Animal Recognisation System based on Combination of Features Using Neural Network

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Abstract - *In this paper classification of animal species using Neural Network is proposed by taking a combination of features. Having accurate, detailed and up to date information of wild-life across several geographic area would help us to study and conserve ecosystem. Animal recognition is one of the research areas in which a few effective technologies have been proposed especially by taking a combination of features. In this paper experiment is done on a dataset of 112 animals and by carefully selecting a combination of features from shape, color, and texture, satisfactory accuracy was achieved. The main goal of this paper is to compare the overall recognition accuracy by taking individual features like shape, color and texture with the combined features.*

Key Words: **Shape features, Color histogram, Gray-level Co-occurrence Matrix, Neural Network**.

1. INTRODUCTION

Animal detection and recognition based on image processing is a widely concentrating field in research. To better understand the complexities of natural eco-system and to manage and protect them, it is necessary to classify the animal species. The motivation for this project is to build an automatic system for detection and recognizing animal species for animal researchers and wild life photographers. The DSLR cameras that we use in the industries are quite expensive and there is limitation in shutter on-off cycle. Hence it must have a proper recognition system. In this work a combination of both domestic and wild animals is considered. Technology used in this research can be further extended to use in monitoring and security purposes. In this work a viewpoint independent inter-species animal recognition method is proposed using a combination of shape, color and texture features. This method has been tested on four different animal species. Neural network was used to classify the animal species. Detailed research was carried out about how individual features perform and the performance of combined features.

2. PREVIOUS WORK

There are a number of works related to animal classification. A multiple feature detection of predator animal was proposed and tested by using MLP and SVM classifier in [1]. Various color and texture features for automated detection and classification of animals images using various classifier was proposed in [2]. An animal classification system using block based approach and tested using Probabilistic neural network and K-nearest neighbors was proposed in [3]. Animal classification system based on Image processing and Support Vector Machine for wild life photographers and animal researchers was proposed in [4]. A method for image retrieval predication based on local invariant shape features that utilizes the Harris-Laplace corner method to classify an object into one of the several pre-defined categories was proposed in [5]. Automated identification of animal species in camera trap images that extracts global features using weighted sparse coding and max pooling techniques and classified using SVM classifier was proposed in [6]. Classification of African wild life species using CNN and deep learning was proposed in [7]. A deep learning convolution network based on Keras and Tensorflow deployed using Python was proposed in [8]. Guinea pig classification using deep learning imaging methods was performed in [9]. Classification of birds using HOG and RGB features from photos by CNN was performed in [10].

3. PROPOSED METHOD

Animal recognition is one of the research areas in which few effective technologies has been proposed. In the present method inter-class recognition of animal species is done by taking a combination of shape, color and texture features independent of view-point and configuration. Fig.1 depicts the process flow diagram of the proposed method and has been illustrated below.

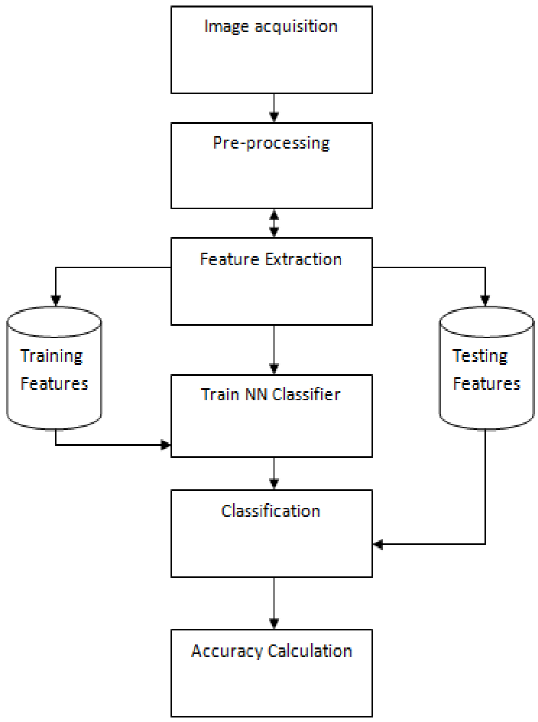

Fig-1: Process Flow Diagram of Proposed Method

3.1 ACQUISITION AND PRE-PROCESSING

The images are downloaded from the website and to introduce sufficient variations the images are depicted from different viewpoints and configurations.The pre-processing steps includes resizing the images to standard dimensions, so as to reduce the computational load. Relevant portion of the images are segmented from the background using black and white and color segmentations respectively.

