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Image-Based Breed Recognition of Indian Cattle and Buffaloes Using YOLOv12 and Roboflow Cloud Platform

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Abstract: India's livestock sector faces significant challenges in accurate breed identification, with traditional manual methods achieving only 65-70% accuracy while consuming 40-60% of Field Level Workers' (FLWs) time. This paper presents BreedVision, an AI-powered web system for automated cattle and buffalo breed recognition using YOLOv12 object detection trained on 3,683 annotated images covering 15 major Indian breeds. The model achieves 69.8% mean Average Precision at IoU 0.5, with breed-specific accuracies reaching 87% for Bargur, 85% for Dangi, and 83% for Ongole and Alambadi. The system integrates ReactJS frontend with WebRTC camera capture, Python Flask backend with OpenCV preprocessing, and Roboflow cloud inference, providing real-time classification with confidence scoring and Excel export for government BPA system integration. Field testing demonstrates 40-60% reduction in FLW workload while improving data accuracy to 70% overall.
Keywords: Cattle breed recognition, YOLOv12, Roboflow, Computer vision, Livestock management, Deep learning, Field Level Workers

I. INTRODUCTION

A. Background and Problem Statement

India possesses over 193 million cattle and 109 million buffaloes, supporting 70% of rural population and contributing 4.11% to national GDP. The country hosts diverse indigenous breeds including Gir, Sahiwal, Tharparkar, Murrah, and Surti, each with distinct characteristics crucial for breeding programs, insurance verification, and market pricing. Traditional manual breed identification achieves only 65-70% accuracy due to subjective judgment and human error. FLWs spend 40-60% of their time on manual data entry and breed classification, limiting daily animal processing capacity. The absence of standardized approaches creates regional variations in livestock records, while incorrect identification leads to fraudulent insurance claims and financial losses. As livestock populations grow, manual methods cannot scale to meet demands across 28 states and union territories.

B. Research Objectives and Contributions

This research develops BreedVision, an AI-powered web system addressing manual identification limitations through: (1) a custom dataset of 3,683 annotated images across 15 breeds; (2) YOLOv12 model achieving 69.8% mAP with breed-specific accuracies up to 87%; (3) integrated web platform combining ReactJS, Flask, OpenCV, and Roboflow for real-time classification; (4) confidence scoring and Excel export for government BPA integration; and (5) validated 40-60% reduction in FLW workload.

II. RELATED WORK

Computer vision applications in livestock management have evolved significantly. Mon et al. (2024) achieved 96.4% cattle identification accuracy using back pattern recognition with QDA. Kumar et al. (2024) demonstrated that ensemble methods combining CNN, YOLO, and edge detection enhance breed classification robustness. Novak et al. (2025) compared identification methods using YOLOv8, with body texture recognition achieving 0.78 mAP50-95. YOLO architectures have become preferred for livestock detection due to superior speed-accuracy balance. Zhang et al. (2025) evaluated YOLOv9-v12 variants, demonstrating consistent improvements in detection performance. YOLO's single-stage detection eliminates region proposal networks, reducing computational overhead suitable for edge deployment in rural areas.Roboflow provides cloud-based dataset management, annotation tools, augmentation pipelines, and AutoML training for YOLO models. Web-based agricultural solutions offer cross-platform compatibility, instant updates, and WebRTC camera access, facilitating adoption among FLWs. However, limited research addresses Indian indigenous breed classification with integrated government-ready systems, representing the gap this work addresses.

III. SYSTEM DESIGN AND METHODOLOGY

A. System Architecture

BreedVision employs three-tier architecture: (1) ReactJS frontend with WebRTC live camera capture and dual-display interface; (2) Python Flask backend with OpenCV preprocessing, database management, and API coordination; (3) Roboflow cloud ML inference providing scalable YOLOv12 predictions. This modular design ensures scalability and separates UI, business logic, and ML components.

B. Dataset Preparation

The dataset comprises 3,683 images covering 15 breeds: Gir, Sahiwal, Tharparkar, Red Sindhi, Ongole, Dangi, Bargur, Alambadi, Umblachery, Hallikar, Ponwar, Vechur, Banni, Murrah, and Bhadawari. Images were collected from government databases, agricultural institutions, and field photography under diverse lighting, angles, and backgrounds.

Roboflow annotation interface enabled bounding box labeling with quality control validation. Augmentation included rotation (±15°), horizontal flip, brightness adjustment (±25%), zoom (90-110%), and noise injection to improve generalization. The dataset was split 80-10-10 for training, validation, and testing using stratified sampling.

