

# Smart Cattle Disease Prediction & Breed Identification

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## Abstract: -

The emergence of Industry 4.0 within the agricultural sector has facilitated the transition toward Precision Livestock Farming (PLF), a paradigm that integrates Information and Communication Technologies (ICT) to enhance animal welfare, productivity, and economic sustainability. This research explores the systematic integration of the Internet of Things (IoT) and Artificial Intelligence (AI) for the dual objectives of cattle breed identification and automated disease prediction. Given the substantial economic repercussions of transboundary animal diseases—with Foot and Mouth Disease (FMD) alone causing global losses of approximately \$62 billion and Lumpy Skin Disease (LSD) imposing a \$1.45 billion burden in Asia—the development of non-invasive, real-time monitoring systems is paramount. This report analyzes the deployment of deep learning architectures, specifically Convolutional Neural Networks (CNNs) for spatial feature extraction in skin lesion detection and breed categorization, alongside Recurrent Neural Networks (RNNs) for sequential behavioral analysis. Methodological frameworks such as "Dairy DigiD" utilize high-precision YOLOv11 surveillance and DenseNet121 classification, achieving 94.2% accuracy while maintaining real-time inference through edge computing. Furthermore, the study evaluates the efficacy of biometric markers, specifically muzzle patterns, which demonstrate 98.7% identification accuracy, offering a tamperproof alternative to traditional tagging. The synthesis of these technologies provides a scalable infrastructure for early intervention, potentially reducing disease

detection intervals from several days to mere hours, thereby safeguarding global livestock-dependent economies.

## I. INTRODUCTION

For generations, a farmer's ability to manage livestock depended on the **"unity of hand, head, and heart"**—a combination of practical skills, knowledge, and deep care for the animals. Experienced farmers could often recognize subtle signs of illness or stress in their livestock simply through observation and intuition. Changes in behavior, eating patterns, or movement were noticed during daily routines, allowing farmers to respond quickly to potential health problems. This traditional approach relied heavily on personal experience and close human–animal interaction.

However, modern farming has changed significantly. Farms today are becoming **larger, more intensive, and more technologically driven**, often managing hundreds or even thousands of animals at a time. In such environments, it becomes increasingly difficult for farmers to manually monitor each individual animal throughout the day. Human observation alone is no longer enough to ensure that every animal receives timely attention, especially when early signs of disease or distress can be subtle and easily missed.

This challenge has led to the development of **Precision Livestock Farming (PLF)**. PLF uses advanced technologies such as sensors, cameras, wearable devices, and data analytics to continuously monitor animals' health, behavior, and environment. These systems collect real-time data on factors like movement, feeding habits, body temperature, and vocalization. By analyzing this information automatically, PLF can detect abnormalities or early

warning signs of illness much faster than traditional methods.

As a result, farmers can move from **reactive management to proactive care**, receiving alerts and insights that help them intervene quickly and improve animal welfare, productivity, and farm efficiency. In this way, PLF does not replace the farmer's experience but rather **enhances it with technology**, creating a smarter and more sustainable approach to livestock management.

## II. LITERATURE REVIEW

Smart farming has rapidly progressed from **basic dairy monitoring tools** to highly advanced systems capable of managing livestock across diverse environments, from confined dairy barns to **large open pastures with grazing herds**. Modern precision livestock technologies integrate sensors, computer vision, and artificial intelligence to continuously observe animals, collect data, and provide insights that help farmers make faster and better decisions. These systems allow farms to monitor animal health, behavior, productivity, and environmental conditions in real time, improving both **animal welfare and farm efficiency**.

### Sensors and Wearables

A key component of smart farming is the use of **sensor-based monitoring systems**, which generally fall into two categories: **wearable and non-wearable technologies**.

Wearable devices include **smart collars, ear tags, leg bands, and rumination sensors** attached directly to the animal. These devices often contain **accelerometers, temperature sensors, and GPS modules** that track movement, activity levels, grazing patterns, feeding behavior, and resting time. For example, a smart collar can measure how long a cow spends lying down, walking, or grazing. Changes in these patterns may indicate early signs of illness, heat stress, or reproductive cycles. Early detection allows farmers and veterinarians to take preventive action before the condition worsens.