3.2 FEATURE EXTRACTION

After completion of pre-processing steps, the shape, color and texture features are extracted and is used to train a neural network.

Shape Features: First the color image is converted to grayscale image. Then it is converted to black and white image using Otsu Threshold with a threshold level of 0.94. Then the color features like Area, Centroid, MajorAxisLength, MinorAxisLength, Perimeter and FilledArea are extracted. For each image the shape features are represented by 7 element vectors.

FS = {Area, Centroid, MajorAxisLength, MinorAxisLength, Perimeter, FilledArea}

Color Features: Color image is split into three separate color channels H(Hue), S(Saturation), V(Value). **The HSV color space provides a close representation of human visual perception of color than the R, G, B color space. Then the histograms are computed for each channel. The histogram of a digital image with N levels is a discrete function** $h(r_k) = n_k$, where r_k is the k-th level and n_k is the number of pixels in the image having level r_k. To denote the three color channels, the symbols n_{hk}, n_{sk}, n_{vk} are being used extensively. Mean , standard deviation, variance, skewness and kurtosis are computed for each color channels separately. Here μ_h, μ_s, μ_v denote the mean values. Standard deviations are represented as σ_h, σ_s, σ_v for three color channels respectively as denoted in Eq. (1) to (3).

$$\sigma_h = \sqrt{\frac{\sum_{k=0}^{N-1}(n_{hk}-\mu_h)^2}{N}} \tag{1}$$

$$\sigma_s = \sqrt{\frac{\sum_{k=0}^{N-1}(n_{sk}-\mu_s)^2}{N}} \tag{2}$$

$$\sigma_v = \sqrt{\frac{\sum_{k=0}^{N-1}(n_{vk}-\mu_v)^2}{N}} \tag{3}$$

Variance is represented as $\sigma_h{}^2, \sigma_s{}^2, \sigma_v{}^2$ for three color channels respectively. Skewness and kurtosis for three color channels are respectively denoted in Eq. (4) to (9).

$$Skewness_h = \frac{\sum_{i=1}^{N}(n_{hk}-\mu_h)^3 / N}{\sigma_h{}^2} \tag{4}$$

$$Skewness_s = \frac{\sum_{i=1}^{N}(n_{sk}-\mu_s)^3 / N}{\sigma_s{}^2} \tag{5}$$

$$Skewness_v = \frac{\sum_{i=1}^{N}(n_{vk}-\mu_v)^3 / N}{\sigma_v{}^2} \tag{6}$$

$$Kurtosis_h = \frac{\sum_{i=1}^{N}(n_{hk}-\mu_h)^4 / N}{\sigma_h{}^4} \tag{7}$$

$$Kurtosis_s = \frac{\sum_{i=1}^{N}(n_{sk}-\mu_s)^4 / N}{\sigma_s{}^4} \tag{8}$$

$$Kurtosis_v = \frac{\sum_{i=1}^{N}(n_{vk}-\mu_v)^4 / N}{\sigma_v{}^4} \tag{9}$$

For each image the color features are represented by 15-element vectors.

$$FC = \{ \mu_h, \mu_s, \mu_v, \sigma_h, \sigma_s, \sigma_v, \sigma_h{}^2, \sigma_s{}^2, \sigma_v{}^2, Skewness_h, Skewness_s, Skewness_v, Kurtosis_h, Kurtosis_s, Kurtosis_v \}$$

Texture Features: Texture refers to visual patters or spatial arrangement of pixels. It cannot be described by a single color or intensity value. It is modeled by variations of gray level over the image. It is computed from a set of gray-level co-occurrence matrices (GLCM). GLCM defines the probability of gray level *i* in neighbourhood of gray level *j* at a distance *d* and angle θ . Formally,

$$G = \Pr(i, j \mid d, \theta)$$

Directional GLCMs can be computed along three other directions viz. Right-diagonal($\theta = 45^\circ$), vertical($\theta = 90^\circ$) and left-diagonal($\theta = 135^\circ$).GLCM based features are contrast(GC), homogeneity(GH), energy(GE), correlation(GN) respectively. Here P(i,j) represents the (i,j)-th element of a normalized symmetrical GLCM and N denotes the number of gray levels then

$$GC = \sum_{i=1}^{N} \sum_{j=1}^{N} P_{i,j} (i-j)^2 \tag{10}$$

$$GH = \sum_{i=1}^{N} \sum_{j=1}^{N} \frac{P_{i,j}}{1+|i-j|} \tag{11}$$

$$GE = \sum_{i=1}^{N} \sum_{j=1}^{N} (P_{i,j})^2 \tag{12}$$

$$GN = \sum_{i=1}^{N} \sum_{j=1}^{N} \frac{(i-\mu i)(j-\mu j) P_{i,j}}{\sigma_i \sigma_j} \tag{13}$$

