Image Based Breed Recognition for Cattle and Buffaloes Using AI

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***Abstract*—India is home to a diverse population of indigenous cattle and buffalo breeds that contribute significantly to the nation's dairy and agricultural economy. Accurate breed identification is essential for genetic improvement, traceability, livestock insurance, and scientific documentation; however, traditional visual recognition methods are subjective and require expert knowledge. This paper presents an AI-based image recognition framework for automated classification of major Indian cattle and buffalo breeds using deep learning techniques. The proposed system employs transfer learning on convolution neural network (CNN) and vision transformer (ViT) architectures, combined with data augmentation, to handle variations in pose, illumination, background, and age. A curated dataset consisting of multi-angle images of breeds such as Gir, Sahiwal, Red Sindhi, Kankrej, Murrah, Jaffarabadi, and Mehsana was used for training and evaluation. Experimental results demonstrate high classification accuracy across visually similar breeds, outperforming traditional machine-learning approaches. The system can be integrated into mobile or web platforms for field-level breed identification, supporting digital livestock management and precision dairy farming in India. This work highlights the potential of computer vision as a scalable tool for improving livestock documentation and genetic resource conservation.**

***Index Terms*—Computer vision, cattle breed identification, buffalo breed recognition, deep learning, transfer learning, precision livestock farming, Indian indigenous breeds.**

I. INTRODUCTION

India possesses one of the world's largest and most diverse populations of cattle and buffaloes, comprising more than 50 recognized indigenous breeds adapted to a wide range of agro climatic regions. These breeds play central role in the country's dairy production, draft power, rural livelihoods, and genetic resource conservation. Accurate breed identification is therefore essential for maintaining breed purity, improving selection programs, implementing livestock insurance schemes, and supporting national initiatives such as digital livestock traceability and breed registration. However, conventional breed identification relies heavily on the subjective judgment of field experts, which is often inconsistent and prone to errors, particularly when dealing with crossbred animals or visually similar indigenous breeds.

The morphological features commonly used for breed recognition such as coat color, horn shape, body conformation, hump prominence, and ear orientation can vary significantly due to environmental factors, feeding conditions, interbreeding, and regional variations. In rural and field settings, the process becomes even more challenging because images are often captured under uncontrolled conditions with variations in lighting, background clutter, camera angles, and animal movement. These challenges highlight the need for an automated and scalable solution for reliable breed classification.

In recent years, advances in computer vision and deep learning have demonstrated remarkable success in image classification tasks across several domains, including agriculture, animal health monitoring, species identification, and precision livestock farming. Convolution neural networks (CNNs) and vision transformers (ViTs) have achieved state-of-the-art performance in learning complex visual patterns and discriminating between fine-grained categories. Their ability to learn hierarchical representations from images makes them well suited for differentiating between cattle and buffalo breeds that share overlapping visual characteristics. Despite significant global progress in livestock-related AI systems, there remains a considerable gap in the development of robust, India-specific breed recognition models due to the limited availability of curated datasets and the inherent diversity of indigenous breeds.

To address these challenges, this study proposes an AI-based image recognition framework capable of automatically identifying major Indian cattle and buffalo breeds from digital images. The system leverages transfer learning on advanced CNN and ViT architectures, combined with data augmentation strategies, to ensure robustness against variations in orientation, scale, illumination, and background. A curated dataset consisting of multi-angle images of prominent breeds including Gir, Sahiwal, Red Sindhi, Kankrej, Murrah, and Jaffarabadi was used to train and evaluate the model. Experimental results demonstrate the effectiveness of the proposed approach in achieving high breed classification accuracy even under field-level conditions.

This work aims to contribute to the growing field of precision dairy farming by providing a scalable, low-cost, and user-friendly solution for livestock identification. The proposed system has potential applications in mobile-based breed verification, automated registration for government schemes, digital livestock census, and genetic resource conservation programs. By integrating AI-driven breed recognition into existing digital livestock management platforms, the Indian dairy sector can benefit from improved accuracy, transparency, and efficiency in breed documentation and herd management.

