AI-Driven Framework for Cattle Breed Identification to Support Sustainable Livestock and One Health

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Abstract: In developing nations, livestock has a significant impact on public health and food security, making them a critical source of income, nutrition, and agricultural resilience. The identification of breeds accurately remains a challenge for small-scale producers, resulting in suboptimal nutrition, inadequate disease control, and reduced sustainability. This research establishes an effective framework for cow breed detection via transfer learning, assessed on an enhanced dataset of 6,040 photos spanning five breeds. A comparison was conducted between four architectures: LaVin-DiT, CoAtNet, EfficientNetV2, and lightweight DAMambaNet. EfficientNetV2 attained exceptional accuracy (95.6%), but DAMambaNet provided practical benefits (6.18 MB, 0.5 ms inference) for mobile deployment in rural areas. Advancing One Health objectives, the framework facilitates precise breed identification to inform reproduction, vaccination, and nutritional decisions. Field validation continues to be indispensable for verifying the agronomic advantages.

Keywords: Public Health, Sustainable Livestock, One Health, Breed Detection, Transfer Learning.

1. Introduction

Millions of small-scale farmers depend on cattle for food, income, and traditional significance. Although precise breed identification is frequently perceived as a straightforward task, it remains a difficult endeavor to execute in practice. Food security and household stability can be further complicated by incorrect breed recognition, which can result in mismatched rations, inadequate vaccination schedules, poor genetic selection, and ineffective disease surveillance [19].

Accurate breed identification is not just technical; it can help create livestock systems that are safer and more effective. This is because One Health highlights the linkages between human, animal, and environmental health [16],[22],[23]. Traditional methods like as eye

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inspection, ear tagging, and branding are ineffectual due to inadequate lighting, overlapping phenotypes, and tag loss. Even promising biometric techniques are confronted with implementation complexity and accuracy limitations [12].

The solution is provided by artificial intelligence (AI), specifically deep learning models that are capable of deriving high-dimensional image features that are undetectable by humans, such as coat patterns, facial geometry, and horn shapes. Deep learning models have been demonstrated to be capable of supporting breed classification and related health monitoring from images in recent research. Nevertheless, their deployment in rural areas is restricted by the substantial data and compute requirements of many models [20],[21],[4].

By modifying pre-trained models to domain-specific datasets, transfer learning potentially enables deployment on entry-level smartphones, thereby addressing these challenges [1],[11]. This research presents a strategy for identifying cow breeds tailored for rural environments. Using an updated dataset of 6,040 photos from five breeds, we assess four contemporary architectures (LaVin-DiT, CoAtNet, EfficientNetV2, and DAMambaNet) to examine trade-offs between accuracy, model size, and inference time. The framework underscores practical implementation: a user captures an image, obtains an on-device prediction, and integrates that information into decisions on feeding, vaccination, and breeding. Although we exhibit model effectiveness in controlled environments, it is crucial to validate real-world decision impacts and public health outcomes, along with substantiating these advantages through field studies, as a significant avenue for future research.

Focusing on model efficiency, our methodology illustrates AI's capability in resource-limited settings to advance collective health goals [2]. Essential practical attributes encompass offline capability, model transparency, and user-friendly interfaces [9].

2. Related Work and Research Gap

A variety of computer vision and machine learning techniques have been employed in recent studies to detect cattle and classify breeds; however, the majority of these studies have concentrated solely on technical performance without taking into account the One Health perspective. Gupta et al. and Yılmaz et al. employed YOLOv4 for bovine breed detection [7],[24], but their accuracy was relatively low at approximately 81%. Sarızeybek and Işık combined VGG-16 with Random Forest to enhance their performance [15], but their accuracy was only 88.77%. Conventional models, such the SVM method by Duraiswami et al. [5], did not utilize deep learning and achieved an accuracy of 93.3%; the research did not assess alignment with integrated animal-human-environment health objectives. Likewise, Qiao and Tang et al. attained intermediate accuracy (about 93% and 89%, respectively) but were constrained by limited datasets and substantial processing expenses [13],[18].

