Bovines' Texture Feature Extraction Based on Discrete Wavelet Transform

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Abstract— **Animals especially bovines and its products growth very quickly every day, so Ministry of Animal Resources pay great attention and efforts for saving bovines' products. The main goal of this work is to identify and clearly distinguish between huge different bovines and achieving high accuracy rate. This work proposed two different techniques in the last phase which is the classification phase based on Naive Bayes and decision tree. The complete proposed two models divided into four phases namely; data base acquisition phase, muzzle image pre-processing phase, muzzle texture feature extraction and bovine classification phase. Data base acquisition phase is defined as the process starting with pressing down the camera button until saving the muzzle images in the hard memory. The muzzle images database consists of fifty-two different bovine. Pre-processing phase consists of linear filter and Non-linear filter for noise removing from muzzle images. The third phase is the important phase which based on Discrete Wavelet Transform (DWT) algorithm for muzzle texture feature extraction. The forth phase consists of Naïve Bayes in the first proposed model and used decision tree in the second proposed model. The experimental result accuracy rate denote that in case of using fifty-two different bovines group is 75.09% in case of decision tree model and 72.45% in Naive Bayes model. This accuracy rate is excellent with comparing with authors previous work where the accuracy rate in the fifty-two different group and based on box-counting for feature extraction and Artificial Neural Network (ANN) is 14%.**

Keywords:- bovine classification; average filter; Median filter; Discrete Wavelet Transform (DWT) algorithm; Naive Bayes and Decition tree.

Introduction

Nowadays, Ministry of Animal Resources makes enormous efforts for helping in saving animals especially the bovines' products. The quickly increasing in the products of livestock is the crucial point. The rapid growth leads the Ministry of Animal Resources and veterinarians to spend their effort in tracing and follow bovines that have infected with the wide spread diseases. There are found more than one traditional technique used for solving this crucial problem but all the traditional techniques cannot get rid of the reputation, managing the growth of the bovine's products and deceitful farmers' problems. The main goal in this work is helping the Ministry of Animal Resources and veterinarians by build two models for solving the main three different problems that the traditional techniques cannot solve them. All farmers can remove the ear tag from bovine's ear easily after these bovine die and use this ear tag for another bovine. The proposed two different intelligent models can help in achieving justice. This work helps the end users to save the animal record and connect it with the bovine muzzle print. These models help the Ministry of Animal Resources to trace the non-healthy bovines. The important point in this work is to identify each bovine in the required 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 work 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 Discrete Wavelet Transform (DWT), which is used in the second phase in the proposed two models in this work.

This work used two different techniques in the classification phase; Naive Bayes and decision tree Algorithms then it compares 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 Discrete Wavelet Transform (DWT) 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) [12]. Spatial domain feature extraction consists of CBIR algorithm that based on image histogram, VQ [13] [14] [15] and BTC [16] [17] [18]. 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 [19].

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 [20]. 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 Discrete Wavelet Transform (DWT) algorithm in the feature extraction part and then compares between the accuracy rates of the classification process that depends on Naïve Bayes and decision tree techniques. This is the continual contribution for the authors and this is one of the best accurate models 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 Identification model in detail. Experimental results are discussed in Section 4. Conclusions and future work are discussed in Section 5.

1. 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 [21]. 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)

2.2 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 [22] [23].

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

2.3 Discrete Wavelet Transform (DWT) feature extraction technique

Wavelet Transform theory is a strong mathematical based tool and it has major applications. The major scientific fields apply the wavelet transform, such as digital image compression, digital image feature analysis, time frequency analysis, communication systems, etc. wavelet theory is consider as unfamiliar technique in some scientific fields and in other fields it works very well. In this paper texture feature extraction is the essential goal from using discrete wavelet transform (DWT) [24]. The wavelet term is defined as function produced from single function (W) based on translations and dilations. Wavelet transform essential idea is the representation of qualitative function like wavelets overlapping. Any overlapped decomposes function to various scales while every decomposed level is furthermore decomposed with decision appropriate adaptive for this level. The discrete wavelet transform like the hierarchical structure representation of sub band. Sub bands defined as the logarithmically spread frequency and represents octave-band decomposition [25].

