

Image-Based Breed Recognition System for Cattle and Buffaloes of India: A Review of Computer Vision and Deep Learning Approaches

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Abstract- Reliable breed identification underpins conservation, breeding, registration and traceability in India's cattle and buffalo sectors, yet it still depends largely on expert visual judgement. This review examines how computer vision and deep learning have been applied to image-based breed recognition of Indian cattle and buffaloes. A structured narrative search was carried out in October 2026, and 17 records were examined: studies on Indian breeds, adjacent non-Indian breed-classification and identification work, a public dataset, and an earlier systematic review of cattle identification. Reported accuracies for Indian cattle range from 72.5% for the visually similar Tharparkar and Hariana pair to about 95% for a lightweight CNN on four zebu breeds, while a YOLOv12 system covering 15 breeds reported 69.8% mAP at IoU 0.5. These figures cannot be compared directly because datasets, class definitions, data splits and metrics differ. No peer-reviewed, breed-level study of Indian buffaloes was identified, and the buffalo evidence is limited to a muzzle-based individual-identification study from Türkiye. Recurrent weaknesses include small and imbalanced datasets, unclear animal-level splitting, absent external validation, internal inconsistencies in reporting, and little attention to crossbreeds, explainability and low-cost deployment. We synthesise these gaps and outline a conceptual, not yet validated, framework that combines image-quality control, multi-view fusion, uncertainty-aware output and expert verification.

Keywords— Cattle; Buffalo; Breed recognition; Deep learning; Transfer learning; Indian livestock breeds; Computer vision

I. INTRODUCTION

India holds a very large and diverse population of cattle and buffaloes, and the Indian Council of Agricultural Research (ICAR) now lists 258 registered indigenous breeds across all livestock species, plus four synthetic breeds [1]. Correct breed identification matters for several practical reasons: it supports conservation of indigenous genetic resources, informs mating and breeding decisions, enables breed-specific schemes and registries, and contributes to traceability along the dairy and meat chains. In the field, breed is usually judged by a veterinarian, a field-level worker or an experienced farmer from coat colour, horn shape, hump, dewlap, ear shape and body conformation. This judgement is subjective, difficult to scale, and hard to audit.

Computer vision offers a way to standardise this task. Since convolutional neural networks (CNNs) became

practical for small-data problems through transfer learning [2], [3], [4], a growing number of studies have tried to classify breeds from photographs. Much of the activity, however, appears in conference papers, student projects and journals of uneven visibility, and the reported figures are rarely comparable. A review that separates strong evidence from weak evidence is therefore more useful at this stage than a catalogue of accuracies.

The objectives of this review are: (i) to map the image-based methods applied to breed recognition of Indian cattle and buffaloes; (ii) to describe available datasets and their limits; (iii) to examine how models were evaluated and whether results can be compared; (iv) to identify obstacles to deployment in Indian farming conditions; and (v) to propose evidence-based research gaps and a conceptual framework for future work. The scope is breed-level recognition. Individual-animal

identification, for example by muzzle pattern, is included only as adjacent context [5], [6].

II. BACKGROUND OF INDIAN CATTLE AND BUFFALO BREEDS

Indian cattle are broadly divided into indigenous humped zebu (*Bos indicus*) breeds, exotic taurine breeds such as Holstein Friesian and Jersey, and crossbreeds between them. Well-known zebu dairy and dual-purpose breeds include Gir, Sahiwal, Red Sindhi, Tharparkar, Hariana and Kankrej. The principal buffalo breeds include Murrah, Jaffarabadi, Mehsana, Surti and Nili-Ravi. These breeds are associated with particular home tracts, and breed descriptors are maintained by ICAR institutes such as the National Bureau of Animal Genetic Resources (NBAGR). Breed registration is continuing: an August 2026 ICAR announcement brought the registered total to 262 breeds, including four new cattle breeds and one new buffalo breed [1].

