Research Article *Open Access*

Journal of Pioneering Artificial Intelligence Research

ISSN: 3069-0846

DOI: doi.org/10.63721/26JPAIR0141

An Intelligent IOT Framework for Cattle Tracking and Health Monitoring Using Machine Learning Prediction

Dr. Prabha Seetaram Naik[1*], Bhagya M[2], Mahalakshmi J[3], Mahesh N[4], Jyothi N[5] and Anupooja AN[6]

[1,2] Associate Professor, Department of CSE, Cambridge Institute of Technology North Campus Bengaluru, India
[3,4,6] Assistant Professor, Department of CSE, Cambridge Institute of Technology North Campus Bengaluru, India
[5]Assistant Professor, Department of AI and ML, C Byregowda Institute of Technology, Kolar, India

Citation: *Dr. Prabha Seetaram Naik, Bhagya M, Mahalakshmi J, Mahesh N, Jyothi N, et al. (2026) An Intelligent IOT Framework for Cattle Tracking and Health Monitoring Using Machine Learning Prediction. J of Poin Artf Research 2(3), 1-4 WMJ-JPAIR-141*

Abstract

The livestock industry plays a critical role in the agricultural economy, where animal health, productivity, and mobility directly influence farmer income. Traditional monitoring methods rely heavily on manual observation, which is time- consuming, labor-dependent, and prone to delays in detecting early signs of disease or abnormal behavior. With advancements in automation and intelligent sensing, the integration of Internet of Things (IoT) and Machine Learning (ML) enables real-time, data- driven livestock monitoring. This paper presents an IoT-based smart cattle monitoring system capable of tracking cow location, collecting physiological and environmental parameters, and predicting health risk categories using a Random Forest classifier. Additionally, a Random Forest regressor is used to estimate milk yield based on temperature, activity levels, and feed patterns. The system incorporates GPS, temperature, and accelerometer sensors to collect live data, which is processed and visualized on a stream lit dashboard for improved decision-making. Results demonstrate successful implementation of real-time monitoring, accurate disease risk classification, and consistent milk yield prediction, enabling proactive management and improved farm efficiency. This approach contributes towards scalable, automated, and cost-effective dairy solutions suitable for small to large-scale farms.

***Corresponding author**: Dr. Prabha S Naik, Associate Professor, Department of CSE, Cambridge Institute of Technology North Campus Bengaluru, India

Submitted: 11.05.2026 **Accepted**: 15.05.2026 **Published**: 25.05.2026

Keywords: IoT, Machine Learning, Random Forest, Livestock Monitoring, Disease Prediction, GPS Tracking, Smart Dairy Farming

Introduction

Dairy farming is an essential part of the agricultural sector, where livestock health and movement directly influence productivity and farmer income. Traditional monitoring methods rely on manual observation, which is time- consuming, labor-intensive, and often leads to delayed identification of illness or missing cattle. As herd sizes grow, maintaining continuous supervision becomes increasingly difficult and inefficient. This project presents an IoT-enabled cattle monitoring system equipped with machine learning- based prediction models. The system tracks movement, monitors physiological indicators, and uses a Random Forest model to classify disease risk and estimate milk yield.

A stream lit dashboard provides real-time visualization and alerts, enabling farmers to make informed, data-driven decisions. The solution aims to offer an affordable, scalable, and automated monitoring framework suitable for modern dairy farms. Furthermore, the integration of IoT and ML simplifies real-time livestock supervision by reducing manual intervention and improving response time to abnormal conditions. By combining sensor data with predictive analytics, farmers can identify potential health risks early and optimize feeding, environment, and management strategies. The system supports better decision-making, enhances animal welfare, and contributes to increased overall farm productivity.

Literature Review and Background

Early IoT-Based Livestock Monitoring Systems: Initial approaches focused primarily on integrating simple IoT devices for livestock tracking and health monitoring. Systems using GPS modules and temperature sensors allowed farmers to monitor basic parameters such as animal movement and body temperature. These methods improved monitoring but lacked predictive intelligence and required manual interpretation of sensor data.

