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Intelligent Cattle Detection and Recognition system Using ANN-Fourier Descriptor Techniques

Buhari Ugbede Umar [1], Abiodun Musa Aibinu [2], Olayemi Mikail Olaniyi [3] and Edoghogho Olaye [4]

[1,3]Computer Engineering Department, Federal University of Technology, Minna, Nigeria
[2]Mechatronics Engineering Department, Federal University of Technology, Minna, Nigeria
[4]Computer Engineering Department, University of Benin, Benin, Nigeria

Corresponding author: Buhari Ugbede Umar (e-mail: buhariumar@futminna.edu.ng).

ABSTRACT Reoccurring Fulani-farmer crisis in Nigeria as a result of the destruction of farmland and arable crops by cattle during grazing has led to a high rate of loss of life and properties. To address this problem, this research work proposed a shape-based ANN-Fourier descriptor cattle recognition system. Twenty samples of each of cattle, deer, dog, elephant, horse, and camel were obtained from the UCL database. Colour space conversion and a simple image binarization were performed to obtained image segmentation. Edges of the images were extracted, and Discrete Fourier Transform was applied on the edges to obtain the Fourier descriptors. Ten Fourier descriptors were used to train feed-forward back propagation artificial neural networks for cattle recognition systems. The effect of increasing database size, the number of images used for training and testing, and threshold value were investigated. It was observed that there was no effect of increasing the size of the database on the system performance. For better accuracy, sensitivity, specificity, and precision, it was observed that a good threshold value must be carefully chosen and 75% of the image must be used for training and 25% for testing respectively. With twenty image samples, each for cattle, deer, camel, dog, horse, and elephant in the database, fifteen out of twenty samples were used for training, five for testing, and the threshold value of 0.6, 98.7% sensitivity, 98.8% specificity, 98.8% accuracy and 94.5% precision were achieved. This result provides a good method for cattle detection and recognition system.

KEYWORD: ANN-Fourier Descriptor, Cattle Recognition System, Shape-Based.

I. INTRODUCTION

Animal recognition systems have received a lot of attention and propagation due to their wide range of applications and use in the domains of animal biometrics, computer vision, pattern recognition, and cognitive science. The cattle recognition system can be used for a variety of purposes, including animal registration, traceability, monitoring, identifying missing, exchanged, or reallocated cattle, and verifying bogus insurance claims [1]. The Fulani people of northern Nigeria have traditionally relied on cattle production as a source of income. Herders wander from one location to another as nomads in quest of greener grass for their cattle [2, 3]. Because of the destruction of crops, properties, and arable land by the cattle during grazing, the movement of livestock from one site to another seeking greener pasture generally resulted in a conflict between Fulani herdsmen and farmers. If the problem is not addressed, it will pose a political, social, economic, agricultural, and security threat to the country [4-9].

The current methods of identifying cattle in the vicinity are still based on the traditional approach, which entails physically searching for livestock. These techniques are inefficient and time-consuming. As a result, a reliable cattle recognition system is required to avoid the Fulani-farmer crisis by identifying the presence of cattle in the area. As a result, this research proposes image processing and pattern recognition techniques for cattle detection and recognition using shape-based Fourier descriptor features and an artificial neural network.

Animal biometrics has been a highly popular and promising research field in recent years. When it comes to making management decisions concerning their animals or their entire herd, precision in animal identification is critical. Livestock identification is crucial in animal traceability systems [10]. Cattle identification is a word used to describe a way of successfully recognizing cattle [11-13], and it is a new field of animal biometrics-based recognition systems research. As a common manner to keep livestock, it has gotten a lot of study attention. Identification accuracy and processing time are two important obstacles for any cattle identification technology [10]. It is critical to assess the number of cattle in a grazing area frequently while managing grazing cattle. Herders can estimate where and how many cattle are in the field by comparing the counting result with the actual number of cattle in the field. Physically searching for animals in this manner is inefficient and time-consuming [14].

The remainder of the paper is structured as follows: the review of related work is presented in section 2, section 3, describes the research methodology and the flow diagram, while the result and discussion are presented in section 4. Finally, the conclusion of the research work is presented in section 5.

II REVIEW OF RELATED WORK TN SHAPE RECOGNITION

In the domain of using image processing, Fourier descriptors, and artificial neural networks to object detection and recognition, there are several related publications in the literature. For shape recognition, researchers in [15] employed a Fourier descriptor and a neural network and found that the Fourier description contains a collection of important properties that can be used to recognize the shape. It also demonstrates that the Fourier description has the advantages of being simple to compute, rotation, scale, and rotational invariant. Similarly, [16] presented a novel sign language translation based on Fourier description and shape signature for normalizing and representation. Overall, 70% accuracy was achieved. Using the Fourier descriptor in shape retrieval, a comparative analysis of distinct shape signatures was undertaken. The centroid distance-based Fourier descriptor outperformed the complex coordinates, cumulative angular function, and curvature signature-based Fourier descriptor [17]. For image shape retrieval, a comparison of Fourier descriptor and curvature scope spaces was proposed in [18]. In terms of retrieval performance, resilience, indexing efficiency, and minimal processing, the Fourier descriptor outperform the curvature scale space.