Two features of this background shape the recognition problem. First, several indigenous breeds are visually close. For instance, Tharparkar and Hariana are both described as white or grey zebu breeds [7], and confusion among zebu breeds such as Tharparkar, Ongole, Gir and Sahiwal was the main error source in one recent study [8]. Second, a large part of the national herd is not of a described breed, and crossbreeding is common. A closed-set classifier that must assign every image to one of N breeds therefore has no natural way to say that an animal is a crossbred or an undescribed type. This point is discussed further in Sections IX and X.

III. LITERATURE SEARCH STRATEGY AND REVIEW METHODOLOGY

Publisher platforms (Springer, MDPI, ICAR e-publications, IJERT and others), PubMed, IEEE DataPort, Zenodo, DergiPark and arXiv were searched with terms combining cattle, bovine, buffalo and livestock with breed recognition, breed classification, deep learning, CNN, transfer learning, ResNet, MobileNet, EfficientNet, YOLO, vision transformer, muzzle, dataset, India and individual

breed names. Publications from 2021 to 2026 were prioritised, while earlier studies were retained where they established a method or survey still in use. Studies were included when they addressed Indian cattle or buffalo breed recognition directly, or provided closely related breed-classification or identification methods and datasets. Each study record was verified against a publisher page, DOI record or repository entry; one PubMed record whose details could not be retrieved is retained by title only and is labelled as such, while code repositories, listings from low-cost journals and unconfirmed records were excluded. Because Scopus, Web of Science and IEEE Xplore searches could not be logged, the review is structured and narrative rather than systematic.

IV. EVOLUTION OF IMAGE-BASED BREED RECOGNITION TECHNIQUES

Early vision-based work on cattle relied on handcrafted descriptors such as local binary patterns (LBP), SIFT and SURF, fed to classical classifiers such as support vector machines, k-nearest neighbours and artificial neural networks. A systematic review of cattle identification found that the machine-learning studies it covered addressed identification only, that muzzle prints and coat patterns were the most distinctive cues, and that deep-learning studies were the ones to handle both detection and identification [5]. That review concerns individual identification rather than breed, but it documents the same transition from engineered features to learned features.

The adoption of deep CNNs changed practice mainly through transfer learning. Residual networks [2], light MobileNet-type models designed for mobile hardware [3] and compound-scaled EfficientNets [4] can be fine-tuned from ImageNet-pretrained weights on a few thousand images. In a five-breed taurine dataset, ResNet-50 reached 95% with pretrained weights against 81% from scratch [11], which is consistent with the general expectation that pretraining matters most when data are scarce. Object detectors in the YOLO family [12] bring localisation and classification together, which is attractive for photographs taken in cluttered farm

settings. Vision transformers [13] are now common in general image recognition, but no application of them to Indian cattle or buffalo breed recognition was found among the records we examined.

Explainability tools have entered the literature more recently. Grad-CAM [14] was used in a 2026 EfficientNet-B3 study to inspect which regions drive breed predictions [15]. Among the Indian studies examined here, two used lightweight designs aimed at low-resource deployment [7], [16], and one applied segmentation before classification [7].

V. CRITICAL REVIEW OF EXISTING RESEARCH

1. Studies on Indian cattle breeds

Table 1 summarises the records examined. The most carefully described Indian study is that of Arya et al. [7], who addressed the hardest sub-problem, separating Tharparkar from Hariana. They used a lightweight segmentation network of about 3.27 million parameters (about 618 ms per image) followed by a multi-input CNN on masked colour and grey-scale images, and reported 72.5% overall classification accuracy, with F1 of 71.8% and 73.2% for the two breeds. The split appears to be at animal level (95 cows per breed for training and 20 for testing), which is methodologically sound, but the paper's text and its own table disagree on animal numbers. The modest accuracy is informative in itself: when breeds are visually close and the split is by animal, a lightweight model does not reach the 90%+ figures seen elsewhere.

