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Automated goat breed identification using CNN-based transfer learning with VGG16 and mobilenetv2

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Abstract

Effective management of livestock genetic resources and the implementation of breeding programmes require accurate identification of indigenous breeds. However, under field conditions, goat breed identification is often challenging due to phenotypic similarities among breeds and reliance on subjective visual assessment. Therefore, the present study aimed to develop an automated image-based deep learning framework using transfer learning for the classification of two morphologically related indigenous goat breeds, Barbari and Jamunapari, employing convolutional neural network (CNN) architectures. A curated dataset consisting of 640 images collected from 160 goats (80 animals per breed) was developed, where four images per animal were captured: two frontal and two left-lateral views. The dataset was partitioned at the animal level into training, validation and testing subsets using a 70:10:20 split (training: validation: testing) to ensure independent evaluation. Two transfer learning architectures, VGG16 and MobileNetV2, pretrained on ImageNet, were fine-tuned for binary breed classification. Model performance was evaluated using confusion matrix-derived metrics including accuracy, precision, recall, F1-score and AUC-ROC, along with computational efficiency parameters such as inference time and memory usage. On the independent test set, MobileNetV2 achieved the highest classification accuracy (94.53%), with precision of 93.85%, recall of 95.31% and F1-score of 94.57%, whereas VGG16 achieved an accuracy of 93.75%, with precision of 95.16%, recall of 92.19% and F1-score of 93.65%. ROC analysis indicated strong discriminative capability for both models, with AUC-ROC values of 0.94 for MobileNetV2 and 0.95 for VGG16. Overall, the results demonstrate that deep learning-based image classification can effectively distinguish closely related goat breeds and provide a scalable tool for automated breed identification.

Keywords: Animal biometric recognition, computer vision, deep learning, image-based phenotyping indigenous goat breeds, livestock identification, precision livestock farming

1. Introduction

Goat production plays an important role in sustaining the livelihoods and nutritional security of small and marginal farmers, particularly in developing countries where livestock systems are predominantly smallholder-based. Goats provide meat, milk and income and often serve as a financial buffer in resource-limited rural production systems (Jegoda *et al.*, 2022) ^[11]. Globally, the goat population exceeds one billion animals distributed across several hundred recognized breeds adapted to diverse agro-ecological conditions. India possesses one of the largest goat populations globally, accounting for approximately 27% of the global goat population, with nearly 148.88 million goats representing 43 registered breeds (Department of Animal Husbandry and Dairying, 2019; ICAR-National Bureau of Animal Genetic Resources, 2025) ^[5, 9]. However, a substantial proportion of these animals are categorized as non-descript due to extensive interbreeding and weak phenotypic differentiation, which complicates accurate breed identification under field conditions (Yaro *et al.*, 2017) ^[2]. Accurate breed identification is essential for genetic improvement programmes, conservation of indigenous genetic resources and maintenance of breed purity. Traditionally, breed identification relies on morphological traits, yet observer subjectivity and phenotypic overlap often reduce the

reliability of such assessments (Brito *et al.*, 2020) ^[4]. Recent advances in computer vision and artificial intelligence have created new opportunities for automated livestock phenotyping. Deep learning approaches, particularly convolutional neural networks (CNNs), have demonstrated strong capability in extracting complex visual features from images and performing automated classification tasks (Bergman *et al.*, 2024) ^[3]. CNN-based systems reduce dependence on manual evaluation and enable standardized, reproducible phenotypic analysis from large digital image datasets. These technologies are increasingly applied in livestock research for animal identification, breed classification and monitoring, thereby improving management, traceability and documentation of genetic resources (Bachmann *et al.*, 2022) ^[2]. Among widely used CNN architectures, VGG16 and MobileNetV2 represent two models with contrasting computational characteristics (Habibullah *et al.*, 2023; Ince *et al.*, 2025) ^[8, 10]. VGG16 is a deep convolutional network with sequential convolutional layers that enable hierarchical extraction of fine-grained visual features, allowing detection of subtle morphological variations. In contrast, MobileNetV2 is a lightweight architecture that utilizes depthwise separable convolutions to reduce computational cost and parameter size while maintaining competitive classification performance, making it suitable for real-time and mobile-based applications (S *et al.*, 2024) ^[15].

