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IDENTIFICATION OF GOAT BREEDS BY DIGITAL IMAGE USING CONVOLUTION NEURAL NETWORK

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Abstract : Diversity in domestic animals in most of the species is depicted in the form of breeds. Phenotypic and genotypic characterizations are the tools for breed identification of livestock species. Variation within breed or similar looking breeds make it difficult to confirm breed identity of individual animal. An experiment was conducted with the aim of identification of breed of an individual goat by the help of its image using Inception model v3; a convolutional neural network. More than 500 digital images of individual goat captured in restricted (to get similar image-background) and unrestricted (natural) environment without imposing stress to animals. Six different purebred goats (Blackbengal, Beetal, Jamunapari, Barbari, Jakhrana and Sirohi) which have been reared and maintained by reputed government research organizations in India were used for training and testing the model. 10% of the captured images were used for testing the trained model. Breed confirmation was made by seeing the value (probability) in output terminals corresponding to six different breeds under study which best described an input image. 56 images out of the 60 images used in the test were successfully interpreted for breed identity by the trained model and thus the model was 93.33% accurate. Output probability of more than or equal to 0.95 was taken as minimum confidence limit for determination of breed. Value less than 0.95 was considered as unsuccessful test. Upon testing with images from breeds for which the model was not trained on, the output values could not provide confirmatory result. Therefore, the technique has great potential to solve confusion on breed identity. It would also be useful in implementation of Global Plan of Action for animal genetic resource (AnGR).

Keywords: Livestock, Goat Breed Identification, Deep Learning, Convolutional Neural Network, Confidence Level.

1. INTRODUCTION

Most of the domestic animal species show their diversity in the form of breeds. It is necessary to identify these breeds for various reasons including implementation of Global Plan of Action for Animal Genetic Resources (AnGR) as framed by Food and Agricultural Organization (FAO) of the United Nations. According to FAO, phenotypic and genotypic characterizations are the two pillars for recognition of breeds of domestic animal. The phenotypic characterization encompasses recognition, quantitative and qualitative description, documentation of populations, information of the natural habitats and production systems of a breed [1]. The genetic-characterization is done to understand the diversity and distinctiveness of a genetic resource for the purpose of framing policy for improving the value of the resource and its scope for utilization [2]. FAO had formulated and had been duly upgraded from time to time, the detailed guidelines for the process of characterization of AnGR. One of the aims of this effort is to build an information systems or databases that can serve a variety of different purposes including research, training, planning, public awareness, decision-making and many more.

Image classification and identification is an important and exciting topic over past few decades. Photographic identification has been used to identify aquatic animals such as dolphins and whales [3]. Nose-prints as a method of identification in cattle has been used to avoid the potential for fraud associated with traditional marking methods such as branding, tattooing and ear tags [4]. In general, identification helps claiming insurance and other benefits in case of the death of the animal. External characters like body markings, color rings etc. can be photographed or filmed for recognition of animals [5]. Facial recognition has been investigated for sheep and was adapted from an independent-components algorithm for human face recognition [6].

India is one of the few countries in the world, which has a major contribution to the international livestock-gene-pool and improvement of animal production in the world. It possesses about 125.46 million goat population which is the second highest in the world after China [7]. The country has so far registered 34 goat breeds as per report [8] of the ICAR-NBAGR, Karnal, Hariana. Declaration of breed identity by phenotypic characters many times seems unsatisfactory because of variations within a breed as well as presence of similar looking breeds especially, when purity of the breed is concerned. Genotypic characterization involves availability of expensive laboratory facility. In the present article, a new approach has been described, based on research trial to distinguish breed of goat with the help of image classification through deep learning convolution neural network. The process would complement as well as supplement the existing system of breed identification through noninvasive technique and also would be able to eliminate ambiguity in selecting pure bred animals.