None of the current studies employed a One Health-oriented approach, which facilitates targeted disease surveillance, optimized feeding for zoonotic risk mitigation, and sustainable breeding practices, nor did they fully utilize advanced deep learning architectures for effective cattle monitoring in resource-limited settings. To rectify these deficiencies, we assess EfficientNetV2 (and baselines) on a five-breed dataset with systematic augmentation, attaining superior reported accuracy compared to numerous previous studies and elucidating how such tools could correspond with One Health priorities.

3. Methodology

To classify cattle breeds in remote areas with limited resources, we built a deep learning system. The methodology includes dataset preparation, preprocessing, model training by transfer learning with ImageNet-pretrained weights, and thorough performance evaluation.

3.1 System Architecture and Workflow

The system consists of an AI inference module and a data pipeline. Images obtained from mobile devices in rural environments are subjected to preprocessing and augmentation prior to model inference. The inference module facilitates rapid decision-making for breeding, health, and sustenance by providing breed predictions through an intuitive mobile interface upon completion of the training regimen. All procedures are encapsulated in Fig. 1.

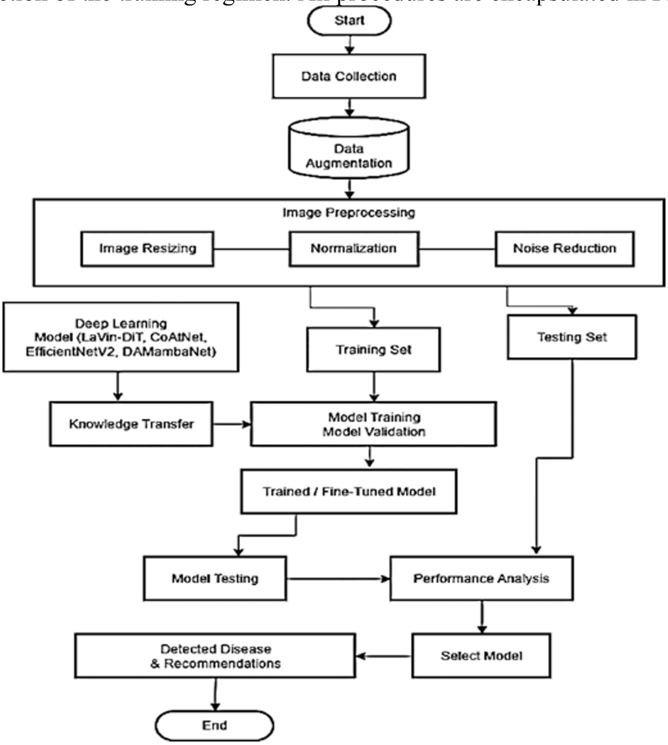

Fig. 1. System workflow: data capture (mobile), preprocessing and augmentation, model inference (on-device/cloud), and decision support outputs.

3.2 Dataset Description

The dataset comprises 1,208 images from the Kaggle Cattle Breeds Dataset [14], encompassing five breeds: Ayrshire, Brown Swiss, Holstein Friesian, Jersey, and Red Dane cattle. Images represent a variety of real-world settings, including lighting, angles, and backdrops. The dataset was divided into training, validation, and test sets (80%/10%/10%) utilizing stratification by breed to guarantee balanced representation across subgroups.

3.3 Preprocessing and Data Augmentation

Images were resized to (224×224) pixels and normalized to $([0,1])$:

$$x_{\text{norm}} = \frac{x - x_{min}}{x_{max} - x_{min}} \quad (1)$$

where x_{norm} *is* the normalized pixel value, x is the original pixel value, and x_{min}, x_{max} typically 0 and 255.

Denoising was optionally employed to diminish background noise and highlight prominent characteristics (coat patterns, facial structure). Data augmentation increased the effective training set to 6,040 images using random horizontal and vertical flips (p=0.5), rotations (±15°), and ColorJitter adjustments (brightness/contrast ±0.2).
Note: augmented images do not increase real-world data diversity.