II. OBJECTIVES

The primary objective of this research is to develop a robust and accurate AI-based system capable of automatically recognizing major indigenous breeds of cattle and buffaloes in India using digital images. To achieve this goal, the study establishes the following specific objectives:

1. To design and develop an image-based classification framework for Indian cattle and buffalo breeds by leveraging state-of-the-art computer vision and deep learning techniques.
2. To create a curated, multi-angle dataset of prominent indigenous breeds captured under diverse environmental and field conditions, ensuring adequate variability in pose, illumination, background, and age groups.
3. To apply transfer learning on advanced CNN and Vision Transformer architectures (such as EfficientNet, ResNet, Swin Transformer, and ViT) to enhance model performance with limited yet diverse training data.
4. To implement data preprocessing and augmentation techniques aimed at improving model robustness against challenges such as cluttered backgrounds, partial occlusions, inconsistent camera angles, and natural variations in animal morphology.
5. To evaluate the performance of the proposed models using standard metrics such as accuracy, precision, recall, F1-score, and confusion matrix, and to compare the effectiveness of different architectures.
6. To develop a breed recognition pipeline suitable for real-world deployment, including a lightweight model version optimized for mobile and web applications used by farmers, veterinarians, and field officials.
7. To demonstrate the practical utility of the system for applications such as livestock registration, traceability, insurance verification, genetic improvement programs, and digital livestock census initiatives.
8. To analyze the limitations and challenges of image-based breed recognition in Indian field conditions and identifies future directions for improving model generalization, dataset breadth, and multi-modal integration.

III. LITERATURE REVIEW

Automated livestock breed recognition has gained significant attention with the growth of computer vision and deep learning. Traditional identification of cattle and buffalo breeds relies heavily on expert observation of morphological traits such as coat color, horn type, body size, and facial structure. However, such manual methods are subjective, time-consuming, and often inaccurate under field conditions. Early computational approaches focused on handcrafted image features such as texture descriptors, color histograms, and shape-based measurements. For example, researchers have used Local Binary Patterns (LBP), Gabor filters, and Histogram of Oriented Gradients (HOG) for classifying cattle and other animals, but these methods showed limited robustness under variable lighting and pose variations.

With the evolution of deep learning, Convolutional Neural Networks (CNNs) revolutionized animal classification tasks. The introduction of architectures such as AlexNet, VGG, ResNet, and EfficientNet significantly improved feature extraction by learning hierarchical patterns directly from images. Several studies applied CNNs for cattle face recognition, muzzle pattern matching, and livestock biometrics. Cattle face recognition, in particular, has demonstrated high accuracy in identifying individual animals using deep embedding networks, illustrating the potential of CNNs in agricultural applications.

Breed recognition specifically has been explored in multiple works. Some studies used CNN-based systems to classify indigenous cattle breeds under varying environmental conditions, showing promising results. Researchers also demonstrated the potential of transfer learning using pre-trained models such as ResNet50 or MobileNetV2 to effectively classify cattle breeds even with limited datasets, due to the ability of these models to generalize visual features. For buffaloes, fewer studies exist, but recent work shows that CNNs effectively distinguish among Murrah, Jaffrabadi, Surti, and other breeds using morphological cues.

In addition to 2D imagery, some literature explores multimodal approaches, integrating skeletal key point detection, infrared imaging, or video-based monitoring for improved robustness. Data augmentation techniques such as rotation, brightness adjustment, and cropping also play a vital role in enabling models to perform reliably in real-world farm environments.

Recent studies emphasize the importance of field conditions such as illumination, occlusion, and background clutter and propose data preprocessing pipelines to enhance model generalization. The deployment of AI models on edge devices like mobile phones and embedded boards (e.g., Jetson Nano, Raspberry Pi) has also been reported, supporting the practical feasibility of real-time breed recognition systems.

