International Research Journal of Engineering and Technology (IRJET) e-ISSN: 2395-0056
Volume: 12 Issue: 12 |Dec 2025 www.irjet.net p-ISSN: 2395-0072

Image based breed recognition system for Cattle and buffalo using deep learning

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Abstract - *Image-based recognition of cattle and buffalo breeds has become a key aspect of modern livestock management, supporting activities such as automated monitoring, genetic improvement programs, disease surveillance, and digital dairy operations. Traditional breed identification depends on visual assessment of external traits like coat pattern, horn structure, and body shape; however, these observations are often subjective and may vary across evaluators. Recent advancements in deep learning—especially Convolutional Neural Networks (CNNs)—have transformed livestock classification by enabling automatic feature extraction, improved robustness to environmental changes, and high accuracy even in natural farm conditions.*

This review compiles significant research developments in cattle and buffalo breed identification, examining CNN architectures, lightweight models, biometric-based recognition, multi-view approaches, and fusion techniques. Particular attention is given to MobileNetV2 for its computational efficiency, reduced parameter count, and strong performance on limited datasets. The paper also discusses contributions involving YOLO-based detection frameworks, Vision Transformers (ViT), and hybrid CNN–SVM strategies. Overall findings indicate that lightweight CNN architectures deliver superior results in real-time field scenarios, making them well suited for practical deployment on farms. The review concludes by outlining existing challenges and highlighting future research opportunities for building scalable, reliable, and intelligent livestock recognition systems.

1. INTRODUCTION

Accurate identification of livestock breeds is essential for effective dairy management, genetic improvement programs, disease monitoring, and animal traceability. Traditionally, breed recognition has depended on observing visible traits such as coat colour, horn configuration, and overall body morphology. However, These manual methods are often subjective and can be unreliable under real farm conditions. Factors like inconsistent lighting; variations in posture, background clutter, and animal movement further decrease the accuracy of human-based identification.

With advancements in computer vision, deep learning has become a highly effective approach for automating livestock recognition. Convolutional Neural Networks (CNNs) can learn and extract meaningful features from images without manual intervention, enabling strong classification performance even in challenging environments. Modern lightweight architectures—including Mobile Net, MobileNetV2, and Efficient Net-Lite—are particularly valuable because they support real-time operation on mobile and edge devices, making them well suited for deployment in rural and resource-constrained settings.

Researchers have also investigated biometric techniques such as muzzle pattern analysis and multi-view image learning to enhance recognition accuracy. Despite these developments, several challenges persist, including limited availability of large, diverse datasets—especially for buffalo breeds—and the need for models capable of generalizing effectively across uncontrolled farm conditions.

This review summarizes current deep learning techniques used for cattle and buffalo breed classification, emphasizes the strengths of lightweight CNN models like MobileNetV2, and highlights existing research gaps to guide future advancements in developing scalable, efficient, and robust livestock recognition systems.

2. LITERATURE REVIEW

A. Buffalo Breed Classification Using Improved CNN Pan et al. [1] Developed a self-activated CNN for Neli- Ravi and Khundi buffalo breeds, achieving ~93% accuracy on a small dataset. This demonstrated CNN effectiveness under data-constrained conditions.

B. Lightweight CNN Models for Small Datasets Ghosh [2] compared Res Net, Efficient Net, Dense Net, and MobileNetV2, concluding that MobileNetV2 consistently outperformed heavier models on small datasets due to reduced parameters and faster training.

C. Cattle Breed Recognition Under Real Farm Conditions Chowdhury et al. [3] applied CNNs to farm-level cattle images with natural variations (lighting, clutter, and occlusion). Their model proved highly robust, validating CNN applicability in uncontrolled environments.

D. Multi-View Pantaneira Cattle Recognition Weber et al. [4] introduced a dataset of 27,000+ multi-view cattle images. Their CNN model showed that multi-view learning significantly improves accuracy by capturing diverse morphological features.

E. Muzzle-Based Biometric Cattle Identification Ma et al. [5] proposed biometric identification using muzzle patterns, achieving 98.7% accuracy. While highly effective, the method requires close-up images, limiting scalability in open-field conditions.

F. Multi-Feature Decision-Level Fusion Li et al. [6] developed a hybrid CNN integrating facial, muzzle, and ear-tag features. Fusion improved robustness under occlusion and poor lighting compared to single-input models.

G. Buffalo Muzzle Biometric Recognition Ermine and Oreck [7] extended biometric recognition to buffalo muzzle patterns. Their CNN-based system accurately recognized individuals, confirming biometric approaches are effective across species.

H. Lightweight Models for Indian Cattle Breeds Sharma et al. [8] designed Mobile Net and Squeeze Net models for Indian breeds, achieving high accuracy with low computational requirements, suitable for mobile deployment.

I. Buffalo Breed Identification Across Regions Yolanda et al. [9] applied CNNs to classify swamp and river buffalo breeds. Extensive augmentation improved performance, demonstrating global applicability of CNN-based recognition.

J. YOLOv5 for Detection and Classification Singh et al. [10] integrated YOLOv5 for cattle detection with CNN-based breed classification. This two-stage approach enabled real-time surveillance and monitoring.