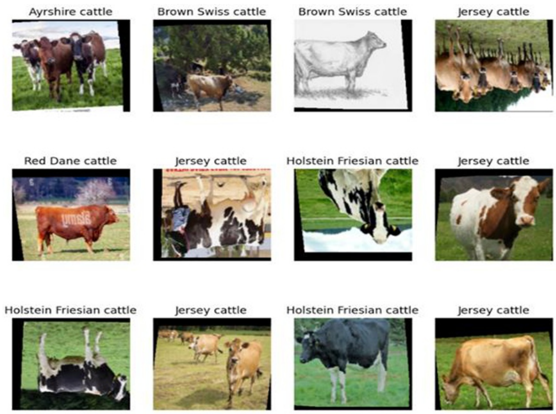

Fig. 2. Examples of augmented images (random flips, rotations, brightness/contrast).

3.4 Model Selection

Four architectures were evaluated:

- **LaVin-DiT:** Vision Transformer for long-range spatial dependencies [22].
- **CoAtNet:** CNN-Transformer hybrid for local-global feature integration [3].

- **EfficientNetV2:** Scalable CNN with fused-MBConv blocks [17].
- **DAMambaNet:** Lightweight state-space model for edge deployment [6].

EfficientNetV2 was selected for its accuracy-efficiency trade-off and achieved 95.6% test accuracy in our experiments. All models used ImageNet-1k pretraining followed by fine-tuning.

3.5 Training Protocol

Fine-tuning employed the Adam optimizer [8]:

$$\theta_{t+1} = \theta_t - \eta \cdot \frac{\widehat{m_t}}{\sqrt{\widehat{v_t}} + \epsilon} \tag{2}$$

where θ_t is the model parameter at step t, η is the learning rate, $\widehat{m}_t$ and $\hat{v}_t$are the bias-corrected first and second moment estimates of the gradients, and ϵ is a small constant for numerical stability, and categorical cross-entropy loss:

$$\mathcal{L} = -\sum_{i=1}^{C} y_i \log(\widehat{y_i}) \tag{3}$$

where $(C = 5)$ (number of breeds), (y_i) is the true label, and $(\widehat{y_i})$ is the predicted probability.

To balance speed and memory, we used a batch size of 32. Models were trained for up to 100 epochs with early stopping (patience=10) to mitigate overfitting. Training utilized NVIDIA Tesla V100 GPUs.

3.6 Evaluation Metrics

We selected accuracy, precision, recall, F1-score, and ROC AUC to provide complementary views of classification performance across classes:

$$\text{Precision (p)} = \frac{TP}{TP + FP} \tag{4}$$

$$\text{Recall (R)} = \frac{TP}{TP + FN} \tag{5}$$

$$F1 = 2 \cdot \frac{P \cdot R}{P + R} \tag{6}$$

where $(TP), (FP), (FN)$ represent true positives, false positives, and false negatives.

3.7 Design Rationale

Transfer learning was selected due to limited dataset size$((N = 1{,}208))$. EfficientNetV2 was chosen for accuracy and generalization, whereas DAMambaNet was included for its low inference time and small memory footprint, attributes desirable for resource-constrained deployment.

4. Results and Comparative Analysis

Model performance was evaluated using accuracy, precision, recall, F1-score, and ROC AUC metrics on the held-out test set (10% of augmented data). Table 1 presents classification performance across all metrics on the test set (10% of augmented data).

Table 1. Comparative performance of the four models. Values are macro-averaged over

breeds on the held-out test set.

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)	ROC-AUC (%)
LaVin-DiT	87.60	88.24	87.60	87.63	96.81
CoAtNet	92.56	92.85	92.56	92.55	99.00
EfficientNetV2	**95.60**	**95.24**	**95.60**	**95.07**	**98.16**
DAMambaNet	66.94	70.74	66.94	67.11	90.29

These metrics illustrate overall and per-class performance, highlighting each model's strengths and failure modes. Diagonal values in confusion matrices represent correct classifications; off-diagonal values indicate misclassifications.