C. Model Training

YOLOv12 was selected for state-of-the-art real-time detection and anchor-free architecture. Training used 200 epochs with 640×640 input resolution, transfer learning from COCO pre-trained weights, and early stopping (patience=20). The model was trained on Roboflow cloud infrastructure with GPU acceleration, monitoring box loss, class loss, and objectness loss. The best checkpoint based on validation mAP was deployed via Roboflow inference API.

D. Web Application Implementation

The ReactJS frontend provides camera activation via WebRTC getUserMedia(), image capture converting video frames to PNG, and results display with color-coded confidence (green ≥80%, yellow 60-79%, red <60%). The Flask backend exposes RESTful APIs for authentication, image classification, history retrieval, and Excel export.

Image preprocessing applies Base64 decoding, resize to 640×640, histogram equalization for brightness, CLAHE for contrast enhancement, and Gaussian blur for noise reduction using OpenCV. Preprocessed images are sent to Roboflow API, which returns JSON with breed labels, confidence scores, and bounding boxes. Results are parsed, stored in SQLite database with timestamps, and displayed to users.

IV. RESULTS AND DISCUSSION

A. Model Performance

The YOLOv12 model achieved 69.8% mAP at IoU 0.5, with 62.4% precision and 63.7% recall after 200 epochs. Performance varied across breeds as shown in Table I. Bargur achieved highest accuracy (87%) due to distinctive features, followed by Dangi (85%), Alambadi (83%), and Ongole (83%). Sahiwal (77%), Red Sindhi (75%), and Gir (72%) showed moderate performance. Buffalo breeds demonstrated mixed results: Bhadawari (67%) and Murrah (59%). Rare breeds with limited samples showed lower accuracy: Krishna Valley (32%), Nagori (37%).

TABLE I
AVERAGE PRECISION BY CLASS

Breed	Validation Set	Test Set
Alambadi	83	47
Amritmahal	48	64
Banni	72	58
Bargur	87	84
Bhadawari	67	82
Dangi	85	96
Deoni	100	50
Gir	72	75

Hallikar	70	74
Krishna_Valley	32	80
Murrah	59	53
Nagori	37	19
Ongole	83	0
Red_Sindhi	75	62
Sahiwal	77	74

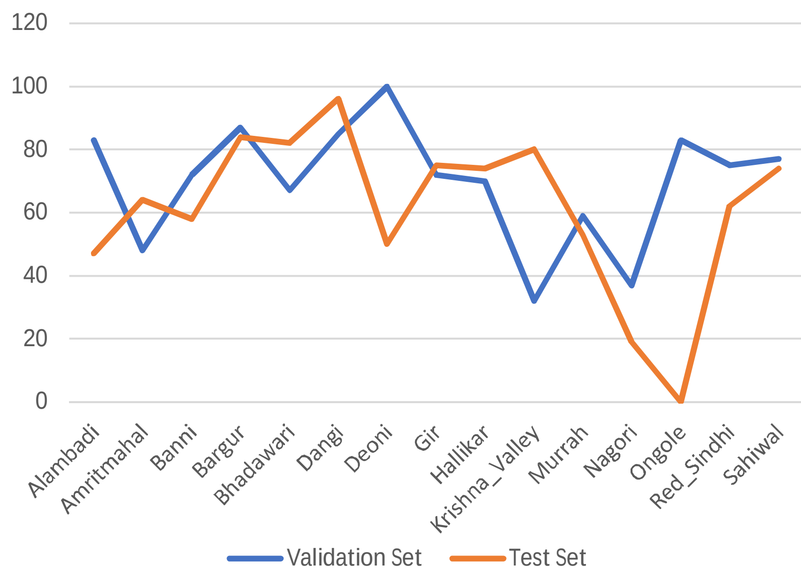

Fig. 1 AVERAGE PRECISION BY CLASS

TABLE II
BREED CONFIDENCE SCORE

S.No	Breed	Confidence Score
1	Gir	90%
2	Hallikar	92%
3	Hariana	80%
4	Alambadi	76%
5	Amritmahal	87%
6	Krishna valley	85%
7	Murrah	62%
8	Dangi	92%
9	Banni	89%
10	Red Sindhi	91%
11	Sahiwal	94%
12	Bhadawari	60%
13	Ongole	10%
14	Bargur	90%