[19], reported a comparison analysis of various Fourier descriptors for shape retrieval and representation, with retrieval and representation performance measured using a typical database. In terms of convergence speed, computational complexity, resilience, and performance retrieval of its Fourier descriptor, the centroid distance outperformed cord length, complex coordinate, curvature signature, and cumulative angular function. [20], suggested a modified genetic Fourier descriptor for image retrieval. The new technique generates a large number of feature vectors. A basic neural network for visual character recognition was also presented in [21]. The study outlined the neural network's advantages over other traditional methods. An experimental investigation was conducted on several descriptors and matching methods, and the Universidade Nova de Lisboa-Fourier description was shown to be the best among the many shape descriptions studied [22]. A new integrated strategy for shape representation and retrieval employing Fourier descriptor and freeman code was proposed in [23]. When compared to the ex1stmg Fourier descriptor based on shape representation and retrieval, the new technique claimed to perform better.

For human shape recognition, [24] utilized a Fourier descriptor with a neural network and an SVM as a classifier. The accurate classification rate was 96 percent.

[25] Using wavelet and neural networks, the research proposed a new method termed substance-based image classification. The results suggest that the new strategy reduced misclassification occurrence and accurate shape of object retention by about 10-15%. For Bangla character identification and representation, the Fourier descriptor and K-nearest neighbor were utilized in [26]. For training and test data, the accuracy of 98.4 percent and 89.3 percent were achieved, respectively. Three distinct neural networks, namely Kohonen self-organizing network, multilayer perception (MLP), and hybrid of self-organizing layer and multilayer perception sub-network connecting in cascade, were employed for shape recognition utilizing a combination of wavelength and Fourier descriptor. In-plane shape identification is improved when wavelet pre-processing is combined with self-organizing neural network structures [27]. For leaf classification, comparison analyses of three different techniques were used: PNN, SVM-BDT, and Fourier MOMENT. The SVM-BDT method outperforms the Fourier and PNN methods [28].

Fourier descriptors obtained from a shape may be utilized for object identification and recognition; ANN can be trained for Cattle detection; and a combination of ANN-Fourier descriptors can be used for Cattle detection and recognition, according to the review literature. This is the motivation behind this study's development of a Cattle detection and recognition system based on the ANN-Fourier descriptors approach.

III RESEARCH METHODOLOGY

The research work adopts the method of Fourier descriptors features extraction from the centroid distance and training of a supervised neural network to group images into two categories. Cattle images are in category one while other images are in category two. This is motivated by the fact that contour-based centroid signature is good for generating Fourier descriptors for a shape and it is the most used shape signature for Fourier descriptors because of its convergence speed, lesser computational complexity, the robustness of its Fourier series, and performance retrieval of its Fourier descriptor. A database comprising training and testing data was created. There is a total of thirty-three different images in the database, with each of the thirty-three different images containing a total of twenty images of its type. Therefore, there is a total of 660 (33x20) images in the database. The images used for training are categorized into three stages with a uniform step size of six and five for total images in the database and the images used for training respectively. Also, with a threshold ranging from 0.3 to 0.99 for each of the training stages and testing stages respectively. Figure 1 presents the system block diagram for the research work. The figure shows different stages of the process involved in the development of a Fourier descriptor-based Cattle recognition system. The image pre-processing stage involves the performance of a different operation on the input images. The aim of image pre-processing is to separate the region of interest of the image from the background. Image pre-processing defines pattern compact representation.

The technique of converting RGB Colour space images to greyscale or any other Colour scheme is known as Colour conversion. The RGB Colour is made up of three-Colour channels, each of which is defined by the amount of red, green, and blue it contains. Each of these Colour components had a memory capacity of up to twenty-four bits. The RGB images were normalized using equations 1, 2, and 3. Equation 4 for grayscale image conversion.

$$r = \frac{R}{R+O+B} \tag{1}$$

$$g = \frac{O}{R+O+B} \tag{2}$$

$$b = \frac{B}{R+O+B} \tag{3}$$

A grayscale image is represented by the shades of grey. Grayscale images are binary images in three-dimensional space.