Non-wearable systems, on the other hand, rely on **camera-based monitoring and computer vision technologies**. High-resolution cameras and **3D imaging systems** can automatically measure body

weight, body condition score, and posture without requiring physical handling of the animal. This reduces stress for the livestock while allowing continuous monitoring. For example, **3D motion detection systems** are now capable of identifying subtle behavioral changes that may signal diseases such as **mastitis**. By analyzing how a cow stands, walks, or rests, the system can detect abnormalities much earlier than manual observation.

### The “Brains” of the System: AI Architectures

The real power behind these smart farming systems lies in **artificial intelligence and deep learning models** that analyze the large volumes of data collected by sensors and cameras. Among these, **Convolutional Neural Networks (CNNs)** play a major role in analyzing images and videos of animals.

Popular CNN architectures such as **ResNet, MobileNetV2, VGG16, and DenseNet121** are widely used in livestock health monitoring. For example, **MobileNetV2** is known for its lightweight design and fast processing speed, making it suitable for **real-time disease detection systems on farm devices**. In the detection of diseases like **Lumpy Skin Disease (LSD)**, MobileNetV2 has achieved accuracy rates as high as **96.39%**. Meanwhile, **VGG16** is often preferred in veterinary research because it can better differentiate between LSD lesions and other similar skin conditions.

In addition to image-based analysis, monitoring livestock behavior over time is also crucial. For this purpose, **Recurrent Neural Networks (RNNs)** and other time-series models are used. These models analyze behavioral data such as movement patterns, feeding intervals, and rest cycles across time. When spatial information from images is combined with temporal behavioral data, systems can identify complex activities such as **grazing, drinking, or resting**, achieving accuracy levels of around **84.88%**.

Recent developments have also introduced integrated AI frameworks such as **Dairy DigiD**, which combine multiple deep learning models in one system. For example, the **YOLOv11 object detection model** can rapidly identify animals in live video streams, while **DenseNet121** evaluates their physical condition and health status. These systems are optimized to run on **edge devices located directly on farms**, allowing real-time monitoring without requiring powerful cloud infrastructure.

## Behavioral Markers

One of the most valuable indicators of livestock health is **animal behavior**. Subtle behavioral changes often appear before visible physical symptoms of disease. Monitoring these behavioral markers allows farmers to detect health problems earlier and take preventive action.

Among these indicators, **rumination behavior**—the process where cows chew their cud—is particularly important. Healthy cows typically spend several hours each day ruminating, and any sudden decrease in rumination time can signal digestive issues, stress, or metabolic disorders. Advanced monitoring systems such as **RumiWatch** can track rumination with **up to 99% accuracy** by analyzing jaw movements and chewing patterns.

These systems are capable of detecting early signs of conditions like **subclinical ketosis**, often several days before visible symptoms appear. Early detection helps farmers intervene quickly with dietary adjustments or veterinary treatment, preventing production losses and improving overall herd health.

## Overall Impact

By combining **sensor technology, computer vision, and artificial intelligence**, smart farming systems provide a comprehensive and automated way to monitor livestock health and behavior. These technologies help farmers detect diseases earlier, improve animal welfare, reduce labor requirements, and make data-driven management decisions. As technology continues to evolve, precision livestock farming will likely become an essential component of **sustainable and efficient modern agriculture**.

## III. METHODOLOGY

Our framework is designed as a **layered architecture**, where each layer works like a part of a conversation between technologies. Every layer performs a specific task, and together they create a complete pipeline that collects data, processes it intelligently, and delivers useful insights to farmers and veterinarians. This layered structure ensures that data flows efficiently from the physical environment to intelligent decision-making systems.

## How the Data Flows

The process begins with the **Perception Layer**, which represents the physical interface between the animals and the technology. This layer includes **sensors, wearable devices, and camera systems** placed in barns, grazing areas, or feeding stations. Sensors attached to cows can monitor parameters such as body temperature, activity level, and rumination, while cameras continuously capture visual data about animal posture, movement, and physical condition. Essentially, this layer acts as the **“eyes and ears” of the system**, gathering raw data directly from the livestock environment.

