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# Image Based Bovine Breed Recognition System

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## Abstract
*Accurate identification of cattle and buffalo breeds is vital for livestock management, genetic conservation, productivity enhancement, and the implementation of national agricultural initiatives. Traditional identification techniques such as ear tagging, branding, and RFID are often invasive, error-prone, and inefficient in large-scale farm environments. Recent advancements in Artificial Intelligence (AI) and Computer Vision (CV) have enabled non-invasive, automated, and highly accurate livestock identification using image-based techniques. This paper presents a comprehensive review of image-based bovine breed recognition systems, analysing research published between 2018 and 2025. It examines the evolution from classical machine learning approaches to advanced deep learning models, including Convolutional Neural Networks (CNNs), transfer learning, attention mechanisms, object detection frameworks (YOLO), and video-based recognition systems. The review also highlights biometric identification methods such as muzzle pattern and facial recognition, lightweight architectures for edge deployment, and the integration of AI models with IoT-enabled smart farm management systems. Finally, key challenges related to dataset limitations, environmental variability, computational constraints, and adoption barriers are discussed, along with future research directions aimed at developing scalable, robust, and real-time AI-driven livestock identification solutions.*

***Keywords:*** *Image-Based Bovine Breed Recognition, Computer Vision, Deep Learning, Convolutional Neural Networks (CNN), Muzzle Pattern Recognition, Facial Recognition, Transfer Learning, Object Detection (YOLO), Precision Livestock Farming, Edge AI*

## 1. Introduction
India and several other agricultural economies rely heavily on cattle and buffaloes for dairy production, agricultural support, and livelihood sustainability. With over fifty recognized indigenous bovine breeds in India, accurate identification and classification play a crucial role in improving productivity, ensuring genetic purity, and supporting national missions such as the Rashtriya Gokul Mission. Traditional identification methods such as ear tagging, branding, and RFID implantation are often invasive, time-consuming, and prone to errors or tampering. As a result, Artificial Intelligence (AI) and Computer Vision (CV) have emerged as transformative technologies in livestock management. The integration of Deep Learning (DL)—particularly Convolutional Neural Networks (CNNs)—has enabled automated, non-invasive, and real-time identification of cattle and buffaloes based on visual and biometric traits like muzzle patterns [2], facial structure, and body morphology. This review paper analyses and synthesizes findings from fifteen research papers published between 2018 and 2025, focusing on the evolution, models, and applications of AI-driven livestock identification [3] systems.

## 2. Evolution of Image-Based Livestock Identification
Initial studies primarily used classical machine learning models such as Support Vector Machines (SVM), K-Nearest Neighbor (KNN), and Random Forest (RF). Anil Kumar et al. (2018) pioneered

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muzzle print-based identification for cattle, demonstrating the uniqueness of muzzle textures similar to human fingerprints. Singh et al. (2024) later utilized morphological features such as horn shape and facial markings, applying SVM and CNN models for buffalo breed recognition. These early studies established the foundation for visual livestock identification [3] but were limited by manual feature extraction and smaller datasets. The shift toward deep learning brought significant progress. CNN-based architectures eliminated manual feature engineering by automatically learning image patterns through multiple convolutional layers. Ghosh et al. (2021) and Vijayalakshmi et al. (2023) demonstrated that CNN and ensemble learning [14] methods outperformed ResNet [6]), achieving 98.42% accuracy in cattle face recognition. Similarly, Shijun Li et al. (2021) presented a lightweight CNN with SE attention modules, maintaining 97.95% accuracy with reduced model complexity [5].

## 3. Recent Advancements in AI-Based Breed Identification

Convolutional Neural Networks (CNNs) remain the foundation of most image-based recognition models due to their ability to automatically extract hierarchical features from raw images [7], [8]. Pan et al. (2022) developed a self-activated CNN model combined with transfer learning for classifying Nili-Ravi buffalo breeds [9], achieving an impressive 93% accuracy. The model used pretrained architectures to enhance feature extraction from limited datasets. Bai et al. (2024) constructed a large-scale biometric dataset of Horqin Yellow Cattle that included measurements like body length, height, and girth. Using CNN-based models, the study successfully correlated physical features with breed identity, enabling more precise animal profiling. These works demonstrated that transfer learning significantly enhances model generalization, reduces training time, and supports applications where labelled datasets are limited (Figure 1). While CNNs excel in static image classification, real-time applications require continuous object detection and tracking [10]. Zhao et al. (2024) employed a hybrid model combining YOLOv5 and DeepSORT for real-time cattle detection and tracking [10] in complex farm environments. The system maintained high accuracy even under varying lighting and movement conditions, effectively distinguishing between overlapping animals.

