

AI-Based Smart Cow Shelter Analysis and Management System Using Internet of Things and Machine Learning

Adarsh Pandey¹; Dr. Prabhash Chandra Pathak²

¹Department of Computer Applications Babu Banarasi Das University, Lucknow, India

¹Master of Computer Applications (MCA) Session 2026–2027

²Under the Guidance of

²Associate Professor / Head & Director, School of Computer Application

Publication Date: 2026/10/22

Abstract: Cow shelters need coordination between animal identification, health observations, activity tracking, environmental factors, feed and water supplies, vaccination schedules, medical records, and operational actions. Precision livestock farming has created useful tools using sensors, identification systems and artificial intelligence. Recent reviews still show problems with combining information, checking data quality, making systems work together, and supporting decisions [1] [2] [7] [10] [24]. This paper introduces a cow-shelter system that connects RFID animal tagging, different types of IoT sensors, ESP32-based data collection at the edge, Wi-Fi communication, Flask web services, MySQL databases, clear rule-based alerts, and machine learning—all within a single management process. The system links animal data with shelter-zone details and keeps track of time, data quality, management actions, and past alerts. The analysis is done in stages: simple rules give alerts, and machine learning comes later once enough labelled and checked data is available. Features used in the analysis include sensor readings, changes over time, average trends, activity summaries, environmental data, and feed and water status. A repeatable way to test the system is created, measuring sensing delay, alert timing, data transmission reliability, dashboard speed, recovery after failure, and how well predictions work. The main contribution is not in technology but in the full system design: an information-to-action process built around animal identity, multiple sensors, resource tracking, records, analysis, alerts, and human input. The paper does not give accuracy or timing results and does not claim the individual parts are new.

Keywords: Artificial Intelligence, Internet of Things, Smart Cow Shelter, Machine Learning, Precision Livestock Farming, Decision Support, Multimodal Sensing.

How to Cite: Adarsh Pandey; Dr. Prabhash Chandra Pathak (2026) AI-Based Smart Cow Shelter Analysis and Management System Using Internet of Things and Machine Learning. *International Journal of Innovative Science and Research Technology*, 11(10), 1155-1165. <https://doi.org/10.38124/ijisrt/26oct728>

I. INTRODUCTION

Cow shelters are places where animal well-being, available resources, environmental conditions, past records, and human choices all affect each other. As the number of animals grows, so does the amount of data from observations and daily tasks. Keeping track manually becomes hard. Precision livestock farming (PLF) helps by using sensors, data processing, and digital tools to watch over each animal and its surroundings continuously or repeatedly [18] [19]. The real challenge isn't just turning paper records into digital ones. It's creating a system that connects animal identity, time-stamped data, shelter conditions, management logs, and information that leads to timely actions.

Recent studies show progress in AI, IoT, wearable sensors, environmental monitoring, and smart decision-making for livestock [1] [2] [7] [10] [24]. Sani et al. looked at cattle sensor research and grouped it into sensor types, data interpretation, integration, and decision-making. They pointed out that many studies focus on sensors but don't connect them well to management systems [1]. Distant et al. found progress in AI for animal recognition, detecting problems, and monitoring health and welfare. They noted that environmental and overall system integration is still not well developed [2]. These findings push for a system where sensing, data storage, analysis, and management are linked, not treated separately.

Existing systems prove that combining technology is possible. They also show the need for careful thinking about what a new system brings. Kaur and Virk made a collar for cows using temperature, pulse data, activity tracking, cloud analytics and a mix of AI models [3]. SmartCattle360 uses UHF RFID, sensors for animals and the environment, ESP32 hardware, cloud storage, a web dashboard and machine learning to find diseases [4]. Reviews of accelerometer systems show that each technology can give useful insights about behaviour or health. Questions remain about data quality, how different environments affect readings, and how well results apply to other farms [12] [14] [15]. So this study does not claim that RFID, ESP32, sensors, web dashboards or machine learning are new. Instead, it tests how these pieces fit together into a workflow for managing a cow shelter. The goal is to keep animal identity, shelter resources, records, alerts and human checks in one traceable chain.

The process follows this order: observation → identification and data collection at the edge → data quality checks → data transmission → central storage → rule-based or machine learning analysis → data display → alert creation → human review and action. This way, things like sensor placement, calibration, missing data, network issues, animal movement and model uncertainty are treated as parts of the research. It also follows the idea that technology should help managers understand and act on data, not just collect data [1] [18] [24].

Low-cost edge devices and wearable sensors are now practical for farm use. Systems based on ESP32 hardware and inertial sensors are becoming common [3] [12] [23]. Recent work also shows that edge-based cattle monitoring is still an active area of research [23]. So this system is not claiming that ESP32-based monitoring is new. It's about how all parts work together in a shelter management setup.

II. RESEARCH GAP AND RELATED WORK

Precision livestock farming has moved from measurements to connected systems that include sensing, data processing and decision tools. General IoT frameworks have set up layers for sensing, communication, processing and applications [5]. Surveys on AI and deep learning show that data-driven methods are growing in agriculture [6]. Cattle-specific reviews cover behaviour tracking, health monitoring, wearable sensors, environmental sensing, identification and computer vision [7] [10]–[15] [17].

Recent reviews are especially useful for this work. Marin et al. stressed the need for sensor types and better testing that includes context and multiple measures [7]. Nsabiyeze et al. found that system integration, scaling, cost and real-time decision support are still issues in precision farming [8]. Maheshwari et al. reviewed uses of PLF including sensors, RFID, AI, behaviour tracking, and health care [9]. Yin et al. and Xu et al. showed that combining multiple sensor types and non-contact methods is advancing fast. They also said that real-world use, data quality, standards, and connecting everything are still open problems [10] [11]. Posam et al. built a dairy farm system using sensors, RFID/GPS, feed and waste automation, and machine learning for disease detection [22]. This shows that full farm integration with IoT and machine learning is already a growing area.