2. MATERIALS AND METHODS

2.1 Convolutional Neural Network (CNN)

The Convolutional Neural Network (CNN) simulates the function of visual cortex of animal brain, and is used to differentiate all the classes of images. The output of the network is same as number of classes to classify. The numbers of hidden layers are increased for better performance of network that is known as deep learning. The deep learning mostly uses convolution neural network whose layers are much more specialized and efficient [9]. It becomes computationally expensive, especially when layers are repeatedly stacked in a deep learning architecture [10]. CNN mainly consist of three components, such as Convolutional layers, Pooling layers and Fully connected layers.

2.2 Convolutional Layer

This layer is responsible for feature extraction from an input image based on a mathematical calculation. The mathematical calculation is basically an element wise multiplication with respect to filter and matrix. If the input image matrix is of dimension $[a * b * c]$ and filter matrix is of dimension $[e * f * c]$ then the dimension of output matrix will be $[(a-e+1) * (b-f+1)*1]$ as shown in Fig. (1).There may more than one convolution layer present in a CNN[11].

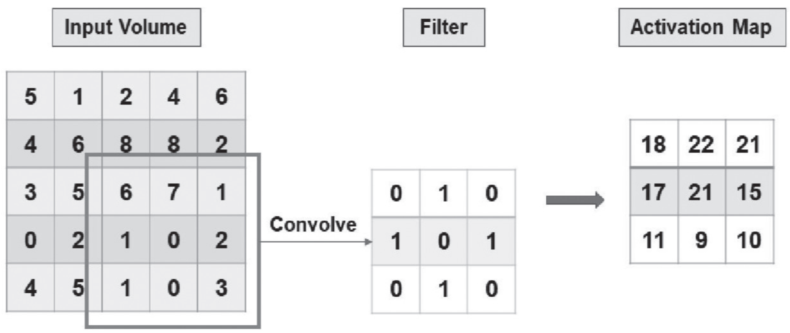


Fig. 1: Convolution Operation

2.3 Pooling Layer

It is responsible for reduction in the dimension of the feature matrix obtained from the convolution layer in order to reduce computational cost as well as to prevent over-fitting [12]. Among different types of pooling max pooling is popular and widely used for its ability to reduce the dimension without losing important information (Fig. (2)). The Max Pooling Layer operates independently on every depth slice of the input and resizes it spatially, selecting the maximum value from within the filter.

2.4 Fully Connected Layer

After creating the convolutional feature vector, it is then passed through a dense neural network for classification (whether the input image is cat or dog or tree or anything) (Fig. (3)). This dense network is called fully connected layer. Actually, in the fully connected layer the classification is determined by the activation function like Softmax, ReLu,Tanh, etc.[13].