For each image the texture features consists of four GLCM based features calculated along 4 directions $(0^\circ, 45^\circ, 90^\circ, 135^\circ)$ leading to a total of 16- element vectors.

$$FT = \{GC_{0^\circ}, GC_{45^\circ}, GC_{90^\circ}, GC_{135^\circ}, GH_{0^\circ}, GH_{45^\circ}, GH_{90^\circ}, GH_{135^\circ}, GE_{0^\circ}, GE_{45^\circ}, GE_{90^\circ}, GE_{135^\circ}, GN_{0^\circ}, GN_{45^\circ}, GN_{90^\circ}, GN_{135^\circ}\}$$

Combined Features: A combination of shape, color and texture features is carefully selected to make the classification process much more efficient. These features include Area, Centroid, MajorAxisLength, MinorAxisLength, Perimeter, FilledArea, Mean, Standard deviation, Contrast, Energy, Homegeneity, Correlation respectively. It is represented by a 29-element feature vector for each image.

$$F = \{FS, FT, \mu_h, \mu_s, \mu_v, \sigma_h, \sigma_s, \sigma_v\}$$

3.3 CLASSIFIER

A multi-layer perceptron using back propagation algorithm has been used (MLP). In the training phase the input feature vector is mapped to the known output class. Weights are iteratively adjusted to reduce the error at output. At the end of the training phase the correct weights are determined. In the testing phase an unknown feature vector is mapped to an estimated class using pre-determined weights. The test samples are not exactly same as the training samples. 54% of the images in the dataset are fed to the neural network to learn the characteristics shape, color and texture, while the other 46% are subsequently treated as unknown test samples to evaluate the performance of the system. The percentage classification results are reported in the experimentations section.

4. Experimentations and Results

To test the performance of the proposed system, experiments were performed on a dataset of 112 images of 4 animal species that includes both domestic and wild animals: Cow, Deer, Elephant, Zebra. The training dataset contains 60 images whereas the testing dataset contains 52 images. Samples of the training and testing dataset are shown in Fig. 2 and Fig. 3 respectively with four images of each class.

(a) (b) (c) (d)

(e) (f) (g) (h)

(i) (j) (k) (l)

(m) (n) (o) (p)

Figure-2: Training Samples: Cow class A(a,b,c,d); Deer class B(e,f,g,h); Elephant class C(i,j,k,l);Zebra class D(m,n,o,p)

(a) (b) (c) (d)

(e) (f) (g) (h)

(i) (j) (k) (l)

(m) (n) (o) (p)

Figure-3: Testing Samples: Cow class A(a,b,c,d); Deer class B(e,f,g,h); Elephant class C(i,j,k,l); Zebra class D(m,n,o,p)

The classes are denoted as A, B, C and D. All the images are downloaded from the websites. To introduce sufficient variations, the images are depicted from different viewpoints and angles. As a part of pre-processing step the images are resized to standard dimensions 256×256 and stored in JPG format. Then it is segmented from the background using black and white and color segmentation techniques in which the threshold level was taken as 0.94 and 0.93 respectively as shown in Fig. 4 and Fig. 5