Devi et al. [16] compared a lightweight CNN with MLP, random forest and kNN on four zebu breeds (Sahiwal, Red Sindhi, Hariana and Tharparkar) photographed from frontal and left-side views, giving eight view-breed classes. The CNN reached about 95%, the MLP and random forest about 90%, and kNN about 88%, with PCA used to reduce dimensionality. The abstract does not state dataset size or split, so the result cannot be placed against others. The result does suggest that classical models are not far behind on this task, which deserves testing on harder, field-collected data.

Priyanka et al. [8] fine-tuned EfficientNetV2-S on 2,427 images from a Kaggle dataset covering 10 cattle breeds, using a stratified 70/15/15 split, focal loss, a weighted sampler and test-time augmentation, and reported 90.68% test accuracy. Their breed list mixes Indian zebu breeds (Gir, Tharparkar, Sahiwal, Ongole, Mewati) with exotic and other breeds (Holstein Friesian, Jersey), which makes the task easier than a zebu-only one, and their confusion analysis shows that errors concentrate among zebu breeds. The source also contains internal inconsistencies, such as differing macro-F1 and lowest per-class F1 values between abstract and table, and describes training as both 'from scratch' and from ImageNet-21k pretraining. A stratified image-level split from a public Kaggle dataset also leaves open whether near-duplicate images of the same animal appear in both training and test sets.

Gupta et al. [17] reported 80.81% validation accuracy for an EfficientNetV2 and ResNet50V2 ensemble on 1,340 images of 10 Indian breeds. Only the abstract page was accessible, so the breed list, split and test protocol are not verified here, and the figure is a validation, not a test, accuracy. Chauhan et al. [18] built a web system around YOLOv12 trained on 3,683 annotated images of 15 breeds and reported 69.8% mAP at IoU 0.5, precision 62.4% and recall 63.7%, with breed-level accuracies of up to 87%. The paper's own per-breed table shows far lower values for some breeds (for example 0% for Ongole), and its breed lists disagree between sections. Claims about field-worker workload reductions are not supported by a described measurement protocol in the material we saw.

Chavhan et al. [19] addressed the Deoni breed with a frozen YOLOv5s feature extractor and a Siamese network trained with triplet loss. Reported accuracy was 94.0 to 96.5%, against 55 to 60% for contrastive loss, using 450 Deoni and 450 non-Deoni images, where the negatives came from a public Kaggle cow and buffalo dataset. This is a one-versus-rest verification design, which is easier than multi-class recognition, and its metric-learning approach is notable because it can in principle extend to new breeds without full retraining. The paper's confusion-matrix tables contain duplicate labels and

inconsistent false-rejection rates. Prakash et al. [20] describe a 35-breed system, including Gir, Sahiwal, Tharparkar, Murrah, Mehsana and Jaffarabadi, with about 3,575 images across a strongly imbalanced table (from 366 images for Sahiwal to 22 for Kherigarh). It reports no measured results; the accuracy figures it gives are expected values from a project still in progress, and must not be treated as findings. A 2026 survey [21] proposes an integrated platform for breed identification, pedigree monitoring and inbreeding assessment, but reports no performance data in the page we could access.

2. Evidence on buffaloes

We did not identify a peer-reviewed study that classifies Indian buffalo breeds such as Murrah, Jaffarabadi, Mehsana, Surti or Nili-Ravi from images and reports a measured result. Buffaloes appear in a few multi-species systems: the YOLOv12 system [18] and the planned 35-breed system [20] include buffalo breeds, and the IEEE DataPort collection has Surti and a 'Desi Buffalo' folder [22]. The one empirical buffalo study found, by Ermetin and Örnek [6], identified individual water buffaloes from muzzle patterns in Türkiye, with AlexNet, SqueezeNet, GoogLeNet and ResNet101 all above 99% accuracy. That is a different task (individual identification, not breed) on a different population. It used 4,263 images with a random 80/20 split, 11 animals according to one passage and 40 according to

another, and its authors note limited generalisability. Its near-perfect scores are most plausibly explained by images of the same animal appearing in both training and test sets, so it should not be read as evidence for breed recognition. Buffalo breed recognition from images in India is thus effectively an open research area, and this absence of evidence is itself a finding of this review.