Machine Learning for Animal Health Prediction: Machine learning models such as Support Vector Machines (SVM), Logistic Regression, and Decision Trees have been applied for disease prediction and behavioral analysis in cattle. These models demonstrated improved accuracy over manual observation but struggled with complex nonlinear datasets and variability caused by environmental conditions.

IoT-based cattle monitoring systems utilize a network of sensors such as GPS modules, temperature sensors, and accelerometers to collect real-time data related to animal location, physiological conditions, and behavioral patterns. GPS technology enables precise tracking of cattle movement and helps prevent issues such as theft or boundary violations.

Random Forest-Based Precision Livestock Systems:

Recent studies show that Random Forest models outperform traditional machine learning techniques due to ensemble-based decision processing, noise tolerance, and ability to handle mixed feature types. They have been successfully used for disease risk categorization, milk yield forecasting, and behavioral anomaly detection, making them a suitable choice for real-time agricultural applications.

IoT Integration with Smart Dashboards: Modern livestock systems have begun incorporating real-time dashboards, enabling visualization of live sensor data and generating automated alerts. Frameworks such as stream lit and cloud-based platforms allow remote monitoring of cattle, but many existing systems lack unified prediction and decision support components.

Research Gaps in Current Systems: Despite technological advancements, most existing solutions are either expensive, lack predictive analytics, or are not scalable for small- to medium-sized farms. There remains a gap in developing an integrated solution that combines real-time tracking, machine learning-based prediction, and user-friendly visualization at an affordable cost.

Problem Definition and Objectives

Problem Definition: Traditional livestock management depends on manual supervision, which is time-consuming, labor-intensive, and often inconsistent in detecting early signs of illness. Farmers lack real-time access to cattle data such as body temperature, movement behavior, and environmental stress factors, leading to delayed decision-making. Existing monitoring solutions are either costly, require advanced technical expertise, or lack machine learning-based analytics for prediction and alerts. Missing cattle, theft, or boundary escape incidents remain a challenge due to lack of continuous location tracking. There is limited integration of multiple sensor modalities such as GPS, accelerometers, and temperature sensors in a unified monitoring platform. Current solutions rarely provide predictive insights such as milk yield estimation or health risk scoring based on behavioral and environmental data patterns.

Therefore, there is a need for a scalable and affordable system that combines IoT sensing, predictive analytics, and automated visualization to improve livestock management efficiency.

Objectives: To design an IoT-based real-time monitoring system for tracking cattle movement, location, and health-related parameters. To classify disease risk levels using a Random Forest classifier based on temperature, activity, and environmental patterns. To predict milk yield using a Random Forest regressor and provide performance-based insights to farmers. To develop a centralized dashboard for live visualization, alerts, and analytics using stream lit. To reduce dependency on manual efforts and support automated decision-making through intelligent data processing. To create a low-cost and scalable solution suitable for small, medium, and large-scale dairy farms. To improve farm productivity, animal welfare, and operational efficiency through predictive modelling and continuous monitoring.

Proposed System

System Overview: The system enables automated cattle monitoring using IOT sensors combined with machine learning prediction models. It collects real-time physiological and environmental data such as body temperature, movement, and location. Machine learning models process and classify data to detect abnormalities and predict milk yield. The solution aims to reduce manual intervention and support efficient, data-driven farm management.

IOT Sensor Layer: A GPS module is used to track real-time cattle location and detect geofencing boundary violations. Temperature and humidity sensors monitor thermal conditions, stress factors, and early illness indicators. The accelerometer captures movement levels to identify abnormal behavior such as restlessness or inactivity. Sensor data is continuously transmitted to the processing unit for analysis and prediction.

Data Collection and Processing: Raw sensor data undergoes cleaning to remove noise, inconsistencies, and missing entries. Feature engineering is performed to derive enhanced parameters such as Heat Stress Index and movement classification. Normalization and encoding techniques prepare the data for machine learning processing. The final dataset is stored and used for training, validation, and real-time inference.

Machine Learning Model Development: A Random Forest Classifier predicts disease risk levels categorized as Low, Moderate, or High. A Random Forest Regressor estimates milk yield based on behavior, environmental factors, and historical patterns. The model is trained using labeled datasets to ensure high accuracy and robust performance under noisy inputs. Random Forest is selected due to its stability, scalability, and strong handling of nonlinear mixed-sensor datasets.