$$\text{Grayscale image} = \frac{R+O+B}{3} \tag{4}$$

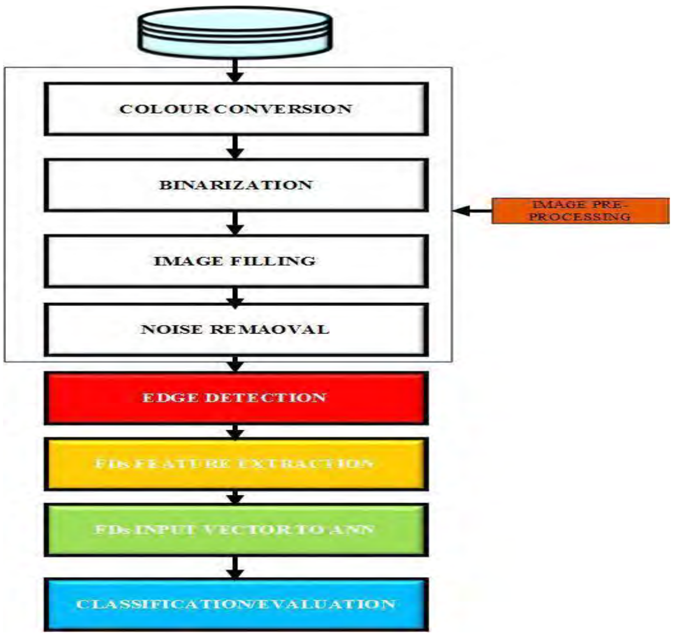

Figure 1. System Block Diagram

To produce image segmentation, a basic binarization is conducted to the greyscale image using the UCL database. The process of transforming a grayscale image to a binary image is known as binarization. All pixels in the input image with a brightness greater than the level with the value one (white) are replaced with value zero in the binary output image (black). The binary image has a value between 0 and 1. (0, 1). The binary images are used to gain edge detection for the development of centroid-based Fourier descriptors. The process of filling a hole in a binary image is known as image filling. A hole is a group of background pixels that can't be reached by filling the image's backdrop from the edge. For good edge detection, the pictures are filled to erase the hole in the images. A group of connected pixels that create a border between two different locations is referred to as an edge. In image processing, edge detection is a crucial stage [29]. They're typically utilized for image segmentation, reconstruction, enhancement, sharpening, and information extraction [30]. By integrating different image distinctions, it finds or locates where there is a sharp discontinuity in an image [31].

It's critical to choose appropriate edge detection for each shape since different shapes respond differently to different edge detection approaches [32]. Edge detection can be done in a variety of ways. These methods are divided into two categories: first gradient and Laplacian-based methods. The image's finite difference approximation in a vertical or horizontal direction is calculated using the gradient operator-based edge detection approach. They're also known as masks in digital images. The first-order derivative is used to calculate the gradient. The magnitude of the gradient is used to implement them. For example, ifI (i,j) is the input image, equation 5 is used to compute the image's gradient. Equations 6 and 7 present the magnitude and gradient direction respectively.

$$\Delta f(i,J) = i\frac{dI(i,J)}{di} + j\frac{dI(i,j)}{dj} \tag{5}$$

where $\frac{dI(i,J)}{dI}$ is the gradient in the I direction and di (i, j) is the gradient in the j direction. The magnitude of the gradient can be calculated using the formula

$$|O| = \sqrt{Oi^2 + O/}$$ or M(i,J)=magnitude =

$$|O| = \sqrt{Oi^2 + O/} \tag{6}$$

Simplifying the computation $M(i,J) = Oi2 + OJ^2$ or using absolute value

$$M(i,J) = |Oi| + |OJ| \tag{7}$$

The gradient direction is the $O = \tan^{-1}$ (8)

The most frequent classical edge detection approach is the Sobel edge detection procedure. It's a discrete differentiation method for edge detection that computes an estimated gradient of an image intensity function. It's done by using a left kernel to filter an image. Another kernel is used to filter the image. Compute the root of the two results by adding them together. As shown in equation 9 is a 3X3 convolution kernel for Sobel-based operations. The most frequent classical edge detection approach is the Sobel edge detection operation. It's a discrete differentiation method for edge detection that computes an estimated gradient of an image intensity function.

cJt -: -; and c)/ I, 21 (9)
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Although its computational ability is slow, it is less sensitive to noise compared to Robert's operation due to its large mask.

A shape signature is a one-dimensional representation of two-dimensional boundaries. The shape signature is an image of the shape that encapsulates some of its characteristics. Although a shape signature does not completely describe the shape, it is difficult to recreate the shape from it. The shape is a key element of human perception [33], hence it is one of the most important image features. Due to affine transformation among distinct images, recognizing shape is the most difficult task in pattern recognition [34]. Complex coordinate, centroid distance, cumulative angular function, and curvature function are some of the shape signatures as shown in Equations 10,11, and 12 respectively. Because of its lower computational complexity, resilience, speed, and convergence distance, the centroid distance is employed as a form signature in this research. The centroid distance xc, ye is defined as the distance between the boundary and the center distance [35].

$$R(n)=([x(n)-xcr +[y(n)-yc\ J\ )^{1/2} \quad (10)$$

$$\text{Where } Xe=\frac{1}{L}\sum_{n=0}^{L-1} x(n), \quad Ye=\frac{1}{L}\sum_{n=0}^{L-1} Y(n), \quad (11)$$

$$0 = \arctan \frac{y-Ye}{x-xc} \quad (12)$$

The xe and yc make the shape representation invariant to translation [17]. For any given shape, represented by closed curve C and at the same time represented by one-dimension function s(k) which is called a shape signature. The Discrete Fourier Transform (DFT) of s(k) is given by equation 13:

$$Fn=\frac{1}{k}\sum_{n=1}^{k-1} s(k)e^{-(rn\ I / K)} \quad (13)$$

F_O Coefficient, were k =0, 1. .. k-1 is also used to obtain the F_O for the shape. In general, the Fourier coefficient generated from the original contour translation, changing of starting point from the original shape and by rotation is presented in equation14.

$$Fne^{-(Jne)} -e^{-(J<t>.s.i;l)}$$

(14)

a_0C^0l is the nth Fourier coefficient of the original contour. Ten FDs are used for recognition as that is sufficient for shape representation as stated in [18]. Discrete Fourier Transform of one-dimensional signal x[n] sequence is given from the interval [0: N - 1] as shown in equation 15.

$$X(k)=X("n\ IJ\ I= \frac{}{N} \sum_{n=O} x(n)e^{-J^2 irnf} \quad (15)$$

where k = 0, 1, 2... N-1, applying this to an image $I(x,y)$ of the size (MxN) gives equation 16.

$$S[kx,ky]= \sum_{x=O}\sum_{y=O} I(x,y)e^{-}\} \quad (16)$$

The two-dimensional Discrete Fourier Transform is given in equation 17.

$$I(x,y)=\frac{1}{MN}\sum_{x=O}\sum_{y=O} S[kx,ky] \ldots (W_{ky}\ I\ +ti \quad (17)$$

Were x, y are the frequency variables, x and y are spatial variables, kx = 0,1...N-1 and ky = 0,1...M-l. Feature extraction and representation are important in image processing and multimedia representation. In this research work, FDs shape-based feature using centroid distance signature was used due to its lesser computational complexity, robustness, speed, and convergence distance.

