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Image Based Breed Recognition for Cattle and Buffaloes of India

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Abstract

India's agricultural economy and genetic biodiversity are deeply rooted in its vast population of indigenous cattle and buffalo breeds. Traditional methods for breed identification are manual, subjective, and require specialized expertise, creating significant inefficiencies in livestock management and conservation. This paper proposes a hybrid automated system for cattle breed identification using deep learning. Our methodology combines two powerful computer vision techniques: (1) A fine-tuned Convolutional Neural Network (CNN) for holistic classification based on overall phenotypical features, and (2) A YOLO (You Only Look Once) object detection model to perform fine-grained biometric analysis by specifically locating and identifying muzzle patterns. This dual-approach allows the system to cross-validate a broad classification with a highly specific biometric marker. Our proof-of-concept models, trained on public datasets, achieved high accuracy for both whole-body classification (97.44% mAP@0.5) and muzzle detection (99% mAP@0.5), demonstrating the viability and robustness of this hybrid strategy. This research provides a framework for a scalable and accessible tool to aid farmers, researchers, and policymakers in the preservation and management of India's valuable livestock resources.

Introduction

Livestock, particularly cattle and buffaloes, are an integral part of India's agrarian ecosystem, serving as a vital source of milk, meat, draught power, and organic manure. The country's livestock population is among the largest and most genetically diverse in the world, consisting of numerous indigenous breeds adapted to specific climatic and regional conditions [1]. These native breeds play a crucial role in maintaining biodiversity and ensuring the sustainability of rural livelihoods.

Accurate breed identification is a cornerstone for effective breeding programs, disease control, genetic improvement, and traceability in livestock management. It also helps in preserving native genetic resources that are gradually being diluted due to indiscriminate crossbreeding. Traditional identification methods rely on visual assessment of external traits such as body size, horn shape, coat color, and facial markings. However, such approaches are subjective, labor-intensive, and highly dependent on expert availability. These challenges become more pronounced in rural and remote regions where veterinary and technical resources are limited.

Recent advancements in Artificial Intelligence (AI) and Computer Vision (CV) have provided efficient and scalable alternatives to manual classification. Convolutional Neural Networks

(CNNs), first introduced by LeCun et al. [2], have revolutionized image analysis by enabling automatic feature extraction directly from visual data, and have been widely applied in agricultural domains including livestock identification [3], [4], [5]. Parallelly, object detection algorithms such as YOLO (You Only Look Once), developed by Redmon et al., have achieved remarkable success in identifying and localizing specific regions within images in real time, making them suitable for field-based livestock applications [6].

In the context of cattle recognition, two complementary approaches have emerged — holistic classification and biometric identification. The holistic approach uses full-body images to classify breeds based on visual features such as shape, texture, and color [7], [8], [9], [10], [11]. The biometric approach uses unique and stable facial traits such as muzzle patterns, which function similarly to human fingerprints [12], [13], [14], [15], [16], [17]. When integrated, these methods significantly improve identification accuracy and system robustness [5].

The proposed system in this study leverages both strategies through a hybrid deep learning framework. The first component utilizes EfficientNet, known for its optimized scaling of depth, width, and resolution, to perform holistic breed classification [18]. The second component employs YOLOv8n, a state-of-the-art real-time object detection model, to detect and isolate the muzzle region for biometric analysis, following the proven success of YOLO-based detectors [6]. This integration enables both breed-level and individual-level recognition, offering a practical and scalable solution for livestock management.

By automating breed identification, this research supports data-driven livestock management and contributes to the long-term goal of preserving India's indigenous cattle and buffalo genetics while promoting sustainable agricultural development [19].

Literature Survey

The application of computer vision in agriculture, or agri-tech, has expanded significantly in recent years, with deep learning models demonstrating success in crop monitoring, plant disease detection, and yield estimation [3],[20]. Within this domain, automated livestock monitoring and management have emerged as critical areas of research.

