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EAR IMAGE-BASED INDIVIDUAL PIG IDENTIFICATION BY USING STATISTICAL PARAMETERS

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ABSTRACT

One of the most popular methods for addressing the shortcomings of traditional identification methods is biometric-based animal identification. The animal's phenotypic characteristics, such as its muzzle, retina, ear venation pattern, and iris, can be used in identification. The most important characteristic for pig identification is the pattern of venation in the ears. However, it is somewhat difficult to capture the entire venation web due to the thickness of ear skin. This research attempted to identify the 'Yorkshire' pig using the images of their ears. An artificial ambience was also created to block out the external noise. In present work, a total of 165 images from 5 distinct pigs were captured. The acquired images were used to collect eight statistical features. Four machine learning-based techniques, including Support Vector Machine, Decision Tree, K-Nearest Neighbor, and Random Forest, were used to assess and categorize the obtained statistical characteristics in order to forecast the specific pig. In comparison to the other approaches, Random Forest classifier showed the best identification accuracy (90.9%), followed by Support Vector Machine, Decision Tree, and K-Nearest Neighbor. The technique will help us analyze the vein patterns in pig ears to identify specific pigs.

Keywords: Animal identification, decision tree, ear image, entropy, random forest

INTRODUCTION

Due to the falsification or duplication of tag and fraudulent attacks on the animal, the conventional techniques of animal identification result in enormous losses (Mustafi *et al.*, 2021). Traditional techniques like freezing, ear notching, tattooing, etc. have an immediate effect on the health and behaviour of animals. Health concerns for individual identification can be excluded with biometric-identification. Phenotypic and genotypic traits are used in biometric-based identification. Body colour, face structure, retina, venation pattern of ears, and iris pattern are the examples of phenotypic characteristics of animal that can be employed as biometric qualities. However, only the gene has been used to explain genotypic traits. Information based on phenotypes is less expensive than genotypic traits. Given that most animals such as cows, pigs, and goats, have substantially less variety in their bodies, identifying them on the basis of facial characteristics and coat colour is less successful. On the other hand, because a high-end specialised camera is required, iris and retinal image capture is quite expensive. Another useful phenotypic trait that is maintained throughout the lifespan is the pattern of venation in the ears. Each pig may be identified from other pigs by its own pattern of ear pictures. Any unique object can be classified using statistical attributes (Lambrou *et al.*, 1998; Yuen *et al.,* 2009). Each image has a number of pixels with various orientations (Dan *et al*., 2022). One key technique for distinguishing one visual item from another is the orientation of each pixel. The pixel orientation can also affect the statistical features. Each of ear images carries distinct statistical characteristics that correspond to its pattern. Ten statistical characteristics, including contrast, energy, homogeneity, mean, standard deviation, entropy, variance, smoothness, and inverse difference moment (IDM), were examined in this study. Support Vector Machine, K-nearest Neighbor (KNN), Decision Tree, and Random Forest have all been used to categorise these attributes. Due to the correlation, some features, including mean, standard deviation, RMS, smoothness, and IDM, produce misclassification outcomes. After these traits have been eliminated, classification outcomes can be enhanced. The Random Forest offers the four classifiers' best accuracy. The primary goal of the paper is to present a technique for distinguishing each individual pig using four machine-learning models. To lower the noise level for the experiment, the pig's ear was placed inside the black box. These pig-ear photos have helped to construct a vast database.