A. SYSTEM PERFORMANCE EVALUATION

According to [36], there are different measures used in evaluating the performance of a classifier or learning model. Such performance measurements are accuracy, sensitivity, and specificity. Sensitivity determines how good a classifier recognizes positive cases and specificity determines how well it ascertains the negative cases. Accuracy is the measure of specificity and sensitivity. The performance of the developed system was evaluated using the following metrics: sensitivity, specificity, accuracy, and precision. Mathematically they are represented in equations 18, 19, 20, and 21 respectively [37].

$$\text{Sensitivity}=\frac{TP}{TP+TN} \quad (18)$$

$$\text{Specificity}=\frac{TN}{TN+FP} \quad (19)$$

$$\text{Accuracy}=\frac{TP+TN}{TN+TP+FN+FP} \quad (20)$$

$$\text{Precision}=\frac{TP}{TP+FP} \quad (21)$$

Where TP (True Positive) correctly classified positive cases; TN (True Negative) correctly classified negative cases; FP (False Positive) incorrectly classified negative cases; FN (False Negative) incorrectly classified positive cases.

B. ARTIFICIAL NEURAL NETWORK TRAINING

In this research, the database comprised of thirty-three different images was created, with each of the thirty-three images containing twenty of its types. A total of 33x20 (660) images were created and stored in the database. The images used for the training are divided into three stages. Stage one contains six different images out of the thirty-three different images in the database. Each of the six different images contained twenty of its type. Stage one contains a total of 6x20 (120) images in the database. With a step size of five for the number of images used for the training and threshold of the range, 0.3 to 0.99, five, ten, and fifteen out of the twenty images were used for the training respectively. With a step size of six for a total number of images in the database, stage two contains a total of twelve images out of thirty-three images in the database. Each of the twelve images in the database contains twenty different of its type. Therefore, stage two contains a total of 12x20 (240) in the database. With a step size of five for the training data and threshold in the range of 0.3 to 0.99, five, ten, and fifteen out of the twenty images were used for the training respectively.

Also, with a step size of six for the number of images in the database, stage three contains a total of eighteen different images out of thirty-three different images in the database. Each of the eighteen images contains twenty different of its type. Stage three contains 18x20 (270) in the database. With a uniform step size of five for the number of images used for training and threshold in the range of 0.3 to 0.99, five, ten, and fifteen out of the twenty images were used for the training respectively. The three stages in the ANN-based pattern recognition were accomplished to ascertain the effect of the following: Increased number of images in the database on the overall system performance; Variation in the threshold value to determine the appropriate threshold value for cattle detection and recognition system, and increase and decrease the number of images for the training and testing on the system performance. In all three stages, FDs were obtained from each of the shapes, the FDs were used to train the ANN using a feed-forward backpropagation algorithm. Figure 2 presents the neural network architecture for the training. The FDs were obtained ten times and iteration was performed ten times. The mean of the sensitivity, accuracy, specificity, and precision of the images was computed. The neural network training block diagram is shown in Figure 3.