3. Adjacent non-Indian studies

Several studies on non-Indian breeds illustrate method choices. Gupta et al. [23] used YOLOv4 on 1,835 web-mined images of eight breeds and reported 81.07% test accuracy and a kappa of 0.78. Li et al. [24] proposed RTDETR-Refa, a real-time detector with a ResNet18 backbone, reporting 91.6% average accuracy on its classification set, with the dataset not identified in the page we accessed. Çakmakçı et al. [25] classified Holstein, Simmental and Brown-Swiss cows from 2,004 UAV images, where Xception was best and ResNet50 weakest (accuracy 0.74). Rijal and Khotimah [11] and Mukasheva et al. [15] used taurine breeds with public Kaggle data. A PubMed-indexed study of attention-augmented transfer learning for phenotypically similar tropical *Bos indicus* breeds exists [10] and is directly relevant, but we could not retrieve its details and therefore make no claims about its content.

Table 1. Studies examined, with reported results (E = evidence level: F full text consulted, A abstract or landing page only)

Ref.	Breeds / scope	Data	Method	Reported result and key caveat	E
[7]	Tharparkar vs Haryana (India)	120 cows/breed, 4 images each; split by cow	Lightweight CNN segmentation + multi-input CNN	Accuracy 72.5%; F1 71.8 / 73.2%. Text and table differ on animal numbers	F
[16]	Sahiwal, Red Sindhi, Haryana, Tharparkar; 2 views (India)	Not reported	Lightweight CNN vs MLP, RF, kNN (PCA)	CNN ~95%; MLP, RF ~90%; kNN ~88%. Split not reported	A
[19]	Deoni vs non-Deoni (India)	450 + 450 images; 80/20	YOLOv5s features + Siamese, triplet loss	Accuracy 94.0–96.5%. One-vs-rest design; inconsistent confusion tables	F
[8]	10 breeds, zebu and exotic	2,427 images; stratified 70/15/15	EfficientNetV2-S, focal loss, TTA	Test accuracy 90.68%; macro F1 0.90. Image-level split; errors among zebu breeds	F

Ref.	Breeds / scope	Data	Method	Reported result and key caveat	E
[17]	10 Indian breeds (list not verified)	1,340 images	EfficientNetV2 + ResNet50V2 ensemble	Validation accuracy 80.81%. Test protocol not reported	A
[18]	15 cattle and buffalo breeds (India)	3,683 annotated images	YOLOv12, cloud deployment	mAP@0.5 69.8%; P 62.4%; R 63.7%. Per-breed table inconsistent with headline	F
[20]	35 cattle and buffalo breeds (India)	~3,575 images; imbalanced	CNN / ResNet-based, web app	No measured results; only expected values. Not evidence	F
[21]	Survey / platform proposal	None	Review; proposed platform	No metrics reported	A
[23]	8 non-Indian breeds (incl. Gyr)	1,835 web-mined images	YOLOv4	Test accuracy 81.07%; kappa 0.78	A
[24]	Multi-breed cattle (not stated)	Not identified	RTDETR-Refa (ResNet18 base)	91.6% average accuracy on its classification set	A
[11]	5 taurine breeds	1,251 images	ResNet-50, pretrained vs scratch	95% pretrained; 81% from scratch	A
[15]	Taurine breeds (Kaggle)	Not reported	EfficientNet-B3 + Grad-CAM	Holstein 86%; Ayrshire/Red Dane confused. Overall not reported	A
[25]	Holstein, Simmental, Brown-Swiss; UAV	2,004 images; 70/20/10	Custom DCNN, Xception, VGG19, ResNet50	Xception 1.00; custom 0.98; ResNet50 0.74	A
[6]	Water buffalo, individual ID (Türkiye)	4,263 images; random 80/20	AlexNet, SqueezeNet, GoogLeNet, ResNet101	≥99.3% accuracy. Not breed recognition; probable leakage; 11 vs 40 animals	F
[5]	Cattle identification review	Review	Systematic review	Not a performance study	A