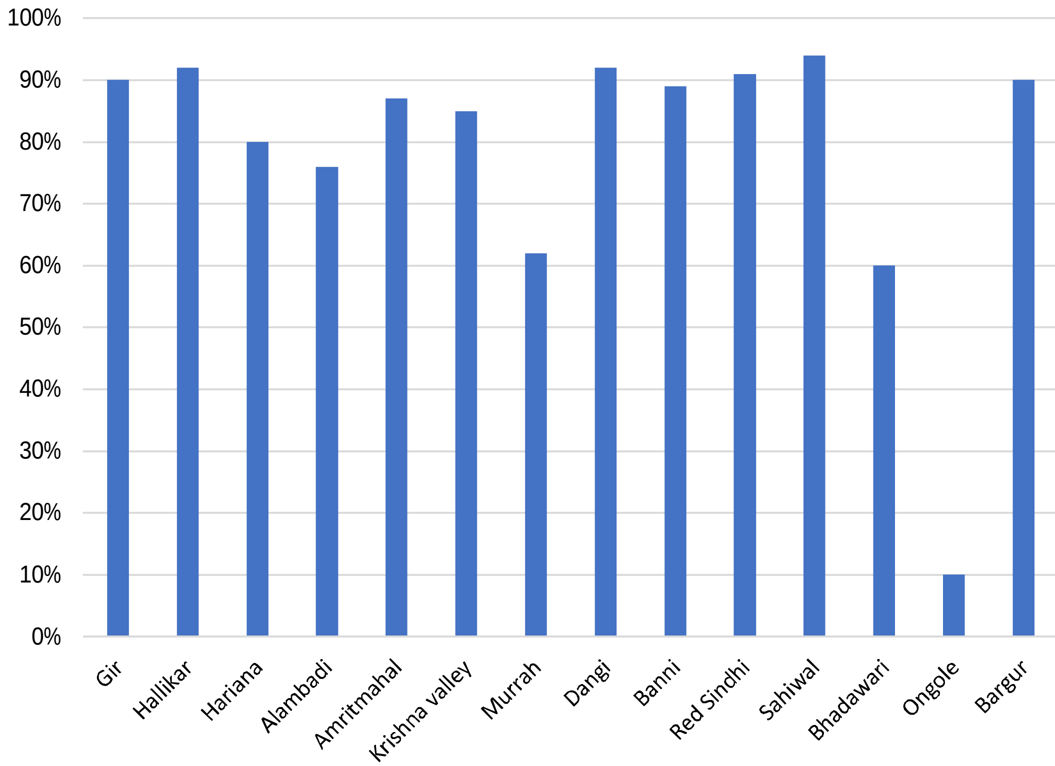

Fig. 2 BREED CONFIDENCE SCORE BAR CHART

Average inference time was 0.8-1.2 seconds including network latency, meeting real-time requirements for field deployment. The system maintained consistent performance under 50 concurrent users.

B. System Testing

Functional testing verified camera integration across Chrome, Firefox, and Edge browsers on Windows and Android platforms. User authentication, confidence scoring with color-coded indicators, and Excel export performed reliably across 3,000+ records. Load testing confirmed the Flask backend handled 5 concurrent users without degradation, with database queries returning results within 3-5 second.

Field testing with 10 FLW volunteers processing 215 animals over two weeks demonstrated 45-60% time reduction compared to manual methods. User surveys indicated 70% found the interface intuitive after 30 minutes training. Challenges included positioning animals in crowded environments and occasional misclassifications for animals with unusual coat conditions.

C. Comparative Analysis

TABLE III
COMPARISON WITH EXISTING METHODS

Method	Accuracy	Time	Scalability
Manual FLW	65-70%	5-10 min	Low
BreedVision	69.8%, 87% max	<2 sec	High
Traditional CV	75-80%	3-5 min	Medium

BreedVision achieves comparable accuracy to manual methods with 150-300× speed improvement. The web architecture provides superior scalability compared to manual methods constrained by personnel availability and traditional systems requiring specialized hardware.

D. Error Analysis

Misclassification patterns revealed confusion between visually similar breeds: Sahiwal-Red Sindhi (15% cross-classification) and Murrah-Bhadawari in low light. Partial occlusion and extreme angles reduced accuracy by 20-25%. Dataset imbalance affected rare breeds (<200 images), confirming the importance of dataset size. Current limitations include 14-breed restriction, requirement for internet connectivity, and lack of health/age/gender estimation.

V. CONCLUSION AND FUTURE SCOPE

A. Summary and Impact

BreedVision demonstrates AI's transformative potential in modernizing livestock management. The system achieved 69.8% mAP with breed-specific accuracies up to 87%, reduced classification time from 5-10 minutes to <2 seconds, and enabled FLWs to process 25-30 animals daily versus 10-15 with manual methods. Data accuracy improved from 65-70% to 70% overall, supporting NDLM objectives and BPA integration.