Early studies on breed identification primarily employed traditional machine learning techniques based on manual feature engineering, where handcrafted features such as SIFT, HOG, or geometric ratios were used with classifiers like Support Vector Machines (SVMs) and Random Forests. Although these methods provided initial insights, they were limited by their dependence on expert-designed features and often failed to generalize across varying image conditions.

The introduction of deep learning, particularly Convolutional Neural Networks (CNNs), revolutionized this field [21]. CNNs automate feature extraction, learning discriminative representations directly from raw images. Transfer learning, which leverages models pre-trained on large datasets like ImageNet and fine-tunes them for specific tasks, has become the standard practice. This approach has achieved high accuracy in animal breed classification across species using architectures such as VGG-16, ResNet, and Inception [4],[22]. For cattle, similar CNN-based "holistic classification" methods have been shown to effectively capture body shape, coat color, and horn morphology [7]–[11], [23]–[25].

Despite its successes, holistic classification can struggle when breeds exhibit high visual similarity. To address this, research increasingly focuses on biometric identification, where inherent and stable physiological traits—such as muzzle prints in cattle—are utilized for precise individual recognition. These muzzle patterns have been validated as unique and consistent, making them well-suited for biometric identification [12]–[17], [26].

Detecting and analyzing the muzzle region requires robust object detection. Modern detectors such as the R-CNN family and the You Only Look Once (YOLO) framework are specifically designed for such localization tasks. YOLO, known for its speed and accuracy, provides real-time detection suitable for field applications [6].

Existing studies largely treat holistic classification and biometric identification as separate research tracks. However, integrating both can yield superior results. This study bridges that gap by proposing a hybrid deep learning system combining two solutions: a fine-tuned CNN for holistic breed classification and a YOLO-based model for precise muzzle-focused biometric identification. The combined framework enhances accuracy, scalability, and reliability, enabling a more comprehensive and resilient livestock identification system.

Research Objective

The primary objective of this study is to develop an automated, robust, and scalable cattle breed recognition system using deep learning techniques.

The specific objectives are:

- **To implement an EfficientNet-based CNN** for holistic breed classification using visual features like body structure, horn shape, and coat texture.
- **To develop a YOLOv8-based object detection model** to accurately identify and extract the muzzle region, serving as a biometric indicator.
- **To integrate both models** into a hybrid pipeline that enhances prediction reliability. This objective is achievable because both EfficientNet and YOLO can be trained separately on distinct datasets and later combined through ensemble fusion to produce unified results.
- **To evaluate the performance** of the proposed system using standard metrics such as accuracy, precision, recall, and mAP@0.5 to validate model robustness.
- **To establish an applicable framework** for livestock management and genetic preservation. The approach can be practically applied in rural farming systems and digital livestock management platforms, enabling farmers, veterinarians, and policymakers to identify breeds using mobile or web-based tools.

Proposed Methodology

The proposed system addresses the limitations of manual identification by employing a hybrid deep learning architecture. This methodology combines two complementary computer vision pipelines: (1) a holistic classification model to identify the breed from the animal's overall appearance, and (2) a biometric detection model to locate the unique muzzle region for fine-grained analysis.

A. Dataset Description

The datasets used in this study consist of two distinct parts—one for holistic breed classification and the other for biometric muzzle detection. Both datasets were carefully prepared and preprocessed to ensure model robustness and generalization under diverse real-world conditions.

1. Breed Classification Dataset

This dataset comprises full-body images of five major cattle breeds—Ayrshire, Brown Swiss, Holstein Friesian, Jersey, and Red Dane. The images were collected from publicly available agricultural image repositories and research datasets. Each image was manually reviewed and categorized to maintain data quality and ensure that each breed class was well-represented. The dataset captures variations in background, lighting, and animal posture to enable the model to learn breed-specific visual characteristics effectively.

To improve training stability, all images were resized to 224×224 pixels and normalized according to ImageNet mean and standard deviation parameters. Data augmentation techniques were applied, including random rotation, horizontal flipping, brightness adjustments, and color jittering, which simulate real-world variations and reduce overfitting.