VI. COMPARATIVE ANALYSIS OF ALGORITHMS AND MODEL ARCHITECTURES

Table 2 compares model families, drawing only on what the examined studies report. The comparison is qualitative because no study evaluated several architectures on one shared Indian benchmark with a common protocol.

The only like-for-like comparisons within a single study are those of Devi et al. (CNN vs MLP, random forest, kNN) [16], Rijal and Khotimah (pretrained vs

scratch ResNet-50) [11], Çakmakçı et al. (custom CNN vs Xception, VGG19, ResNet50) [25] and Chavhan et al. (triplet vs contrastive loss) [19].

These support three modest points: pretrained weights help in small-data settings; the best architecture varies with the dataset, so rankings do not transfer; and loss function and training protocol can matter as much as backbone.

Table 2. Comparison of model families as evidenced in the examined studies

Model family	Evidence in examined studies	Strengths	Limitations
Handcrafted features + classical ML	kNN, RF, MLP at 88–90% on 4 zebu breeds [16]; LBP, SIFT, SURF in identification [5]	Low compute; simple to deploy	Sensitive to pose and lighting; ceiling vs CNN in [16]
Custom or lightweight CNN	[7], [16]	Small size (~3.27 M parameters in [7]); fits low-cost devices	72.5% on near-identical breeds [7]; benefit of pretraining forgone
Transfer-learned CNN (ResNet, EfficientNet, MobileNet)	[8], [17], [11]	Strong with few thousand images; pretrained 95% vs scratch 81% [11]	Mostly closed-set; image-level splits; MobileNet not benchmarked on Indian data in records examined
Detectors (YOLO, RT-DETR)	[18], [23], [24]	Localise and classify in cluttered scenes	69.8% mAP on 15 breeds [18]; mAP differs from accuracy
Metric learning (Siamese, triplet)	[19]	Extensible to new breeds without full retraining	Tested one-vs-rest only; triplet vs contrastive gap large
Vision transformers	None found for Indian breeds [13]	Strong general-purpose backbones	Data-hungry; not evaluated here, so no claim
Explainability (Grad-CAM)	[15]	Shows regions driving predictions [14]	No Indian study using it among those examined

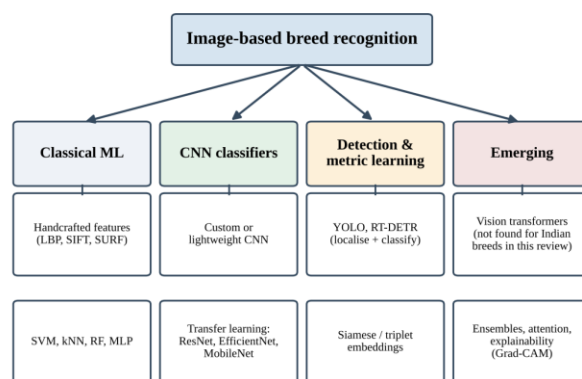


Fig. 2. Taxonomy of image-based breed recognition approaches (original diagram).

VII. DATASET AVAILABILITY, QUALITY AND LIMITATIONS

Public data are thin. Two sources recur in the studies we examined: Kaggle collections of Indian and other cattle breeds (for example, a community dataset of

Indian cattle breeds [26]) and one 2026 IEEE DataPort collection with six classes (Gir, Kankrej, Desi Cow, Surti, Banni and Desi Buffalo) whose image count and licence are not stated on its page and whose files require a subscription [22]. Several studies draw on the same Kaggle sources [19], [8], so apparently independent results may rest on overlapping data. Table 3 summarises dataset characteristics.