Perusal of literature has revealed that the conventional approach to animal identification results in some stressful handling, capture, or restraints (Bugge *et al.*, 2011). The complexity of animal health-related issues, tissue damage, and pain causes are attributed to this marking technique. Therefore, a technique that correctly recognises the animal based on its morphological characteristics is needed. Identification through biometrics is the only option. Animal physical characteristics such as body colour, coat pattern, iris, retina, muzzle, facial structure, and venation pattern are all included in visual biometry. Zebra have been recognised by using their coat pattern (Lahiri *et al.*, 2011). Another crucial characteristic of animal identification that remains constant over time is the pattern of ear venation (Dan *et al.,* 2021). The iris pattern and retinal veins are important identifying characteristics that offer the highest degree of identification accuracy (Ghoshal and De, 2016; Roy *et al.,* 2021). Using a texture-based analysis is another method of identifying animals. Cattle have been recognised by using muzzle prints as well (Tharwat *et al.*, 2014). The surface characteristics of the image, such as appealing, smooth, coarse, and irregularity, can generally be used to evaluate texture (Wu *et al*., 1992). To categorise the texture statistical features, a variety of methods have been used. The automatic model of categorization employing some texture features have been developed (Guru *et al.,* 2010). For classification, the KNN model was employed by the authors. The statistical distribution of grey tone or variable shade of the image pixel's grey level is how the texture is typically defined (Haralick *et al.,* 1973). The grey-level co-occurrence matrix, grey-level histogram, and auto co-relation features are the examples of statistical texture analysis. The statistical distribution between the pixel's intensity at a given point in relation to other pixels determines the texture features in statistical texture analysis (Oo and Htun, 2018). The grey-level co-occurrence matrix, which comprises the main concealable features for each image, contains statistical variables such as entropy, correlation, energy, homogeneity, and others (Arivazhagan *et al.*, 2013). Machine learning methods like support vector machine (Wang *et al.*, 2010), random forest, decision tree, and KNN can classify these features. The primary goal of this research was to identify the best machine learning model among four machine learning model for individual pig identification using their ear images, as well as to supply the data base for the pig ear images.

MATERIALS AND METHODS

The present research involved the following steps as image acquisition, ear image segmentation, feature extraction, and classification of these features using four machine learning algorithms for identification of an individual pig.

Image acquisition

The image database was constructed after collecting the images from the registered farm, ICAR-NRC on Pig, Guwahati (India). A mobile phone with a clear 13-megapixel camera was used to take the pictures of pigs. For making a uniform image, the distance between the camera and pig ear must be fixed as 80-110 mm. Proper visualization of vein web, the ear was position along with X-axis and perpendicular to Y-axis and high illumination torch light was projected on the inner surface of the ear. Some noisy occurrences like interference or reflection of light may create erroneous capturing. To eliminate the light noise, the ear region of pig was placed in a black box. The image-capturing process is depicted in Fig. 1.

Fig. 1: **Image acquisition**; A) High intensity light has projected on the ear leaf of pig, B) Pig ear placed in box, and C) Captured image of ear leaf with proper vein web on the other side of ear using mobile phone

Ear image segmentation

To identify the region of interest, segmentation was performed with only the ear part being necessary in this case. In order to segment ear images, the original images were first transformed to HSV images. Since the hue value of ear area is completely different from its background, therefore, by defining the upper and lower bound of hue, the region of interest was quickly acquired. To obtain the image mask, an upper bound (b_u) and a lower bound (b_l) were specified. After that the Bit-wise AND perform between image mask (M_b) and original image (I) (1). assess the original segmented image (S_b) .

$$S_b = M_b \; AND \; I \quad .... (1)$$

Where $M_b = b_u \& \, b_l$

The mask image contained some unwanted image object. The morphological close operation was performed to reduce the unwanted object and final image object defined as I_f (2).

$$I_f = \text{morphological close}(I) \quad .... (2)$$

The image segmentation process is presented in Fig. 2.

