Pashunetra: Intelligent Image-Based System for Smart Livestock Management

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***Abstract*—Accurate identification of cattle and buffaloes is vital for maintaining comprehensive records, ensuring traceability, and maximizing productivity in Indian livestock management. Traditional, manual identification methods such as ear tagging are invasive, prone to human error, and suffer from tag loss or damage. This project introduces Pashunetra—an AI-powered, non-invasive image-based classification system using deep learning and computer vision to automate livestock identification based on unique body features. The dataset comprises approximately 800 images across three cattle breeds, rigorously collected and augmented to improve model generalization. The system leverages the efficiency of transfer learning, deploying MobileNetV2 and Efficient Net architectures. These lightweight models were selected to balance high classification accuracy with low computational overhead, making the solution ideal for real-time edge deployment. Experimental results, detailed in TABLE I, demonstrate reliable accuracy and superior performance from Efficient Net across all key classification metrics, validating Pashunetra as a highly viable alternative for smart livestock management decisions.**

***Index Terms*—AI-powered system, Breed classification, Computer vision, Deep learning, Efficient Net, Livestock identification, MobileNetV2, Pashunetra, Transfer learning.**

I. INTRODUCTION

The livestock sector is a foundational pillar of the Indian agricultural economy, contributing significantly to both national GDP and rural livelihood. Effective management of large herds of cattle and buffaloes is paramount for monitoring animal health, tracking breeding cycles, ensuring feed efficiency, and ultimately, boosting overall productivity. Current identification practices, such as RFID technology or ear tags, require high initial cost and can negatively impact the cattle's health. Furthermore, non-contact monitoring methods, which are preferred, rely primarily on analyzing video and image data.

The solution is centered on the concept of transfer learning, utilizing highly optimized Convolutional Neural Network (CNN) architectures, namely MobileNetV2 and EfficientNet. These models are strategically chosen for their reduced parameter count and superior computational efficiency, which are critical requirements for potential deployment on resource-constrained edge devices common in farm environments.

II. LITERATURE SURVEY

The integration of Deep Learning (DL) and Computer Vision (CV) into Precision Livestock Farming (PLF) has been widely explored as a modern alternative to traditional identification methods.

Early studies validated the use of complex CNNs for individual animal recognition, such as a Self-Activated Improved CNN model which demonstrated high accuracy for buffalo breed classification. Another study used VGG16 combined with Random Forest and XGBoost classifiers, achieving around 88% accuracy for cattle recognition. While effective, VGG-based models often consist of millions of parameters, making them computationally heavy for real-time farm deployment.

Our selection of MobileNetV2 is critical because its lightweight architecture, utilizing inverted residual blocks and linear bottlenecks, uses significantly fewer parameters (approximately 3.4 million) compared to other popular CNN models, making it highly suitable for resource-constrained edge environments. EfficientNet is chosen for comparison because it employs a compound scaling method to efficiently balance network depth, width, and resolution, generally yielding superior feature extraction capabilities and high accuracy. The current work directly addresses the need for non-invasive, efficient solutions by comparing these two modern, lightweight architectures for application in Indian farming.

III. MATERIALS AND METHODS

The Pashunetra system was developed through a structured, multi-module approach using standard computer vision and deep learning tools, similar to other real-time image processing systems.

A. Hardware, Software, and Input Requirements

The proposed system is developed using easily available computing resources. The software environment consists of Python, TensorFlow, Keras, OpenCV, NumPy, and Pandas. These libraries form the core toolkit, with OpenCV handling image manipulation and TensorFlow/Keras managing the deep learning workflow. The system relies on image inputs which are photographs of cattle and buffalo.

B. Dataset Acquisition and Preprocessing

The dataset comprised approximately 800 labeled images distributed across three common cattle breeds. Data collection involved aggregating samples from public repositories like Roboflow and Kaggle, alongside images captured from local farms to ensure domain specificity.

C. Data Augmentation and Overfitting Mitigation

To significantly increase the effective size and diversity of the limited dataset and prevent overfitting, rigorous data augmentation was employed. Techniques used included random rotations, horizontal flips, zoom transformations (e.g., up to 20%), and minor shear transformations. Augmentation is empirically proven to enhance model robustness and generalization capability, especially when the initial training set is small.

D. Model Architectures and Transfer Learning

The classification task was executed using the transfer learning paradigm, fine-tuning models pre-trained on the massive ImageNet dataset. This involves replacing the final classification layer of the base model with a custom output head tailored to the three target cattle breeds.

The two architectures fine-tuned were:

- MobileNetV2: Selected for its exceptional computational efficiency and low parameter count, making it optimal for lightweight, real-time deployment.
- EfficientNet (B0 variant): Selected for its compound scaling method, which provides a strong balance of accuracy and efficiency, serving as a powerful benchmark for comparison.

IV. RESULTS AND DISCUSSION

The evaluation successfully demonstrated that both MobileNetV2 and EfficientNet, when used with transfer learning, performed with reliable classification accuracy across the different cattle breeds. The results highlight the trade-off between model complexity, efficiency, and predictive performance.

A. Detailed Comparative Performance Evaluation

The comprehensive results, presented in TABLE I, evaluate the two models not only on standard accuracy and speed but also on critical classification metrics such as Precision, Recall, and F1-Score, which are more indicative of the model's reliability in a real-world, multi-class scenario.

TABLE I: DETAILED COMPARATIVE PERFORMANCE OF LIGHTWEIGHT CLASSIFICATION MODELS

Model	Top-1 Accuracy (%)	Precision	Recall	F1-Score	Total Parameters (M)	Inference Time (ms)
MobileNetV2	95.1	0.94	0.96	0.95	3.4	8
EfficientNet B0	97.3	0.97	0.98	0.97	5.3	12

B. Discussion

The inference times for both models remain exceptionally low, confirming their suitability for real-time edge deployment where computational resources are constrained. This successful validation of lightweight, high-performance architectures directly addresses the limitations of older, heavy CNN models referenced in the literature survey.

V. FUTURE SCOPE

The successful implementation of Pashunetra lays the groundwork for significant future expansions:

1. Individual Animal Re-Identification: Moving beyond breed classification to individual identification using unique biometric features (muzzle prints, coat patterns) for precise traceability.

2. Advanced Segmentation: Exploring deep-learning-based segmentation models (such as U-Net or DeepLab) to achieve more accurate and robust masking of the animal, potentially improving performance in complex backgrounds.

3. Edge Device Deployment: Optimizing the final classification model (e.g., using quantization) for deployment on low-power hardware, ensuring real-time performance on-site without continuous internet connectivity.

4. Real-Time Video Monitoring (RTVM): Developing the application to process live video feeds for continuous monitoring of herd behavior and health status.

VI. CONCLUSION

Pashunetra successfully demonstrates the implementation and potential of a deep learning-based, non-invasive system for livestock identification. By effectively leveraging transfer learning with computationally efficient models like MobileNetV2 and the higher-performing EfficientNet B0 on a regionally relevant dataset, the project delivers a high-accuracy solution that is suitable for real-time farm operations. The system eliminates reliance on traditional, error-prone methods, offering a robust foundation for automated, real-time identification. Pashunetra is a significant step toward developing a complete, intelligent smart livestock ecosystem tailored for the efficiency demands of modern Indian farming.

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