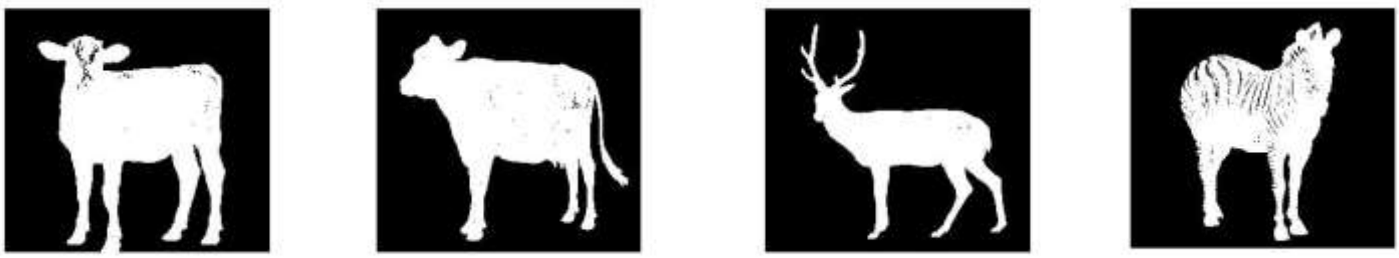

Figure-4: Black and White Segmented images

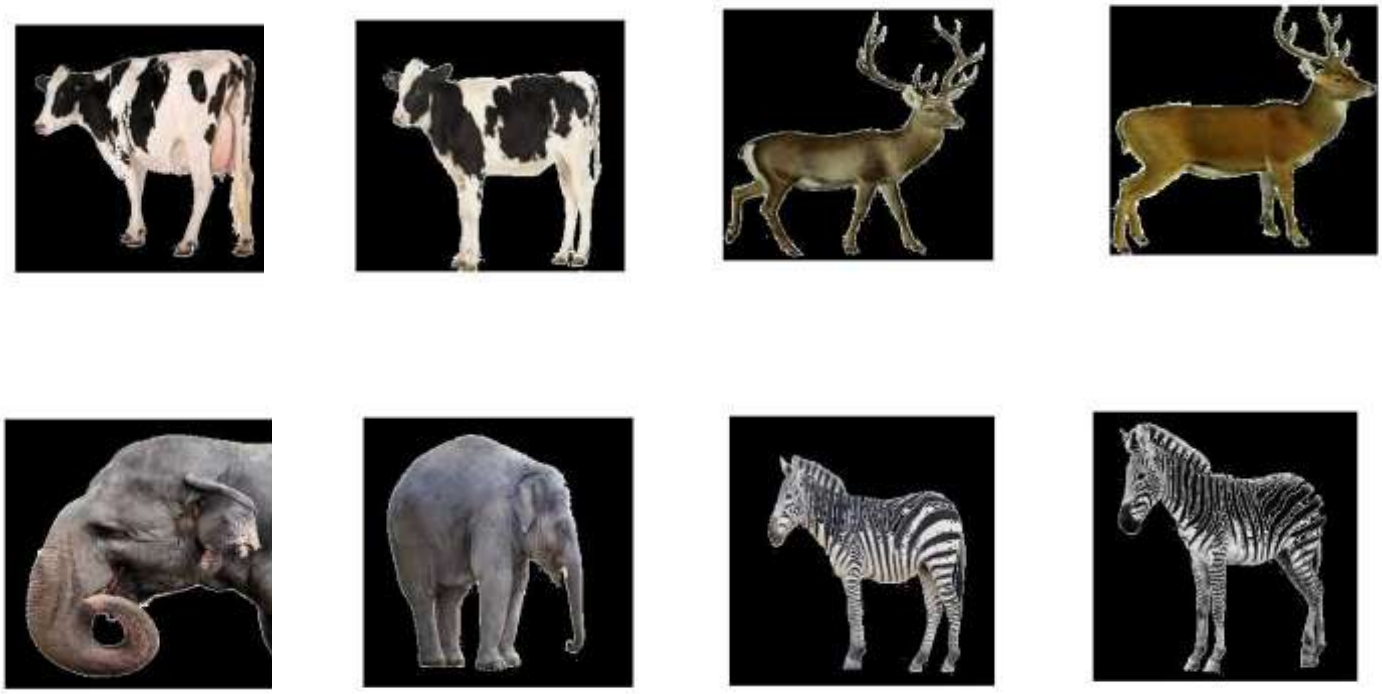

Figure-5: Color Segmented images

The topology of the neural network used for classification of four animal species is shown in Fig. 6. It uses a 29-18-4 architecture i.e. 29 input nodes for the combined feature vector, 18 nodes in hidden layer and 4 output nodes for accommodating 4 animal species A,B,C and D. A Tan-sigmoid activation function $y = \frac{1-e^{-x}}{1+e^{-x}}$ for the hidden layer is used.