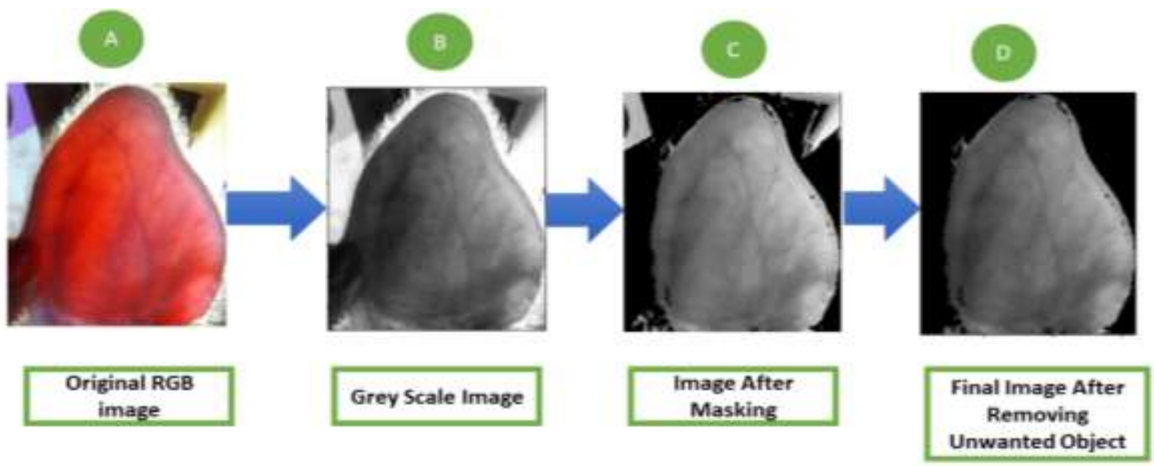

Fig. 2: Image segmentation; A) Original RGB image, B) Grey scale conversion of the RGB image, C) Image after masking operation, and D) Final image after removing the unwanted object using morphological operation

Feature extraction

Only the ear portion from the segmentation process was designated as the region of interest. The crucial features were extracted and used to determine the features from the sample. Generally, image features contained colour, shape, and texture features. Texture features included energy, entropy, homogeneity, etc., which provide essential information to classify the image object. The texture generally implies each image pixel's colour distribution, roughness, and hardness. Texture feature extraction uses Grey level co-occurrence matrix (GCLM) [Haralick *et al.*, 1973]. GCLM is the matrix size N x N with the relative distance between pixel pairs as 'd', and the relative orientation between two pixels with an angle $\emptyset$. The equation of GCLM is presented in equation 3.

$$GCM = N\ x\ N \text{ where } GCM \text{ is the coocurrance matrix}, N\ x\ N \text{ is the size}$$
$$For\ i\ in\ j\ (i \text{ pixel sarraounded by } jth\ pixel)$$
$$\text{Distance} = d(i,j) \ldots\ldots\ldots.\ldots (3)$$
$$\text{Angle} = \emptyset(i,j)$$

The orientation and relative distance between pixel pair as per P1 pixel is depicted in Fig. 3.

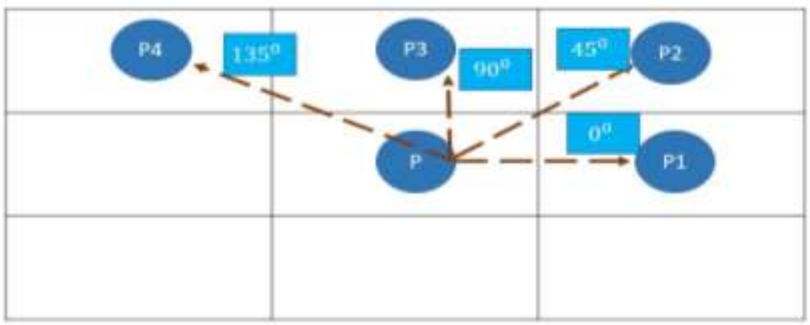

Fig. 3: Pixel orientation according to P1 pixel (P is the reference pixel and evaluate the various pixel orientation such as 0°, 45°, 90°, 135°, etc.)

After calculating the GCM matrix, it was normalized to create the normalized version GCM matrix. From this normalized co-occurrence matrix 2nd order statistical parameter was calculated which was used for classification.