The major two sets that utilize the discrete wavelet transform (DWT) are wavelet functions and Scaling functions. These two functions always linked with the higher pass filters and lower pass filters. The following figure (1) shows the wavelet transform decomposition or segmentation.

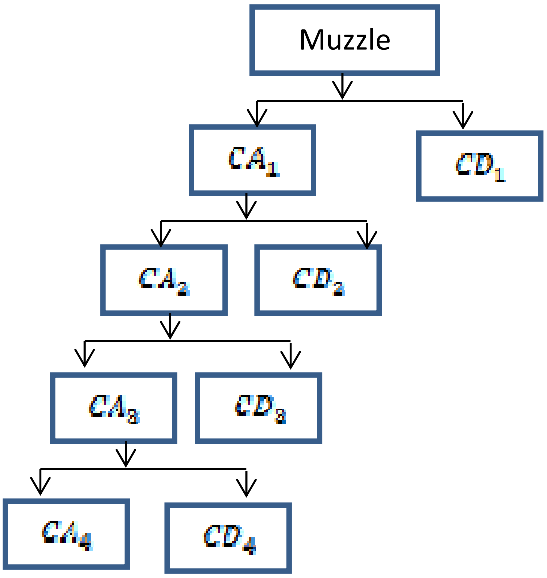

Figure 1. Wavelets transform decomposition

Time signal leads to the sequential lower pass filters and higher pass filters also. This lets the muzzle image decomposition to a lot of different recurrence bands called sub bands. The output of the lower pass filter is the approximation coefficient and the detailed coefficient produced from the higher pass filter. As in figure (1) CA1 denote the adequate wavelet and the four level of decomposition or image segmentation of the image by using the discrete wavelet transform technique. The level of decomposition is optional, this study based on decomposition of the image into four levels. The selection of decomposition levels based on the decomposition parts is correlated to gather in good manner with the necessary frequency for the identification and classification rate achieved after using the DWT. This paper based on the Daubechies approach which was introduced by the Ingrid Daubechies scientist and the name of this approach honor to this scientist. The following algorithm denotes this approach steps. So, usually DBN used for denoting the dabechies approach where the N is the level order. The following algorithm denotes the steps of this Daubechies wavelet approach.

Algorithm 2:- Discrete Wavelet Transform

S→ denoted as a symbol for the signal of length N

Level from j=1 to maximum_level

(a): Producing two different set of coefficients

CA_1→ Denote the approximation coefficients.

CD_1→Denote the detailed coefficients.

(b): CA_1→Obtained by rolling it with the low pass filter Low_D,

CD_1→Obtained by rolling it with the high pass filter High_D.

a.The Equation for calculating→ (A Coefficients)

$$A_j = \sum_k A_k^{(j)} \Phi_{j,k} \text{ and } A_{j+1} = \sum_k A_k^{(j+1)} \Phi_j$$

$$\text{And } A_k^{(j+1)} = \sum_n h_{n-2k} A_n^j$$

$$\tilde{h}(k) = h(-k), \text{ and } F_k^{(j+1)} = \sum_n \tilde{h}_{k-n} An^j$$

b. The Equation for calculating→ (D Coefficients)

$$D_1 = \sum_n \delta_n \Phi_{1,n} \text{ where } \rightarrow \Phi_{j+1,0} = \sum g_k \Phi_{j,k}$$

2.4 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 [26]. 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 3 :- fitting a Naïve Bayes classifier to binary features

<u>INPUT:</u> 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}.

2.5 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 [27]. Breiman et al propose the classification and regression tree (CART) [28] 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 4 :- 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: EU ({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.

2. 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 phase consists of both linear and non-linear filters (average filter and median filter) in order to remove noise form the image of bovine muzzle. The texture feature extraction is the second phase of the proposed model in which we use Discrete Wavelet Transform (DWT) 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 3.

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.

3.2Texture Feature Extraction phase (discrete wavelet transform (DWT) algorithm)

The decomposition of the input muzzle image that it, into different groups of initially waveforms called wavelets this process or function is called wavelet transformation technique. Also the function of wavelet transform is to analysis the input image with examining the weights (Coefficients) of the resulted wavelets. This technique based on breaking the muzzle image down into rough detailed and approximation information implementing the multi-level analysis for the image of interest. Consequently, this technique presents a method for analyzing the image at the various frequencies with various resolutions.