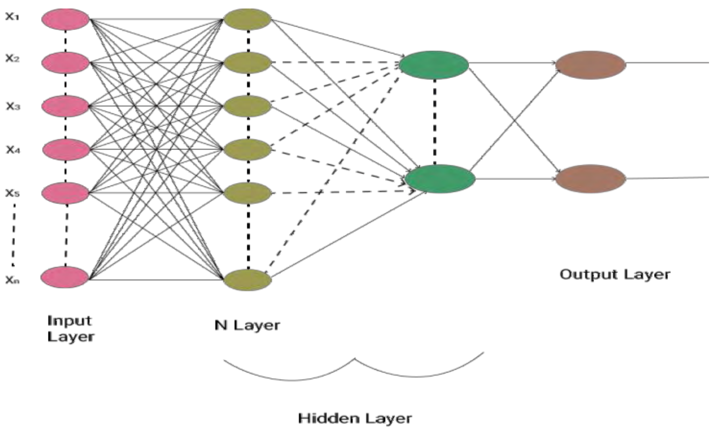

Figure 2. Neural Network Architecture of Cattle Recognition System

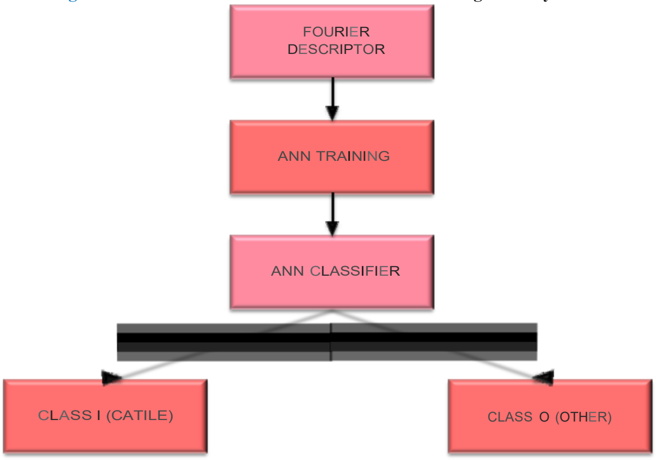

Figure 3. Neural Network Training Block Diagram

IV. RESULTS AND DISCUSSIONS

Images of Cattle, deer, dog, elephant, camel, and Horse images were acquired and pre-processed. The edge detection and Fourier descriptors were obtained. The system was trained and tested. The performance of the system was evaluated using sens1t1v1ty, specificity, accuracy, and precision. The results of the various stages were obtained. Figures 4, and 5 present the result of the acquired and pre-processed images in the database. The images presented here are some of the samples of the 33 different images in the database. Image pre-processing was achieved, and this provides a good edge detection by Comparing 4(b and c) and Figure 5(b and c) to their original image. A good image filling was also achieved.

Figure 4. (a) Cattle Image Acquired

Figure 4. (b) Pre -processed Cattle Image

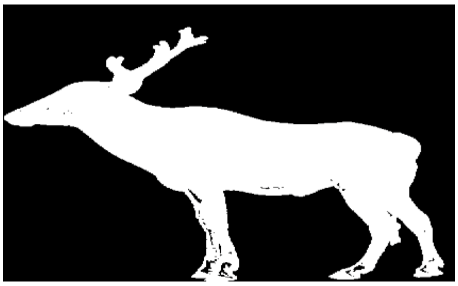

Figure 4. (c) Deer Image Acquired

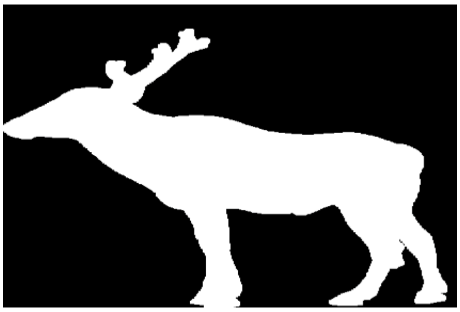

Figure 4. (d) Pre-processed Deer Image

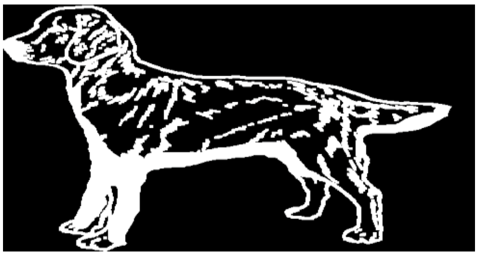

Figure 5. (a) Dog Image Acquire

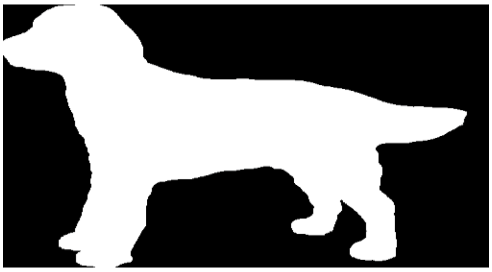

Figure 5. (b) Pre -processed Dog Image

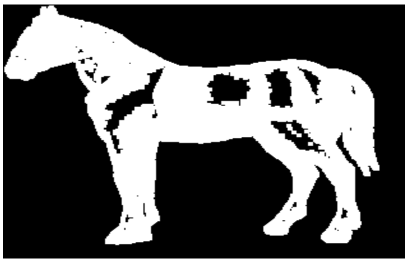

Figure 5 . (c) Horse Image Acquire

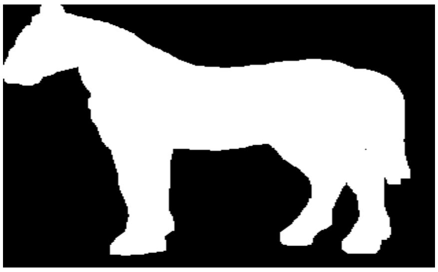

Figure 5. (d) Pre -processed Horse Image

Figure 6(a-d) presents the results of the various edge detection for some of the images in the database. The signature plot is computed from this boundary shape. The shape signature shows a thick and continuous shape boundary. These are good Fourier descriptors for each shape.