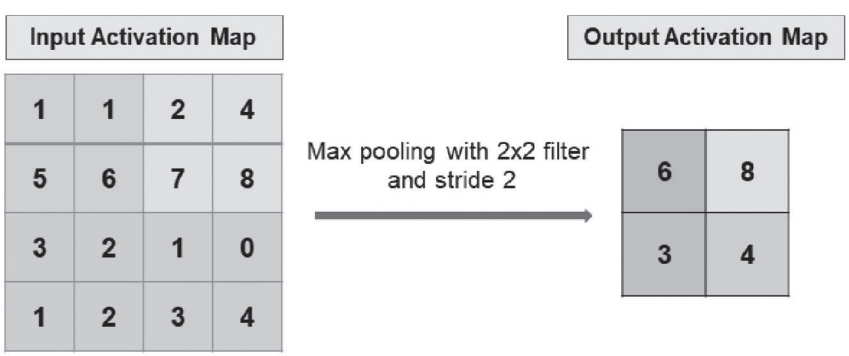


Fig. 2: Max Pooling Operation

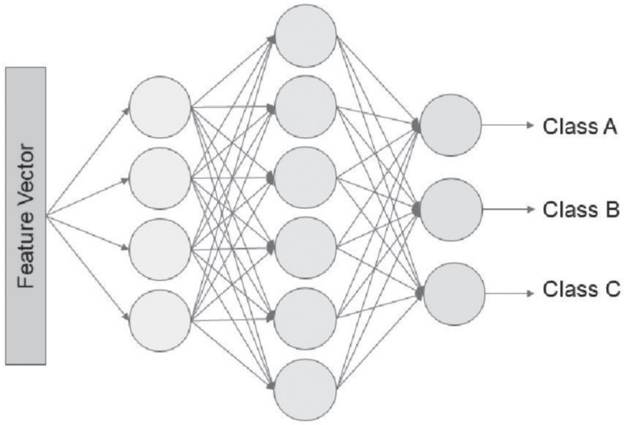


Fig. 3: Fully Connected Layer

2.5 Experimental Subjects

Six different Indian goat-breeds namely, Blackbengal, Beetal, Jamunapari, Barbari, Jakhrana and Sirohi were taken in the study. To get images of individual goat of those breeds, different organized government farms under reputed research institutions, known to maintain pure breed were visited. The organized farms of ICAR-Indian Veterinary Research Institute, Kolkata, West Bengal as well as Uttar Banga Krishi Viswavidyalaya, Cooch Behar, West Bengal for Blackbengal and ICAR-Central Institute for Research on Goat, Uttar Pradesh for Beetal, Jamunapari, Barbari, Jakhrana and Sirohi were visited to capture images of the pure breed goats reared in their farms. The local farms where pure breed animals are maintained were also visited to capture images of goat which does not come under those six breeds. Pictures of goat form other breeds not specified above were also collected from internet.

2.6 Capturing Image of Individual Animals

The image was captured with a cell phone camera by imposing restricted as well as unrestricted condition for the purpose of this experiment. Restricted condition was created to get uniform background of green colour (Fig. (4)).

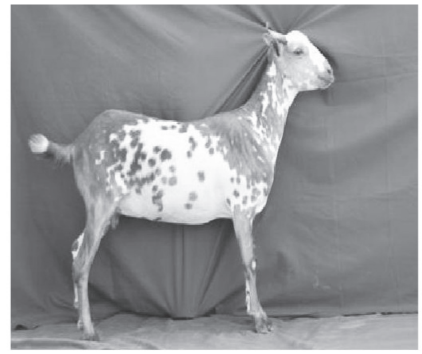


Fig. 4: Photo capture in restricted condition

For this the goat was brought in front of a dangling green coloured cloth which was hanged from an overhead beam. The arrangement was made with in the paddock. For unrestricted photo, the goat was approached from aside while the animal was in standing position within the farm premises (Fig. (5)).

Fig. 5: Photo capture in unrestricted condition

When the goat settled in the position and looked stable, multiple snapshots were taken. For capturing photo in both restricted and unrestricted environment, goats were not subjected to any distress condition which could violate welfare of farm animals. The images were captured from a suitable distance keeping the entire side view (left or right) of the goat in the frame.

2.7 Database Creation

To build the database which will be used for goat breed identification, the images need to be categorized into 3 sets, namely Train Set, Validation Set and Test Set. Initially, the individual goat images that are of known breed are separated in to 6 folders, each belonging to a distinct breed. From each of those folders, the images were randomly split into three sets containing 80%, 10% and 10% images respectively. Then for each breed folder, the first split containing 80% images were labelled as train set images, the remaining two splits were labelled validation set and test set. Finally, in the test set, all the images were moved out of their respective breed folders to remove their breed identity and separate images captured, whose breeds are not known are also added in the test set folder. The final goat breed database structure and the number of images in each category is shown in Fig. (6).