From the various statistical parameter, contrast, energy, homogeneity features were considered from GCLM matrix and other feature like mean, average RMS, entropy, standard deviation, variance, EDM and smoothness were evaluated. Some equation regarding the features are shown in equation 4-7.

$$f_1(\text{Contrast}) = \sum_i \sum_i (i-j)^2 GCM(i,j) \ldots\ldots\ldots (4)$$
$$f_2(\text{Eenrgy}) = \sum_i \sum_j GCM(i,j)^2 \ldots\ldots\ldots\ldots\ldots\ldots (5)$$
$$f2(\text{Homogeneity}) = \sum_{i,j} \frac{GCM(i,j)}{1+|i-j|} \ldots\ldots\ldots\ldots\ldots\ldots (6)$$
$$f2(\text{Entropy}) = -\sum_i \sum_j GCM(i,j) \log\big(GCM(i,j)\big) \ldots\ldots..(7)$$

Colour based feature

Mean, standard deviation, variance and root mean square of each plane of a colour space was evaluated from the colour feature of image. For an image (im) the mean (m), standard deviation (σ), variance (σ^2), Inverse difference moment (IDM) and smoothness (sm) were calculated by the following equations 8-13.

$$m = \frac{\sum_i \sum_j im(i,j)}{ixj} \ldots\ldots\ldots\ldots\ldots\ldots\ldots.. (8)$$
$$\sigma = \sqrt{(\tfrac{1}{i+j})} \sum_i \sum_j (im(i,j) - m)^2 \ldots. (9)$$
$$\sigma^2 = \left(\frac{1}{i+j}\right) \sum_i \sum_j (im(i,j) - m)^2 \ldots.. (10)$$
$$x_{rms} = \sqrt{(\left(\frac{1}{i+j}\right)} im(i,j)^2 \ldots\ldots\ldots\ldots (11)$$

$$IDM = \left(\frac{1}{i+j}\right)\left(\frac{im(i,j)}{1+(i-j)^2}\right) \ldots\ldots\ldots\ldots\ldots\ldots (12)$$
$$sm = 1 - \left(\frac{1}{1+a}\right) \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (13)$$

Classification using SVM

Support vector machine is one of the efficient supervised learning methods for solving the classification problem (Priya *et al*., 2012; Islam *et al.*, 2017; Sethy *et al*., 2020). Linear SVM is a tool easily differentiates each class to obtain optimal hyperplane to classify the image feature. However, nonlinear creates a greater degree of complexity. In this study, linear SVM can objectify extract features for individual identification. Equation 13 depicts the classification process of the model.

$$\{(x_t, y_t)\}\text{where t is the training sample}, t = 1,2 \ldots n \; x_t \in R^n y_t = \{-1, +1\} \ldots . (14)$$
$$y_t = \text{column vector indicates the label}$$

The decision boundary D_x can be obtained from the above parameter.

$$D_x = \min_{w,b,\delta}(\frac{1}{2}w^T w + m \sum_{t=0}^{q} \delta_i)$$

Where $p_i(train) = w_i^T x_t + b \geq 1 - \delta_i \; with \; \delta_i \geq 0 \; and \; i = 1,2,..$,q; q and m indicate the positive regularization, w_1 is the weight vector and is the misclassification handler.

Classification using KNN

K-nearest neighbour is one of the classification approaches which predicts the test set by analysing the training problem with known label sets (Guo *et al.*, 2003). A data set with t records has been classified and its K-Neighbour assigned. K-Nearest Neighbour classification is non-parametric classification which provides the classification of any feature using minimum distance metric from the query image with train set. In this study Euclidean distance metric was used as minimum distance metric tool. The equation (15) is depicted as:

$$d_1(x, y) = \sum_1^n |x_i - y_i| \ldots\ldots\ldots\ldots\ldots (15)$$

This equation has classified the K closest sample to query class id C_i. The query feature F_q was classified to the actual class which specify the majority of the occurrence.