Figure 6. (a) Cattle Image Edge detection

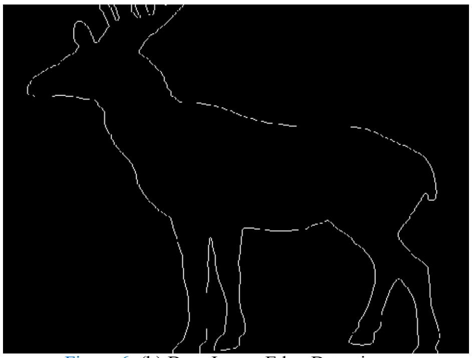

Figure 6. (b) Deer Image Edge Detection

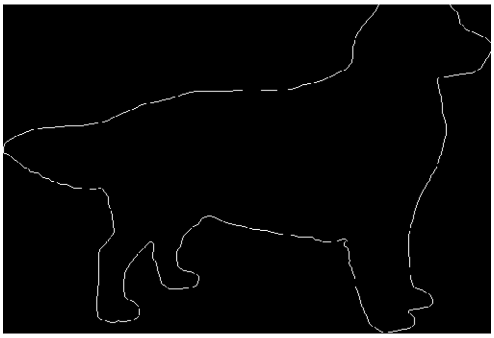

Figure 6. (c) Dog Image Edge Detection

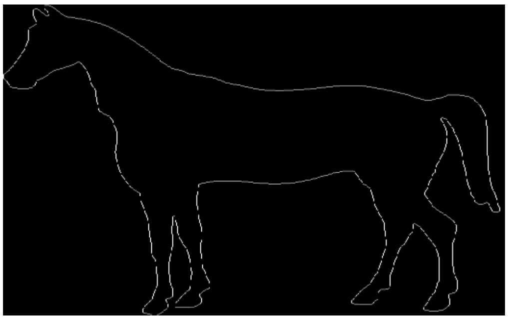

Figure6. (d) Horse Image Edge Detection

Figure 7(a-d) presents the plot of the shape signature for some of the sample images in the database. Fourier descriptors were extracted from the shape signature as features vectors for ANN training. The result shows each of the shapes has a distinct shape signature.

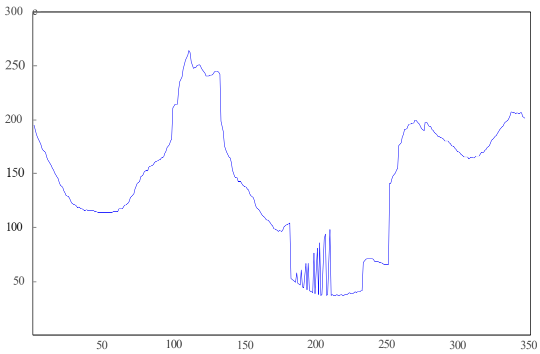

Figure 7 . (a) Signature Plot of the Cattle Image

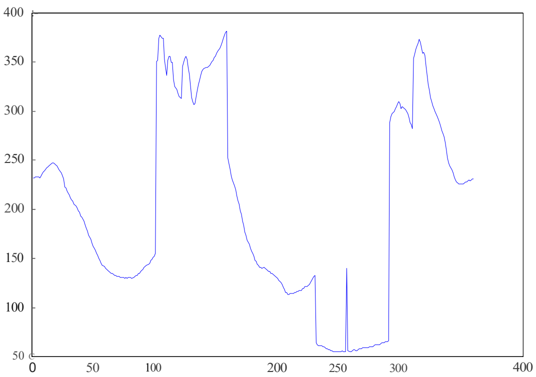

Figure 7 . (b) Signature Plot of Deer image

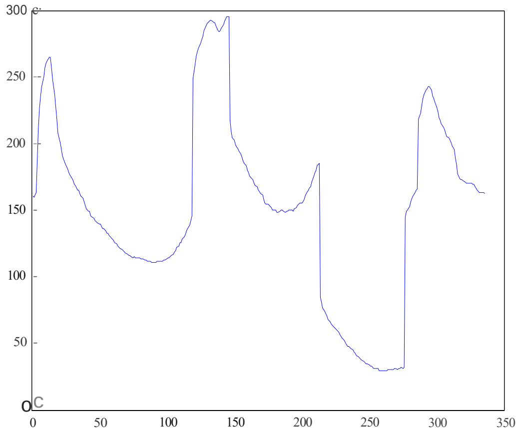

Figure 7. (c) Signature Plot of the Dog Image

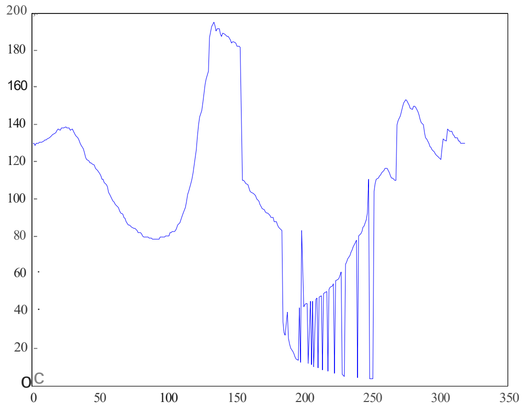

Figure 7. (d) Signature Plot of the Horse Image

Tables 1, 2, 3, 4, and 5 present Fourier descriptor features extracted for Cattle, Deer, Horse, Camel, and Elephant respectively. Ten Fourier descriptors features were obtained for each of the images. The absolute value of the complex Fourier descriptors was used as a feature vector for training a neural network. From the result, each shape has its own Fourier descriptor which is in a particular range different from others. This provides good shape recognition for cattle detection.