The literature points to five gaps this work addresses: (1) animal records and shelter management are often kept apart; (2) animal data is not always tied to the shelter zone's resources and conditions; (3) many systems aim to improve one task—like sensing or prediction—instead of the whole workflow; (4) getting real field data with confirmed labels is hard; (5) system performance and model performance are often evaluated separately [1] [7] [14] [15] [24]. The proposed system answers these by using shared identity or shelter-zone IDs, keeping processed data separate, using simple rules before machine learning, and testing the full journey from sensing to human action.

Table 1 Comparison of Research Directions and Position of the Proposed Work

Research direction	Typical focus	Remaining opportunity	Position of this work
Cattle health IoT [3]	Physiology + AI	Shelter-wide records and resources	Connects health-related observations with shelter management
SmartCattle360 [4]	IoT + dashboard + AI	Different architecture and management scope	Focuses on identity-linked cow-shelter workflow
Sensor/wearable reviews [12], [14]	Behaviour / physiology	End-to-end management integration	Uses validated sensor domains as inputs
Microclimate + behaviour [7]	Multimodal sensing + ML	Operational information chain	Links environment, resources, alerts, and records
PLF integration reviews [1], [19]	Sensors → information → decisions	Practical shelter-level integration	Defines a traceable information-to-action chain
AI/PLF mapping [2], [24]	AI applications and disease detection	Environmental/resource integration and deployment	Stages rules, ML, and human verification

➤ Problem Formulation and Objectives

The research problem is formulated as follows: how can a modular and cost-conscious IoT and machine-learning platform collect, identify, validate, store, analyse, and visualize selected observations from cows and their shelter while producing measurable decision-support alerts and retaining human verification? The emphasis is on system integration and traceability rather than autonomous diagnosis.

The study is guided by six research questions: RQ1—Can RFID and heterogeneous sensor types be combined into a shared identity-linked workflow? RQ2—Can an ESP32, Wi-Fi, Flask, and MySQL pipeline reliably transmit and retain time-stamped observations? RQ3—Can transparent rules generate understandable operational alerts when labelled ML data are insufficient? RQ4—Once verified labels are available, can ML distinguish predefined abnormal-condition or risk categories? RQ5—What are the measured sensor response time, alert latency, transmission reliability, recovery behaviour, and dashboard response? RQ6—Which sensing, data-quality, networking, and deployment factors most strongly influence reliability and generalisation?

• Objectives

- ✓ Create RFID-linked digital profiles for individual animals and maintain a stable identifier across observations and management events.
- ✓ Collect selected health-related, activity, environmental, feeding, and water observations while distinguishing animal-level and shelter-level measurements.
- ✓ Transmit validated, time-stamped observations from ESP32 nodes to a centralized server and retain acquisition and server-receipt times.
- ✓ Maintain sensor observations together with vaccination, medical, feeding, water, alert, device, and user information.
- ✓ Provide a role-aware web dashboard for administrators, caretakers, and veterinary staff.
- ✓ Apply interpretable operational rules first and enable ML only after labels, data quality, and leakage controls have been verified.
- ✓ Evaluate sensing, communication, recovery, alerting, dashboard behaviour, and analytical performance through predefined and repeatable experiments.

• Functional and Non-Functional Requirements

Table 2 Functional and Non-Functional Requirements

Functional requirements	Non-functional requirements
Animal registration + RFID	Reliable operation during temporary network loss
Sensor acquisition + timestamping	Support for additional sensor nodes
Live/history dashboard	Usable by non-technical users
Vaccination + medical records	Maintainable modular design
Feed + water monitoring	Account and data security
Rule alerts + acknowledgement	Auditable records and actions
ML inference when validated	Traceable preprocessing and model versions

➤ Proposed System Architecture

The proposed architecture is organized into five logical layers: sensing and identification; edge acquisition and validation; communication; server-side processing, database storage, and analytics; and management and human interaction. The separation allows individual components to

be tested independently while preserving a shared animal identifier or shelter-zone identifier across the workflow. The architecture is intentionally modular so that additional sensors or analytical modules can be introduced without redesigning the complete data model.

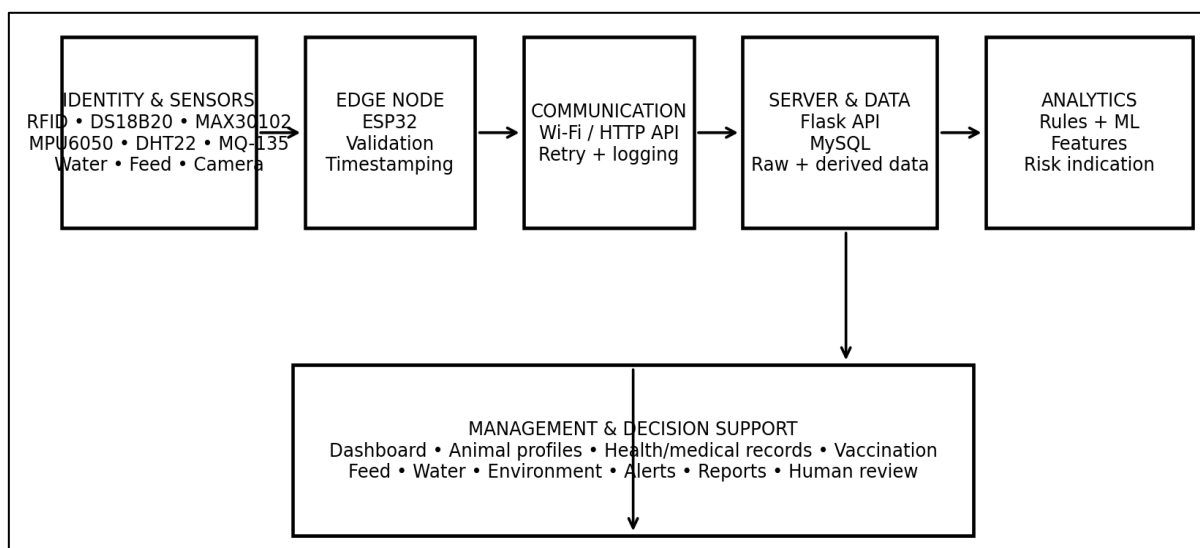


Fig 1 Integrated Five-Layer Architecture for the Proposed Smart Cow-Shelter System.