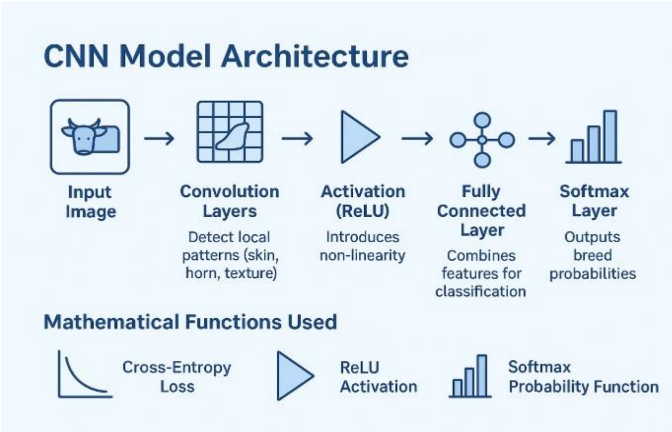

**Figure 1** **CNN Model Architecture**

Munir Ahmad et al. (2023) expanded this approach by integrating YOLOv7 with SIFT-based muzzle feature extraction to ensure accurate and fraud-free livestock insurance verification. The model achieved 100% precision in animal detection and identity matching [11]-[13]. Similarly, Qiao et al. (2021) proposed a unified architecture combining CNN, Bidirectional LSTM (BiLSTM), and self-attention mechanisms for analyzing video sequences. Their model captured both spatial and temporal features of cattle movement, resulting in 93.3% identification accuracy — demonstrating how video analytics can enhance non-invasive monitoring. Recent research has focused on improving accuracy and interpretability using attention-based models. Li, Fang, and Zhao (2025) developed RTDETR-Refa [1], a real-time detection model integrating RepConv and Efficient Multiscale Attention (EMA). This approach enhanced the ability to detect small and overlapping objects while optimizing inference speed. The model achieved 91.6% accuracy in classifying Holstein, Simmental, and Wagyu breeds, outperforming YOLOv8 and EfficientViT. Attention mechanisms enable the network to selectively focus on relevant image regions, improving detection performance in cluttered farm environments. These architectures represent the next generation of deep learning models optimized for real-time multi-breed recognition.

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## 4. Biometric and Facial Recognition Studies

Biometric-based identification has gained significant attention in livestock research as it provides unique, non-invasive, and tamper-proof recognition methods for individual animals. Among the various biometric traits studied, muzzle patterns [2], facial features, and video-based recognition systems have emerged as the most reliable approaches for cattle and buffalo identification. These methods mimic human facial recognition [6] systems, utilizing deep learning architectures such as CNNs, ResNet, SqueezeNet, and attention-based models to ensure precision and scalability across large herds.

### 4.1. Muzzle Pattern-Based Identification

The muzzle print of a bovine is one of the most distinctive biometric traits, comparable to human fingerprints. It remains consistent throughout the animal's life, making it a dependable feature for permanent identification. Anil Kumar et al. (2018) were among the first to explore muzzle pattern [2] analysis for cattle identification, setting the foundation for biometric-based recognition. Later, Munir Ahmad et al. (2023) advanced this concept by combining YOLOv7 object detection with SIFT (Scale-Invariant Feature Transform) algorithms to extract muzzle features. Their AI-driven system achieved 99–100% accuracy, enabling real-time identification and preventing fraudulent insurance claims. The most significant development in this area came from Orhan Ermetin and Humar Kahramanlı Örnek (2025), who utilized a deep-learning-based CNN approach to identify buffaloes through muzzle pattern [2] images. Their study employed four CNN architectures—AlexNet, SqueezeNet, GoogLeNet, and ResNet101—and found that SqueezeNet achieved the highest accuracy of 99.88%, with precision and F1-scores nearing perfection. The authors emphasized that muzzle-based biometric systems are ideal for practical farm conditions, as they are both non-invasive and cost-effective while maintaining high reliability (Figure 2).

### 1.1. Facial and Morphological Recognition Systems

Facial recognition, another branch of biometric analysis, focuses on identifying animals through their eyes, nose, and forehead features using advanced deep learning networks.

He Gong et al. (2022) developed an SK-ResNet [6] (Selective Kernel Residual Network) that incorporated multi-scale receptive fields and adaptive attention to extract facial features. This model achieved an impressive 98.42% accuracy, outperforming traditional architectures like DenseNet and GoogleNet.