Quality issues follow from how these data are assembled. Web-mined or crowd-sourced images vary in label reliability, and none of the studies we examined describes expert verification of labels by NBAGR-trained staff. Class imbalance is visible in the 35-breed table [20]. ‘Desi Cow’ and ‘Desi Buffalo’ are not breeds, so these classes mix many genotypes. Image-level random splits, used or implied in several studies [8], [6], risk placing near-identical frames of one animal in both training and test sets. Only Arya et al. [7] describe a split by animal. Datasets that do not record animal identifiers, farm, season and camera cannot support such splits at all.

Table 3. Datasets and data practices identified

Source	Content	Access	Limitations
IEEE DataPort [22]	Gir, Kankrej, Desi Cow, Surti, Banni, Desi Buffalo; real-world images	Subscription; image count and licence not stated	'Desi' classes are not breeds; labelling method not stated
Kaggle collections [8], [15], [26]	Indian and other cattle breeds, community uploaded	Public	Label provenance and duplicates unclear; reused across studies [19], [8]
Study-specific sets [7], [18], [20]	120 cows/breed [7]; 3,683 images, 15 breeds [18]; ~3,575 images, 35 breeds [20]	Availability not stated	Imbalance [20]; no animal IDs except [7]
Buffalo muzzle images [6]	4,263 images of water buffalo, Türkiye	On request	Individual ID, not breed; small farm sample

VIII. PERFORMANCE EVALUATION AND COMPARISON

Accuracy, precision, recall and F1-score are the usual metrics. With P as precision and R as recall,

$$F1 = 2PR / (P + R) \quad (1)$$

and macro averaging gives each breed equal weight, which matters when classes are imbalanced. Overall accuracy can hide poor performance on rare breeds, as Chauhan et al.'s per-breed table suggests [18]. Detection studies report mAP at an IoU threshold, which is not interchangeable with classification accuracy.

Table 4. Reported performance with evaluation conditions (values as reported; not directly comparable)

Ref.	Task	Headline metric	Cost reported	Condition limiting comparison
[7]	2-breed zebu classification	Accuracy 72.5%; F1 $\approx$ 72%	3.27 M params; 618 ms (segmentation)	Animal-level split; very similar breeds
[16]	8 view-breed classes	Accuracy $\sim$ 95% (CNN)	Not reported	Dataset size and split not reported
[19]	Deoni vs rest	Accuracy 94.0–96.5%; F1 0.96/0.97	Not reported	Binary; negatives from public set
[8]	10-breed classification	Test acc. 90.68%; macro F1 0.90	Not reported	Zebu and exotic mixed; image-level split
[17]	10-breed classification	Validation acc. 80.81%	Not reported	Validation, not test, accuracy
[18]	15-breed detection	mAP@0.5 69.8%; P 62.4%; R 63.7%	0.8–1.2 s incl. network	Detection metric; internal inconsistencies
[6]	Buffalo individual ID	Accuracy $\geq$ 99.3%	Not reported	Different task; probable leakage

Table 4 lists reported results together with the conditions under which they were obtained. Three observations follow. First, the highest figures come from settings that are easier than real breed recognition: few classes, a binary or one-versus-rest design [19], exotic breeds mixed with zebu breeds [8], or possible leakage [6]. Second, the figures from harder settings are much lower: 72.5% for two near-identical zebu breeds [7] and 69.8% mAP for a 15-breed detection system [18]. Third, computational cost is almost never reported. The only figures found are about 3.27 million parameters and 618 ms per image for the segmentation network in [7], and a 0.8 to 1.2 s end-to-end latency including network delay for the cloud system in [18]. Memory, energy and on-device behaviour on low-cost phones are not reported in any study we examined.