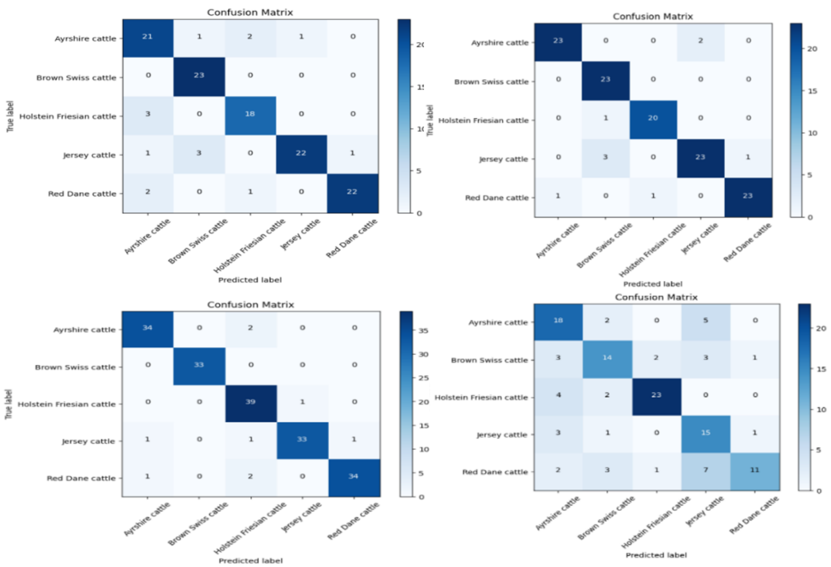

Fig. 3. Confusion matrices for (a) LaVin-DiT, (b) CoAtNet, (c) EfficientNetV2, and (d) DAMambaNet on the test set.

4.1 Model Performance Analysis

DAMambaNet achieved the lowest accuracy (66.94%) and F1-score (67.11%). Despite computational constraints, its ROC AUC of 90.29 indicates reasonable breed discrimination capability.

LaVin-DiT achieved 87.60% accuracy. **For Holstein Friesian cattle, LaVin-DiT achieved high precision and recall (88.9% and 88.0%, respectively).** However, Jersey cattle classification yielded an F1-score of 60%, indicating challenges with morphologically subtle distinctions. ROC AUC (96.81) confirms strong discriminative ability for major breeds.

CoAtNet, which integrates convolutional and transformer components, achieved 92.56% accuracy with balanced precision/recall, demonstrating robust performance across breeds. It achieved perfect Brown Swiss classification and ROC AUC of 99.00—the highest discriminative capability.

EfficientNetV2 delivered superior performance: 95.60% accuracy, 95.24% precision, 95.60% recall, **with an F1-score of 95.07%.** It excelled in generalizability, particularly for Holstein Friesian (89% precision, 97% recall). **Fig.** 4 illustrates example predictions from EfficientNetV2 and corresponding ground truth labels.

Fig. 4. Examples of EfficientNetV2 predictions versus ground truth for the five breeds.

4.2 Comparative Performance Summary

The models exhibit distinct accuracy-efficiency tradeoffs:

- **EfficientNetV2** establishes the accuracy benchmark (95.60%), minimizing misclassification of visually similar breeds through superior feature extraction.
- **CoAtNet** offers balanced performance (92.56%), ideal for fine-grained breed differentiation.
- **LaVin-DiT** provides competitive results (87.60%) but struggles with Jersey cattle distinctions.
- **DAMambaNet** prioritizes edge deployment despite lower accuracy (66.94%).

ROC AUC rankings confirm discriminative superiority: CoAtNet (99.00) > EfficientNetV2 (98.16) > LaVin-DiT (96.81) > DAMambaNet (90.29).

5. Discussion

The test accuracy of EfficientNetV2 was 95.60%, which is 2–15% higher than several prior baselines on this five-breed dataset. The robust in-sample performance, coupled with its small architecture, indicates potential for future mobile implementation in resource-limited settings. This robust in-sample performance, in conjunction with its compact architecture, indicates that it is feasible for future mobile deployment in resource-constrained environments.

Accurate breed identification facilitates targeted vaccination, optimised nutrition, and informed breeding decisions, all of which contribute to the risk of zoonotic diseases, including E. coli O157 and H5N1. This study did not directly evaluate disease outcomes; field investigations are necessary to confirm subsequent health effects [10]. In the One Health continuum, misidentification poses risks of insufficient interventions that could jeopardise animal productivity, human food safety, and environmental sustainability [23].