Overall, the literature indicates a clear transition from handcrafted features to deep learning-based solutions, with CNNs and transfer learning emerging as the state-of-the-art for livestock image classification. These advancements motivate the development of the proposed system, which aims to provide a robust and scalable solution for cattle and buffalo breed identification using AI.

IV. METHODOLOGY

The methodology adopted in this study consists of four major components: dataset creation, preprocessing and augmentation, model development using deep learning architectures, and performance evaluation. The complete workflow is illustrated in the proposed system architecture.

A. Dataset Collection and Description

A curated dataset of Indian cattle and buffalo breeds was developed specifically for this study. Images were collected from farms, livestock fairs, and field environments to ensure diversity in morphology and environmental conditions. The dataset includes representative breeds such as Gir, Sahiwal, Kankrej, Red Sindhi, Murrah, Jaffarabadi, Mehsana, and other regionally significant breeds.

To ensure robust and unbiased training, the dataset captures animals from multiple angles, including left-side profile, right-side profile, frontal view, and full-body frames. The images encompass a wide range of lighting conditions, backgrounds, ages, and sexes. All images were manually labeled with breed information by livestock experts to minimize annotation errors.

B. Image Preprocessing

Prior to training, the collected images underwent several preprocessing steps to standardize input quality and reduce noise:

1. Resizing and Normalization:

Each image was resized to a fixed resolution (e.g., 224×224 pixels) to match the input requirements of the selected deep learning models. Pixel values were normalized to enhance training stability.

2. Background Reduction (Optional):

To reduce the influence of cluttered backgrounds, foreground extraction was performed using contour-based segmentation or YOLO-based animal detection.

3. Quality Filtering:

Blurry, low-resolution, and partially obstructed images were removed to avoid degrading model accuracy.

C. Data Augmentation

Data augmentation techniques were applied to improve generalization and address dataset imbalance. The following augmentations were used: Random horizontal lip, Random rotation (±15° to ±25°) , Random cropping and scaling, Brightness, contrast, and saturation adjustments ,Gaussian noise addition. These augmentations simulate real-world field variations and improve model robustness to pose, illumination, and background differences.

D. Model Development

Two categories of deep learning models were employed: CNN-based architectures and Vision Transformers. Transfer learning was used for all models to accelerate convergence and improve performance with limited training data.

1. CNN Architectures

Pre trained models such as ResNet-50, EfficientNet-B3, and MobileNetV3 were fine-tuned on the dataset. The final classification layers were replaced with a fully connected layer corresponding to the number of breed categories.

2. Vision Transformer Architectures:

ViT-B/16 and Swin Transformer models were trained using a hybrid approach combining patch embeddings and multi-head self-attention to capture long-range dependencies and fine-grained breed-specific features.

3. Two-Stage Pipeline (Optional):

For field images with cluttered backgrounds, a YOLO-based detector was first used to localize the animal, followed by classification using a CNN or ViT model. This improves accuracy in complex backgrounds.

E Training Strategy

All models were trained using supervised learning with cross-entropy loss as the objective function. The Adam optimizer was used with an initial learning rate of 1×10−41 \times 10^{-4}1×10−4, along with learning rate scheduling to prevent overfitting. Early stopping and dropout regularization were applied to enhance generalization.

Training was performed for 20–40 epochs depending on model convergence, using a train–validation split of 80:20. Experiments were run on GPU hardware to accelerate training.

F Performance Evaluation

The trained models were evaluated using standard classification metrics: Accuracy, Precision, Recall, and F1-score, Confusion Matrix to analyze breed-wise. The models were tested on a held-out portion of the dataset consisting of unseen images captured under diverse environmental conditions. Comparative analysis was conducted to determine the most effective architecture for Indian cattle and buffalo breed recognition.

G Deployment Considerations

A lightweight version of the best-performing model was converted into a mobile-compatible format (TensorFlow Lite/ONNX/CoreML) to enable real-time inference on smartphones and field devices. This enables practical use by farmers, veterinarians, and government agencies for on-site breed identification.