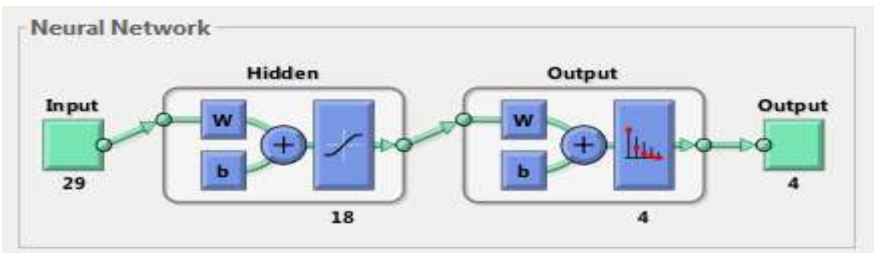

Figure-6: Topology of MLP classifier

The classification accuracy is calculated by Equation 14.

$$AccuracyPercentage = \frac{TruePositive + TrueNegative}{(TruePositive + FalsePositive) + (TrueNegative + FalseNegative)} \times 100 \quad (14)$$

The accuracy obtained using shape features is 63.5% as illustrated in Fig. 7.

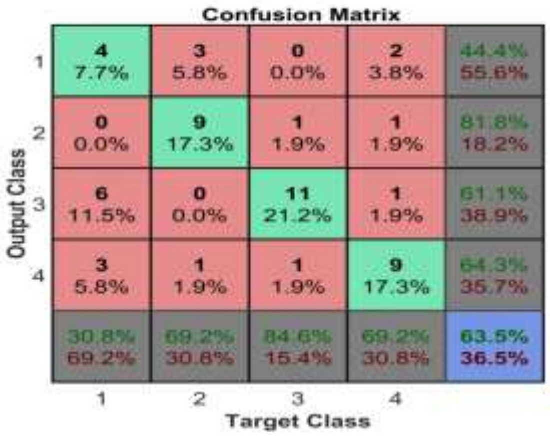

Figure -7: Confusion Matrix using shape features

The accuracy obtained using color features is 26.9% as illustrated in Fig. 8.

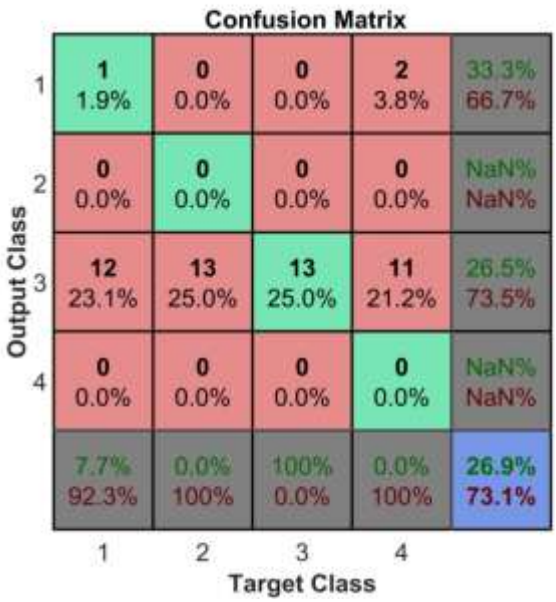

Figure-8: Confusion Matrix using color features

The accuracy obtained using texture features is 78.8% as illustrated in Fig. 9**.**

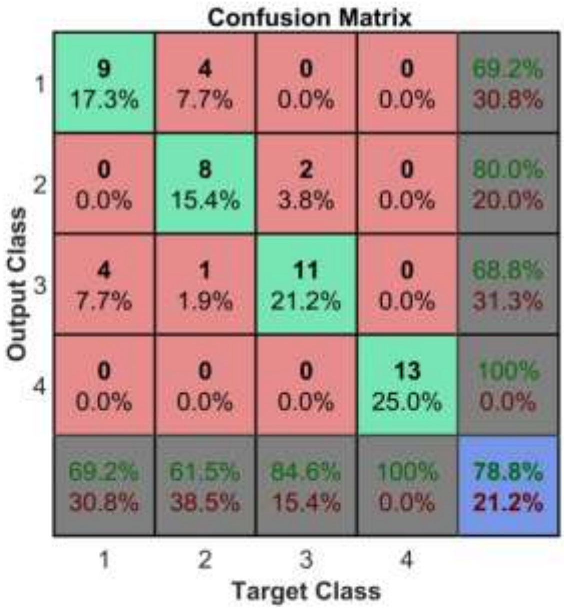

Figure-9: Confusion Matrix using texture features

The accuracy obtained using combined features is 90.4% as illustrated in Fig. 10*.*