Deep learning-based breed identification has been successfully explored in several livestock species including sheep, cattle and camels, where CNN models trained on image datasets have achieved high classification accuracies. These studies demonstrate the potential of automated systems to recognize animals using morphological cues such as facial structure, body conformation and coat pattern distribution (Li *et al.*, 2024) ^[13]. However, research on automated breed identification in goats remains limited, particularly for indigenous Indian breeds that often exhibit considerable phenotypic similarity. In this study, two morphologically related indigenous goat breeds, Barbari and Jamunapari, were selected for automated classification. Barbari goats are typically characterized by smaller body size, straight facial profile, erect ears and variable spotted coat patterns (Singh *et al.*, 2015) ^[18], whereas Jamunapari goats exhibit larger body size, a convex facial profile, long pendulous ears and a predominantly white coat with tan markings on the head and neck (Rout *et al.*, 2000) ^[14]. Despite these distinguishing traits, variations in posture, illumination and image capture conditions can make visual identification difficult under practical farm conditions. Therefore, this study aims to develop an automated image-based framework using transfer learning with pretrained VGG16 and MobileNetV2 architectures to classify Barbari and Jamunapari goats.

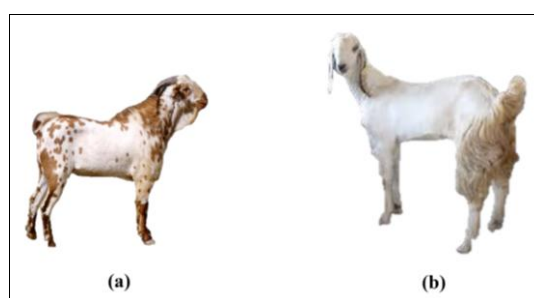


Fig 1: (A) Barbari goat breed (B) Jamunapari goat breed

A summary of major machine learning and deep-learning applications for animal breed and identity recognition is

provided in Table 1 to contextualize the current study within existing literature.

Table 1: CNN Models Applied to Animal Breed and Identity Recognition

Reference	Dataset	CNN model (s)	Performance (Accuracy)
Abu Jwade <i>et al.</i> (2019) ^[1]	Sheep (4 breeds)	VGG16	VGG16: 95.8%
Weber <i>et al.</i> (2020) ^[20]	Cattle (Pantaneira)	DenseNet-201, ResNet50	DenseNet-201: 99.85% ResNet50: 99.78%
Shah <i>et al.</i> (2020) ^[16]	103 dog breeds	custom model	Accuracy: 95.5%
Shah and Sheppard (2020) ^[17]	12,500 cats + 12,500 dogs	InceptionV3	Accuracy: 100%
Dutta (2021) ^[6]	Sheep	custom model	Accuracy: 87.1%

2. Materials and Methods

2.1 Study area and selection of animals

The present study was conducted using two indigenous goat breeds, Barbari and Jamunapari, maintained at the Goat Research and Training Centre, Department of Veterinary Physiology, College of Veterinary Science and Animal Husbandry (CVSc & AH), DUVASU, Mathura, Uttar Pradesh, India. A total of 160 adult goats were selected for the study, comprising 80 Barbari and 80 Jamunapari animals. Animals included in the dataset were between 2 and 5 years of age and represented typical phenotypic characteristics of their respective breeds. Animals were selected to ensure that only purebred individuals with clearly identifiable

morphological traits were included, minimizing ambiguity during model training.

2.2 Image dataset acquisition

A standardized image acquisition protocol was followed to build a curated image dataset for goat breed classification. Digital images were captured using a smartphone camera (12 MP, Sony IMX682 sensor, f/1.8) at 1440 × 1440 pixels under natural daylight conditions within the farm premises. For each animal, four images were captured to represent important morphological perspectives: (i) two frontal images capturing facial profile, horn orientation and ear structure; (ii) two left-lateral images capturing body conformation, head profile and

coat pattern. A total of 640 images were collected from 160 goats, with four images captured per animal, as summarized in Table 2. During image acquisition, the camera was positioned at approximately a distance of 1.5-2.0 m from the

animal to ensure clear capture of body structure and facial characteristics. Images with motion blur, occlusion, poor illumination or partial visibility of the animal were excluded during manual inspection to maintain dataset quality.

Table 2: Image dataset used for goat breed classification showing number of animals, images per animal and total images for each breed

Breed	Animals	Images/animal	Total images
Barbari	80	4	320
Jamunapari	80	4	320
Total	160	4	640

2.3 Dataset partitioning

To ensure unbiased model evaluation, the dataset was partitioned at the animal level, so that images from the same individual did not appear in more than one subset. The dataset

was divided into training, validation and testing subsets using a 70:10:20 ratio. Since each animal contributed four images, the final dataset distribution is presented in Table 3.