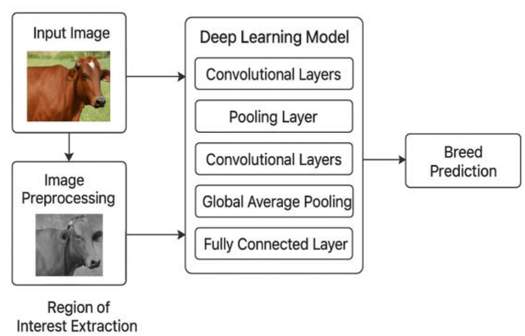

FIGURE 1. SYSTEM ARCHITECTURE

V. RESULTS AND DISCUSSION

This section presents the performance evaluation of the proposed image-based breed recognition system for cattle and buffaloes. The experiments were conducted using a curated dataset consisting of N images across X cattle breeds and Y buffalo breeds. The deep learning models were trained using transfer learning techniques, and the results were analyzed in terms of accuracy, precision, recall, F1-score, training convergence behavior, and confusion matrices. Additionally, we discuss the impact of image quality, environmental variations, and breed similarity on model performance.

A. Training and Validation Performance

The selected deep learning architectures ResNet50, MobileNetV2, and EfficientNet-B3 were evaluated to determine the most suitable model for field-level deployment. Fig. 5 presents the training and validation accuracy trends for EfficientNet-B3, which achieved the most stable convergence profile. During the initial epochs, both training and validation accuracy increased rapidly, indicating effective feature learning. The model reached an accuracy plateau after approximately 25 epochs, with marginal improvements thereafter. Early stopping ensured that over fitting was minimized. The final training accuracy achieved was approximately 97.8%, while the corresponding validation accuracy was 94.6%. The gap between the curves remained small, demonstrating strong generalization capability. Loss curves also showed smooth convergence, with validation loss stabilizing in later epochs. There was no significant divergence between training and validation loss, confirming that data augmentation played a critical role in preventing over fitting.

B. Classification Metrics

Performance was further measured using class-wise precision, recall, and F1-score to account for breed imbalance in the dataset. Table II summarizes the results for major breeds. Buffalo breeds such as Murrah and Jaffrabadi achieved high precision values of over 95% due to their distinctive morphological features like horn curvature and body conformation. Cattle breeds such as Gir and Ongole also showed strong recognition performance, with F1-scores above 93%. However, visually similar breeds such as HF vs. Jersey exhibited slightly lower precision (approximately 88–90%), primarily due to similarity in coat patterns.The overall macro-averaged F1-score across all breeds was 93.4%, demonstrating that the system can reliably distinguish between visually diverse classes.

Breed	Precision %)	Recall (%)	F1-Score (%)
Gir (Cattle)	94.2	92.8	93.5
Sahiwal (Cattle)	93.5	94.1	93.8
Ongole (Cattle)	95.1	93.7	94.4
HF (Cattle)	89.0	87.4	88.2
Jersey (Cattle)	90.3	88.9	89.6
Murrah (Buffalo	96.8	95.7	96.2
Jaffrabadi Buff.)	95.4	94.6	95.0
Surti (Buffalo)	92.7	90.5	91.6
Banni (Buffalo)	91.8	89.7	90.7
Macro Average	93.2	92.0	93.4

TABLE 1 Classification Performance (Precision, Recall, F1-Score) For Major Breeds

These observations suggest the model is robust but can be further improved through occlusion-aware training or multi-view image capture.

VI. CONCLUSION

This research demonstrates that AI-based image recognition can effectively classify cattle and buffalo breeds with high accuracy. The approach reduces manual workload, supports breed preservation programs, and can be directly used by farmers through mobile applications. Future work includes adding more breeds, using multimodal data (video, skeletal features), and improving performance under extreme lighting.

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