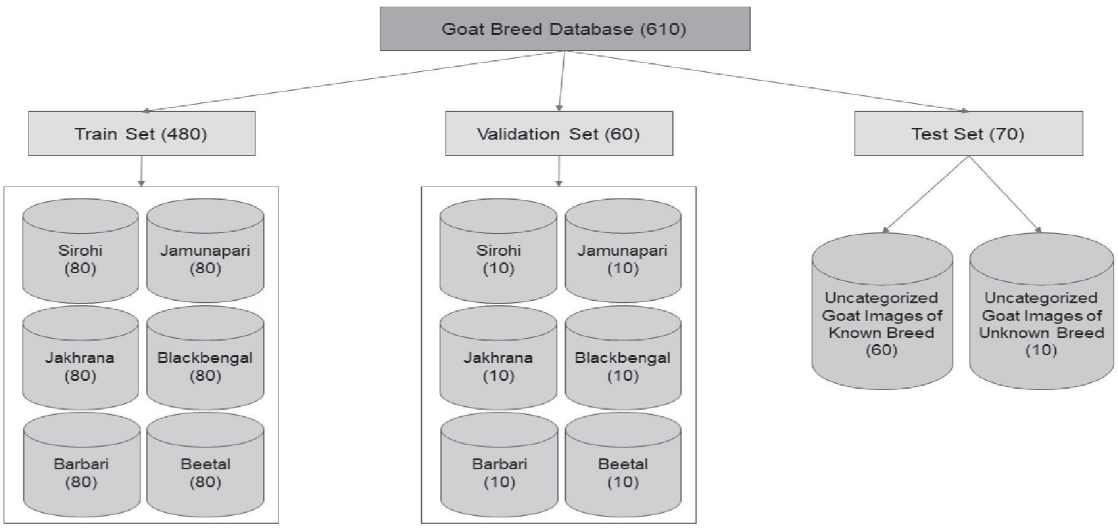


Fig. 6: Structure of the Goat Breed Database

2.8 Inception-v3

The CNN model used in this study is called Inception-v3 . This network has more than 42 layers with many different combinations of convolutional layers, pooling layers, concatenation layers, batch normalization layers. The schematic diagram of this model is shown in Fig. (7) [15].

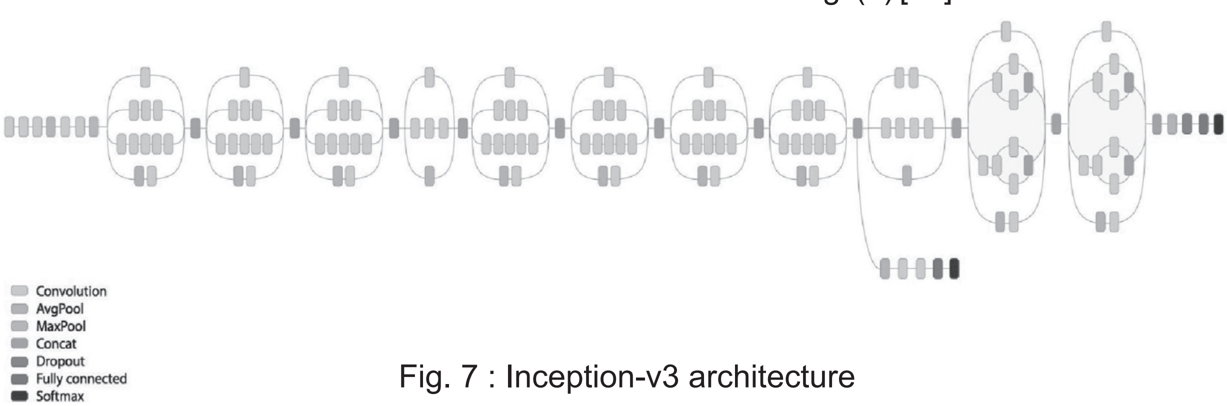


Fig. 7 : Inception-v3 architecture

2.9 Proposed Method

Inception-v3 is an excellent model for multi-class classification. But training such a large network end-to-end is very time consuming. To overcome this, a technology called transfer learning [16] is used in this paper. The basic idea behind that is to make use of a pretrained model (Inception-v3) which has been already trained on a very large database (ImageNet [17]) and then fine-tune it to match the specific requirements needed for the current scenario. End-to-end training of Inception-v3 on ImageNet data is shown in Fig. (8).