Table 3: Distribution of animals and images across training, validation and testing datasets used for model development and evaluation

Dataset	Animals	Images per animal	Total images
Training	112	4	448
Validation	16	4	64
Testing	32	4	128
Total	160	4	640

The training dataset was used for model learning, the validation dataset was used for hyperparameter tuning and monitoring model convergence, and the independent testing dataset was reserved exclusively for final performance evaluation.

2.4 Image preprocessing and data augmentation

All images were resized to match the input dimension requirements of the CNN architectures used in the study. Prior to training, pixel values were normalized using architecture-specific preprocessing functions to ensure compatibility with pretrained ImageNet weights. To improve model generalization and reduce overfitting, data augmentation was applied during training using real-time image transformations. The augmentation pipeline included: Random rotation ($\pm 20^\circ$), horizontal translation ($\leq 25\%$ of image width), vertical translation ($\leq 25\%$ of image height), zoom variations ($\leq 25\%$), horizontal flipping and brightness adjustment (0.8-1.2 range). These transformations simulate natural variations in orientation, illumination and animal posture that commonly occur during field photography. Validation and testing images were not augmented, ensuring that model evaluation was performed on unaltered images.

2.5 Deep learning models and transfer learning framework

Two convolutional neural network architectures, VGG16 (Jiang *et al.*, 2021)^[12] and MobileNetV2 (Gulzar, 2023)^[7], were used for automated goat breed classification. Both architectures were initialized with pretrained ImageNet weights, allowing the models to leverage previously learned hierarchical visual features. The original classification layers of the pretrained networks were removed and replaced with a custom classification head consisting of: Global Average Pooling layer, fully connected dense layer (512 units), Batch normalization, LeakyReLU activation, Dropout layer (0.5) and final dense layer with softmax activation for two classes (Barbari and Jamunapari). Initially, the convolutional base of each architecture was frozen to perform feature extraction.

Subsequently, selected deeper layers were unfrozen for fine-tuning, enabling the models to adapt high-level features to the goat breed classification task. All models were implemented using TensorFlow with Keras in a Python environment.

2.6 Model training

Model training was performed using Stochastic Gradient Descent (SGD) optimization with momentum. The key hyperparameters used for training the CNN models are summarized in Table 4.

Table 4: Training configuration and hyperparameters used for CNN model training

Parameter	Value
Batch size	16
Initial learning rate	1e-4
Loss function	Categorical cross-entropy
Activation function	LeakyReLU
Output activation	Softmax
Total epochs	50

During training, the training dataset was shuffled and augmented, while validation images were used to monitor model convergence and detect potential over fitting. The model parameters corresponding to the highest validation accuracy were retained as the final trained model.

2.7 Model evaluation

Model performance was evaluated on the independent test dataset using standard classification metrics derived from the confusion matrix. The evaluation metrics and their corresponding formulations are presented in Table 5. These metrics provide a comprehensive evaluation of classification performance by assessing both correct predictions and misclassification patterns between the two goat breeds. Additionally, confusion matrices were generated to visualize class-wise prediction performance for Barbari and Jamunapari goats.

Table 5: Evaluation metrics used for assessing CNN model performance in goat breed classification

Metric	Formula
Accuracy	$\frac{TP + TN}{TP + FP + TN + FN}$
Precision	$\frac{TP}{TP + FP}$
Recall	$\frac{TP}{TP + FN}$
F1-score	$\frac{2 \times \text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}$