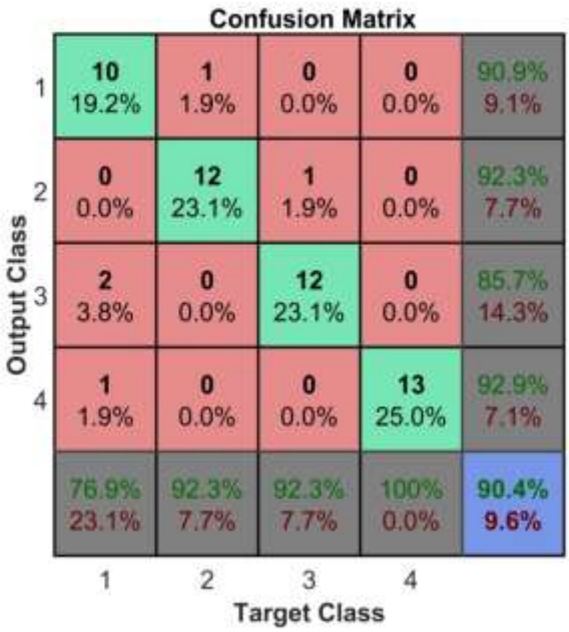

Figure-10: Confusion Matrix using combined features

5. ANALYSIS

From the previous section, it is evident that the classification accuracy has increased when features have been combined then when individual features have been used. Fig. 11 summarizes the result indicating how the performance varies for the four type of animals based on features used.

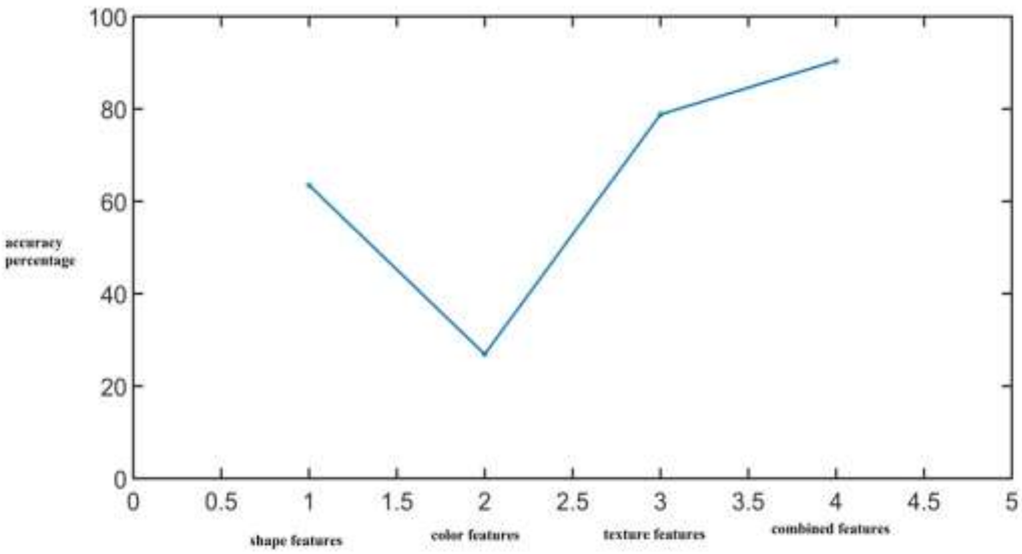

Figure-11: Overall accuracy variations of different animals with classification features

Comparing our proposed method with the work done earlier indicates superiority of our proposal in distinguishing between various animal species. It is evident from 90.4% accuracy in our method than 82% accuracy using MLP in [1]. The reason for the lower performance in approach [1] is due to the fact that it has taken shape and color features for animal classification only as compared to combined features in our approach. Previous work [2] achieved an accuracy of 88% when classified animals on the basis of color and texture feature only using SVM classifier. Hence, the present work shows more robustness when classifying animals on the basis of combined features especially when configuration and viewing angle changes.

6. CONCLUSIONS AND FUTURE SCOPES

This paper proposes a technique for inter-class recognition of animal species for both domestic and wild animals using a careful selection of combination of features that achieved a good accuracy of 90.4% for MLP. The proposal used combination of shape, color and texture feature on 112 animal dataset. A comparison of accuracies for individual features and combined features is also performed. This work offers much social significance in studying and conserving ecosystem by studying wild-life across several geographical areas. The main contribution of the work is that the proposed system offers more robustness when the camera view-point and configuration of animals changes. It provides acceptable results for a dataset that contains both domestic and wild animals.Future work will involve intra-class recognition of animal species using combined features as well as recognizing a specific animal from within a collection.

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