At the sensing layer, RFID provides animal identity. DS18B20 provides temperature observations; MAX30102 provides pulse-related optical information subject to placement and calibration; MPU6050 captures movement; DHT22 measures shelter temperature and humidity; MQ-135 provides a general air-quality response; an ultrasonic sensor estimates water level; and a load cell with HX711 estimates feed quantity. Camera input remains optional because its utility depends on image quality, privacy requirements, and the availability of reliable labels. These devices should be treated as measurement components rather than direct disease detectors. Similar reviews emphasize that sensor outputs must be validated against appropriate reference observations before they are interpreted as biological or clinical indicators [12], [14], [24].

The ESP32 edge node performs sampling, time stamping, basic range and plausibility checks, quality marking, and packet preparation. Observations are transferred through Wi-Fi/HTTP to a Flask service. Failed transmissions are logged and retried, while event identifiers or server-side duplicate detection can prevent repeated records. MySQL stores raw observations and management

records; derived features are stored separately so that preprocessing and ML experiments remain reproducible. This separation also supports later migration to cloud or multi-shelter infrastructure without changing the conceptual data model.

➤ Sensor Integration And Data Quality

Sensor selection is based on the information domains required for shelter management. A key methodological rule is that a sensor must not be described as directly measuring a variable that it does not actually observe. For example, MQ-135 should be treated as a general gas-response indicator requiring deployment-specific calibration, not as a direct clinical gas-concentration measurement. Likewise, pulse-related information from MAX30102 can be affected by contact, movement, optical conditions, and placement. Accelerometer-derived behaviour is useful, but reviews report that performance can vary with preprocessing, sensor position, behaviour class, and deployment environment [12], [15], [16]. The use of accelerometer-derived activity indicators is consistent with prior reviews of sensor-based cattle health and welfare assessment [13].

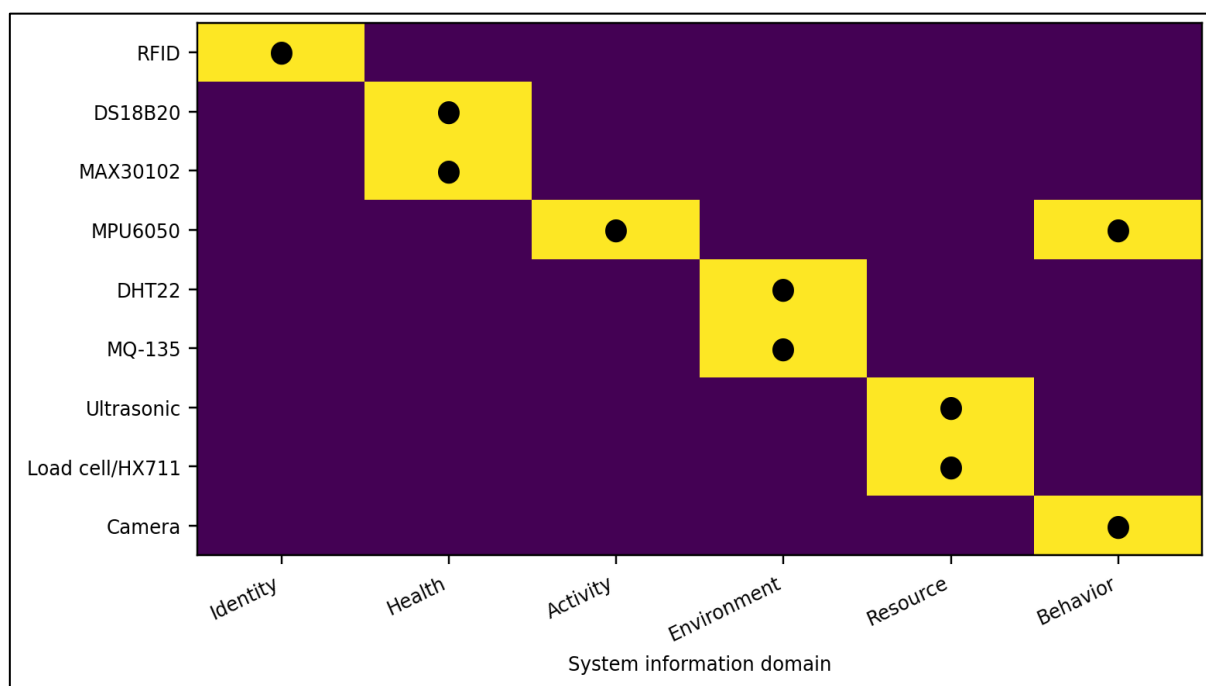


Fig 2 Design-Level Sensor-to-Function Coverage; Markers Indicate Intended Information Domains, Not Measured Performance.

Table 3 Sensor-to-Function Coverage and Key Considerations

Component	Primary role	Data	Critical consideration
RFID	Animal identification	Unique ID	Correct tag-reader association
DS18B20	Temperature observation	Temperature	Placement and calibration
MAX30102	Pulse-related observation	Optical / derived	Sensitive to movement and placement
MPU6050	Activity / motion	Acceleration	Mounting and orientation
DHT22	Shelter environment	Temperature / humidity	Placement and response time
MQ-135	Air-quality indication	Sensor response	Calibration and cross-sensitivity
Ultrasonic	Water-level estimation	Distance	Tank geometry and reflection
Load cell + HX711	Feed quantity	Weight	Mechanical calibration
Camera	Behaviour analysis	Image / video	Lighting, privacy, and labels

• Calibration, Sampling, and Missing Data

Calibration records should include the sensor identifier, calibration date, reference condition, observed reference value, transformation or adjustment, and responsible operator. Sampling intervals should be selected according to the research objective, sensor characteristics, available power, communication capacity, and animal-handling requirements. Where a sensor cannot be validated to a scientifically adequate level, its output should be described as an operational indicator rather than a precise physiological or clinical measurement [12], [14], [24].