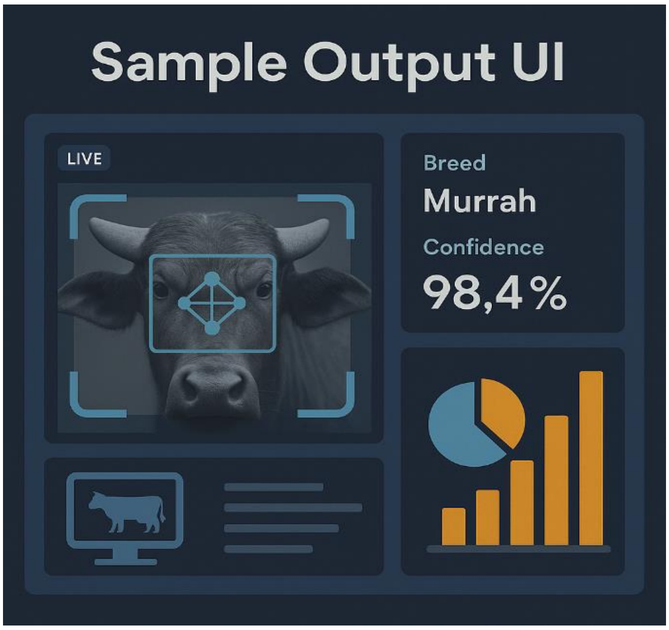


**Figure 2 Muzzle Pattern Sample UI**

Shijun Li et al. (2021) proposed a Lightweight CNN with Squeeze-and-Excitation (SE) attention modules and BasicBlock short-circuit connections, achieving 97.95% accuracy while maintaining a compact model size of 6.51 MB. The lightweight nature of this model enables deployment in real-world farm scenarios where computational resources are limited. Additionally, Yuanzhi Pan et al. (2022) demonstrated a self-activated CNN framework for buffalo breed classification based on facial features, using transfer learning for improved generalization. These methods collectively show that facial recognition [6] provides a scalable and precise alternative to traditional identification systems, ensuring accuracy even under varied environmental conditions.

### 1.2. Video-Based Recognition and Tracking

While static image recognition provides high accuracy, it may not perform well in dynamic farm environments. To overcome this limitation, researchers have turned toward video-based

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recognition and tracking [10] systems that analyze spatio-temporal features. Qiao et al. (2021) designed a hybrid architecture combining CNN and BiLSTM (Bidirectional Long Short-Term Memory) with a self-attention mechanism to identify individual cattle [4] using rear-view videos. The system achieved 93.3% accuracy, effectively capturing both spatial (visual) and temporal (motion) information. This combination allowed the model to recognize cattle from continuous frames, even with partial occlusions or movement variations. Zhao et al. (2024) further extended this work by implementing YOLOv5 with DeepSORT tracking [10], enabling real-time monitoring of cattle herds across different environments. These frameworks mark a significant step toward automated, non-contact monitoring of livestock, reducing manual labor and human error.

### 1.3. Integration of Multi-Feature Recognition

Recent studies have begun to explore multi-feature and multimodal systems, which combine muzzle prints, facial geometry, and body morphology for improved accuracy. Bai et al. (2024) demonstrated that incorporating biometric measurements such as body length, height, and girth with image-based CNN models leads to more comprehensive cattle identification. By integrating visual and physical traits, these hybrid systems enhance reliability, particularly in distinguishing similar-looking breeds or individuals within a herd.

## 2. Integration With Farm Management Systems

The advancement of artificial intelligence (AI) and computer vision in livestock identification [3] has opened avenues for smart and connected farm management systems. Integrating breed identification models with Internet of Things (IoT) devices, cloud computing, and data analytics allows farmers to manage herds more efficiently, reduce manual dependency, and ensure traceability across the production chain. Modern dairy and cattle farms are increasingly adopting AI-driven platforms for real-time monitoring, predictive analysis, and decision-making, transforming traditional livestock management into a data-centric ecosystem (Figure 3).

### 2.1. AI and IoT Integration in Smart Dairy Farming

AI and IoT are at the core of modern Precision Livestock Farming (PLF). Sensors, cameras, and wearable devices capture continuous data related to cattle health, activity, and production, which is then analyzed through AI algorithms for actionable insights. Kumar et al. (2025) explored the potential of AI and IoT-enabled dairy management systems to improve decision-making in feeding, disease detection, and milk yield prediction. Their system used intelligent data pipelines where information from visual recognition models was combined with sensor-based data (temperature, motion, rumination, etc.) to assess cattle well-being.