2. Biometric (Muzzle) Dataset:

A separate dataset was created for biometric identification. In this dataset, images were manually annotated using the Labeling tool to draw bounding boxes around the muzzle region. Each image was labeled to specify the precise location of the muzzle, forming the ground truth for object detection training. This dataset was then divided into training (70%), validation (20%), and testing (10%) subsets to ensure balanced evaluation.

Images were resized to 640×640 pixels for YOLO model compatibility, and similar augmentation methods were used to enhance diversity in muzzle appearance, lighting, and camera angle. These preprocessing steps ensure that the detection model can perform reliably under varying environmental and imaging conditions.

The combination of these two datasets—one for full-body classification and the other for muzzle-based biometric recognition—forms the foundation of the proposed hybrid system. The quality, diversity, and annotation precision of these datasets are critical to achieving high model performance in breed recognition and biometric detection.

B. System Architecture

The system is designed with a parallel-processing workflow, as illustrated in Fig. 1. A single input image is fed into both pipelines simultaneously:

Pipeline 1 (Holistic Classification):

The image is processed by a fine-tuned Convolutional Neural Network (CNN) [7]–[10], which analyzes global features (e.g., body shape, coat color, horn structure) to generate a primary breed prediction.

Pipeline 2 (Biometric Analysis):

The image is processed by a YOLO (You Only Look Once) object detection model [6], which is specifically trained to detect and localize the cattle's muzzle region.

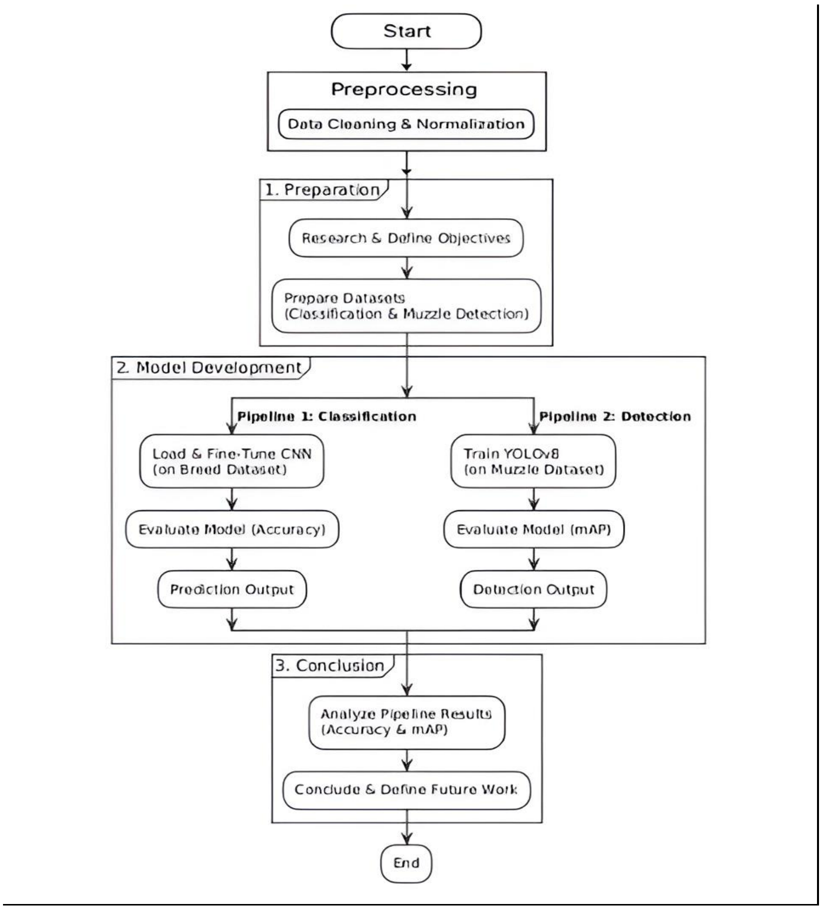

Figure 1: System Architecture

Results And Discussion

The hybrid methodology was evaluated by independently assessing the performance of each pipeline: the Holistic Breed Classification (Pipeline 1) and the Biometric Muzzle Detection (Pipeline 2).