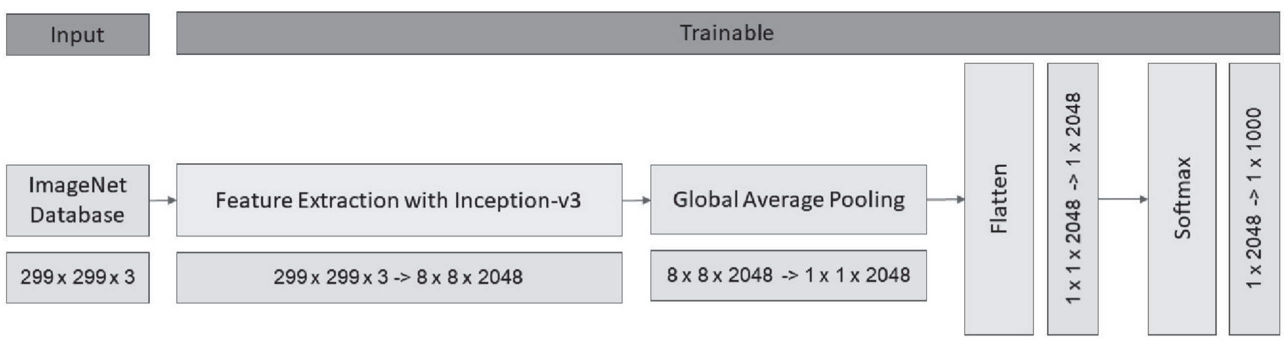


Fig. 8: Training Inception-v3 on ImageNet

Now, this pretrained model is designed to classify between 1000 different image categories. So, for using Inception-v3 for classifying goat breeds, it has been remodelled to an updated structure as shown in Fig. (9). In this new model, the Feature extraction part of the original model obtained from Keras API [18] is retained (frozen) and no updatation in the weighs are performed while training. To improve the classification ability, a new fully connected layer and to reduce overfitting a dropout regularizer layer have been added in the new model. This modified Inception-v3 model is then trained, validated and tested on the Goat breed database.

Model fine-tuning has to be done carefully to prevent overfitting the model. The hyperparameters used for training has been finalized by trial and error after several experimentations. The model was trained for 100 iterations and then validated after every 10 iterations, with a learning rate of 0.01. The training and validation accuracy and loss curves obtained are shown in Fig. (10).

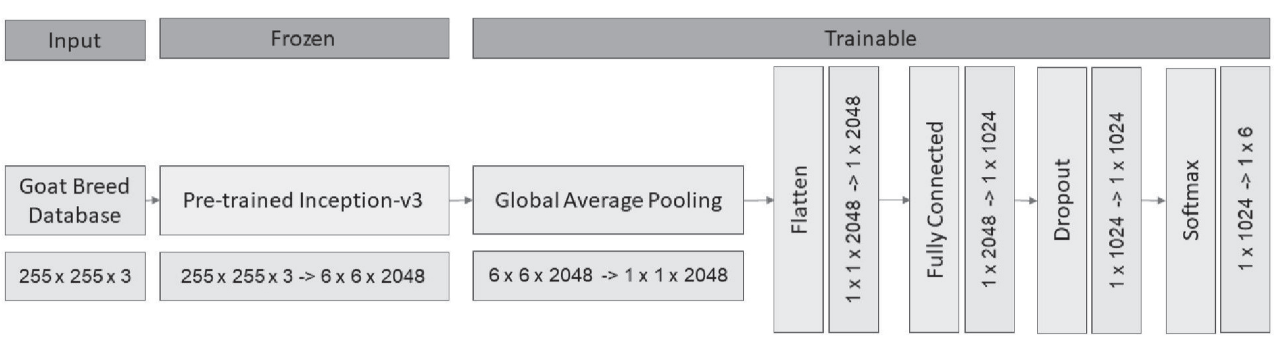
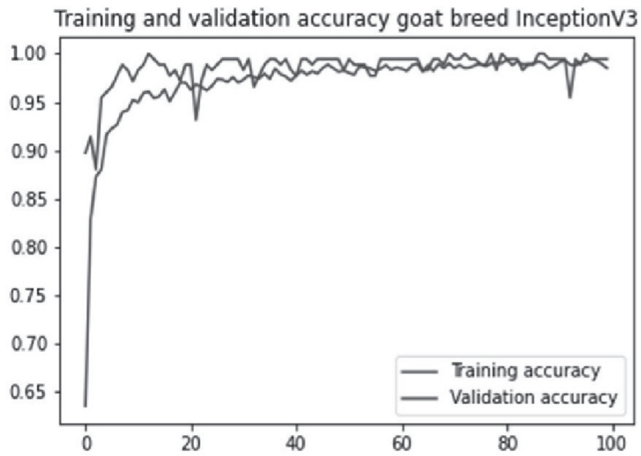


