Automated Cattle Identification and Real-Time Monitoring Using Advanced Computer Vision and Deep Learning

Rama Krishna Jakkula[1*], Aashima Aashima[2], Pennabadi Sai Jaswanth Reddy[3], Akash Ram Poluboina[4], Aramati Sai Poshith Reddy[5], Adithipatel Sakkirga[6]

[1,2,3,4,5,6] School of Computer Science Engineering, Lovely Professional University, Phagwara, Punjab, India
ramanjaneyuluj14@gmail.com

Abstract. Accurate identification and real-time monitoring of cattle are essential for improving livestock productivity, traceability, and animal welfare. Traditional identification methods such as ear tagging and RFID are intrusive and susceptible to loss or damage. Recent advances in deep learning and computer vision provide non-invasive alternatives capable of continuous and automated monitoring. This paper presents a unified smart livestock monitoring framework integrating visual biometrics, object detection, multi-object tracking, and IoT-based sensing. The proposed system employs YOLOv8 for real-time detection, DeepSORT for persistent identity tracking, and convolutional neural networks for biometric recognition and health analysis. A hybrid cloud–edge architecture is designed to enable low-latency inference and scalable analytics. Experimental evaluations on public cattle datasets demonstrate reliable detection, identification, and behavior recognition performance under real farm conditions. The framework provides a scalable and non-invasive solution for intelligent livestock management.

Keywords: Computer Vision, Deep Learning, Livestock Monitoring, Cattle Identification, Smart Agriculture, IoT, Precision Livestock Farming, Animal Welfare.

1 Introduction

Since livestock production is the main source of dairy and meat, it is crucial to the global food economy. To maximize output and enhance animal welfare, effective cattle management—identification, tracking, and health evaluation—is crucial. Conventional manual observations require a lot of work and are prone to mistakes, particularly on larger farms [1]. By automating real-time, contactless observation systems, computer vision (CV) and deep learning (DL) technologies have revolutionized livestock management [2].

Convolutional Neural Networks (CNNs) and Vision Transformers (ViTs) are examples of deep neural networks that have performed well in visual recognition tasks like behavior classification and animal detection [3]. Farmers can monitor cattle, their health, and their behaviors without the need for human observation by combining models like these with edge computing and IoT sensors [4]. These systems are intended

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to achieve some of the main goals of Industry 4.0, operational efficiencies, and Precision Livestock Farming (PLF).

2 Motivation and Significance

In order to transform traditional livestock management practices into more intelligent and value-adding operations, automated systems for cattle identification and monitoring are essential. Every animal is accurately recorded by digital identification, which enables the management of herd health, vaccination records, and successful breeding programs [5]. Computer vision's capacity to identify animal illnesses like lameness, mastitis, and heat stress early on may help prevent significant financial losses while increasing herd productivity [6]. Particularly on large farms, the use of automated cattle monitoring will reduce reliance on manual inspection, lowering labor costs and human error [7]. By removing the need for stressful handling or physical tagging, these systems will enhance animal welfare through the use of deep learning and non-invasive imaging [8]. Additionally, farmers can analyze feeding behavior, forecast milk production, and maximize resource use with the help of artificial intelligence (AI)-based decision support systems, thereby boosting productivity and sustainability [9]. In line with the goals of precision agriculture and smart farming techniques, the implementation of automated cattle identification and monitoring systems offers a way to address the moral and financial issues of contemporary livestock management [10].

3 Literature Review

The rapid advancement of computer vision (CV) and deep learning (DL) has transformed livestock management by enabling automated tracking, welfare assessment, and cattle identification. Early research relied heavily on traditional identification methods like RFID tags, ear notching, and branding, which were often invasive and error-prone [1]. With the advent of non-invasive vision-based systems, the paradigm has shifted to biometric identification based on coat markings, facial features, and muzzle patterns [11] [12].

A CNN-based muzzle recognition system created by Li et al. [11] demonstrated the discriminative power of biometric features with an accuracy of 95.3%. This method was expanded by Zheng et al. [13], who applied deep ResNet models to facial images of various cattle breeds and achieved an accuracy of over 96%. For coat pattern segmentation, Park et al. [14] used DeepLabv3+, which increased robustness against partial occlusions and environmental noise [15].