Generalisation was not tested externally in any study. No record described training on one set of farms and testing on others, or evaluation across seasons, cameras or states. Reported accuracy should therefore be treated as in-distribution performance on a single dataset.

Challenges and Limitations in Real-World Indian Farming Conditions

The following challenges are drawn from the studies examined and from the structure of the problem. We distinguish what the evidence shows from what remains a plausible hypothesis.

Visually similar breeds. Established in the evidence: errors concentrate among white or grey zebu breeds [7], [8]. Plausible but untested: fine cues such as hump shape, ear shape or facial profile may carry more information than coat colour, and may need higher resolution or part-based models.

Crossbreeding and undescribed animals. Not addressed in any examined study. All classifiers

examined here are closed-set, so a crossbred is forced into one of the trained classes. This is a design gap, and its size in practice is unknown.

Class imbalance and data scarcity. Visible in [20] and in per-class F1 spread in [8]. Mitigations used include focal loss, weighted sampling and augmentation [8], but their effect has not been compared on a common dataset.

Image quality, lighting, pose and background. Acknowledged by authors [20] but not quantified in any study. Farm images contain occlusion by other animals, partial views, dust and variable sunlight. Only Arya et al. [7] explicitly segment the animal from the background.

Data leakage and validation. Image-level splits, unreported splits and the absence of external test sets make most accuracy figures optimistic by an unknown amount.

Explainability and trust. Only one examined study used saliency maps, and for non-Indian breeds [15]. Field workers and registries need to know why a label was assigned and how confident the system is.

Deployment. Studies that deploy do so through web interfaces and cloud inference [18], [20], which depends on connectivity. Lightweight on-device models [7], [16] are better matched to rural conditions, but no study reports measured performance on low-cost phones.

Research Gaps and Future Directions

Table 5 lists gaps that follow from the comparison above. We label each as established (supported by what the examined studies show or fail to show) or hypothesis (a plausible direction not yet tested).

Table 5. Research gaps and future opportunities

#	Gap	Basis in reviewed evidence	Opportunity	Status
1	No peer-reviewed buffalo breed-recognition benchmark	None found for Murrah, Jaffarabadi, Mehsana, Surti, Nili-Ravi; buffalo only in multi-species systems [18], [20]	Expert-labelled buffalo breed dataset and baselines	Established (within this search)

#	Gap	Basis in reviewed evidence	Opportunity	Status
2	No shared expert-verified benchmark	Kaggle data reused [19], [8]; DataPort details missing [22]	Public multi-state dataset with animal, farm and camera IDs and fixed splits	Established
3	Weak validation design	Image-level splits [8], [6]; only [7] animal-level; no external test sets	Animal- and farm-level splits; external-site tests	Established
4	Visually similar zebu breeds	72.5% [7]; confusion in [8]	Part-based, high-resolution or multi-view models	Established problem; solutions are hypotheses
5	Crossbreds and undescribed animals	All studies closed-set	Open-set or uncertainty-aware classification	Established gap; benefit untested
6	Poor reporting and reproducibility	Inconsistencies in [7], [19], [8], [18]; projections only [20]	Reporting checklist; released code and splits	Established
7	No low-cost device evidence	Cost mostly unreported; cloud inference [18]	Quantised models tested on budget phones	Hypothesis
8	Little explainability	Grad-CAM only in non-Indian study [15]	Saliency and calibrated confidence for field users	Hypothesis
9	Transformers and foundation models untested	None found for Indian breeds	Benchmark ViT and self-supervised backbones	Hypothesis

IX. PROPOSED CONCEPTUAL FRAMEWORK

Fig. 3 proposes a framework for a field-usable recognition system. It is a design proposal derived from the gaps in Table 5; it has not been implemented or validated, and its components should be read as hypotheses to be tested. The framework starts from a guided capture protocol (front, side and rear views, with herd metadata) and a quality gate that asks for recapture when an image is blurred, badly lit or does not contain the whole animal. A detector and segmenter isolate the animal; a lightweight, quantised classifier then fuses the available views and produces calibrated class probabilities together with an explicit 'uncertain or crossbred' outcome. Saliency maps support review. Low-confidence cases are routed to a human expert, and verified labels, linked to a herd register, feed periodic retraining. Evaluation should use animal-level and farm-level splits and at least one external site.