Fig. 9: Modified Inception-v3 used in this paper



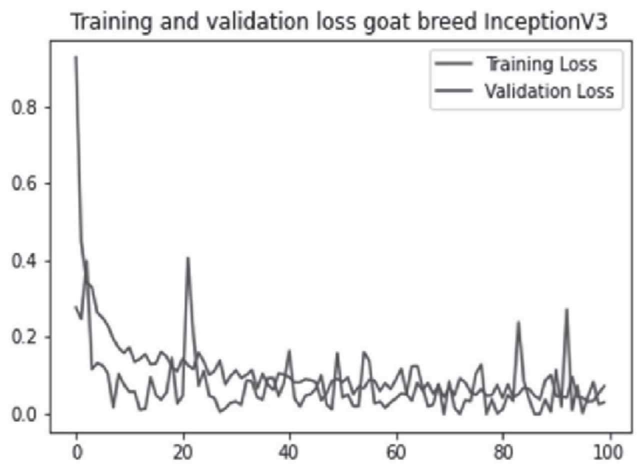


Fig. 10: Accuracy and Loss Graph of Training and Validation

3. RESULTS

3.1 Breed Prediction Results of Breeds Used in Training

The trained model was tested with the images from the test set. Each input image came out with probability value in six different output terminals, corresponding to six different breeds taken in the study. The resultant probability value in the output terminals for a test image confirmed the breed identity. When the highest probability value was more than or equal to 0.95 in any output terminal (Table 1), the test was considered successful. Input images produced output value less than 0.95 was considered unsuccessful test and no decision was taken on the part of breed identity from such cases. Thus 0.95 was taken as the minimum confidence for breed assignment. For example, the maximum probability value of the test image 'G1' (Table 1) was 0.9981 which corresponds to the breed 'Barbari', which indicated that the model is 99.81% confident that the goat in the image was of breed Barbari. This decision was found correct after comparison from the stored database. Likewise, the test result for six more images, are shown in the Table 1.

Table 1: The decision of breed identity of individual goat of known breed

Test Image Id.	Probability in six different output terminals						Decision on breed identity	Remark on the decision (✓/x)
	Barbari	Beetal	Black Bengal	Jakhrana	Jamunapari	Sirohi		
G1	**0.9981**	0.0005	0.0004	0.0002	0.0007	0.0001	Barbari	✓
G2	0.0000	**0.9992**	0.0000	0.0007	0.000	0.0000	Beetal	✓
G3	0.0000	0.0000	**0.9999**	0.0000	0.0000	0.0000	Blackbengal	✓
G4	0.0000	0.0007	0.0001	**0.9992**	0.0000	0.0000	Jakhrana	✓
G5	0.0000	0.0000	0.0000	0.0001	**0.9998**	0.0000	Jamunapari	✓
G6	0.0000	0.0000	0.0000	0.0001	0.0000	**0.9998**	Sirohi	✓

The actual images of known breed according to the Test Image Id. are shown in Table 2.

Table 2: Raw images corresponding to the assigned Id. for known breed

 Id: G1 (Barbari)	 Id: G2 (Beetal)	 Id: G3 (Blackbengal)
 Id: G4 (Jakhrana)	 Id: G5(Jamunapari)	 Id: G5 (Sirohi)

3.2 Breed Prediction Results of Breeds Not Used in Training

The input images of goat from breeds unknown to the trained network failed to confirm breed identity of individuals (Table 3). The probability values in each case were lower than 0.5 and with very small difference among the terminals making it difficult to come to a decision on breed identity of the individual used as input. This indicates the smartness of the model by disqualifying the unknown animal without giving it a chance to be confused in deciding the breed identity of input image of individual goat.