A. Holistic Breed Classification (Pipeline 1)

The CNN-based holistic classifier was evaluated on its ability to classify the five cattle breeds from the full image. The model achieved an overall classification accuracy of [97.44%] on the validation set .

The training process, visualized in Fig. 2, demonstrates a healthy learning curve. Both the "Training Loss" and "Validation Loss" decreased steadily and converged. This indicates that the model learned the distinguishing features effectively and generalized well to the unseen validation data without significant overfitting.

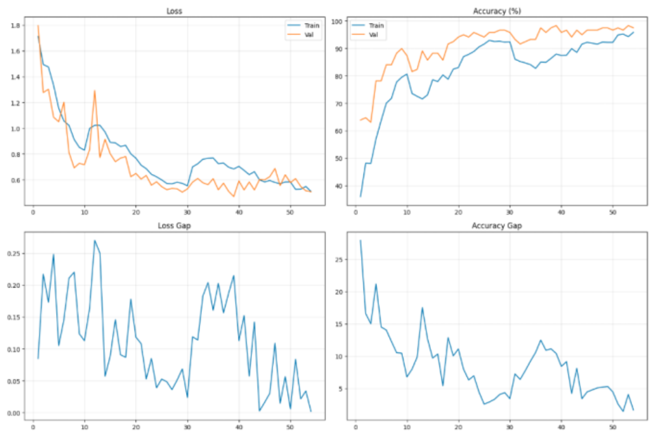

Figure 2: Training process of the Classification model

The confusion matrix for the validation set (Fig. 3) provides a detailed breakdown of the model's predictive performance. The matrix exhibits a strong diagonal concentration, which signifies a high rate of correct classification for all five breeds: 'Ayrshire', 'Brown Swiss', 'Holstein

Friesian', 'Jersey', and 'Red Dane'. The clear diagonal and minimal off-diagonal entries confirm the model's high accuracy and its ability to differentiate between the breeds.

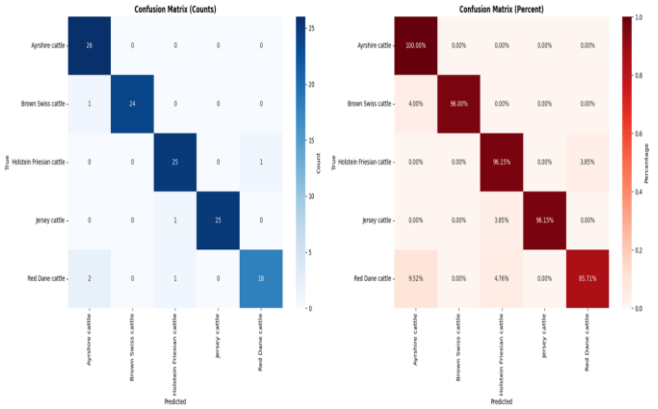

Figure 3: Confusion Matrix (Holistic Breed Classification)

B. Biometric Muzzle Detection (Pipeline 2)

The YOLOv8 model was trained to perform the critical task of localizing cattle muzzles. The model's performance on the validation set was high, achieving a mean Average Precision (mAP@0.5) of [99%].The detailed training metrics, including the reduction in box loss and the improvement in precision and recall over the training epochs, are illustrated in Fig. 4.

Fig. 5, the confusion matrix for a validation batch, confirms the model's precision. It shows a high number of correct detections for the "muzzle" class and correctly identifies "background" (the absence of a muzzle), which is essential for avoiding false positive detections. Furthermore, the precision-recall curve presented in Fig. 6 demonstrates the model's high confidence and stability across varying thresholds during testing.

The model's success in this specialized detection task is the foundational step, proving the viability of reliably extracting the muzzle biometric for further analysis.