Missing observations may arise from Wi-Fi outages, sensor disconnection, invalid readings, power loss, or server-side failures. Missing values must not be silently converted to zero. The preprocessing pipeline should explicitly record missingness, deletion or imputation decisions, outlier

handling, and data-quality flags. Both acquisition time and server-receipt time should be retained so that communication delay can be measured. This is important because real-world PLF performance is affected by deployment conditions, sensor reliability, and data-quality variation [10], [14], [24].

➤ Data Acquisition and Database Design

Each structured data packet should contain an animal identifier or shelter/device identifier, sensor type, value, unit, acquisition timestamp, device status, and optional quality indicators. Shelter-level measurements, such as DHT22 readings and water-tank level, should be linked to the relevant shelter zone rather than incorrectly assigned to an individual animal. This distinction is central to the proposed integrated model because it permits animal-level and environmental information to be joined during analysis without creating false biological associations.

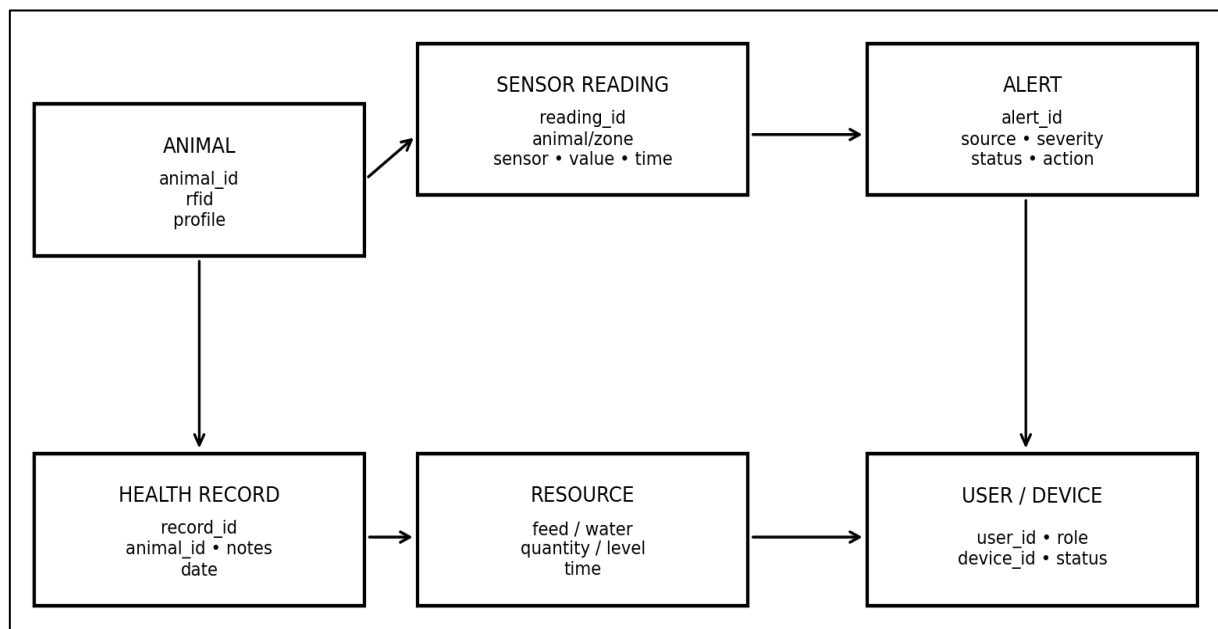


Fig 3 Logical Data Entities Supporting Identity-Linked Management and Analytics.

The database includes Animal, SensorReading, Vaccination, MedicalRecord, FeedRecord, WaterRecord, Alert, User, and Device entities. The model links time-series observations with longer-term management information and supports historical trend analysis, audit trails, and repeatable ML preprocessing. The design also permits a distinction between raw measurements, derived features, model outputs, and human-verified outcomes, which is important for traceability and later error analysis [1], [24].

III. ARTIFICIAL INTELLIGENCE AND MACHINE-LEARNING METHODOLOGY

The ML component is designed to classify predefined abnormal-condition or potential health-risk categories rather than to produce unsupported veterinary diagnoses. Target labels must be established before training and should be supported by verified observations, domain-reviewed records, or a clearly documented operational definition. A sensor threshold must not automatically be treated as a

disease label unless the threshold itself is the defined research target. Recent reviews emphasize the importance of defensible case definitions, external validation, and human interpretation for sensor-based cattle health systems [1], [2], [24].

➤ Feature Engineering

Temporal information can be more informative than an isolated measurement because deviations from an individual animal baseline may indicate a meaningful change. For a measurement x , the change across k sampling intervals is:

$$\Delta x(t) = x(t) - x(t-k)$$

A moving average can reduce sensitivity to individual noisy observations:

$$MA_w(t) = (1/w) \sum_{i=0}^{w-1} x(t-i)$$

Candidate feature groups include current temperature and activity values, temporal changes, moving averages, duration of inactivity, environmental variables, feed quantity, water level, and justified time-of-day information. Features must be generated using only information available at or before the prediction time so that future information does not enter training data. Behaviour-monitoring reviews similarly recommend explicit preprocessing and careful validation of generalisation across animals and conditions [15], [16].

➤ *Baseline Model and Validation Strategy*

Random Forest is selected as a baseline for structured tabular classification because ensemble decision trees can model nonlinear feature relationships and provide a strong, interpretable reference model [21]. Logistic Regression, Decision Trees, Gradient Boosting, Support Vector Machines, or neural-network methods may be evaluated when dataset size and research scope justify them. The final model should be selected from observed validation performance rather than assumed in advance [2], [7].

Longitudinal animal data create a substantial risk of information leakage. With a simple row-level random split, closely related observations from the same animal may appear in both training and testing sets, producing an overly optimistic estimate. Therefore, evaluation should use animal-level separation, time-aware separation, or another protocol that matches the intended deployment setting. Class imbalance, missing observations, sensor noise, and label

uncertainty should be documented rather than concealed. These issues are repeatedly identified in livestock ML literature as barriers to reliable generalisation [7], [15], [20], [24].