Classification using Decision Tree

Decision tree helps to find out the optimal selection of space for possible observation using the subsequent recursive split (Heyat *et al.*, 2019). Decision tree provides tree-like structure where its leaf node specifies the label, and its branch indicates the test outcome of the internal node (Patel *et al.*, 2012). While evaluating the best selection for decision tree, a technique was used that is known as attribute selection measure (ASM). This ASM can be done by using the information gain and entropy reduction. The equation (16 and 17) are described as:

$$I_{gain} = \text{Entropy}(x) - W_{avg} * E(x_i)\text{where } W_{avg}\text{specify the weighted average of each feature and } E(x_i) = \text{entropy of each feature} \ldots\ldots\ldots\ldots\ldots (16)$$

Entropy $E(x_i)$ is defined as

$$E(x_i) = \sum_i^n - plog_2 p_i \; \ldots\ldots (17)$$

Wherein n is the number of label p_i is the ration belong to class x_i

Classification using Random Forest

Random forest is the combination approach of multiple number of decision tree to improve the prediction accuracy (Ramesh *et al.*, 2018; Geetha *et al.*, 2019). It is an ensemble learning multiple decision tree aggregate with bootstrap technique. Each decision tree constructed with the best feature selecting points provides the optimum level of result accuracy (Fraiwan *et al.*, 2012). The classifier records each best opinion using voting technique. Class label is given which get most of the vote. The equation of the random forest is given in equation 18.

$$\Delta E = -\sum_i \frac{|P_i|}{P} E(P_i) \ldots\ldots\ldots\ldots (18)$$

where ΔE indicates information gain and P is feature vector $P_i \epsilon P$ and $E(P_i)$ is the entropy of sample P_i.

Feature engineering

Correlation is a vital feature of engineering processes to classify output objects. Correlation analysis is a statistical tool used to determine the strength of a linear relationship between two variables and compute their association. A high correlation indicates a strong association between the two variables, whereas a low correlation indicates a low correlation. A strong correlation of features is problematic for classifying the independent objects due to their relationship with other features. So, it should be omitted to recognize the actual observation. Nevertheless, data loss could happen during this type of feature engineering. It should be focused on omitting the correlation issues using less data loss.

RESULTS AND DISCUSSION

A total of 165 images from 5 individuals were considered as the dataset for our experiment. The data set were divided into different number of train and test set (Table 1). During experiment, 4 machine learning models with different set of training and validation set were used. In the 1st case of Table 1, the train and validation ratio were 70 and 30, in 2nd case the ratio was 75 and 25, in 3rd case the ratio was 80 and 20, in 4th case the ratio was 85 and 15 and in last case the ratio was 90 and 10. The observed maximum validation accuracy after careful investigation was 85.36% using Random Forest method, which is not an optimum level of accuracy. The detailed results are depicted in Table 1. We need the feature engineering method to rectify the accuracy level.

Table 1: Training and validation accuracy measure with 5 case study (Case study depended on the 5 set of training and validation set of different algorithm like SVM, Decision Tree, Random Forest, KNN)

Case study	Validation split (%)	SVM training accuracy (%)	SVM validation accuracy (%)	Decision Tree training accuracy (%)	Decision Tree validation accuracy (%)	Random Forest training accuracy (%)	Random Forest validation accuracy (%)	KNN training accuracy (%)	KNN validation accuracy (%)
1	30	99.56	18.36	100	68.36	100	80.61	100	43.87
2	25	99.59	25.60	100	74.86	100	85.36	100	43.78
3	20	99.61	27.27	100	78.78	100	84.84	100	53.03
4	15	99.63	24.48	100	69.38	100	81.63	100	53.06
5	10	99.65	18.18	100	60.60	100	78.78	100	45.45

Feature engineering for detection of highly correlated features

The correlation of collected features are depicted in Fig. 4. The Table 1. It is clearly observed that accuracy is not marked as the optimum level due the correlation and skewness present in dataset. After removing the columns which is responsible for correlations and also transformed the column to get optimum level of accuracy.

As depicted in Fig. 4, some features seem to create a high correlation value. Five features like mean, standard deviation, RMS, smoothness, and IDM have created high values responsible for the erroneous result. After removing the correlated features, it was observed that there was no correlation in the dataset. Fig. 5 demonstrates the correlation of new dataset. It was observed that there were no highly correlated values in samples. The column was rejected for obtaining higher accuracy for mean, standard deviation, RMS, smoothness and IDM. After rejecting above parameter, the 4 model again re valuated and displayed in the Table 2.

