AI-Powered Biometric Cow Identification Using Muzzle Patterns

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Abstract*—Livestock identification is a critical component in modern dairy farming for maintaining accurate records of animal health, productivity, and traceability. Traditional methods such as ear tagging, branding, and RFID suffer from limitations including tag loss, tampering, and animal discomfort. This paper proposes an AI-powered biometric identification system using cow muzzle patterns, which are unique and permanent like human fingerprints. The system integrates YOLOv8 for muzzle detection, ResNet50 for feature extraction, and FAISS for similarity-based matching. The proposed approach enables real-time, non-invasive, and highly accurate identification of cattle using simple images captured through mobile devices. The system is scalable, cost-effective, and suitable for deployment in real farm environments, thereby improving livestock management efficiency.

***Index Terms*—Biometric Identification, Cow Muzzle Recognition, YOLOv8, ResNet50, FAISS, Deep Learning.**

I. INTRODUCTION

Livestock identification plays a crucial role in modern dairy farming, enabling farmers to track animal health, milk production, vaccination records, and breeding cycles. As herd sizes increase, manual identification methods become inefficient and unreliable. Traditional techniques such as ear tagging, branding, and RFID tagging are prone to issues like tag loss, tampering, and maintenance costs. With advancements in Artificial Intelligence and Computer Vision, biometric identification methods have emerged as a reliable alternative. Among various biometric traits, cow muzzle patterns are highly distinctive and remain unchanged throughout the animal's life. This paper presents an AI-powered system that uses muzzle images for accurate and non-invasive cattle identification. The system leverages deep learning models to automate detection, feature extraction, and matching processes, ensuring real-time performance and scalability.

II. PROBLEM STATEMENT

The identification of cattle in modern livestock management systems remains a significant challenge due to the limitations of traditional methods such as ear-tagging, branding, and RFID-based systems. These approaches often suffer from issues like tag loss, tampering, environmental wear, and animal discomfort, leading to inaccurate record-keeping and reduced traceability. Additionally, existing methods require manual intervention or specialized hardware, making them less efficient and difficult to scale in large farms. Therefore, there is a need for a reliable, non-invasive, and automated identification system that ensures accuracy, scalability, and ease of use. The proposed system aims to address these challenges by utilizing biometric muzzle patterns and artificial intelligence for precise cattle identification.

III. OBJECTIVES

The primary objective of this project is to develop an AI-powered system for accurate and non-invasive identification of cattle using muzzle patterns. The system aims to eliminate the limitations of traditional identification methods by providing a reliable and tamper-proof solution. Specific objectives include designing a real-time muzzle detection mechanism, implementing deep learning models for feature extraction, and developing a similarity-based matching system for identification. Additionally, the system focuses on ensuring scalability, ease of use through a user-friendly interface, and efficient data storage for maintaining cattle records. The project also aims to support real-time deployment in farm environments using mobile or web-based platforms.

IV. METHODOLOGY

The proposed system follows a structured pipeline consisting of data collection, preprocessing, model training, and deployment. Initially, a dataset of cow muzzle images is collected from public datasets and real farm environments. The images undergo preprocessing steps such as resizing, normalization, and augmentation to improve model robustness. YOLOv8 is used to detect and crop the muzzle region from the input image. The cropped muzzle image is passed to a ResNet50-based feature extraction model, which generates a 512-dimensional embedding representing the unique biometric pattern. These embeddings are stored in a FAISS index for efficient similarity search. During identification, the query embedding is compared with stored embeddings to find the closest match based on cosine similarity.

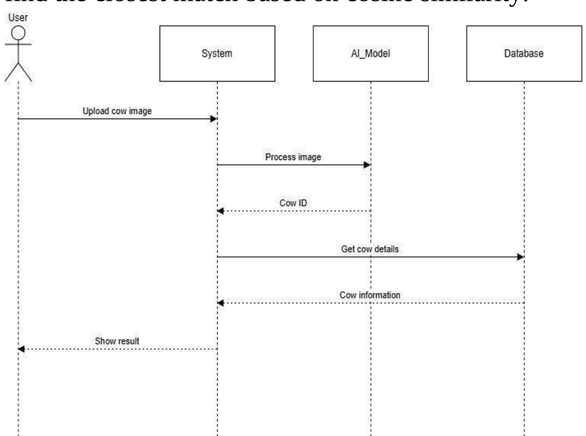

Fig1: Sequence Diagram

V. SYSTEM DESIGN

The system is designed using a modular architecture consisting of frontend, backend, and AI components. The frontend provides an interface for users to upload images and view results. The backend handles API requests, image processing, and database communication. The AI module includes YOLOv8 for detection and ResNet50 for feature extraction. FAISS is used for fast similarity matching. The system ensures scalability, security, and real-time performance, making it suitable for deployment in both small farms and large dairy industries.