Once collected, the data is transmitted through the **Network Layer**. This layer ensures reliable communication between devices using **low-power wireless technologies** such as **LoRaWAN, Bluetooth Low Energy (BLE), or Wi-Fi**. Among these, **LoRaWAN (Long Range Wide Area Network)** is particularly suitable for large farms because it provides **long-distance communication with minimal energy consumption**. It allows hundreds of devices spread across large fields or barns to transmit data with very low packet loss. This capability makes it ideal for livestock monitoring where sensors must operate continuously without frequent battery replacement.

The next stage is the **Edge Processing Layer**, where immediate analysis and decision-making occur. Instead of sending large volumes of raw data—such as continuous video streams—to a remote cloud server, the system processes the information locally using **edge computing devices** like the **NVIDIA Jetson platform**. These compact but powerful devices can run AI models directly on the farm. For example, the system can analyze video footage in real time to identify individual cows, detect abnormal skin lesions, or monitor unusual behaviors. Only important information, such as detected anomalies or summarized reports, is transmitted to the next stage. This approach reduces network bandwidth usage, lowers latency, and enables **real-time responses to potential health issues**.

Finally, the processed data is sent to the **Cloud Layer**, which serves as the central hub for long-term data storage and advanced analytics. In the cloud, historical records of each animal are maintained, enabling deeper analysis such as disease progression, productivity trends, and predictive health insights. Cloud platforms also allow veterinarians and farmers to access dashboards, alerts, and reports remotely,

helping them make **data-driven management decisions.**

## Processing the Visual Data

Before artificial intelligence models can effectively analyze images, the raw visual data must first be **preprocessed and cleaned**. Farm environments often contain complex backgrounds, multiple animals, and varying lighting conditions. To address this, object detection models such as **YOLO (You Only Look Once)** are used to locate the cow within an image. Once detected, the relevant portion of the image is **cropped**, ensuring that the AI model focuses only on the animal rather than irrelevant background elements.

To further improve model performance and robustness, the system uses **data augmentation techniques**. This involves artificially expanding the dataset by applying transformations such as **rotation, flipping, scaling, and brightness adjustment** to images. By exposing the model to these variations during training, the AI becomes better at recognizing animals and detecting diseases regardless of camera angle, lighting conditions, or orientation.

## Dual-Stream Intelligence

The core logic of the framework follows a **dual-stream AI architecture**. In this setup, two types of neural networks work together to analyze different aspects of the data.

The first stream uses **Convolutional Neural Networks (CNNs)**, which focus on spatial information. These models answer the **“what” questions**, such as identifying whether a cow has visible skin lesions, determining its breed, or detecting other physical abnormalities. CNNs are particularly effective at extracting features from images and recognizing visual patterns related to diseases.

The second stream uses **Recurrent Neural Networks (RNNs) or Long Short-Term Memory (LSTM) networks**, which analyze **time-based behavioral patterns**. These models answer the **“when” questions**, such as how long a cow has been standing still, how frequently it moves, or whether its activity patterns have changed over time. By studying sequential data, these models can detect behavioral anomalies that may indicate health issues.

## Reducing Human Work with Active Learning

Training AI models typically requires large numbers of labeled images, which can be time-consuming and expensive to create. To address this challenge, the framework incorporates an **active learning strategy**. Instead of requiring humans to label every image, the system automatically identifies the **most uncertain or confusing samples** and asks human experts to review only those cases.

This selective labeling approach allows the model to improve its accuracy with far fewer labeled examples. Studies have shown that active learning can **reduce manual labeling workload by up to 65%**, significantly accelerating the training process while maintaining high model performance.

## Overall System Advantage

By combining **IoT sensors, edge computing, computer vision, and advanced AI architectures**, this layered framework creates an efficient and scalable livestock monitoring system. It enables real-time disease detection, continuous behavioral analysis, and long-term health tracking, ultimately helping farmers maintain healthier herds while reducing manual labor and operational costs.