➤ *Rules + ML Staging*

Rules are used as the first analytical layer because they are transparent and can operate before a sufficiently labelled ML dataset exists. Conditions such as persistently low water level, a validated sensor anomaly, or another project-defined operational condition can trigger an alert. ML is introduced only after the dataset passes predefined quality and validation checks. The staged design is consistent with the broader PLF transition from sensing and data interpretation toward information integration and decision support [1], [18].

➤ *Human-in-the-Loop Decision Support*

A sensor anomaly may be caused by animal movement, sensor drift, incorrect placement, environmental variation, device failure, or communication problems. The system therefore validates incoming data, applies the configured rule or model, generates an alert when criteria are met, and presents the authorized user with the relevant animal profile, recent history, and surrounding shelter context. The user can then inspect the animal or equipment and document the observed outcome. This human-in-the-loop design avoids presenting an algorithmic indication as a veterinary diagnosis and creates a feedback record for future label refinement and error analysis [19], [24].

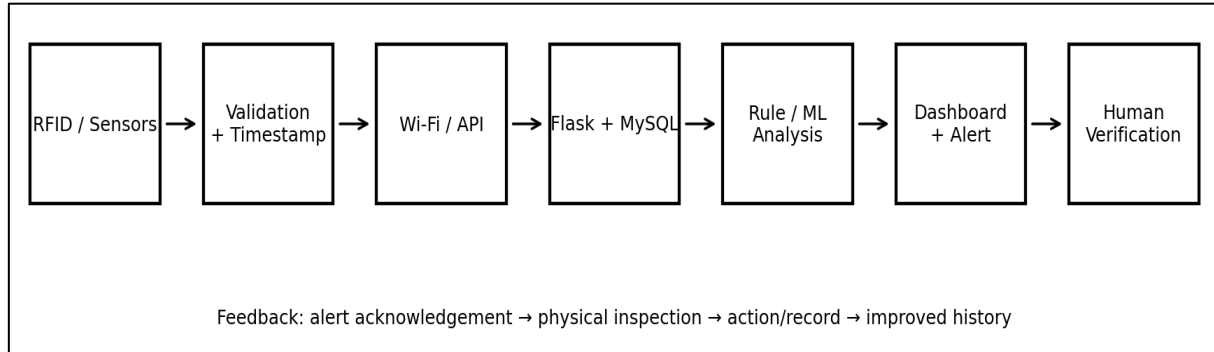


Fig 4 End-to-End Identity-Linked Data and Decision Workflow.

The workflow explicitly distinguishes operational alerts from health-risk indications and records uncertainty. A confirmed or rejected alert can be stored as a human-verified outcome, allowing later comparison of sensor conditions, rule decisions, and ML predictions. This feedback mechanism is an important part of the proposed management architecture because the value of an alert depends not only on detection but also on whether it leads to an appropriate and traceable management action.

IV. EXPERIMENTAL METHODOLOGY

The evaluation follows a staged system-experiment process: requirements analysis, hardware integration, data acquisition, preprocessing, software development, labelling, ML development, integration, failure testing, and final evaluation. Each stage produces traceable evidence. No accuracy, latency, or reliability value is claimed unless it is obtained from the implemented prototype. The final dataset description should report the number of animals, observation period, sampling interval, sensor placement, missingness, label source, train/test separation, and test environment [14], [15], [24].

Table 4 Experimental Phases and Evidence

Phase	Activity	Evidence
1	Requirements and parameter definition	Specification
2	RFID and sensor integration	Working sensor node
3	Time-stamped data collection	Raw dataset
4	Validation and feature engineering	Clean dataset / pipeline
5	Flask, MySQL, and dashboard development	Web application
6	Labelling and training/testing	Validated model if feasible
7	End-to-end integration	Integrated prototype
8	Failure, alert, and UI testing	Test logs
9	Metric evaluation	Experimental results

➤ *Test Scenarios*

- Normal sensing with successful data transmission.
- Temporary Wi-Fi loss followed by successful recovery and data-consistency verification.
- Disconnected sensor or invalid sensor reading.
- RFID identification followed by retrieval of the correct animal profile.
- Water-level measurement crossing a configured operational threshold.
- Feed measurement change and corresponding dashboard update.
- Activation of a rule for a persistent abnormal operational condition.
- Alert acknowledgement followed by documented resolution or rejection.
- Dashboard refresh and report generation using a predefined dataset size.

➤ *Performance Metrics*

For binary or multiclass classification, the principal evaluation measures are defined as follows:

$$\text{Accuracy} = (\text{TP} + \text{TN}) / (\text{TP} + \text{TN} + \text{FP} + \text{FN})$$

$$\text{Precision} = \text{TP} / (\text{TP} + \text{FP})$$

$$\text{Recall} = \text{TP} / (\text{TP} + \text{FN})$$

$$\text{F1} = 2 \times (\text{Precision} \times \text{Recall}) / (\text{Precision} + \text{Recall})$$

For multiclass problems, macro-averaged and class-specific precision, recall, and F1-score should be reported together with a confusion matrix. System-level measurements are also required. Sensor response time is defined as $T_{\text{sensor}} = t_{\text{server}} - t_{\text{acquisition}}$. Alert latency is $T_{\text{alert}} = t_{\text{alert}} - t_{\text{detection}}$. Transmission reliability is $R_{\text{tx}} = N_{\text{successful}} / N_{\text{attempted}} \times 100$. Recovery experiments should additionally record failed packets, successfully recovered packets, duplicate records, and final database consistency. Dashboard evaluation should include API/page response time, refresh behaviour, chart rendering, database-query duration, and report-generation time for a specified dataset size.