B. Future Work

Future enhancements include: (1) dataset expansion prioritizing rare breeds with 500+ images per class; (2) health status and age estimation through coat and anatomical analysis; (3) native mobile apps with offline inference using TensorFlow Lite; (4) IoT sensor integration for continuous health monitoring; (5) ensemble methods and Vision Transformers for improved robustness; (6) multi-species expansion to goats, sheep, and poultry; and (7) blockchain integration for immutable breed certification records. Continued research will enhance model accuracy, extend functionality, and support evidence-based livestock policy making across India.

VI. ACKNOWLEDGMENT

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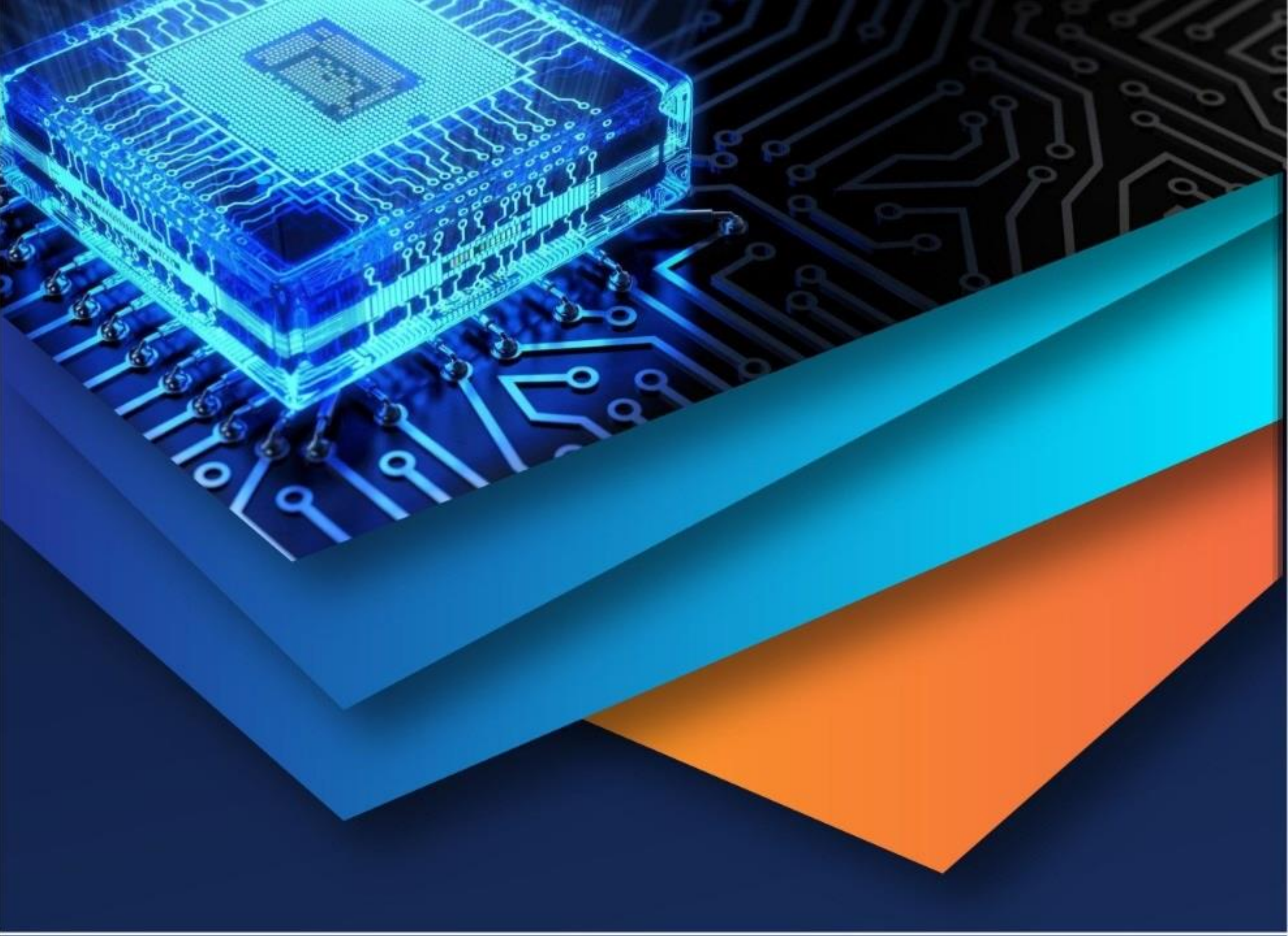

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