Table 1. Fourier Descriptors Feature Extraction for Cattle Image

SIN	Cattle 1	Cattle 2	Cattle 3	Cattle 4	Cattle 5
	49296.80	79000.980	77844.60	63364.250	64301.890
2	6763.579	10987.980	13435.30	8266.594	7390.172
3	11082.60	20256.340	20018.40	11729.840	12080.670
4	3171.911	3366.347	3846.452	4779.310	4830.703
5	3285.586	4855.046	4659.623	2476.808	3592.350
6	2807.881	2669.094	2201.645	2997.042	1894.168
7	1426.161	4374.287	4766.901	2018.556	2282.893
8	1195.107	2340.632	2079.855	1446.386	2133.940
9	904.569	1797.649	1549.466	1753.454	3071.995
10	534.495	827.698	1030.056	1827.624	854.518

Table 2. Fourier Descriptors Feature Extraction for Deer Image

SIN	Deer **1**	Deer2	Deer 3	Deer4	Deer 5
1	60408.12	66097.644	72722.53	72055.514	64920.328
2	2279.133	4019.683	10415.18	9823.950	4477.533
3	9083.493	11615.364	14795.26	19359.297	10767.829
4	9863.528	11092.714	5485.146	2412.180	12031.527
5	5484.072	10235.656	9524.552	9393.120	10917.742
6	1022.869	2293.265	5387.169	3541.028	3469.653
7	4574.586	2795.473	6074.513	1268.790	1505.268
8	2433.975	5102.499	6326.403	3888.875	4841.066
9	208.945	2522.767	968.492	1830.588	3346.036
10	2871.332	1245.637	2301.921	2861.494	1087.012

Table 3. Fourier Descriptors Feature Extraction for Horse Image

SIN	Horse 1	Horse 2	Horse 3	Horse 4	Horse 5
1	66130.64	71313.578	31067.62	31458.328	33237.556
2	6593.949	3054.918	4661.072	4135.109	4842.102
3	15549.38	11486.324	8175.250	8466.112	6448.281
4	9944.077	3670.862	2388.781	1305.119	2443.365
5	3356.926	6222.201	708.059	1055.120	1010.892
6	3541.108	4314.358	3797.236	3095.823	1211.529
7	1670.654	2359.751	1509.728	1856.724	872.894
8	4171.238	4578.725	2393.591	1819.777	1057.208
9	2730.392	1307.268	922.369	1548.104	1180.935
10	2125.110	2632.213	1097.755	1566.733	264.377

Table 4. Fourier Descriptors Feature Extraction for Camel Image

SIN	Camel 1	Camel 2	Camel 3	Camel4	Camel 5
	39807.00	35903.544	40396.51	46024.673	31154.459
2	2273.973	4968.848	8853.266	6232.577	2563.359
3	3345.747	2110.631	4529.962	4327.955	3944.257
4	2429.700	2586.064	1836.238	1824.788	2762.381
5	3903.257	2621.490	1064.127	3281.229	2232.774
6	1901.117	2141.263	980.096	1871.562	1988.682
7	2944.631	1448.169	1987.730	778.344	2197.088
8	829.499	2086.985	971.068	1422.561	1551.155
9	2691.012	1489.357	1497.059	1764.461	2165.948
10	944.220	2642.197	906.029	1465.624	1067.314

Table 5. Fourier Descriptors Feature Extraction for Elephant Image

SIN	Elephant 1	Elephant 2	Elephant 3	Elephant 4	Elephant 5
	88543.346	91077.764	48011.259	94682.548	90611.852
2	20073.148	13706.632	8433.423	14044.585	13308.483
3	9100.601	7235.078	2164.579	8594.655	4446.395
4	6544.198	1345.893	1762.894	7177.748	2409.087
5	535.449	5257.203	2794.044	8433.894	539.891
6	1380.400	4008.339	3334.098	5053.864	1965.911
7	2200.044	6839.593	1570.075	1192.578	5774.958
8	465.640	4108.323	684.620	5538.872	4746.322
9	3526.945	3007.078	785.228	5678.889	3203.535
10	2207.493	2013.998	1145.470	1440.369	3099.426

Ten Fourier descriptors were obtained. Ten different iterations were performed to observe the effect of variation in the threshold, increasing the number of images used for training and testing respectively. Figure 8 - 10 present the mean and standard deviations for the sensitivity, accuracy, specificity, and precision for ten iterations using five, ten, and fifteen images for training (5x6, 10xl2, and 15xl8), with a total of six, twelve, and eighteen different images in the database. It observed that a good threshold value must be selected for correct classification. Figures 8, 9, and 10 show that variation in threshold greatly affects the sensitivity, accuracy, specificity, and precision of the system. Irrespective of the number of images in the database, it is equally observed that good classification is achieved at a threshold value between 0.5 and 0.7. It's also, observed that as the number of images in the database increases there was a decrease in sensitivity and precision value. This effect of the number of images in the database is insignificant at a threshold of 0.6. With a carefully selected threshold value and good Fourier descriptors, this can be minimized. Lastly, it is observed that as the number of images used for the training increases, overall system accuracy, specificity, sensitivity, and precision increases as well. Therefore, it is recommended that a large percentage of the image should be used for the training. That is 75% should be used for the training and 25% for testing.