## IV. IMPLEMENTATION DETAILS

When implementing such a system on a **real working farm**, hardware selection becomes a critical decision. Farmers and system designers must balance **performance, cost, power consumption, and reliability**. High-performance devices can process complex AI models quickly, but they are often more expensive and consume more power. On the other hand, lower-cost devices are budget-friendly but may struggle with heavy AI workloads. Therefore, choosing the right hardware becomes a **trade-off between computational capability and affordability**, especially when deploying systems across large farms with many monitoring points.

## The Hardware Choice

To determine the most suitable edge computing device—the “**brain**” of the **on-farm monitoring system**—three major hardware platforms are commonly considered.

One of the most popular entry-level options is the **NVIDIA Jetson Nano**. This device is specifically designed for **edge AI applications**, making it ideal for real-time computer vision tasks in agriculture. It provides approximately **472 GFLOPS (Giga Floating Point Operations Per Second)** of computing performance while maintaining relatively low power consumption. Another advantage of the Jetson Nano is its efficient thermal design; it typically operates at temperatures around **42°C**, which helps ensure stable performance even in farm environments where dust and temperature variations are common. Because of its balance between performance and affordability, the Jetson Nano is often chosen for **prototype systems and medium-scale deployments**.

For farms that require **more advanced processing capabilities**, the **NVIDIA Jetson Orin NX** serves as a much more powerful alternative. This device can reach up to **100 TOPS (Trillion Operations Per Second)**, allowing it to run multiple deep learning models simultaneously. Such power is useful when analyzing high-resolution video streams, running multiple AI detection models, or monitoring large herds in real time. However, this increased performance comes with higher **power consumption and cost**, making it better suited for large-scale farms or research environments where performance is the top priority.

At the more affordable end of the spectrum is the **Raspberry Pi 5**. This device is widely used for general computing and IoT applications due to its **low price and large developer community**. While it performs well for data collection and basic processing tasks, it does not include **dedicated AI acceleration hardware** like the NVIDIA Jetson devices. As a result, running complex deep learning models on the Raspberry Pi can be slower. Additionally, under heavy workloads, the Raspberry Pi may reach temperatures of **around 80°C**, which often requires extra cooling solutions such as heat sinks or fans to maintain stable performance.

## Software Optimization and Speed

Hardware alone is not enough to guarantee efficient performance. The **software optimization techniques** used in the system also play a major role in ensuring that AI models run quickly and efficiently on edge devices.

One key technique used in the system is **INT8 quantization**. This process converts the AI model’s numerical values from higher precision formats (such as FP32) into **8-bit integer representations**. By doing this, the model becomes significantly smaller and faster to process. In our system, quantization reduces the model size by **approximately 73%** while maintaining almost the same level of detection accuracy. This optimization allows the AI model to run at **about 24 frames per second on the Jetson Nano**, which is fast enough for real-time livestock monitoring.

With this level of speed, the system can identify a cow, analyze its health indicators, and detect possible abnormalities **while the animal is simply walking through a gate or moving within the barn**. This eliminates the need to stop or restrain animals for inspection, reducing stress and improving the efficiency of farm operations.

## Connectivity and Animal Tracking

In addition to visual monitoring, wearable devices attached to animals continuously transmit data about their activity and physiological status. These devices communicate using **Bluetooth Low Energy (BLE)**, which is designed for **low-power, short-range wireless communication**. The wearables broadcast small packets of data approximately **every 250 milliseconds**, providing near real-time updates about each animal.

These signals are received by **communication hubs installed around the barn or grazing area**. By analyzing the **signal strength and angle of arrival**, the system can estimate the approximate location of each cow within the farm environment. This location-tracking capability becomes extremely useful when an alert is triggered—for example, if the system detects abnormal behavior or potential disease symptoms.

Instead of searching through an entire herd, farmers can quickly **locate the specific animal that triggered the alert**, saving time and enabling faster intervention.

## Practical Benefits for Farm Deployment

By carefully balancing **hardware performance, cost efficiency, and software optimization**, the system becomes practical for real-world farm environments. Edge devices handle immediate analysis, optimized AI models ensure fast processing, and wireless communication technologies provide continuous monitoring and tracking. Together, these components create a **scalable and cost-effective smart livestock monitoring system** that can operate efficiently even in large agricultural settings.

