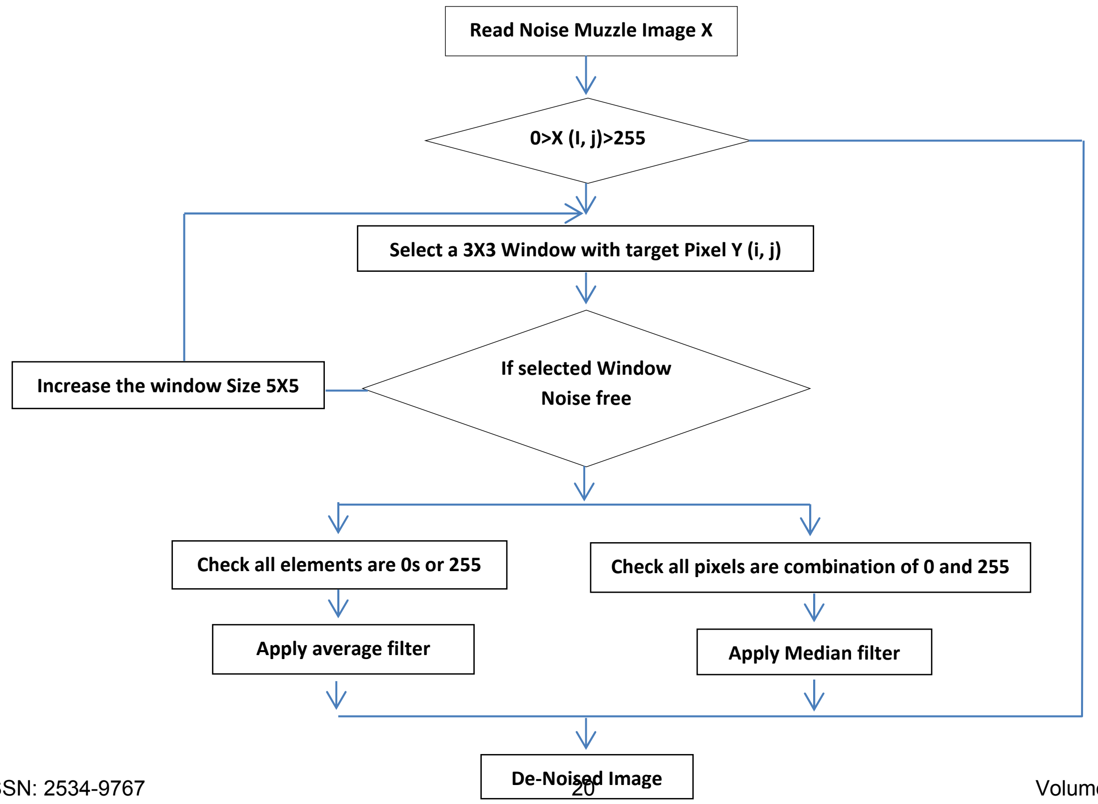

Figure 2. Muzzle image noise removing flow chart

3.2 Texture Feature Extraction phase

The Texture Feature Extraction is the second and critical phase of the proposed models. This phase is used in the proposed two models. Texture feature extraction phase still the critical challenging point in bovine muzzle identification because it depends on a number of features which are contained in the feature vector. More elements in the feature vector, lead to more accurate classification results. In this phase, we use Gray level co-occurrence matrix (GLCM) algorithm.

3.3 Gray level co-occurrence matrix (GLCM) algorithm

After applying GLCM algorithm on the bovine muzzle images the texture feature vector contains of twenty-two different feature denoted with Energy (Angular Second Moment), Entropy, Dissimilarity, Contrast, Inverse difference, correlation, Homogeneity (Inverse difference moment), Autocorrelation, Cluster Shade, Cluster Prominence, Maximum probability, Sum of Squares, Sum Average, Sum Variance, Sum Entropy, Difference variance, Difference entropy, Information measures of correlation (1), Information measures of correlation (2), Maximal correlation coefficient, Inverse difference normalized (INN) and Inverse difference moment normalized (IDN)

3.4 Naïve Bayes Algorithm

After applying texture feature extraction phase and get on the feature vector. The first model uses Naïve Bayes in the last phase in order to classify and identify the proposed bovine muzzle images. Then the result accuracy compare with the accuracy rate with decision tree classifier and state which algorithm has the highly accurate classification rate.