Fig. 4: Correlation of collected features for pig identification using ear image

Table 2: Accuracy measurement of training and validation after rejecting five parameters (5 parameter mean, standard deviation, RMS, smoothness, IDM have removed from the training and validation set and measure the accuracy)

Case study	Validation split (%)	SVM training accuracy (%g)	SVM validation accuracy (%)	Decision tree training accuracy (%)	Decision tree validation accuracy (%)	Random forest training accuracy (%)	Random forest validation accuracy (%)	KNN training accuracy (%)	KNN validation accuracy (%)
1	30	95.17	25.51	100	72.44	100	82.65	100	31.63
2	25	97.13	26.82	100	78.04	100	87.80	100	34.14
3	20	94.23	30.30	100	74.24	100	84.84	100	36.36
4	15	96.02	28.57	100	77.55	100	81.63	100	32.65
5	10	94.19	30.30	100	69.69	100	90.90	100	39.39

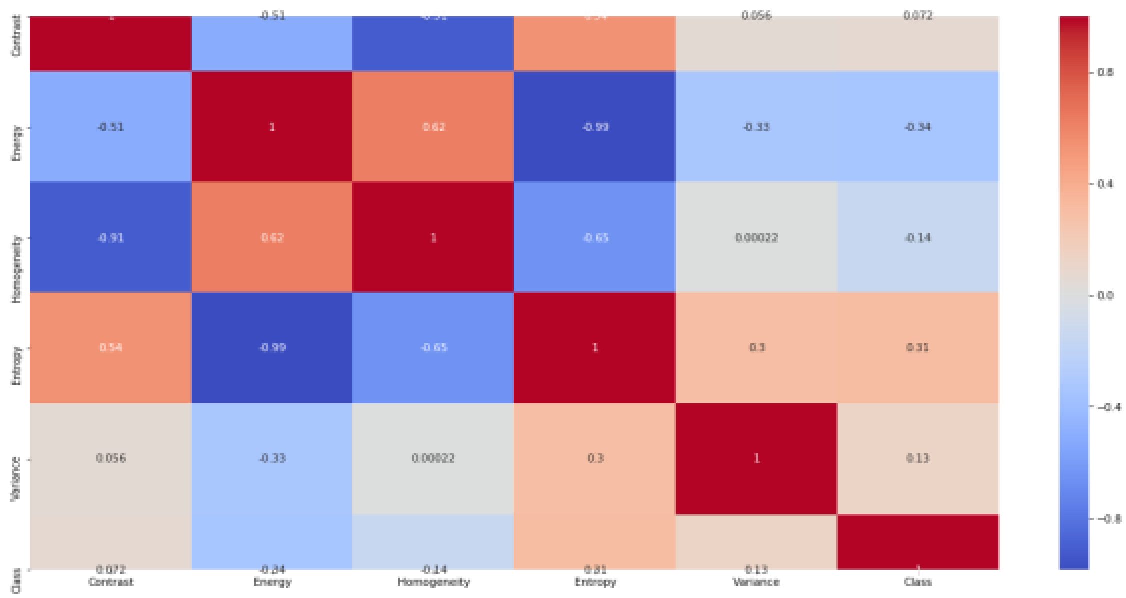

Fig. 5: Correlation after removing all correlated features for pig identification using ear image

Conclusion: An individual pig can be recognized by using ear images. Machine learning techniques can be used to identify the individual pigs using their ear images. The region of interest in each image may be observed using image segmentation techniques. Each segmented image provided GLCM features develops the identification system using machine learning. This research recognized that five statistical features can create erroneous results due to their relationship with other features. Any erroneous result could not be acceptable for individual identification techniques. After removing these correlated features, the accuracy is enhanced. The Feature analysis-based machine learning results are more accurate and specific. The Random Forest model showed highest accuracy (90.9%) among the other machine learning models used.

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