Proposed System / Methodology

Hardware Implementation: IOT modules such as GPS, accelerometer, and temperature sensors were interfaced for real-time data acquisition. The ESP8266 microcontroller was used for wireless data transmission between sensors and the cloud/dashboard. Sensor readings were tested under different conditions to ensure consistency and stability during live monitoring. Proper power regulation and wiring ensured reliable hardware performance during field-level deployment.

Software Implementation: Python was used as the primary development language for data processing, machine learning model integration, and dashboard control. The machine learning models (Random Forest Classifier and Regressor) were trained using Scikit-learn. Preprocessing, feature extraction, and prediction logic were implemented as modular scripts for better maintainability. The stream lit framework was used to build an interactive dashboard for displaying live sensor values and model outputs.

Model Integration: The trained models were exported using Joblib, allowing seamless integration into the live system pipeline. Real-time sensor data was fed into the prediction layer to generate output without manual intervention. Predictions such as disease risk and milk yield were displayed dynamically on the dashboard. The system structure ensured low latency to support continuous monitoring and immediate feedback.

Power and Connectivity Management: Wi-Fi communication through ESP8266 enabled remote data transfer and dashboard updates. Battery-powered sensor modules ensured continuous operation during field deployment. Network retries and fallback logic improved communication reliability in fluctuating signal conditions.

Results and Discussion

Model Evaluation: The Random Forest Classifier accurately categorized cattle health status into Low, Moderate, and High-risk levels. Training and testing results showed consistent prediction performance across varying sensor inputs. The Random Forest Regressor demonstrated stable and realistic milk yield estimation based on behavioral and environmental data. Performance metrics such as accuracy, RMSE, and confusion matrix indicated reliable classification and regression results.

Real-Time Monitoring Output: GPS-based tracking successfully captured cattle movement and displayed location updates on the dashboard. Temperature and accelerometer readings enabled live behavioral monitoring and early detection of abnormal patterns. The system generated alerts for unusual temperature spikes, reduced movement, or boundary violations. The live feed ensured farmers could observe changes instantly without manual monitoring requirements.

Dashboard Visualization: The stream lit dashboard provided a clear visual representation of real-time sensor readings, prediction results, and cattle location. Data visualization tools such as graphs, maps, and status indicators enhanced interpretability for non-technical users. Color-coded alerts enabled quick assessment of cattle health conditions and risk severity. Historical trend graphs helped identify recurring behavioral and environmental patterns.

System Performance and Limitations: The system performed efficiently in real-time operation, maintaining stable connectivity and response time. Accuracy varied based on environmental conditions such as weather, terrain, and GPS signal strength. Dataset size and diversity limit long-term prediction precision, especially for behavioral forecasting [1-9].

References

1. SS Goswami, SK Sahoo (2024) Secure and Sustainable Framework for Cattle Recognition using Wireless Multimedia Networks and Machine Learning Techniques. International Journal of Computer and Communication Engineering.
2. L Breiman (2001) Random Forests. Machine Learning 45: 5-32.
3. MA Rahman, R Islam (2024) Real-Time Livestock Monitoring using IoT Sensors. International Journal of Smart Agriculture Systems 12: 88-98.
4. Alahi Y Yue, F Wang (2023) Behavior Analysis of Farm Animals Using Machine Learning. IEEE Transactions on Automation Science and Engineering 20: 1248-1259.
5. K Das, R Kumar (2023) IoT-Based Animal Tracking and Health Monitoring System. IEEE International Conference on Intelligent Computing Systems 142-148.
6. ESP8266 (2023) Wi-Fi Module Technical Reference Manual, Espressif Systems https://www.espressif.com.
7. Neo-6M GPS Module Datasheet, u-blox AG, Switzerland https://www.u-blox.com.
8. Sharma, M Prasad (2024) Streamlit for Real-Time Visualization of IoT Data. Journal of Data Science and AI Applications 5: 52-60.
9. Scikit-Learn Documentation (2024) Random Forest Classifier and Regressor. https://scikit-learn.org.