3.5 Decision tree classifier

Decision tree classification phase depends on the following steps:-

Step 1: select training bovine muzzle image dataset for learning.
Step 2: find mapping between every individual feature vector attribute to bovine classes.
Step 3: find all possible values for every features and that equivalent possible bovine classes.
Step 4: then count values of each feature which belongs to unique bovine class.
Step 5: Make root node to that feature which have minimum number of values having unique bovine class.
Step 6: Likewise select other feature for next level in decision tree from residual feature the basis of minimum number of values having unique bovine class.

4. Experimental Results

a. Bovine Muzzle Print Database

The first challenge in this paper was the lack of the real live printed bovine muzzle database. Therefore, the critical point in this research was to collect a muzzle image database which consists of fifty-two bovine. A sample printed muzzles for two different individual bovines are shown in Figure 3 where during the capturing phase, a special care was made for the quality of collected bovines muzzles. The identification scenarios: 3, 5, 10, 15 and 52 groups of bovines muzzle used in the training phase to calculate the accuracy of implementing the Naïve Bayes and decision tree classification models. The use of Naïve Bayes and decision tree comes after extracting the feature vector of each bovine image by using Gray level co-occurrence matrix (GLCM) algorithm. The bovine muzzle in the testing phase is correctly classified if it is found that the similarity between input images feature vector equals the tested image feature vector.

Figure 3. A sample of different bovines' printed images. This figure represents print images for bovine muzzle that have taken from two different bovine.

b. Evaluated Results

- **First: the accuracy rate after using Gray level co-occurrence matrix (GLCM) algorithm in the second phase for feature extraction and Naïve Bayes in the classification phase.**

As table I show that the accuracy rate increases especially in cases that use large number of different bovine groups. By comparing this accuracy rate with the accuracy rate of the authors' previous work in which they use the artificial neural network (ANN) instead of Naïve Bayes classifiers and used the box-counting instead of Gray level co-occurrence matrix (GLCM) in the second phase for feature extraction the accuracy rate was very bad in the ANN model specially with the large number of the bovine groups.

TABLE I

Accuracy rate in case of using 3, 5, 10, 15 and 52 different groups of muzzle. (**Artificial Neural Network classifier and Naïve Bayes classifier**)

	3 groups	5 groups	10 groups	15 groups	52 groups
Naïve Bayes model	100%	100%	94%	92.15%	75.38%
ANN model	100 %	80 %	48 %	40 %	14 %

TABLE II

Accuracy rate in case of using 3, 5, 10, 15 and 52 different groups of muzzle. (**Artificial Neural Network classifier and Naïve Bayes classifier**)

	3 groups	5 groups	10 groups	15 groups	52 groups
Naïve Bayes model	100%	100%	94%	92.15%	75.38%
decision tree model	100%	100%	96.6%	94%	89.64%

Figure 4 shows the statistical representation between Naïve Bayes model and ANN model. The statistical representation show the big difference of using the Naïve Bayes in the classification part instead of artificial neural network and using gray level co-occurrence matrix (GLCM) in the second phase for feature extraction. The accuracy rate in case of using Naïve Bayes and ANN to classify and differentiate between 52 different bovine groups are 75.38% and 14% respectively. As shown in figure 4 the Naïve Bayes classifier made a huge difference in the accuracy rate also, the number of the features in the texture feature vector extracted after using gray level co-occurrence matrix (GLCM) algorithm is twenty-two which help in increasing the model accuracy rate.