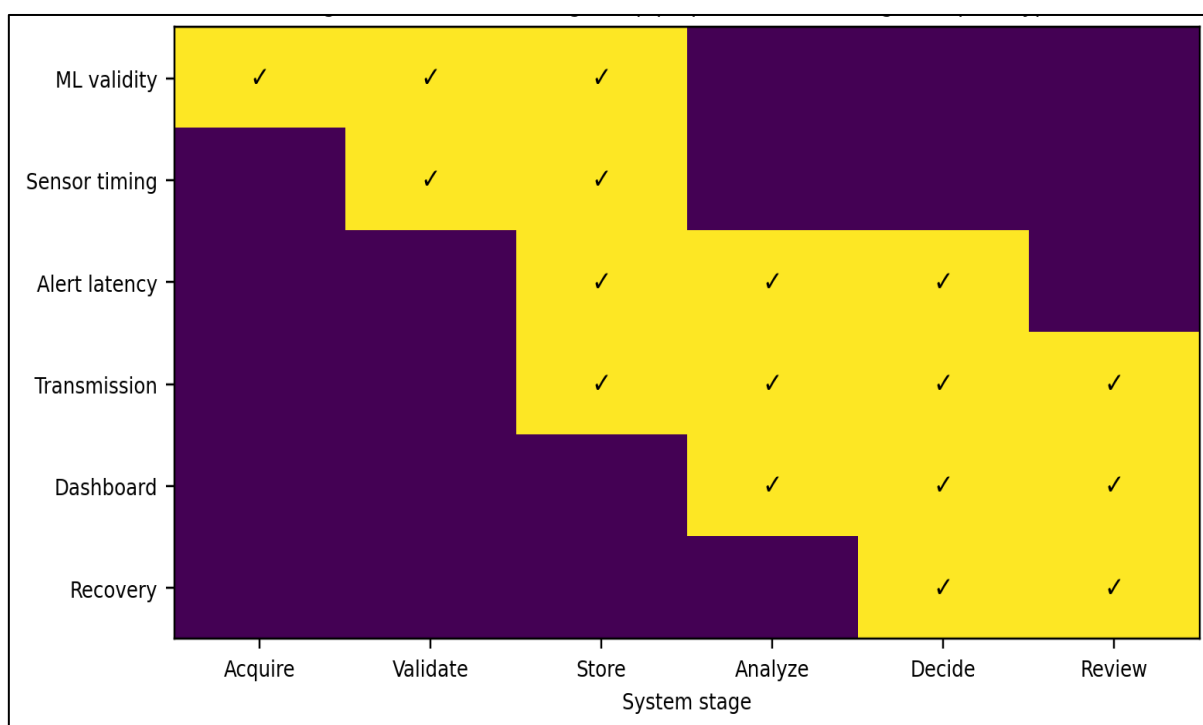


Fig 5 Evaluation Coverage Map Proposed for the Integrated Prototype; It is a Test-Design Figure, Not a Result Chart.

Where repeated measurements are available, summary statistics such as mean, median, standard deviation, confidence intervals, and failure counts should be reported. Classification results should be stratified where appropriate by animal, time period, environmental condition, and target class. This reporting approach reduces the risk that a single aggregate metric hides poor performance for specific animals or conditions [7], [15], [24].

V. RESULTS REPORTING AND DISCUSSION FRAMEWORK

Measured prototype results are not reported in this paper, and no values are given for accuracy, precision, recall, F1-score, sensor delay, alert latency, or transmission reliability. These metrics are defined below and are to be filled in from experiments on the implemented system, together with the number of animals, observation period, sampling interval, missing records, label source, train/test separation, hardware/software versions, and test environment.

Table 5 Performance Metrics and Reporting Status

Metric	Definition	Final value
Accuracy	Overall classification correctness	To be measured
Precision	Correctness of positive/risk predictions	To be measured
Recall	Ability to identify target cases	To be measured
F1-score	Harmonic balance of precision and recall	To be measured
Sensor response	Server receipt time – acquisition time	To be measured
Alert latency	Alert generation time – detection time	To be measured
Transmission reliability	Successful packets / attempted packets × 100	To be measured
Dashboard response	Measured API/page response under a defined workload	To be measured

➤ Interpretation of Expected Evidence

The contribution should be examined at both component and end-to-end levels. Reliable sensor operation alone does not guarantee reliable alerts because identification, communication, preprocessing, rules, model inference, and visualization can each introduce errors. An end-to-end trace should therefore connect a physical observation with its database entry, analytical decision, dashboard event, and human verification outcome. This is particularly important for integrated PLF systems, where interoperability and deployment reliability are often as important as algorithmic accuracy [1], [10], [24].

When the ML model produces strong results, the discussion should test whether performance remains consistent across animals, time periods, environmental conditions, and target classes. If results are weak, the paper should investigate causes such as limited data, class imbalance, noisy sensors, uncertain labels, overlapping features, sensor placement, or information leakage. Rule-based monitoring should be contrasted with ML conceptually: rules are transparent and can operate with limited labelled data, whereas ML can capture more complex relationships but depends on representative and validated datasets [2], [7], [20].

➤ Security, Privacy, Safety and Ethics

The connected platform should protect user accounts, animal records, device credentials, and audit information. Role-based permissions can distinguish administrator, caretaker, and veterinary responsibilities. Passwords must not

be stored in plain text. Security evaluation should include input validation, authorization checks, database access control, audit logging, and recovery testing. The system should also separate operational data from model-development data so that changes to the analytical pipeline remain traceable.

Optional camera use introduces additional privacy and governance concerns because people may appear in captured images. Camera deployment should follow institutional requirements and applicable legal provisions. Animal welfare must remain a priority: sensor installation should minimize unnecessary handling, and close-contact measurements should be reviewed with appropriate domain professionals. Experimental sensor outputs must not be presented as unquestionable medical facts. Recent welfare reviews similarly emphasize the gap between controlled sensing performance and robust real-world interpretation [14], [24].

➤ Cost, Scalability and Deployment

The architecture is designed to remain modular and cost-conscious through ESP32-class edge hardware, commonly available sensors, open software components, and a web interface. Actual deployment cost depends on animal population, sensor-node density, shelter layout, power availability, network coverage, protective housing, calibration requirements, maintenance, and component replacement. Scalability should therefore be evaluated experimentally rather than inferred only from component cost [8], [9], [10].