The feature vector extracted from discrete wavelet transform (DWT) based on wide range of the mathematical estimators. If the assumptions of the Nth sample of decomposed wavelets at the level (i) is Di(N), so The following lines contains the features that form the feature vector extracted from DWT algorithm. For every decomposed image the minimum feature value is calculated based on the Minimum = Min[D_i]. The maximum feature value is calculated by using Maximum = Max{D_i}. The image average amplitude for Di is calculated by using the mean absolute value (MAV) for each segment I with N cases in length. The mean absolute value is calculated by $MAV = \frac{1}{n}\sum D_i$ the root mean square (RMS) used for calculating the amplitude of adjusted Gaussian random variable process. RMS is closely related to standard deviation and calculated with $RMS = \sqrt{\frac{1}{n}\sum_{i=1}^{n} D_i^2}$. The energy of

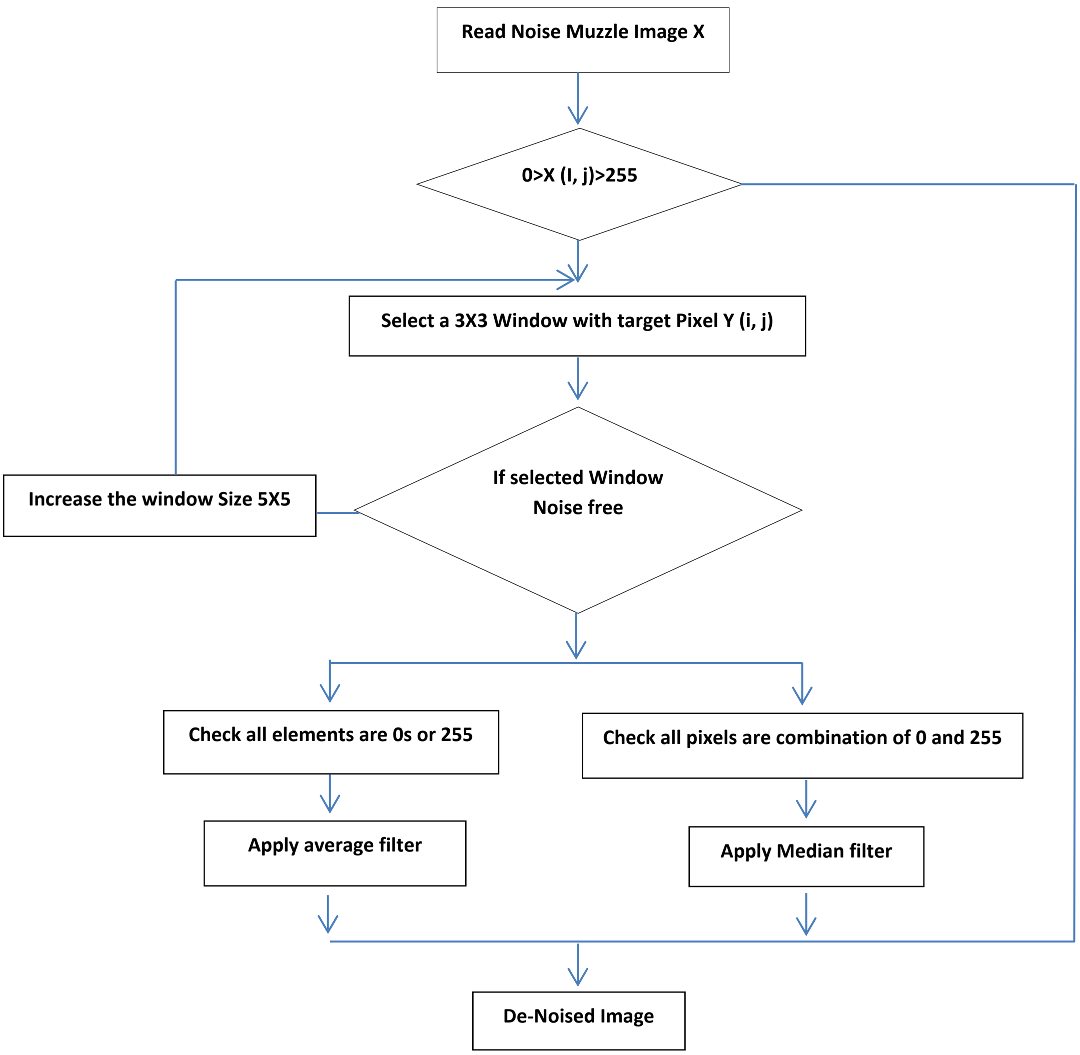

Figure 2. Muzzle image noise removing flow chart

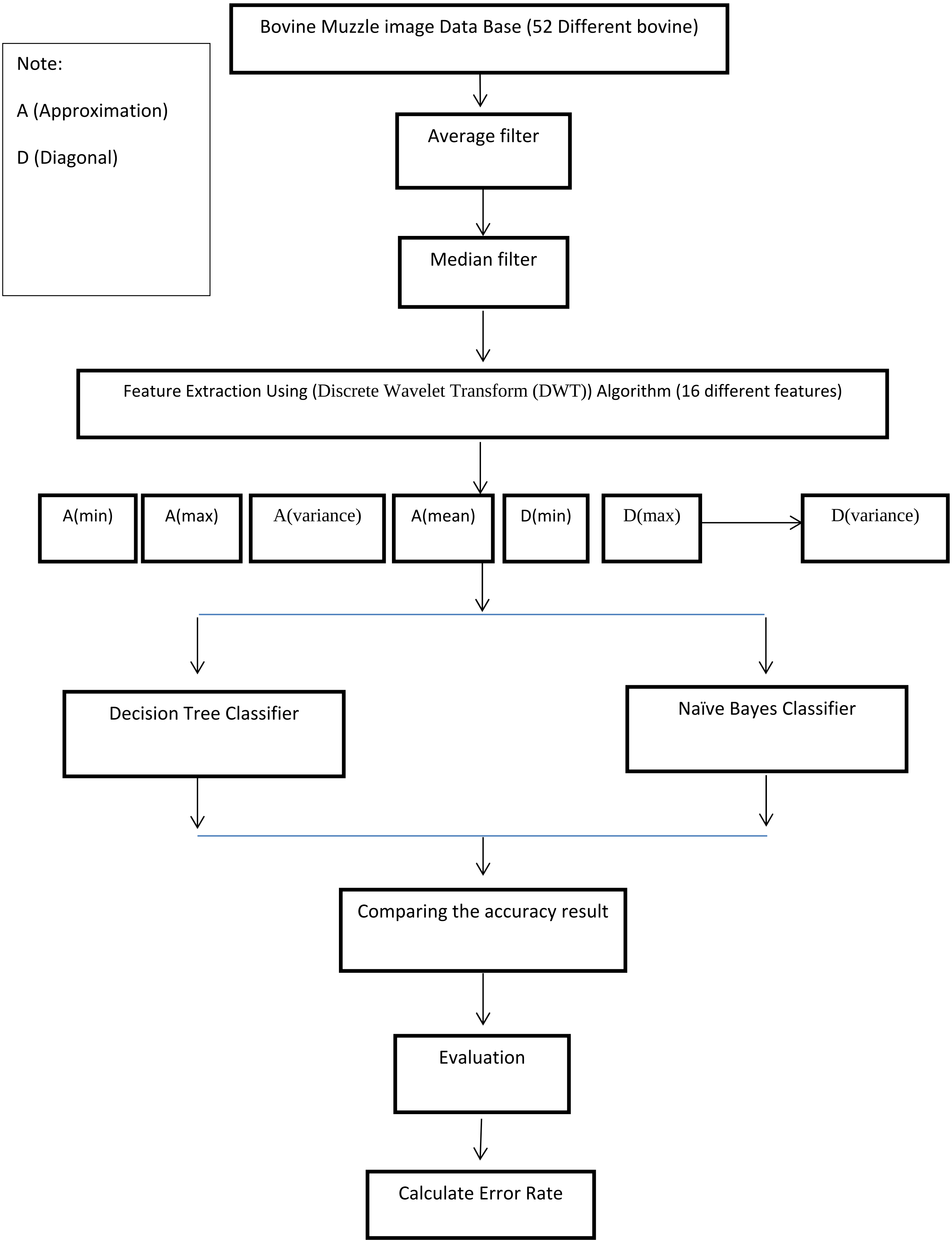

Figure 3. The Proposed bovine Classification Models

The muzzle image segment used (SSI) simple square integral as one of its features and calculated it with $SSI = \sum_{n=1}^{n} \left| D_n^2 \right|$. The variance usually calculated to determine the mean square value of the deflection of the variable. The variance is calculated using $Variance = \frac{1}{N-1} \sum (x_i - \mu)^2$. Average Amplitude Change (AAC) is the calculation of