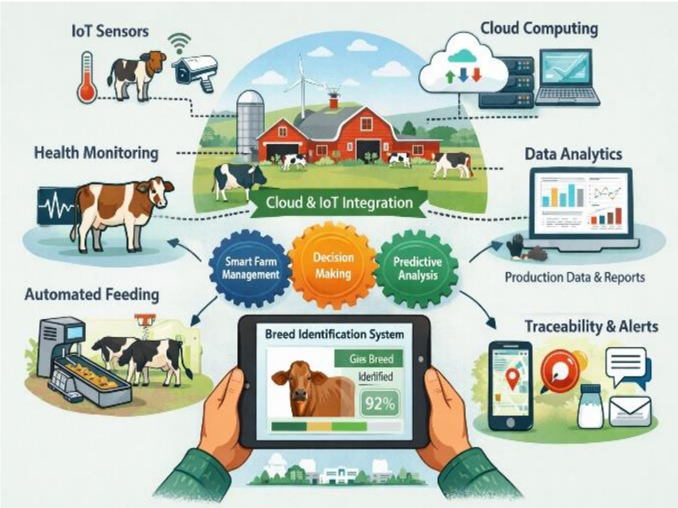


**Figure 3 Smart Farm Management System**

Similarly, Zhao et al. (2024) demonstrated how real-time tracking [10] systems based on YOLOv5 and DeepSORT could be integrated into IoT networks for automated cattle movement monitoring. Such systems alert farmers to unusual behavior, early signs of illness, or loss of livestock, enabling preventive healthcare.

### 2.2. Data Analytics and Predictive Farm Management

The combination of AI-based recognition systems with data analytics has revolutionized predictive farm management. Large-scale image and sensor data can be analyzed to generate forecasts on milk yield, breeding potential, and animal health conditions. Munir Ahmad et al. (2023) highlighted how integrating muzzle-based identification with insurance and health data ensures accurate record-keeping and fraud prevention. Their system automatically validates insurance claims by matching

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cattle identity through image recognition, significantly reducing human intervention. Kumar et al. (2025) emphasized the use of predictive analytics to anticipate disease outbreaks and optimize feeding schedules based on individual animal performance. Such predictive models can lower production costs, enhance milk yield, and support sustainable herd management practices.

### 2.3. Cloud Computing and Edge AI in Livestock Monitoring

One of the key enablers of large-scale livestock digitization is cloud computing. Storing and processing cattle data on the cloud allows farmers and veterinarians to access historical records, track breed lineage, and make data-driven decisions. However, continuous internet dependency can pose challenges in rural environments. To address this, researchers have proposed Edge AI models that perform image processing locally on devices such as smartphones or embedded boards (like Raspberry Pi). Shijun Li et al. (2021) and He Gong et al. (2022) designed lightweight CNNs and SK-ResNet [6] models that can operate efficiently with limited computational resources, making them ideal for on-field deployment without needing constant cloud access. These approaches combine speed, cost-efficiency, and scalability, ensuring that even small-scale dairy farms can benefit from AI-enabled solutions (Figure 4).

### 1.1. Automation, Traceability, and Decision Support Systems

AI-integrated cattle management systems contribute significantly to traceability, which is essential for food safety and animal welfare. Through unique biometric identification, every animal can be tracked across its lifecycle—from birth and breeding to milk production and disposal. Systems developed by Ahmad et al. (2023) and Li, Fang & Zhao (2025) showcase how integrating breed identification with decision support modules allows automated alerts, report generation, and compliance monitoring for farms. Such frameworks are crucial for implementing government policies like the Rashtriya Gokul Mission and global traceability standards set by the Food and Agriculture Organization (FAO). Additionally, automated systems can detect abnormalities in milk yield, feeding behavior, or mobility patterns, enabling early intervention and reducing financial losses.