The proposed AI-driven framework integrating breed identification with One Health decision support is illustrated in Fig. 5.

Fig. 5. The proposed AI-driven framework for cattle breed identification and decision support. The workflow illustrates the transition from (1) field-based image capture to (2) image preprocessing and augmentation, followed by (3) on-device inference using EfficientNetV2 and lightweight DAMambaNet architectures, and finally (4) delivering actionable insights for livestock management within a One Health perspective.

Architectural Perspectives:

The exceptional performance of EfficientNetV2 arises from compound scaling and fused-MBConv blocks, facilitating multi-scale feature extraction for morphologically analogous breeds. The CNN-Transformer hybrid of CoAtNet achieved balanced outcomes, with an accuracy of 92.56%, with notable performance on Brown Swiss cattle. LaVin-DiT (87.60%) revealed the limitations of Transformers in distinguishing Jersey cattle, but DAMambaNet's lightweight architecture sacrificed accuracy (66.94%) for usability in edge deployment. Performance discrepancies indicate architectural priorities: depth versus efficiency. This mobile-first strategy may enhance access to breed categorisation; however, future implementation studies are necessary to assess decision support and infrastructure needs.

Strengths and Limitations

Strengths:

- Highest reported accuracy (95.60%) among evaluated architectures on augmented Kaggle dataset.
- One Health framing positions breed ID as zoonotic surveillance enabler.
- DAMambaNet enables practical mobile deployment (6.18 MB, 0.5 ms inference).

Limitations:

- Five-breed scope limits generalizability; real-world multi-breed testing required.
- Kaggle dataset may not capture all rural conditions (occlusion, extreme lighting).
- No direct measurement of downstream impacts (vaccination efficacy, farmer adoption).
- DAMambaNet accuracy is insufficient for standalone production use.

Future Directions

1. **Field validation** across diverse geographies and breeds.
2. **Federated learning** for privacy-preserving farmer data collection.
3. **IoT integration** with vaccination tracking systems.
4. **Multi-modal inputs** (images + metadata for health status prediction).

This framework advances precision livestock tools for smallholders, balancing technical excellence with deployment feasibility pending real-world validation.

6. Conclusion

This research introduces an AI-based methodology for identifying cow breeds through transfer learning, assessed on an enhanced dataset of 6,040 photos from five breeds. EfficientNetV2 obtained the highest accuracy (95.60%) among the four evaluated architectures, indicating a strong tendency to generalize to morphologically similar breeds. Despite its lower accuracy (66.94%), DAMambaNet provides practical advantages with a 6.18 MB model size and a 0.5 ms inference time, rendering it appropriate for mobile deployment in resource-constrained rural environments.

Accurate breed identification, which is rooted in the One Health framework, provides support for targeted vaccination, breed-specific nutrition, and zoonotic disease surveillance, thereby enhancing the health outcomes of animals, humans, and the environment. The present investigation is confined to controlled dataset conditions; downstream health effects and actual farmer adoption were not directly assessed.

Future research should concentrate on the integration of IoT with livestock health monitoring systems, privacy-preserving data collection through federated learning, and field validation across diverse geographies. In low-resource contexts, this framework establishes a fundamental step toward scalable, AI-assisted livestock management for smallholder farmers.

Declaration of generative AI and AI-assisted technologies in the writing process

The writers used "ChatGPT," "Grammarly," and "QuillBot" to improve the language and readability. The authors take full responsibility for the content of the published paper and have reviewed and revised it as needed after use.

CRediT Authorship Contribution Statement

Shourav Dey: Methodology, Software, Formal Analysis, Writing, Supervision – Original Draft. **Aishwarya Debnath Ayshi:** Data Curation, Formal Analysis, Writing – Original Draft. **Arthy Roy Chowdhury:** Writing – Review and Editing.

All authors have read and approved the final manuscript.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data Availability

The dataset used in this study is publicly available. The primary training dataset (Sahu, 2023) is available via Kaggle. (https://www.kaggle.com/datasets/anandkumarsahu09/cattle-breeds-dataset).

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