the difference between two followed partitions and then takes the average of them. AAC calculated by $AAC = \frac{1}{N} \sum_{n=1}^{N} \left| D_i(n+1) - D_i(n) \right|$. Calculate the median by sort the Di and take the median value. The median is calculated with $Median = D_i\left(\frac{n}{2}\right)$ if n is odd and $Median = (D_i\left(\frac{n}{2}\right) + D_i(\frac{n}{2}+1) \big/ 2)$ if n is even. This paper based on calculating the feature vector that consists of minimum, maximum, average and mean for each segment or decomposition.

3. 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 4 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 discrete wavelet transform (DWT) 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 4. 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 Discrete Wavelet Transform (DWT) 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 Discrete Wavelet Transform (DWT) 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.

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 Discrete Wavelet Transform (DWT) 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 72.45% and 14% respectively. As shown in figure 5 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 Discrete Wavelet Transform (DWT) algorithm is twenty-two which help in increasing the model accuracy rate.

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%	96.55%	85%	86.53%	72.45%
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%	96.55%	85%	86.53%	72.45%
decision tree model	100%	100%	91.66%	90.38%	75.09%

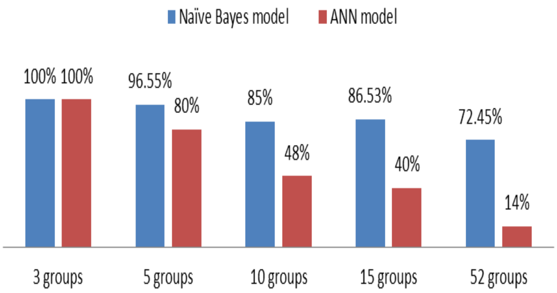

Figure 5. Accuracy rate in case of using 3, 5, 10, 15 and 52 different groups of muzzle. (**Artificial Neural Network classifier and Naïve Bayes classifier**)

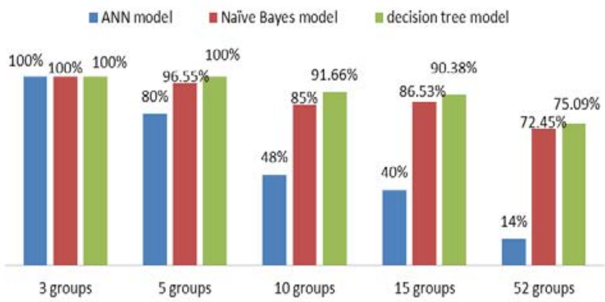

Figure 6. Accuracy rate in case of using 3, 5, 10, 15 and 52 different groups of muzzle. (**ANN classifier, Naïve Bayes classifier and decision tree classifier**)

Second: the accuracy rate after using Discrete Wavelet Transform (DWT) 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 Discrete Wavelet Transform (DWT) 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 6 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 75.09% comparing to 72.45% and 14% in case of using Naïve Bayes model and ANN model respectively.

4. 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 Discrete Wavelet Transform (DWT) to extract different vectors. The Discrete Wavelet Transform (DWT) feature vector consists of sixteen 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%, 91.66%, 90.38% and 75.09% respectively. In case of using Naïve Bayes classifier, the accuracy results were: 100%, 96.55%, 85%, 86.53% and 72.45%

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 [29] [30] [31] [32]. Secondly, the experimental results showed that the Discrete Wavelet Transform (DWT) 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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