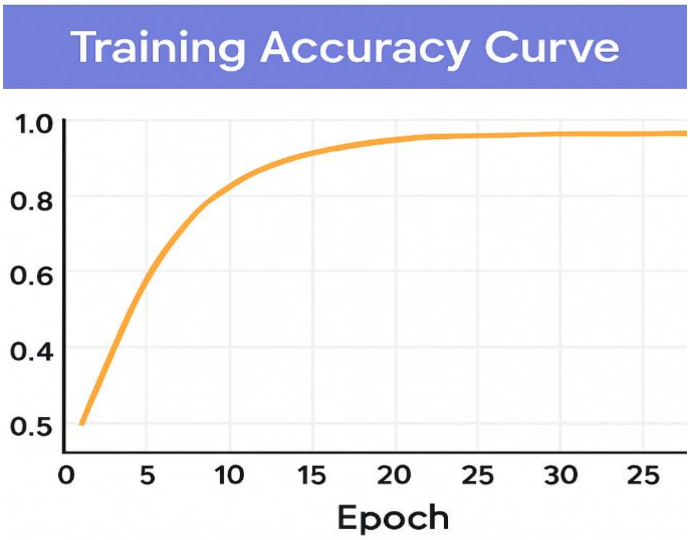


**Figure 4 Training Accuracy Curve**

## 2. Challenges and Future Directions

| Category | Key Issues / Directions |
|---|---|
| **Dataset & Annotation Challenges** | • Lack of standardized, large-scale datasets across breeds, ages, and regions<br>• Dependence on small, localized datasets with limited diversity<br>• Manual annotation of muzzle and facial features is time-consuming and error-prone<br>• Absence of open-access datasets with uniform labeling standards<br>• Underrepresentation of indigenous and crossbreeds |
| **Environmental &** | • Variations in lighting, weather, shadows, and background clutter |

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| | |
|---|---|
| **Field Constraints** | • Motion blur and occlusion in real-time image/video capture<br>• Performance degradation in real farm environments compared to controlled settings<br>• Need for environment-adaptive and noise-resilient models<br>• Requirement of rugged imaging hardware for outdoor deployment |
| **Computational & Hardware Limitations** | • High computational cost of CNNs and attention-based models<br>• Limited availability of GPUs in rural areas<br>• High energy consumption and maintenance cos<br>• Need for lightweight architectures (SqueezeNet, MobileNet, Edge AI)<br>• Requirement of edge computing to reduce cloud dependency |
| **Socio-Economic & Adoption Barriers** | • Limited awareness and technical training among farmers<br>• High initial setup cost of cameras, sensors, and servers<br>• Poor internet connectivity in rural regions<br>• Resistance to replacing traditional methods (tagging, branding)<br>• Need for government incentives, subsidies, and training programs |
| **Ethical & Data Privacy Concerns** | • Data ownership and privacy issues related to biometric information<br>• Requirement of secure data storage and encryption<br>• Ethical use of AI models and datasets<br>• Ensuring animal welfare through non-invasive image capture |
| **Future Research Directions** | • Development of global open-source livestock datasets<br>• Hybrid models combining visual, biometric, and sensor data<br>• Optimization for real-time inference on low-power devices<br>• Expansion to cross-species recognition (cattle, buffalo, goat, sheep)<br>• Integration with IoT and blockchain for traceability and insurance<br>• Collaboration among researchers, dairy boards, and governments<br>• Adoption of Edge + Cloud hybrid architectures |

## Conclusion

The integration of **Artificial Intelligence (AI)** and **Computer Vision (CV)** in livestock management has revolutionized the process of cattle and buffalo identification, enabling automation, precision, and scalability. From early machine learning techniques [15] like SVM and KNN to advanced deep learning architectures such as CNN, ResNet, and YOLO, research progress has continuously enhanced accuracy and robustness [16]. Studies have shown that deep CNN-based models, particularly when combined with transfer learning and attention mechanisms, can achieve near-perfect classification results under diverse farm conditions [17]-[25]. These developments not only streamline livestock monitoring but also significantly reduce human effort and error in animal identification, health tracking [10], and record management. The adoption of AI-driven identification systems has paved the way for **Precision Livestock Farming (PLF)**—a paradigm that emphasizes efficiency, animal welfare, and data-driven decision-making. Integrating breed recognition models with IoT sensors, cloud systems, and predictive analytics enables real-time insights into animal health, feeding, and productivity. Such frameworks promote sustainable farming practices, prevent fraud in insurance systems, and ensure traceability across the livestock supply chain. The synergy of biometric, facial, and behavioral recognition models strengthens the agricultural ecosystem by bridging traditional animal management with digital innovation. However, challenges such as limited datasets, variable environmental conditions, and infrastructural constraints still restrict large-scale deployment. The future of livestock AI research lies in developing **lightweight, explainable, and adaptive algorithms** capable of functioning efficiently in real-world farm environments. With collaborative efforts among researchers, government agencies, and the dairy industry, AI-based identification systems have the potential to redefine livestock management in India and globally — ensuring sustainability, transparency, and technological empowerment for farmers worldwide.

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