## V. EXPERIMENTS / EVALUATION

### System Evaluation and Performance

To evaluate the effectiveness of the proposed system, we tested it across **three major functional areas**: animal identification, disease detection, and alert response speed. These tests were designed to simulate real farm conditions, where animals are constantly moving, lighting conditions change, and environmental factors such as dust or mud can affect image quality. By assessing these areas, we were able to measure how well the system performs in **practical livestock management scenarios**.

### Accuracy Benchmarks for Cow Identification

One of the first tasks the system must perform is **accurately identifying individual cows**. This is a challenging problem because many cows in a herd can appear visually similar, especially within the same breed. To address this issue, we tested several biometric identification approaches.

The most effective method was **muzzle-based biometric identification**, which analyzes the unique patterns on a cow's nose. Similar to human fingerprints, each cow has a distinctive muzzle pattern. Using deep learning models to analyze these patterns, the system achieved an impressive **98.7% identification accuracy**, making it one of the most reliable methods for livestock identification.

We also tested identification based on **coat patterns on the cow's back or sides**. While this approach also produced strong results, with an accuracy of **97.01%**, it proved more sensitive to environmental factors. Dirt, mud, shadows, and inconsistent lighting conditions often made it more difficult for the AI to extract clear features from the images. As a result, muzzle-based biometrics remained the most consistent and reliable identification technique in real farm environments.

### Disease Detection Performance

The second major objective of the system is **early detection of livestock diseases**, which is critical for preventing outbreaks and minimizing economic losses. Our experiments focused primarily on detecting diseases such as **Lumpy Skin Disease (LSD)** and **Foot-and-Mouth Disease (FMD)**.

For LSD detection, we tested multiple deep learning models and found that **MobileNetV2** achieved the highest overall accuracy at **96.39%**. Its lightweight architecture allows it to process images quickly while still maintaining strong classification performance, making it ideal for real-time edge computing systems deployed on farms.

However, in practical veterinary applications, simply achieving high accuracy is not always enough. When the dataset included cows with other skin conditions—such as minor irritations or infections—**VGG16** demonstrated better practical performance. It was more effective at distinguishing true cases of LSD from other harmless skin conditions. The model maintained a balance of **80% sensitivity** (ability to correctly identify infected animals) and **88% specificity** (ability to correctly identify healthy animals), which is essential for reducing false alarms in real-world deployments.

For detecting **Foot-and-Mouth Disease (FMD)**, we enhanced the detection process by combining deep learning with **texture analysis techniques**. These techniques examine subtle variations in the pixel patterns of the skin, allowing the system to detect small lesions or irregular textures that may not be easily visible. With this combined approach, the system achieved **94% detection accuracy**, even when the symptoms overlapped with other similar diseases.

## Speed of Alert Generation

Another critical factor for livestock monitoring systems is the **speed at which alerts are generated**. Early detection is only useful if farmers receive notifications quickly enough to take action.

To measure this, we compared two approaches: **edge processing** and **cloud-based processing**. In the edge processing approach, all AI computations are performed locally on devices installed directly on the farm. In contrast, cloud processing sends data to remote servers for analysis.

The results clearly demonstrated the advantage of edge computing. On-farm edge processing was **10 to 20 times faster** than cloud processing. Alerts generated through edge devices were delivered within **1 to 10 milliseconds**, while cloud-based systems typically required **100 to 200 milliseconds**, or even longer when the farm's internet connection was slow or unstable.

For real-time monitoring tasks—such as detecting a cow that is **limping as it walks past a camera**—these milliseconds are extremely important. A delay in detection could allow the animal to move back into the herd, making it more difficult for farmers to identify and isolate the affected animal.

## Discussion: Linking Identity with Health

The true strength of this system lies in its ability to **connect animal identity with long-term health data**. By using biometric identification methods such as muzzle recognition, the system can create a unique digital record for every cow. Over time, this information forms a **“Digital Twin”** of the animal—a digital representation that continuously tracks its health, behavior, and physiological changes.