Table 6 Current Prototype and Scalable Extensions

Current prototype	Scalable extension
RFID-linked records	Multi-shelter identity management
ESP32 node	Multiple nodes with gateway

MySQL	Cloud or replicated database where justified
Rules + ML	Model registry with continuous evaluation
Web dashboard	Mobile and multi-shelter dashboard
Optional camera	Validated computer vision
Manual calibration records	Automated device-health monitoring

➤ *Novelty and Contributions*

The novelty claim is deliberately bounded by the literature search. RFID, ESP32, individual sensors, web dashboards, IoT communication, and machine-learning algorithms are established technologies. Recent work already demonstrates integrated cattle health monitoring, sensor fusion, dashboards, cloud systems, AI-based disease or behaviour analysis, and broader dairy-farm automation [3], [4], [7], [10], [22], [23]. Therefore, it would not be scientifically defensible to claim that IoT, AI, or automated cattle monitoring has never been applied to this domain. The proposed contribution is the specific shelter-management integration in which animal identity, multimodal observations, shelter-zone conditions, feed and water resources, vaccination and medical records, operational alerts, analytics, and human verification share a traceable data structure. The design also explicitly separates animal-level from shelter-level observations and stages transparent rules before ML deployment. Based on the literature examined for this paper, an exact peer-reviewed system matching this complete workflow was not identified; this is therefore presented as a literature-based novelty position rather than an absolute claim of worldwide first use.

- Identity-linked multimodal observations using shared animal or shelter-zone identifiers, timestamps, and quality indicators.
- Joint representation of health-related observations with shelter environment, feed, water, vaccination, medical, and alert records.
- A staged rules-plus-ML analytical pathway that remains operational when sufficient ML labels are not yet available.
- A centralized management dashboard connecting observations, records, alerts, reports, and human verification.
- A system-level evaluation framework covering sensing, communication, recovery, alerting, dashboard behaviour, and ML performance.
- A modular design that can be extended to multiple shelters, mobile access, cloud synchronization, computer vision, and edge intelligence.

VI. LIMITATIONS

- Sensor outputs can vary because of placement, calibration, animal movement, environmental conditions, and device ageing.
- Pulse-related information from MAX30102 may be affected by movement and physical contact quality.
- MQ-135 provides a general sensor response and requires deployment-specific calibration and interpretation.

- Camera-based analysis is influenced by lighting, viewing angle, privacy requirements, and the availability of labelled images.
- Small or unbalanced datasets can reduce statistical power and generalisation.
- Operational thresholds require documented justification and must not be interpreted as universal clinical limits.
- Wi-Fi failures, device drift, power constraints, and maintenance requirements can reduce long-term reliability.
- The proposed platform is a decision-support system and is not an autonomous veterinary diagnostic system.
- Validation across multiple shelters, seasons, breeds, animal-management practices, and independent test animals is required before making broad claims.

VII. FUTURE RESEARCH

Future research should focus on longer longitudinal datasets and multi-shelter validation so that individual-animal baselines can be learned without leakage. Edge AI and TinyML may reduce communication requirements for selected tasks, while explainable ML can provide feature-level context for risk indications and support error investigation. Computer vision may be introduced for behaviour, posture, locomotion, and identification when image quality and reliable labels are sufficient. Other extensions include cloud synchronization, mobile applications, model version control, sensor-drift detection, resource forecasting, and predictive maintenance [10], [11], [23].

An important next step is to move beyond technical integration toward measurable management outcomes. Future studies should examine whether alerts reduce inspection time, improve record completeness, improve feed and water tracking, reduce unresolved operational events, or produce other measurable improvements. Such evidence would distinguish a technically functional prototype from a decision-support platform with demonstrated practical value [1], [18], [24].

VIII. CONCLUSION

This paper proposed an AI-based smart cow-shelter analysis and management architecture that combines RFID identification, heterogeneous IoT sensing, ESP32 edge acquisition, Wi-Fi communication, Flask services, MySQL storage, rule-based alerts, machine-learning analysis, and a web dashboard. The architecture associates animal-level and shelter-level observations with identifiers and timestamps, supporting live monitoring, historical analysis, digital records, and structured decision support.

The main contribution is not a new sensor or ML algorithm, but an integrated and measurable workflow for cow-shelter management. The literature review indicates that individual technologies and several integrated cattle-monitoring platforms already exist; therefore, the paper positions its novelty at the level of the complete shelter-management information chain. The proposed design also emphasizes research validity: performance claims must be based on measured prototype data, labels must have a defensible basis, animal-level leakage must be controlled, and sensor uncertainty must be reported. After implementation and independent field validation, the platform can provide a practical foundation for further research in smart livestock and shelter management.