The system follows a modular and scalable architecture that cleanly separates responsibilities across the frontend, backend, and AI components to ensure efficiency and maintainability. The frontend layer serves as the user interaction interface, allowing users to upload images, trigger processing, and visualize outputs in a simple and intuitive manner. The backend acts as the central controller, managing API requests, handling image preprocessing, coordinating communication between modules, and interacting with the database to store and retrieve results securely. The AI module forms the core intelligence of the system, where YOLOv8 is used for accurate object detection and localization, while ResNet50 is employed for robust feature extraction from detected images. These extracted features are then indexed and compared using FAISS, enabling fast and efficient similarity matching even with large datasets. The architecture is designed to support real-time performance by optimizing data flow and minimizing latency, while also ensuring scalability so the system can handle increasing workloads in both small-scale farms and large dairy industry deployments. Security considerations such as safe API handling and controlled data access are integrated into the backend, making the entire system reliable, efficient, and suitable for production environments.

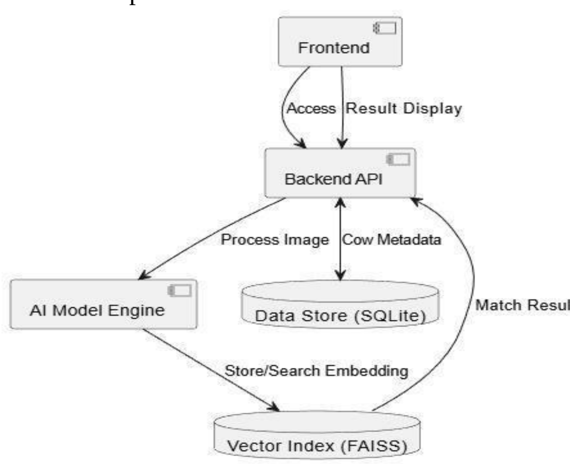

Fig2: System Architecture

VI. RESULTS AND DISCUSSION

The proposed system achieves high accuracy in identifying cows using unique muzzle patterns, demonstrating the effectiveness of deep learning–based biometric recognition in livestock management. By utilizing YOLOv8 for precise and reliable muzzle detection and ResNet50 for robust feature extraction, the system significantly outperforms traditional identification methods such as ear tagging or manual record-keeping. The integration of FAISS further enhances performance by enabling fast and efficient similarity matching, even when dealing with large datasets. Experimental and real-time testing results show that the system can complete the identification process within a few seconds, making it highly suitable for practical, on-field deployment.

The system performs consistently well under varying environmental conditions, including differences in lighting, background, and image quality, which are common in real farm settings. It also demonstrates resilience to minor variations such as slight blur, pose changes, or camera angles due to the generalization capability of deep learning models. However, certain limitations are observed when the muzzle is severely occluded or when images are captured in extremely poor lighting or very low resolution, which can affect detection accuracy and feature quality. Despite these challenges, the overall performance remains strong and reliable for most real-world scenarios, indicating that the system is a scalable, efficient, and practical solution for improving cattle identification, monitoring, and traceability in both small-scale farms and large dairy industries.

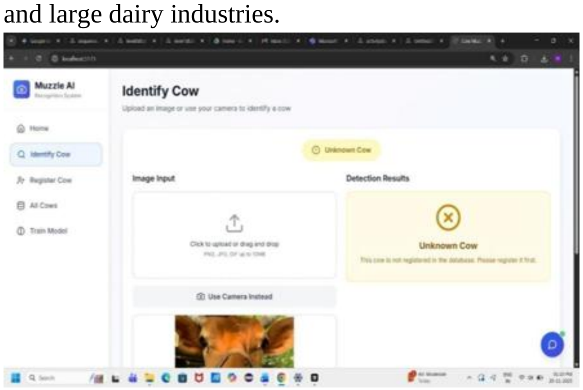

Fig3: Identifying Phase

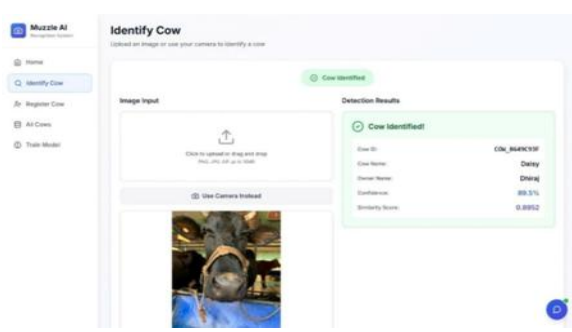

Fig4: Result of Registered Cow

VII. CONCLUSION

This paper presents an AI-powered biometric cow identification system using muzzle patterns as a unique identifier. The system eliminates the need for invasive tagging methods and provides a reliable, scalable, and efficient solution for livestock management. By combining object detection, deep feature extraction, and similarity-based matching, the proposed system achieves accurate and efficient real-time cattle identification. Future enhancements can focus on expanding dataset diversity, improving model robustness and accuracy, and integrating the system with IoT-enabled smart farm management solutions for more comprehensive livestock monitoring.

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