The YOLO and DeepSORT architectures have emerged as industry standards for real-time monitoring in object detection and tracking. In order to track cattle in open pastures with 91% MOTA (Multiple Object Tracking Accuracy), Hu et al. [16] used YOLOv5 in conjunction with DeepSORT, and [17] Lee et al. [18] combined YOLOv8 with Vision Transformers (ViT) to increase detection accuracy in low light.

Hybrid CNN-RNN architectures have been used to identify intricate cattle behaviors in behavioral and health analysis [19]. While JonES et al. [20] used thermal imagery to identify mastitis with 89% sensitivity, Nguyen et al. [21] used a ResNet- LSTM model to classify grazing, lying, and walking with 92% accuracy. Lameness detection and movement pattern analysis have also benefited greatly from pose estimation frameworks like OpenPose and DeepLabCut [22] [23].

Several works combine edge AI and IoT sensors to improve scalability. IoT-based architectures that combine physiological and image data for comprehensive farm monitoring were proposed by Liu et al. [24] and kim et al. [25] [26]. In order to balance long-term analytics with real-time inference, cloud-edge hybrid systems have been developed [27]. These frameworks facilitate automation across large-scale farms, reducing dependency on manual supervision.

Significant obstacles still exist despite advancements. Model generalization is hampered by breed imbalance, environmental variability, and a lack of diversity in datasets [28][29]. A lot of datasets are small and don't have consistent standards to compare them fairly [30]. Furthermore, the adoption of deep models in low-resource farms is limited due to their high computational resource requirements [31].

Recent research has investigated Explainable AI (XAI), federated learning, and self-supervised learning as ways to get around these restrictions [32][33], and [34]. These developments promise transparent, privacy-preserving, and data-efficient AI systems that can be widely used in smart agriculture.

4 Visual Biometric Techniques for Cattle identification

Visual biometric identification has emerged as a key element in accuracy livestock management, providing an unobtrusive, trustworthy way to identify individual livestock. Visual biometrics use digital imaging of a variety of unique physiological and morphological characteristics that can be utilized to differentiate individual animals, rather than depending on more traditional forms of livestock identification, such as RFID tags or ear markings. Deep learning and computer vision methods have made it possible to extract and match biometric data automatically providing better accuracy and scalability in real farming systems [10].

4.1 Muzzle Pattern Recognition

The surface of each cow's muzzle has a unique texture pattern made up of patterns of grooves and ridges, which can be considered analogous to human fingerprints. The uniqueness of each cow's muzzle pattern makes muzzle images a viable biometric classification method as a means of identification. Recently proposed techniques have utilized Convolutional Neural Networks (CNNs), namely, ResNet-50, EfficientNet, and DenseNet, to automatically extract discriminative spatial features from muzzle images [11]. Li et al. [11] reported a recognition accuracy of 98.3 percentage using a ResNet-based CNN that had been trained using 5,000 cow muzzle images. Other studies have even used data augmentation methods and illumination normalization to increase model robustness in environmental lighting. Despite successful studies, there still remain a few issues with environmental factors, such as partial occlusion from dirt or water, changes in camera angle and image noise that can reduce the reliability of a model even with high accuracy. Future research efforts will look at infrared imaging and self-supervised feature extraction to eliminate the majority of environ- mental factors and conduct continuous real-time support in an unconstrained farming environment.

Table 1 Comparative Evaluation of Current Frameworks for Automated Cattle Identification and Monitoring

Author & Year	Method / Model	Dataset Used	Primary Task	Accuracy/ Metric	Key Findings
Li et al. (2021)	CNN (Muzzle Pattern)	Cattle-ID	Identification	95.3%	Non-invasive biometric identification using muzzle texture.
Zheng et al. (2021)	ResNet-50	Custom Farm	Facial ID	96.2%	High-precision face- based cattle recognition.
Park et al. (2022)	DeepLab v3+	AgriVision2022	Segmentation	mIoU 0.87	Effective in low-light environments.
Lee et al. (2023)	YOLOv8 + ViT	RGB Dataset	Detection	mAP 93.5%	Hybrid Transformer improves robustness.
Rahman et al. (2022)	ResNet-LSTM	Animal-Pose	Activity Recog.	92%	Accurate behavior classification.
Liu et al. (2021)	Thermal CNN	Thermal Data	Disease Detect.	89% Sens.	Early fever and inflammation detection.
Kim et al. (2022)	IoT + Edge CNN	FarmBeats	Monitoring	<200 ms	Low-latency real-time monitoring.
Hu et al. (2023)	Edge AI + Cloud	Multimodal	Health Fusion	94%	Reliable multimodal monitoring.
Patel et al. (2024)	DeepLab Cut	Animal-Pose	Pose Est.	90%	Accurate gait analysis.