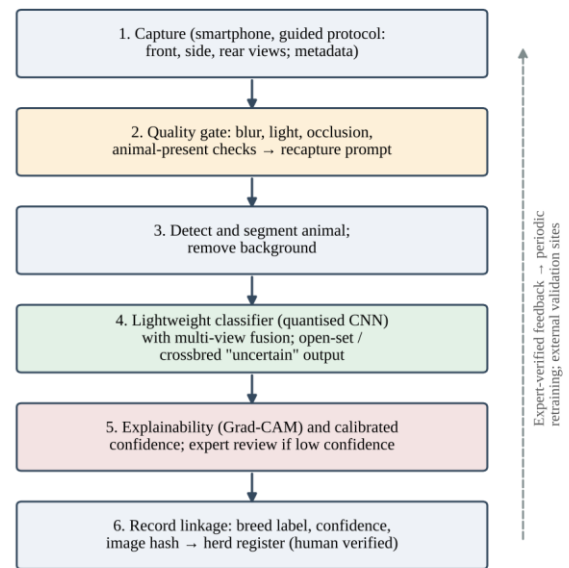


Fig. 3. Proposed conceptual framework for an image-based breed recognition system (design proposal; not validated).

Discussion and Critical Synthesis

The evidence base for image-based recognition of Indian breeds is young, small and uneven. The

studies we examined agree on the direction of the effect (transfer-learned CNNs work reasonably well on a handful of breeds), but they disagree on magnitude, and the disagreement is largely explained by what was measured. Accuracies above 90% come from settings with few classes, mixed exotic and zebu breeds, a binary design or possible leakage; the two studies that tackled close zebu breeds or many classes reported 72.5% and 69.8% mAP. The honest summary is that breed recognition is feasible under controlled conditions and unproven under field conditions.

Three observations deserve emphasis. First, reporting quality is a limiting factor. Internal inconsistencies in four of the examined papers [7], [19], [8], [18], one paper reporting only expected results [20], and incompletely described splits mean that numerical comparison across the literature is unreliable. Second, buffalo breed recognition is almost absent from the evidence, despite the economic importance of buffalo milk in India; the one empirical buffalo study found concerns individual identification abroad [6]. Third, the field lacks a shared, expert-labelled, animal-identified benchmark with predefined splits. Without it, progress cannot be measured, and claims cannot be replicated.

This review has limitations. The search did not use subscription databases, was not run as a formal systematic review, and found records through general web-search tools, so relevant papers may have been missed. Several records were read at abstract level only, and retrieved text was summarised by tools. Venue quality was not assessed for all records. The conclusions about the absence of buffalo studies and of vision-transformer studies are conclusions about what we found and not proof that none exist.

X. CONCLUSION

Image-based breed recognition of Indian cattle and buffaloes is promising but not yet field-ready. The reviewed Indian cattle studies report accuracies from 72.5% to about 95%, with the strongest figures arising from easier settings and the weakest from

visually similar breeds or many classes. Buffalo breed recognition has no measured, peer-reviewed evidence in the records we examined. The most valuable next steps are an expert-labelled, animal-identified, multi-state benchmark with animal-level and farm-level splits; open-set handling of crossbreds; transparent reporting of metrics, splits and computational cost; explainability; and tests on low-cost devices in real farms. We hope that the gap analysis and the proposed, unvalidated framework help to orient that work.

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