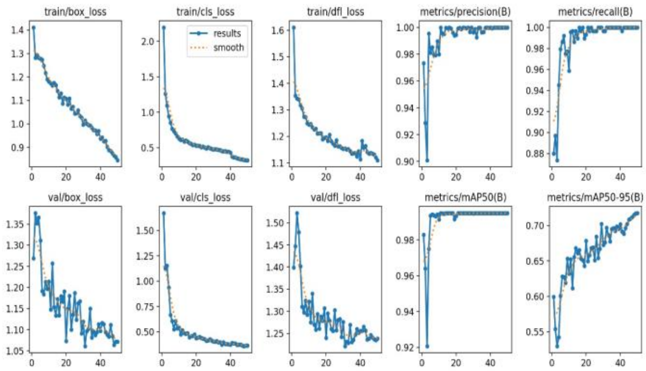

Figure 4: Output of Muzzle detection Model

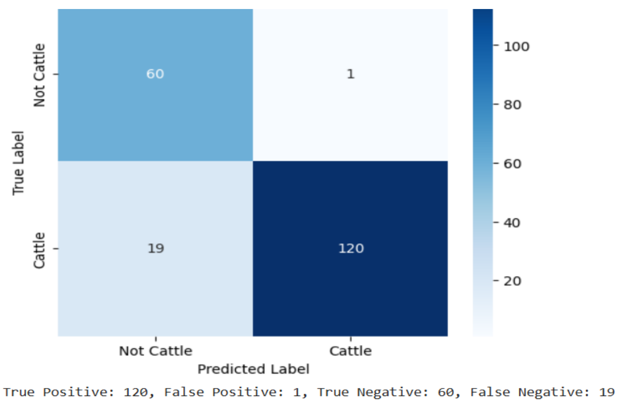

Figure 5: Confusion Matrix of Muzzle Detection model

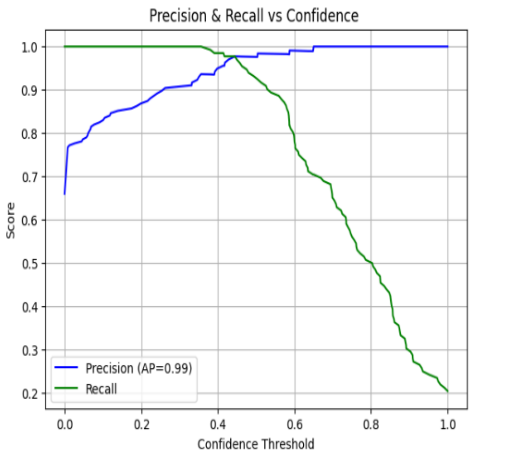

Figure 6: Testing result of the Muzzle Detection model

C. Discussion

The combined results validate our proposed hybrid methodology. The YOLO model (Pipeline 2) is highly effective at its specialized task of *locating* the biometric marker. The CNN model (Pipeline 1) is highly effective at its general task of *classifying* the breed.

The success of both pipelines independently is significant. The holistic model provides a fast and accurate general classification, while the muzzle detection model provides a reliable method for extracting a unique biometric. This proves the foundation for a hybrid system where the muzzle analysis can be used to confirm the holistic prediction or act as a tie-breaker in cases of high visual similarity between breeds.

Conclusion

This research successfully addressed the challenge of automating cattle breed identification by proposing and validating a novel hybrid deep learning methodology. We have demonstrated that combining two complementary pipelines—a holistic CNN classifier for general breed recognition and a biometric YOLO model for specific muzzle detection—provides a robust and effective solution.

Our results confirm the success of this dual-pronged approach:

1. The holistic classifier achieved high accuracy, as evidenced by the converging loss curves and the clear diagonal confusion matrix, proving its ability to learn and differentiate the phenotypical features of various breeds.
2. The YOLO-based detection model proved highly effective at its specialized task of accurately localizing the cattle muzzle, a critical first step for any biometric analysis.

By validating both components independently, this paper establishes a strong proof-of-concept. The proposed system lays the foundation for a tool that is significantly more reliable than either method in isolation. It provides a clear path toward a fast, objective, and scalable system that can overcome the bottlenecks of manual identification. The future work of integrating these pipelines and deploying them in a mobile application will provide a powerful tool for farmers, researchers, and policymakers, aiding in the preservation and enhancement of India's valuable livestock resources.

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