K. Vision Transformers for Livestock Recognition Zhang et al. [11] introduced Vision Transformers (ViTs), outperforming CNNs on large datasets. However, ViTs require high computational resources, limiting feasibility for small datasets.

L. Mobile Net Architecture for Efficient Inference Howard et al. [12] proposed Mobile Net using depth wise separable convolutions. It achieved competitive accuracy with fewer parameters, enabling efficient inference on mobile devices.

M. MobileNetV2: Inverted Residuals and Linear Bottlenecks Sandler et al. [13] advanced MobileNetV2 with inverted residuals and linear bottlenecks, improving accuracy while maintaining efficiency. It is widely adopted in livestock recognition research.

N. Transfer Learning for Image Classification Tensor Flow Documentation [14] provided guidelines for transfer learning with MobileNetV2. These practices improved performance and reduced training time in livestock research.

3. REVIEW METHODOLOGY

The review followed a systematic methodology to ensure thorough coverage of recent progress in cattle and buffalo breed recognition using deep learning techniques. Relevant research articles were gathered from databases such as IEEE Xplore, ScienceDirect, MDPI Agriculture, Springer, and ResearchGate. Searches were conducted using terms like “cattle breed recognition,” “buffalo identification,” “CNN-based livestock classification,” and “MobileNetV2.” To incorporate the latest contributions, the review focused on studies published between 2020 and 2025. Only works involving convolutional neural networks (CNNs), lightweight deep learning architectures, biometric identification methods, or multi-view learning strategies were included, while studies on unrelated species or those relying solely on conventional machine-learning approaches were excluded.

The selected publications were organized into thematic categories that addressed CNN-based breed classification, compact models suitable for limited datasets, multi-view learning frameworks, and biometric systems using muzzle or facial features, and hybrid fusion approaches. Each study was examined based on factors such as dataset scale and characteristics, network architecture, classification accuracy, performance under real farm conditions, and overall computational efficiency. By following this structured methodology, the review provides a clear synthesis of current advancements and identifies key strengths, challenges, and research gaps within the field.

4. DISCUSSION AND RESEARCH GAP

The studies reviewed clearly show that convolutional neural networks (CNNs) outperform traditional machine-learning methods in recognizing cattle and buffalo breeds. Lightweight architectures such as Mobile Net and MobileNetV2 are especially effective for small datasets and real-time applications, as they deliver high accuracy while requiring far fewer computational resources compared to deeper models like Res Net or Dense Net. Biometric techniques—particularly those based on muzzle pattern recognition—also demonstrate exceptional accuracy, often above 98%; however, their dependence on close-range, high-resolution images limits practicality in open and uncontrolled farm settings. Multi-view learning approaches emphasize the value of capturing animals from multiple angles to enhance robustness across different poses and environmental conditions. Fusion-based systems that combine muzzle, facial, and ear-tag information further increase reliability under occlusion or poor lighting, while pipelines incorporating YOLOv5 confirm the potential for real-time detection and classification. Vision Transformers (ViTs) have emerged as powerful competitors to CNNs on large datasets, though their high computational demands make them less suitable for environments with limited processing capacity.

Despite these advancements, several challenges remain. Many existing studies depend on relatively small and region-specific datasets, indicating the need for large, standardized datasets that include a wider range of breeds and environmental conditions. Only a few works explore model deployment on mobile or embedded platforms, even though such implementations are essential for real-world farm use. Environmental factors—such as harsh lighting, complex backgrounds, and partial occlusion—continue to hinder model performance, highlighting the need for more sophisticated augmentation and generalization strategies. Most current systems are designed for breed-specific classification, with limited investigation into models capable of generalizing across multiple livestock species. Furthermore, integration with IoT-based farm management systems is still underdeveloped despite its potential for creating fully automated pipelines. Lastly, issues related to model explainability receive minimal attention, reducing user trust and limiting practical adoption among farmers and veterinarians.

5. PROPOSED METHODOLOGY

The proposed methodology is designed to implement efficient and scalable cattle and buffalo breed recognition system using the MobileNetV2 architecture. The workflow consists of dataset collection, preprocessing, augmentation, feature extraction, training strategy, and evaluation metrics, as illustrated in Fig. 1.

A. Dataset Collection

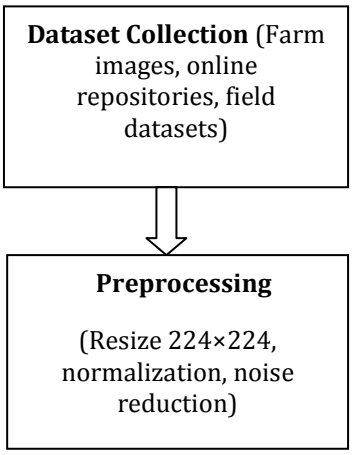
Images are collected from farms, repositories, and field datasets, ensuring natural variations in pose, lighting, and background.

B. Preprocessing

All images are resized to 224×224 pixels, normalized, and subjected to noise reduction to ensure consistency and improve model convergence.