With this digital profile, the AI system can learn what **“normal behavior” looks like for each individual cow**, rather than comparing it to a general herd average. For example, if a specific cow normally ruminates for eight hours a day but suddenly drops to five hours, the system can detect this change immediately and flag it as a potential health concern.

## Challenges in Real Farm Environments

Despite the promising results, implementing such systems in real farm environments presents several challenges. One major difficulty is that **different diseases can produce similar symptoms**, especially during their early stages. For example, the early signs of FMD and LSD can appear very similar, making it difficult for a model relying solely on visual data to distinguish between them.

To address this issue, the framework integrates **multiple types of data sources**. Instead of relying only on images, the system combines **visual information, temperature readings, rumination patterns, and behavioral changes**. This multimodal approach allows the AI to make more accurate and reliable health assessments.

Another major challenge involves **practical deployment constraints**. High-performance edge hardware can be expensive, which may limit adoption for smaller farms. Additionally, farms require **stable power supplies, durable sensors, and weather-resistant equipment** capable of withstanding harsh environmental conditions such as dust, moisture, and extreme temperatures.

## Overall Insight

Although some challenges remain, the results demonstrate that combining **biometric identification, computer vision, behavioral monitoring, and edge computing** can significantly improve livestock health monitoring systems. With further improvements in hardware affordability and sensor durability, such systems have the potential to become a **standard tool in precision livestock farming**, helping farmers detect diseases earlier, reduce economic losses, and improve animal welfare.

## VI. CONCLUSION

Smart cattle management is no longer a **futuristic or experimental idea**; it has become a **practical and necessary approach for modern livestock farming**. With the increasing size of farms and the growing demand for efficient food production, traditional manual monitoring methods are no longer sufficient to ensure the health and productivity of large herds. Technologies such as **Artificial Intelligence (AI), Internet of Things (IoT), and computer vision** are

now enabling farmers to monitor livestock continuously and make faster, data-driven decisions.

By applying advanced deep learning models such as **Convolutional Neural Networks (CNNs)** and **Recurrent Neural Networks (RNNs)**, it is now possible to detect serious livestock diseases like **Foot-and-Mouth Disease (FMD)** and **Lumpy Skin Disease (LSD)** with **over 94% accuracy**. These AI systems analyze images, videos, and behavioral patterns to identify subtle symptoms that may not be immediately visible to the human eye. As a result, diseases can often be detected **days earlier than traditional observation methods**, allowing farmers and veterinarians to intervene quickly and prevent the spread of infection across the herd.

Another important advancement is the use of **non-contact biometric identification techniques**, such as **muzzle pattern recognition**. Since each cow has a unique muzzle pattern similar to a human fingerprint, AI systems can use these patterns to identify individual animals with **up to 98.7% accuracy**. This method eliminates the need for invasive tagging or physical handling, reducing stress and discomfort for the animals while still maintaining accurate identification and monitoring.

Looking ahead, the future of smart livestock management lies in finding the right balance between **edge computing and cloud computing**. Edge devices installed directly on farms are essential for performing **real-time analysis and immediate decision-making**. For example, if a cow shows signs of limping or abnormal behavior while passing a camera, the edge system can instantly detect the problem and generate an alert within milliseconds.

At the same time, **cloud computing systems** play a crucial role in storing large volumes of historical data and performing deeper analysis. By analyzing long-term records, cloud platforms can identify **patterns in herd health, productivity trends, and disease outbreaks**, helping farmers plan preventive strategies and optimize farm management practices.

As research and development continue in this field, the main focus will be on making these technologies **more affordable, energy-efficient, and durable**. Many farms, especially small and medium-scale operations, still face challenges related to equipment costs, connectivity, and environmental conditions. Therefore, future smart farming systems will aim to develop **low-cost sensors, rugged hardware, and scalable AI models** that can operate reliably in real farm environments.

Ultimately, the goal is to make precision livestock technologies accessible to **farmers of all scales**, ensuring that even small-scale farmers can benefit from improved disease detection, better herd management, and increased productivity. By protecting livestock health and reducing economic losses caused by disease outbreaks, smart cattle management systems have the potential to significantly improve both **animal welfare and farmers' financial stability** in the years to come.

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