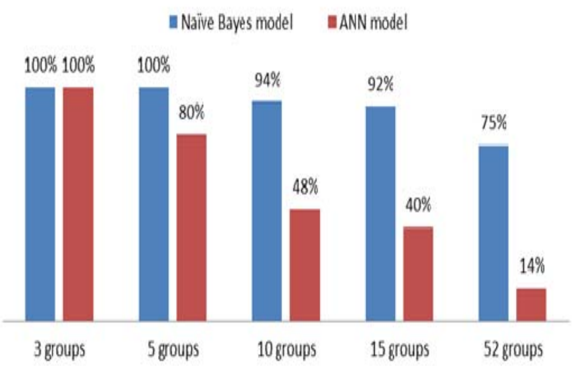

Figure 4. Accuracy rate in case of using 3, 5, 10, 15 and 52 different groups of muzzle. (**Artificial Neural Network classifier and Naïve Bayes classifier**)

Second: the accuracy rate after using Gray level co-occurrence matrix (GLCM) algorithm in the second phase for feature extraction and decision tree in the classification part.

As table II shows that the accuracy rate increases especially in cases that using large number of different bovine groups. By comparing this accuracy rate of using Naïve Bayes classifier with the accuracy rate of using decision tree classifiers and still using Gray level co-occurrence matrix (GLCM) in the second phase for feature extraction the accuracy rate increases in the decision tree model specially with the large number of the bovine groups.

Figure 5 shows the statistical representation between decision tree model, Naïve Bayes model and ANN model. The statistical representation show the decision tree model accuracy rate is the largest accuracy rate specially in case of using 52 different bovines groups. The decision tree model accuracy rate in case of using 52 different bovine classes was 89.64% comparing to 75.38% and 14% in case of using Naïve Bayes model and ANN model respectively.

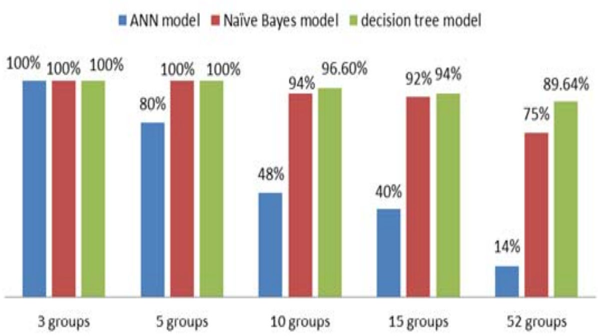

Figure 5. Accuracy rate in case of using 3, 5, 10, 15 and 52 different groups of muzzle. (**ANN classifier, Naïve Bayes classifier and decision tree classifier**)

5. Conclusions and Future Work

This paper has presented two different bovine classification models depends on the bovine muzzle images. Such models consist of three different phases; pre-processing phase which uses average filter and median filter to remove noise respectively. The second phase is the texture feature extraction which is the most important part. It uses Gray level co-occurrence matrix (GLCM) to extract different vectors. The Gray level co-occurrence matrix (GLCM) feature vector consists of twenty-two different features. The last phase used two different classifiers namely; Naïve Bayes classifier and decision tree classifier that is used to compare between the accuracy rates. The accuracy rate has proven the advancement of decision tree classifier than Naïve Bayes classifier. The accuracy rate in case of using the numbers of identification groups of 3, 5, 10, 15 and 52; the decision tree classifier accuracy results were: 100%, 100%, 96.6%, 94% and 89.64% respectively. In case of using Naïve Bayes classifier, the accuracy results were: 100%, 100%, 94%, 92.15% and 75.38% respectively. Firstly, the accuracy of our proposed models to identify bovine animals using muzzle print images has achieved excellent results comparing to all previous models in [31] [32] [33] [34]. Secondly, the experimental results showed that the Gray level co-occurrence matrix (GLCM) algorithm is a more accurate algorithm used for classifying such bovine muzzle image database. Therefore, it's recommended to increase number of features in feature vector to increase the accuracy rate.

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