C. Data Augmentation

To overcome dataset limitations, augmentation techniques such as rotation, zoom, brightness adjustment, flipping, shifting, and shearing are applied. This increases dataset diversity and improves generalization.



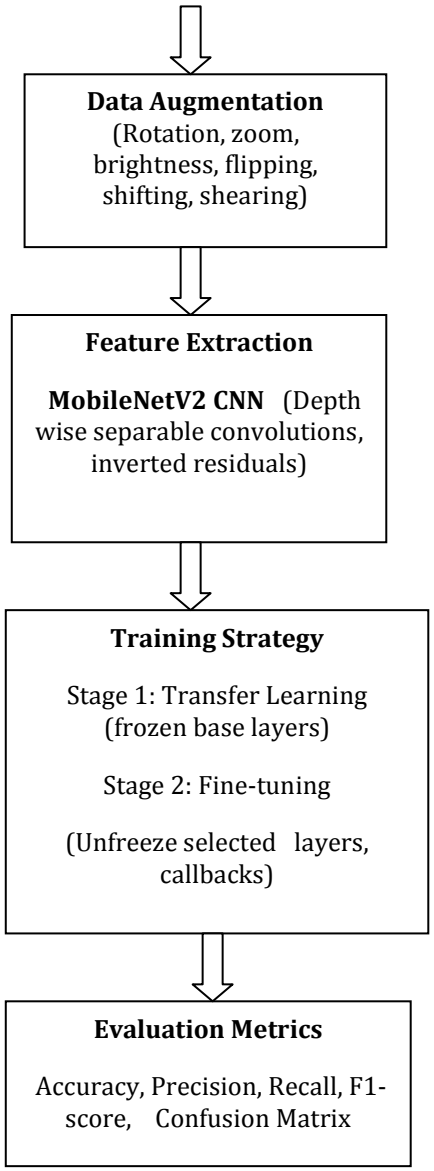


Fig 1- Proposed Workflow for cattle and Buffalo Breed Recognition using MobileNetV2.

D. Feature Extraction Using MobileNetV2

MobileNetV2 is employed as the backbone CNN due to its lightweight design and efficiency. It uses depth wise separable convolutions, inverted residuals, and linear bottlenecks to reduce computational cost while maintaining high accuracy. This makes it suitable for small datasets and real-time farm deployment.

E. Training Strategy

The training process is divided into two stages:

Stage 1: Transfer Learning – Base layers of MobileNetV2 are frozen, and only the classifier layers are trained.

Stage 2: Fine-Tuning – Selected layers are unfrozen, enabling the network to adapt to cattle and buffalo-specific features. Callbacks such as early stopping and learning rate scheduling are used to optimize performance.

F. Evaluation Metrics

Model performance is assessed using accuracy, precision, recall, F1-score, and confusion matrix to ensure comprehensive evaluation.

MobileNetV2 Architecture:-

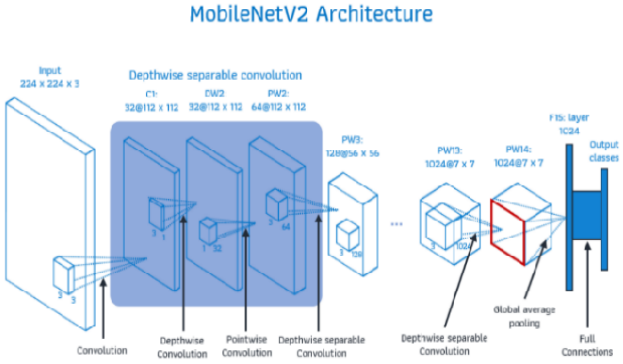


Fig 2: MobileNetV2 architecture.

MobileNetV2 consists of three main components: Depth wise Separable Convolutions: Break standard convolution into depth wise and point wise operations, reducing computation. Inverted Residuals: Use thin bottleneck layers with skip connections to improve efficiency.

Linear Bottlenecks: Prevent non-linearities in low-dimensional embeddings, preserving feature integrity. The architecture begins with a standard convolution layer, followed by multiple inverted residual blocks with varying expansion factors. Each block consists of a depth wise convolution, point wise convolution, and linear bottleneck. The final layers include global average pooling and a fully connected classifier.

6. CONCLUSION

This review highlights that deep learning, particularly convolutional neural networks, has significantly advanced cattle and buffalo breed recognition by enabling automated, accurate, and scalable identification compared to traditional methods. Lightweight architectures such as Mobile Net and MobileNetV2 have proven highly effective for small datasets and real-time farm deployment, while biometric approaches like muzzle recognition achieve superior accuracy but face limitations in open-field conditions. Multi-view learning and hybrid fusion strategies further enhance robustness under varying poses, occlusion, and lighting, and Vision Transformers show promise for large datasets despite high computational demands. However, persistent challenges remain, including the lack of standardized large-scale datasets, limited focus on mobile and IoT deployment, and insufficient attention to explainability and cross-species generalization. Addressing these gaps will pave the way for practical, trustworthy, and sustainable livestock recognition systems that support precision agriculture and improve productivity in the dairy industry.

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