Table 3: The decision of breed identity of individual goat of unknown breed

Test ImageId.	Probability in six different output terminals						Decision on breed identity
	Beetal	Black Bengal	Barbari	Jakhrana	Sirohi	Jamunapari	
G7	0.109	0.125	0.242	0.089	0.396	0.039	Indecisive
G8	0.020	0.061	0.446	0.133	0.028	0.313	Indecisive
G9	0.047	0.257	0.379	0.127	0.071	0.118	Indecisive
G10	0.045	0.196	0.107	0.450	0.080	0.122	Indecisive
G11	0.036	0.379	0.164	0.215	0.082	0.124	Indecisive
G12	0.040	0.186	0.147	0.419	0.108	0.101	Indecisive
G13	0.376	0.204	0.128	0.129	0.111	0.052	Indecisive
G14	0.047	0.257	0.379	0.127	0.071	0.118	Indecisive

The actual images of unknown breed according to the Test Image Id. is shown in Table 4.

Table 4: Raw images corresponding to the assigned Id. for unknown breed

 Id: G7 (Unknown)	 Id: G8 (Unknown)	 Id: G9 (Unknown)	 Id: G10 (Unknown)
 Id: G11 (Unknown)	 Id: G12 (Unknown)	 Id: G13 (Unknown)	 Id: G14 (Unknown)

3.3 Goat Breed Prediction Accuracy

Finally, all the 60 images of known breed from the test set were given to the trained model for goat breed prediction. The correct breed was said to be predicted only when the output probability for each image was greater than or equal to 95%. With this threshold, the prediction accuracy results are shown in Table 5.

Table 5: Goat breed prediction accuracy with 95% confidence

Breed	**Total Test Images**	**Number of Images Predicted Correctly**	**Prediction Accuracy**
Barbari	10	9	90%
Beetal	10	8	80%
Blackbengal	10	10	100%
Jakhrana	10	9	90%
Jamunapari	10	10	100%
Sirohi	10	10	100%
Overall Accuracy	**60**	**56**	**93.33%**

From Table 5 it is inferred that, with minimum confidence of 95%, modified Inception-v3 trained on Goat Breed Database produces 93.33% goat breed prediction accuracy.

4. CONCLUSION

The modified Inception-v3 model used in this has been outstanding in classifying individual animals in its group which in this case is the breed. It successfully classified the individual animal 93.33% of the cases with more than 95% confidence (probability is more than 0.95). Also, low output values for the test images of unknown breed not used to train the network made it smarter for use in breed identification and thus proved its authenticity with high precision. Further research is needed to make the model intelligent enough to characterize goats of unknown breed. Verification of individual goat for identification of the breed to which it belongs by analyzing image of the animal with the click of a mouse will be a problem solving and ready-to-use technology, useful for different stakeholders from various field including those involved in academic and research activities. It would ease the process and also would reduce initial investment for assessment of diversity in animal genetic resource (AnGR), preparation of national inventory and monitoring system of AnGR. It would strengthen the Domestic Animal Diversity Information System (DAD-IS), developed by the FAO. Exploratory approach for phenotypic characterization to investigate the existence of distinct breeds in the study area will be easier with the help of the image analysis.

In this paper, digital images, captured by a cell phone camera, without posing stress to animal were used to a goat breed database for training the model. Thus, a database or repository of the national AnGR of goat may therefore be sufficient to find solution for all kind of debate or imbroglio which would arise out of any confusion on the identity of breed. This will open up many other opportunities on the part for implementation of Global Plan of Action for Animal Genetic Resources (AnGR) apart from usefulness in making the task easy for all stakeholders. Without doubt, the similar approach might also be useful in the species other than goat for various purposes.

With this result it was concluded that the uniqueness present in different breeds might be used to uniquely identify various breeds by using “breed classification” algorithm used in the paper.

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