REFERENCES

- [1]. M. I. Sani, M. van der Voort, B. Tekinerdogan, and H. Hogeveen, "Application of precision livestock farming: challenges and opportunities," *Animal Bioscience*, vol. 39, no. 4, Art. no. 250895, 2026, doi: 10.5713/ab.250895.
- [2]. D. Distante, C. Albanello, H. Zaffar, S. Faralli, and D. Amalfitano, "Artificial intelligence applied to precision livestock farming: A tertiary study," *Smart Agricultural Technology*, vol. 11, Art. no. 100889, 2025, doi: 10.1016/j.atech.2025.100889.
- [3]. D. Kaur and A. K. Virk, "An IoT-Driven hybrid AI model for health monitoring of cows," *Discover Artificial Intelligence*, vol. 5, Art. no. 346, 2025, doi: 10.1007/s44163-025-00610-4.
- [4]. "SmartCattle360: Intelligent Livestock Monitoring & Management System," in *Proc. 9th Int. Conf. I-SMAC (IoT in Social, Mobile, Analytics and Cloud)*, 2025, doi: 10.1109/I-SMAC65734.2025.11597618.
- [5]. L. Atzori, A. Iera, and G. Morabito, "The Internet of Things: A survey," *Computer Networks*, vol. 54, no. 15, pp. 2787–2805, 2010, doi: 10.1016/j.comnet.2010.05.010.
- [6]. A. Kamilaris and F. X. Prenafeta-Boldú, "Deep learning in agriculture: A survey," *Computers and Electronics in Agriculture*, vol. 147, pp. 70–90, 2018, doi: 10.1016/j.compag.2018.02.016.
- [7]. I. Marin, D.-A. Ciungan, R. E. Vasiliu, and D.-N. Enea, "Livestock monitoring based on microclimate and behavior tracking sensors: A systematic review," *IEEE Access*, vol. 13, pp. 185818–185844, 2025, doi: 10.1109/ACCESS.2025.3625600.
- [8]. M. Nsabiyeze, M. Zhang, J. Li, Q. Zhao, and X. Zhang, "Precision livestock farming for climate-resilient livestock management: A review of real-time monitoring and decision support systems," *Journal of Cleaner Production*, vol. 524, Art. no. 146454, 2025, doi: 10.1016/j.jclepro.2025.146454.
- [9]. Maheshwari, S. Shirwal, Santosh, Abhishek A., Satish, Gowtham, and Murali M., "Precision livestock farming systems in India: AI and ML in livestock farming," *Journal of Experimental Agriculture International*, vol. 47, no. 11, pp. 654–669, 2025, doi: 10.9734/jeai/2025/v47i113904.
- [10]. M. Yin, W. Huang, X. Guo, Q. Zhao, G. Ostojic, T. C. Loh, J. Hu, and M. Zhang, "A comprehensive review of wearable sensors for animal information acquisition in precision livestock farming," *Computers and Electronics in Agriculture*, Art. no. 112175, 2026, doi: 10.1016/j.compag.2026.112175.
- [11]. X. Xu, B. Xiong, D. Liu, T. Norton, and H. Song, "Non-contact technologies for cattle monitoring: advances and challenges towards precision livestock farming," *Computers and Electronics in Agriculture*, vol. 248, Art. no. 111785, 2026, doi: 10.1016/j.compag.2026.111785.
- [12]. M. Lee and S. Seo, "Wearable wireless biosensor technology for monitoring cattle: A review," *Animals*, vol. 11, no. 10, Art. no. 2779, 2021, doi: 10.3390/ani11102779.
- [13]. J. M. Chapa, K. Maschat, M. Iwersen, J. Baumgartner, and M. Drillich, "Accelerometer systems as tools for health and welfare assessment in cattle and pigs—A review," *Behavioural Processes*, vol. 181, Art. no. 104262, 2020, doi: 10.1016/j.beproc.2020.104262.
- [14]. A. H. Stygar, Y. Gómez, G. V. Berteselli, E. Dalla Costa, E. Canali, J. K. Niemi, P. Llonch, and M. Pastell, "A systematic review on commercially available and validated sensor technologies for welfare assessment of dairy cattle," *Frontiers in Veterinary Science*, vol. 8, Art. no. 634338, 2021, doi: 10.3389/fvets.2021.634338.
- [15]. L. Riaboff, L. Shalloo, A. F. Smeaton, S. Couvreur, A. Madouasse, and M. T. Keane, "Predicting livestock behaviour using accelerometers: A systematic review of processing techniques for ruminant behaviour prediction from raw accelerometer data," *Computers and Electronics in Agriculture*, vol. 192, Art. no. 106610, 2022, doi: 10.1016/j.compag.2021.106610.
- [16]. J. A. Vázquez Diosdado, Z. E. Barker, H. R. Hodges, J. R. Amory, D. P. Croft, N. J. Bell, and E. A. Codling, "Classification of behaviour in housed dairy cows using an accelerometer-based activity monitoring system," *Animal Biotelemetry*, vol. 3, Art. no. 15, 2015, doi: 10.1186/s40317-015-0045-8.
- [17]. A. I. Awad, "From individual identification to behavioral sensing—A review on cattle identification and tracking," *Computers and Electronics in Agriculture*, vol. 123, pp. 423–435, 2016, doi: 10.1016/j.compag.2016.03.014.
- [18]. C. Aquilani, A. Confessore, R. Bozzi, F. Sirtori, and C. Pugliese, "Review: Precision Livestock Farming technologies in pasture-based livestock systems," *Animal*, vol. 16, no. 1, Art. no. 100429, 2022, doi: 10.1016/j.animal.2021.100429.
- [19]. J. L. Kleen and R. Guatteo, "Precision Livestock Farming: What Does It Contain and What Are the Perspectives?" *Animals*, vol. 13, no. 5, Art. no. 779, 2023, doi: 10.3390/ani13050779.
- [20]. N. Slob, C. Catal, and A. Kassahun, "Application of machine learning to improve dairy farm management: A systematic literature review," *Preventive Veterinary Medicine*, vol. 187, Art. no. 105237, 2021, doi: 10.1016/j.prevetmed.2020.105237.

- [21]. L. Breiman, “Random forests,” *Machine Learning*, vol. 45, pp. 5–32, 2001, doi: 10.1023/A:1010933404324.
- [22]. S. Posam, L. K. Reddy G, and V. C. M., “Automated dairy farm management system powered by IoT and ML,” *Results in Engineering*, vol. 28, Art. no. 107508, 2025, doi: 10.1016/j.rineng.2025.107508.
- [23]. G. Selvakumari and G. R. Kanagachidambaresan, “IoT-enabled edge-based cattle behavior monitoring framework using TinyML and IMU sensor fusion,” *Computers and Electronics in Agriculture*, vol. 250, Art. no. 111918, 2026, doi: 10.1016/j.compag.2026.111918.
- [24]. K. T. Bhandwalkar and D. Jadhav, “Artificial intelligence and internet of things enabled systems for smart veterinary disease detection,” *Discover Artificial Intelligence*, vol. 6, Art. no. 418, 2026, doi: 10.1007/s44163-026-01173-8.