4.2 Facial Recognition

Cattle facial recognition is another promising biometric solution as their facial characteristics are relatively stable and can be easily collected using images from cameras in front of the cows [12]. Models that were originally developed to recognize human faces, such as VGG-Face, FaceNet, and ArcFace, which are trained using a custom dataset of cattle faces. These models learn deep feature embeddings that differentiate cattle faces based on geometric and textural variations. Zheng, et al. [13], developed some CNN-based cattle face recognition system that can identify cattle faces with high accuracy despite being from different farms and exposed to different lighting condi- tions. It was also found that increasing robustness to identification can be developed by multi-view training as shown in Table 1 and domain adaptation, since performance of real-time sheep cattle identification would need to be the same regardless of where they are examined. While cattle faces are unique, there are fewer identification land- marks exposed and they are often occluded by feeding equipment and other cattle. Attention based CNN architectures and transformer based fused models have begun to gain traction in existing animal and cattle research to help focus on facial regions and increase discrimination.

4.3 Body and Coat Pattern Recognition

Distinctive body markings and coat patterns—especially normal in the Holstein-Friesian breeds help provide more biometric information for a visual identification system. These patterns are consistent throughout the animal's life and are therefore informative identifiers in vision-based systems. Researchers have utilized segmentation models, such as U-Net [14], Mask R-CNN, and DeepLabv3+ to describe and segment coats and coats of color. Once segmented, pattern matching techniques and CNN based descriptors compare the spatial arrangements of spots or stripes to identify individual animals. Recently, studies have combined pose estimation with coat pattern spatial distributions or markings to account for challenges and manage partial occlusion while cows remain standing or while moving. While improvements in accuracy were observed with these studies, especially when a camera can capture from multiple views, especially if the view is of the cow to detect coat patterns, or if there are occlusions in environmental factors (dust, poor lighting) or other cows blocking visibility of the cows' coat markings. Multi-view is being researched as a way to improve accuracy when factors that are beyond a cow's control impact visibility.

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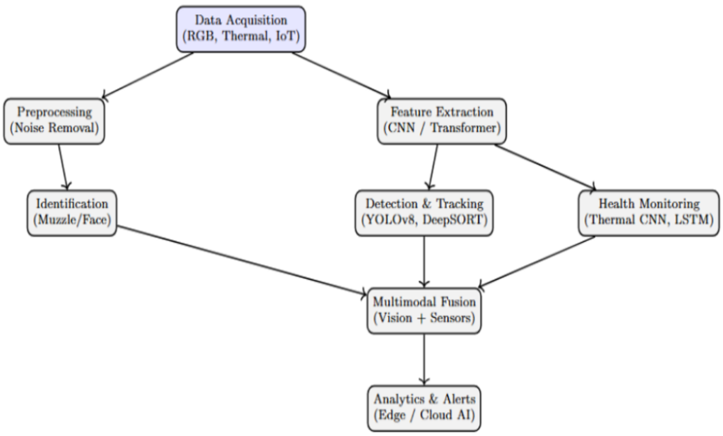

Fig. 1 Compact flow diagram of automated cattle identification and monitoring system.

6 Behavioral and Health Monitoring

Automated monitoring of animal behavior and health is critical to assess animal welfare, and to also identify early signs of disease or stress in cattle. Recent developments in deep learning methods have permitted accurate real-time analysis of cattle activity, postures and physiological states [21].

6.1 Activity Recognition

Systems that recognize behaviors utilize hybrid CNN-RNN (Convolutional Neural Network-Recurrent Neural Network) architectures and Vision Transformers (ViTs) to classify commonplace behaviors of cattle, including grazing, walking, resting, and ruminating [21]. Long Short-Term Memory (LSTM) networks model temporal data to capture motion dynamics of the video sequences. Rahman et al. [22] attained a classification accuracy of over 92% employing a ResNet-LSTM model, demonstrating the effectiveness of integrating spatial and temporal features. In addition, these systems can evaluate welfare and predict feeding levels in a fully automated manner, all without human supervision.