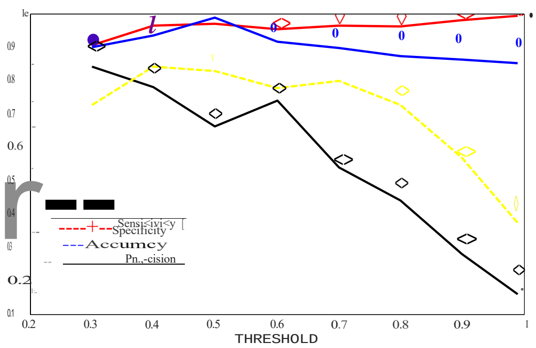

Figure 8. Fifteen Images for Testing (total of six different images in the database)

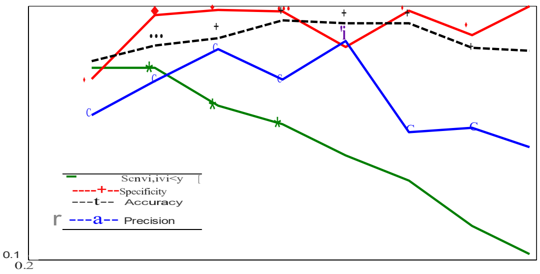

Figure 9. Fifteen Images for Testing (total of twelve different images in the database)

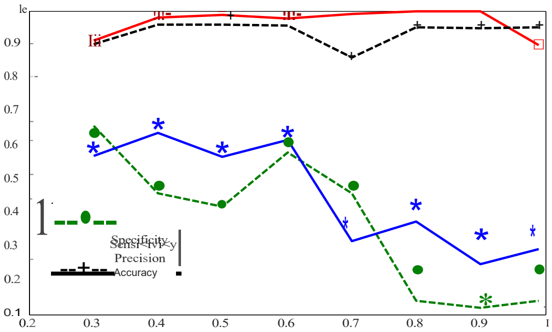

Figure 10. Fifteen Images for Testing (total of eighteen different images in the database)

V. CONCLUSION AND RECOMMENDATION FOR FUTURE DIRECTION

The use of image processing for feature extraction and pattern recognition for cattle detection and recognition is a concept that allows cattle to be detected and recognized in the vicinity without destroying farmland, arable crops, or causing the crisis that is generally connected with it. This study presented a shape-based cattle identification and recognition system based on intelligent Fourier descriptors. Images of cattle, as well as related animals including deer, elephant, dog horse, and camel, were gathered and pre-processed. In a MATLAB environment, the algorithm was created and implemented utilizing image processing and an artificial neural network. The system's performance was assessed using measures like sens1tlv1ty, specificity, accuracy, and precision. The increased number of images in the database does not influence the overall system performance, according to the findings. This was owing to the use of Fourier descriptors and a good threshold value. It was discovered that a decent threshold value must be established, and a good percentage of an image must be used for trammg, to improve accuracy, precision, specificity, and sensitivity. Seventy-five percent of the image must be used for training and twenty-five percent for testing. With six different images in the database, fifteen for training and five for testing, and a threshold value of 0.6, the research was able to achieve 98.7% sensitivity, 98.8% specificity, 98.8% accuracy, and 94.5 percent precision. As a result, these findings provide a good strategy for detecting and recognizing cattle. When deployed in an unmanned aerial vehicle, the technology can be used to monitor and detect the presence of cattle in the area, reducing the damage of farms, arable crops, and the accompanying cnses.

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Abiodun Musa Aibinu is presently a professor with the Department of Mechatronics Engineering, School of Engineering and Engineering Technology, Federal University of Technology Minna. He has published in reputable journals and learned conferences His research interests are: Biomedical Signal Processing; Digital Image Processing; Instrumentation and Measurements; Wireless and Telecommunication system and Digital System Design.

Olayemi M. Olaniyi is an Associate Professor in the Department of Computer Engineering at the Federal University of Technology, Minna, Niger State, Nigeria. He received his Bachelor of Technology (BTech) in Computer Engineering in 2005, Master of Science (MSc) in Electronics and Computer Engineering in 2011, and Ph.D. in Computer Science and Engineering (Computer Security) in 2015 from the Ladoke Akintola University of Technology, Ogbomosho, Nigeria, Nigeria. His research interests include Computer and Information Security, Intelligent/Embedded Systems, and Applied Medical Informatics. His research has appeared in journals such as Taylors and Francis's Journal of Applied Security Research, Inderscience's Journal of Computer and Information Security; International Journal of Information Privacy, Security, Electronic Government-An International Journal, International Journal of Telemedicine and Clinical Practices. He can be contacted at email: mikail.olaniyi@futminna.edu.ng.

Buhari U. Umar is a Lecturer in the Department of Computer Engineering, Federal University of Technology, Minna, Niger State, Nigeria. He obtained his B.Eng. in 2008 and M. Eng in 2015 in Electrical and Computer Engineering and Computer Engineering respectively. He is currently a Ph.D. student at the Department of Computer Engineering, Federal University of Technology, Minna, Niger State, Nigeria. He has published in reputable journals and learned conferences. His areas of research include Information and Computer security, Intelligent systems, Embedded systems, Digital System Design, Biomedical Signal Processing, Artificial Intelligence, and Image Processing. He is a Registered Member of the Council for the Regulation of Engineering in Nigeria (COREN) and the Nigeria Society of Engineers (NSE). He can be contacted at email: buhariumar@futminna.edu.ng.

Edoghogho Olaye currently lectures in the Department of Computer Engineering, University of Benin. He obtained his Ph.D. in 2017 and his areas of research include software quality, embedded system design and system automation. He spends a significant amount of time developing software for research, commercial projects for both the private and public sectors.