3. Results

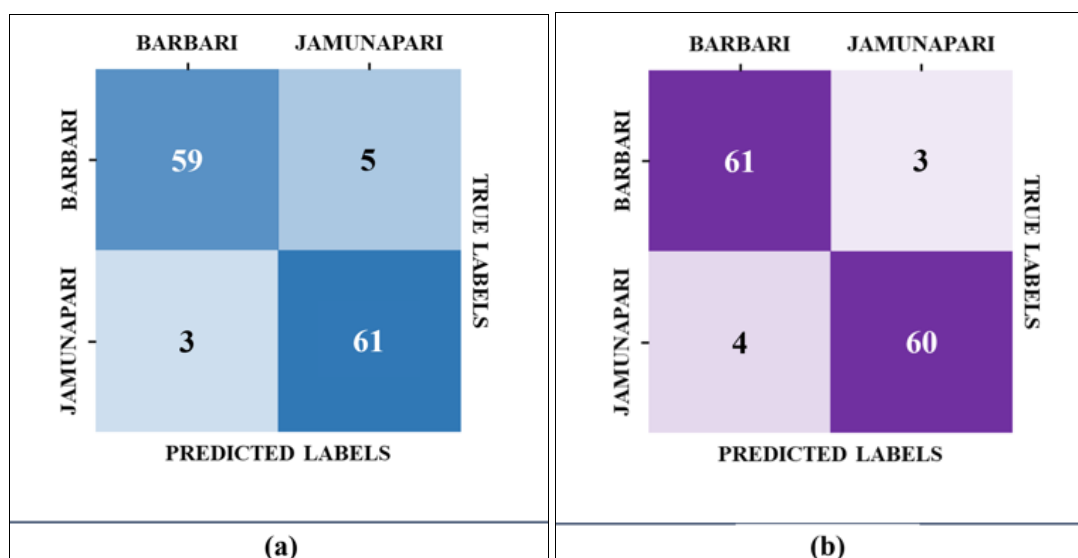
3.1 Training and validation performance

Both convolutional neural network architectures, VGG16 and MobileNetV2, showed stable convergence during the training process. Training and validation accuracy increased steadily during the initial epochs and gradually stabilized as training progressed, while the corresponding loss values decreased consistently. The training and validation curves remained closely aligned throughout the training period, indicating effective model learning. The results demonstrate that both transfer learning models successfully learned discriminative

features from the image dataset for goat breed classification.

3.2 Classification performance on the independent test dataset

The performance of the trained models was evaluated using the independent test dataset comprising 32 animals (16 Barbari and 16 Jamunapari), corresponding to 128 images. Classification outcomes were assessed using confusion matrices and standard evaluation metrics including accuracy, precision, recall and F1-score. The confusion matrices for both models are presented in Figure 2.

**Fig 2:** Confusion matrices illustrating classification performance of CNN models for goat breed identification: (a) VGG16 and (b) MobileNetV2

The results indicate that the majority of test images were correctly classified for both goat breeds, with only a small number of misclassifications observed. For the VGG16 model, 59 Barbari images were correctly classified while 5 were misclassified as Jamunapari. Similarly, 61 Jamunapari images were correctly classified, with 3 images incorrectly predicted as Barbari. For the MobileNetV2 model, 61 Barbari images were correctly identified while 3 were misclassified,

whereas 60 Jamunapari images were correctly classified and 4 were misclassified as Barbari. Based on these predictions, VGG16 achieved an overall classification accuracy of 93.75%, while MobileNetV2 achieved an accuracy of 94.53% on the independent test dataset. The corresponding precision, recall and F1-score values derived from the confusion matrices indicated strong classification performance for both models.

Table 6: Overall classification performance of CNN models for goat breed identification based on the independent test dataset

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-score (%)
VGG16	93.75	95.16	92.19	93.65
MobileNetV2	94.53	93.85	95.31	94.57

3.3 Receiver operating characteristic (ROC) analysis

Receiver operating characteristic (ROC) curves were generated to evaluate model performance across different classification thresholds. The analysis demonstrated strong discriminative capability for both CNN architectures, indicating effective separation between Barbari and Jamunapari goat breeds. The area under the ROC curve

(AUC-ROC) was 0.94 for MobileNetV2 and 0.95 for VGG16, reflecting excellent classification performance. These results indicate that both models produced highly separable prediction distributions across thresholds, with VGG16 showing slightly higher discriminative performance compared to MobileNetV2.

3.4 Comparative performance of CNN architectures

Although both CNN architectures produced highly accurate predictions, differences were observed in computational characteristics. MobileNetV2 required fewer parameters and provided faster inference, making it suitable for deployment in computationally constrained environments. In contrast, VGG16 achieved marginally higher classification accuracy due to its deeper architecture and greater representational capacity. Thus, the results demonstrate that both architectures are effective for automated goat breed identification from images. MobileNetV2 achieved the highest classification accuracy, while VGG16 demonstrated strong predictive performance due to its deeper architecture.

4. Discussion

The present study demonstrates that deep convolutional neural networks can effectively distinguish between morphologically similar indigenous goat breeds using image-based phenotypic data. Both evaluated architectures, VGG16 and MobileNetV2, achieved high classification accuracy, indicating that visual morphological features captured in digital images contain sufficient discriminatory information for automated breed identification. These findings highlight the potential of computer vision approaches as reliable tools for livestock phenotyping, breed documentation and digital livestock management systems.