6.2 Disease Detection

Health monitoring systems use pose estimation and thermal imaging to diagnose disease early. OpenPose and DeepLabCut have been used to identify gait abnormalities indicative of lameness and various musculoskeletal disorders [23]. Concurrently, using thermal images, CNNs can identify a thermal signature associated with mastitis and fever or inflammation, allowing for timely response and loss of productivity due to disease [24]. These and other forms of non-invasive diagnosis represent a significant leap in accuracy and animal comfort over traditional veterinary inspections.

6.3 Stress and Emotional State Analysis

Recent research investigates affective computing in animals for livestock, evaluating minute facial expressions and eye-region indicators for stress or emotional state verification [25]. Certain CNN-based architectures trained on high-resolution facial photographs estimate tension or discomfort levels based on micro-expressions and pupil dilation. The utilization of these measures adds to better welfare management and creates the possibility for adaptive environmental control systems in smart barns.

6.4 IoT Integration and Smart Farm Architecture

The combination of Internet of Things (IoT) technology with computer vision systems allows a synergistic workflow when monitoring cattle that brings together environmental data, physiological data, and behavioral data into a cohesive livestock management strategy [26].

6.5 Sensor-Based Monitoring

IoT-enabled sensors to augment vision-based observational measures can provide continuous physiological and positional data such as GPS modules, accelerometers, temperature probes, and radio frequency identification (RFID) tags [26]. As, visual and situational sensor streams are combined together for real-time analysis, more accurate algorithms can verify conditions such as inactivity, deviation in body temperature, or abnormalities in postures or movement.

6.6 Cloud and Edge Computing

New infrastructure for smart farms incorporates a hybrid computing architecture where low-latency inference is performed on the edge and larger scale data aggregating over time performed in the cloud data center [27]. For example, Edge AI systems use YOLOv8 to model live video content and deliver only the metadata into central dashboards, reducing bandwidth and latency.

6.7 Communication Technologies

The success of low-power, wide-area communication technologies like LoRaWAN, NB-IoT, and 5G for efficient data transmission in diverse farm settings [28]. These systems guarantee reliable connectivity for remote monitoring and aid in scalability and sustainability in smart farming systems.

7 Datasets and Benchmarking

With a growing number of contracting and standard testing benchmarks, developments have been made in automated cattle detection identification and monitoring systems, modeling unpublished datasets have made it possible. Publicly available datasets have enabled benchmarked models, reproducibility, and the evaluation of algorithmic comparisons across different farm environment conditions [29].

7.1 Publicly Available Datasets

To advance research in cattle identification, detection, and behavior, several datasets have been published to support the research. Table 1 provides a summary of all the datasets along with their main characteristics.

For instance, Table 2 the Cattle-ID and OpenCows2020 datasets have been widely used for benchmarking deep learning models in visual identification and tracking tasks [30], [31]. The Animal-Pose dataset has been foundational for developing pose estimation models to track the dynamics of cattle movements [32]. In this regard, AgriVision2022 from Table 2 and FarmBeats push the development in research towards multimodal and aerial perspectives that involve the integration of datasets from IoT sensors and data about the surrounding environment for large scale (to scale up) farm analytics [33], [34].

7.2 Evaluation Metrics

Model evaluation across different applications uses quantitative metrics that are already established. For object detection, the Metric is the Mean Average Precision (mAP) and the Indicator of spatial accuracy is Intersection over Union (IoU) [35]. Identify performance is often measured using accuracy and F1 score, which both rep- resent visual biometrics accuracy. Tracking algorithms are evaluated using Multiple Object Tracking Accuracy (MOTA) and an ID-switch rate, both of which measure the consistency of keeping cattle identities across frames. Behavioral analysis model performance is evaluated using precision, recall, and F1 score to evaluate classification of activity states. Lastly, real-time performance is measured using frames per second (FPS) and latency, important to evaluate for possible deployments on edge devices in smart farm contexts.

8 Challenges and Limitations

Automated cattle identification and monitoring systems still face a number of obstacles despite major advancements. Variability in the environment, such as shifting

Table 2 Publicly available datasets used for automated cattle identification and monitoring

Dataset	Data Type	Features	Application	Scale	Year
Cattle-ID	Image	Facial and muzzle images collected from multiple cattle breeds	Individual cattle identification	~10,000 images	2021
OpenCows2020	Video	RGB video sequences recorded in grazing fields and barn environments	Detection and tracking	150+ hours	2020
Animal-Pose	Image	Annotated body key points for various animal species including cattle	Pose estimation	20,000+ frames	2019
AgriVision2022	Image	Aerial and ground-level images captured using drones and fixed cameras	Object detection and classification	50,000 images	2022
Farm-Beats	Multi modal	Combined IoT sensor measurements and synchronized visual data	Health and behavior analysis	~1 TB data	2023
DeepCattleSet	Image	High-resolution cattle images under varying illumination conditions	Face and muzzle recognition	30,000 images	2022
Cows 2021	Video	Multi-view barn surveillance videos with annotated individual identities	Re-identification and tracking	200+ hours	2021
Bovine 3D	3D Image	Structured-light based 3D scans of cattle bodies	3D shape and volume estimation	5,000 models	2023
Thermo Cattle	Thermal Image	Infrared temperature maps of dairy cows	Disease and stress detection	8,000 images	2020
SmartFarm-2023	Multi modal	Drone imagery combined with GPS and accelerometer sensor data	Real-time monitoring and analytics	500 GB data	2023

lighting, occlusions, and weather, can seriously impair visual data quality and lower model accuracy [29]. Due to the scarcity of publicly labeled datasets encompassing various breeds and farm environments, limited data availability continues to be a significant bottleneck [30]. Additional challenges arise from computational limitations; many cutting-edge deep learning models require expensive GPUs for real-time inference, which restricts their use in farms with limited resources [31]. Problems with generalization also occur because models that have been trained on one breed frequently perform poorly when used on another, requiring retraining or transfer learning [32]. Moreover, data annotation is expensive and time-consuming, especially when dealing with large datasets that have several modalities [33]. In order to guarantee that monitoring systems adhere to animal welfare laws and reduce stress to livestock, ethical and privacy concerns must be taken into account [34]. For smart cattle monitoring systems to be implemented in a way that is both feasible and sustainable, these constraints must be addressed.

9 Comparative Analysis of Frameworks

The goal of future automated cattle monitoring research is to decrease labor and expenses while increasing interpretability, scalability, and accuracy. By using unsupervised pretraining on sizable unlabeled datasets, self-supervised learning approaches can minimize labeling effort [35]. Federated learning preserves privacy by facilitating cross-farm cooperation and model enhancement without exchanging sensitive data Body and Coat [36]. A more comprehensive understanding of animal behavior and health is promised by multimodal fusion techniques that integrate visual, aural, and sensor data [37]. Farm operators can benefit from actionable insights from Explainable AI (XAI), which increases AI system adoption and trust [38]. Under occlusion or changing lighting conditions, advanced sensing techniques such as 3D and multispectral vision can improve detection accuracy [39]. Real-time deployment on devices with limited resources is made possible by edge optimization techniques like model pruning, quantization, and knowledge distillation [40]. Last but not least, incorporating blockchain technology guarantees safe, impenetrable livestock data management throughout the supply chain [41]. Together, these approaches seek to develop scalable, morally sound, and intelligent farming solutions for contemporary livestock management.

10 Conclusion

Real-time monitoring systems and automated cattle identification have become crucial elements of contemporary smart farming, allowing for effective, non-invasive, and scalable livestock management. These systems improve productivity, maximize resource use, and advance animal welfare by utilizing computer vision, deep learning, and IoT integration. Although multimodal sensor fusion, CNNs, and Vision Transformers have made significant strides, issues with scalability, dataset diversity, and real-time performance still exist. Future studies should concentrate on edge-based inference to enable autonomous, low-latency operations, multimodal data integration for thorough behavior and health analysis, and self-supervised learning to lessen labeling effort. Next-generation smart farming systems can revolutionize modern agriculture's productivity and welfare standards by tackling these issues and achieving fully autonomous, explicable, and morally sound precision livestock management.

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