The high classification performance observed in the present study is consistent with previous research demonstrating the effectiveness of convolutional neural networks for animal identification and breed classification tasks. CNN-based architectures are capable of learning hierarchical image representations that capture structural features such as facial morphology, body conformation and coat pattern distribution. Similar success has been reported in earlier livestock classification studies. For instance, CNN architectures achieved classification accuracies of 99.85%, 99.78% and 99.52% for cattle breed recognition using DenseNet201, ResNet50 and InceptionResNet-V2 models, respectively (Weber *et al.*, 2020) [20]. Likewise, a VGG16-based model achieved an accuracy of 95.8% for automated sheep breed identification using image datasets (Abu Jwade *et al.*, 2019) [1]. Furthermore, transfer learning models applied for classification of phenotypically similar cattle breeds reported accuracies ranging from 80% to 86% across MobileNet and EfficientNet architectures (Warhade *et al.*, 2024) [19]. These studies collectively highlight the strong capability of deep learning models for accurate livestock breed identification and demonstrate the increasing applicability of CNN-based approaches in animal biometric recognition.

In the present study, MobileNetV2 achieved slightly higher classification accuracy (94.53%) compared with VGG16 (93.75%), as observed from the confusion matrix-derived evaluation metrics. The high classification performance indicates that the visual characteristics present in the dataset were sufficient for reliable breed discrimination. Although VGG16 produced slightly lower accuracy than MobileNetV2, it maintained strong predictive performance with high precision and F1-score values. VGG16 is a deep convolutional architecture composed of multiple sequential convolutional layers that progressively learn hierarchical visual features from images. This structure allows the model to capture fine morphological patterns such as facial contour, ear structure and coat pattern distribution, which are important distinguishing traits between Barbari and Jamunapari goats.

MobileNetV2 also demonstrated strong classification performance while maintaining lower computational complexity. The architecture employs depthwise separable convolutions and inverted residual blocks, enabling efficient feature extraction with significantly fewer parameters. This design allows MobileNetV2 to achieve high accuracy while requiring lower computational resources and faster inference compared with deeper networks. The ability of both CNN models to correctly classify the majority of test images highlights their effectiveness for automated goat breed identification. Despite the partial phenotypic similarity between Barbari and Jamunapari goats, the models successfully learned discriminative morphological features from the training dataset, enabling reliable classification of the two breeds using image-based inputs.

Conclusion

This study demonstrates the effectiveness of deep learning-based image classification for automated identification of indigenous goat breeds. A curated dataset of 640 images collected from 160 goats representing Barbari and Jamunapari breeds was used to evaluate two transfer learning architectures, VGG16 and MobileNetV2. Both models successfully distinguished between the two morphologically similar goat breeds using image-based features. While VGG16 showed strong predictive performance, MobileNetV2 required lower inference time and memory usage, indicating greater computational efficiency. These findings suggest that lightweight CNN architectures can provide reliable breed identification while remaining suitable for deployment in resource-constrained environments. The proposed framework offers a practical approach for automated livestock breed recognition and can support breed documentation, genetic improvement programmes and conservation of indigenous goat genetic resources through scalable computer vision-based phenotyping systems. However, the dataset was obtained from a single farm environment, which may limit generalization across diverse conditions. Future studies should include larger multi-location datasets and additional breeds to improve model robustness and broader applicability.

CRedit authorship contribution statement

- **Arundhati Sharma:** Data curation; Formal analysis; Methodology; Writing - original draft.
- **Nitish Gaitri:** Formal analysis; Methodology; Software; Validation; Writing - review & editing.
- **Yajuvendra Singh:** Conceptualization; Supervision; Visualization; Writing - review & editing.
- **Rajneesh Sirohi:** Supervision; Writing - review & editing. **Varun Kumar:** Writing - review & editing.
- **Akshat Kaushik:** Writing - review & editing.
- **Aakansha Mathur:** Data curation.
- **Mohammad Danish:** Data curation.
- **Deepak Kumar:** Writing - review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Animal Ethics and Consent to Participate

The study was conducted using non-invasive image acquisition of goats under routine management conditions. Ethical approval was obtained from the Institutional Animal Ethics Committee (IAEC), College of Veterinary Science and Animal Husbandry, DUVASU, Mathura (Approval No. IAEC/25/6, dated 23/05/2025). No experimental manipulation or invasive procedures were performed on animals.

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