Energy-Efficient and Affordable Wearable Solution for Cow Behavior Detection using Machine Learning

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Abstract— **Monitoring cow activity, such as standing, sitting, and ruminating, is essential for optimizing dairy farm management, as these behaviors provide critical insights into animal health, welfare, and productivity. Traditional observation methods are labor-intensive and impractical for large herds, necessitating automated, cost-effective solutions. This study presents an energy-efficient, affordable wearable system for real-time cow behavior detection using accelerometer data and machine learning. The device, built with an ATmega328P microcontroller, nRF24L01 wireless module, and MOSFET-based power management, significantly reduces energy consumption by employing sleep modes, sensor power control, and optimized data transmission strategies. Experimental results show that the XGBoost classifier achieved 94.87% accuracy, outperforming Random Forest (84.81%). The system consumes approximately 23.5 mAh of power per day , enabling long-term operation with minimal maintenance. With a total hardware price of approximately NRs. 3345 (~25 USD), it offers a low-cost, energy-efficient solution. Future improvements could incorporate advanced analytics for estrus and calving detection, further strengthening automated livestock monitoring.**

Keywords—**ATmega328P, Low-power system, zXGBoost classifier**

I. INTRODUCTION

Precision livestock farming (PLF) has revolutionized dairy cattle management by introducing automated monitoring systems that track animal health, behavior, and welfare. Traditional methods for monitoring cow activities, such as standing, eating, sitting, and ruminating, are labor-intensive, time-consuming, and prone to human error. The adoption of sensor-based technologies, particularly accelerometers, gyroscopes, and IoT-enabled devices, has enabled continuous, real-time tracking of animal behaviors with improved accuracy [1]-[3].

Monitoring cow activity is essential for ensuring optimal health and productivity in dairy farms. Changes in routine behaviors can indicate potential health concerns, nutritional deficiencies, or environmental stressors [4], [5]. For instance, a reduction in eating and ruminating time may signal digestive issues, while prolonged periods of inactivity could indicate lameness or illness. Studies have shown that automated movement analysis using accelerometers can detect early signs of lameness and illness more effectively than manual observations [6], [7].

In addition to basic activity monitoring, wearable sensor technologies have been widely explored for detecting estrus and calving events in dairy cattle. Estrus detection is a critical aspect of dairy farm management, as timely identification of heat cycles improves artificial insemination success rates and enhances reproductive efficiency [8], [9]. Previous studies have demonstrated that cows in estrus exhibit increased movement, restlessness, and mounting behavior, which can be detected using accelerometer-based systems [10], [11]. Similarly, calving detection has been investigated through behavioral changes such as increased lying and standing frequency, decreased feeding time, and variations in body temperature [12], [13].

Recent advancements in sensor technologies have further enhanced the capabilities of PLF systems. Martinez-Rau, Mohr, and Dresch developed a real-time acoustic monitoring system for cattle foraging behavior recognition using low-power embedded devices. Their Noise-Robust Foraging Activity Recognizer (NRFAR) algorithm, implemented on an ARM Cortex-M0+ microcontroller, achieved mean power consumption as low as 1.8 mW, addressing computational limitations of previous implementations [13].

Similarly, Vannieuwenborg, De Ketelaere, Berckmans, and Saeys proposed a smart cow monitoring system with a focus on low power consumption and long-term sustainability. Their system utilizes LoRaWAN for communication, NFMI for ear tag data transfer, and UWB for positioning, with a design optimized for a 7-year lifespan and wireless inductive charging [14].

Beyond wearable sensors, Nasirahmadi, Edwards, and Sturm developed an image-based behavior recognition system using deep learning to track cow movement patterns and postures [2]. Similarly, Li, Chen, and Wang utilized convolutional neural networks (CNNs) on surveillance footage to classify cow behaviors, demonstrating high accuracy but with increased computational demands [15].

While our current system is designed to detect fundamental cow activities such as standing, eating, sitting, and ruminating, the collected behavioral data can serve as a foundation for future enhancements in estrus and calving detection. By integrating advanced analytics and machine learning techniques, the system could potentially evolve to provide early estrus alerts or calving predictions based on deviations from normal activity patterns. Such developments would further strengthen automated livestock monitoring, enabling better farm management, reducing labor costs, and ultimately improving dairy productivity.

II. METHODOLOGY

A. Hardware selection

TABLE I. HARDWARE COMPONENTS AND THEIR FUNCTION

Component	Function
ATmega328P	Microcontroller
MPU6050	Accelerometer
nRF24L01	Wireless data transmission
DS3231	Real Time Clock
IRFZ44N	MOSFET
18650 Li-ion Battery	Power Source
MLX90614	Tempreature Sensor

The system consists of carefully selected components to ensure efficient operation:

- ATmega328P (Microcontroller): Manages data acquisition, processing, and communication.
- MPU6050 (Accelerometer & Gyroscope): Measures motion and orientation for monitoring.
- nRF24L01 (Wireless Module): Enables low-power, long-range data transmission.
- DS3231 (Real-Time Clock): Provides precise timekeeping for event logging.
- IRFZ44N (MOSFET): Used for efficient power switching and control.
- MLX90614 (Infrared Temperature Sensor): Measures non-contact temperature.
- 18650 Li-ion Battery (Power Source): Supplies power, ensuring portability and long battery life.

B. Power management: Atmega328p

To ensure efficient power consumption, the ATmega328P microcontroller supports multiple sleep modes. Each mode disables certain system components while allowing wake-up through specific sources. Fig. 1, illustrates the various sleep modes of the ATmega328P microcontroller, along with their associated active clock domains and possible wake-up sources. For this project, the Power-down mode was selected due to its ability to minimize power consumption by disabling the CPU, Flash memory, and peripheral clocks. The system is configured to wake only upon an external interrupt (INT0/INT1) or when the Watchdog Timer (WDT) triggers an event, as described in the ATmega328P datasheet [18].

Sleep Mode	Active Clock Domains					Oscillators		Wake-up Sources								
	clk_{CPU}	clk_{FLASH}	clk_{IO}	clk_{ADC}	clk_{ASY}	Main Clock Source Enabled	Timer Oscillator Enabled	INT1, INT0 and Pin Change	TWI Address Match	Timer2	SPM/EEPROM Ready	ADC	WDT	Other I/O	Software BOD Disable
Idle			X	X	X	X	$X^{(2)}$	X	X	X	X	X	X	X	
ADC noise Reduction				X	X	X	$X^{(2)}$	$X^{(3)}$	X	$X^{(2)}$	X	X	X		
Power-down								$X^{(3)}$	X				X		X
Power-save					X		$X^{(2)}$	$X^{(3)}$	X	X			X		X
Standby$^{(1)}$						X		$X^{(3)}$	X				X		X
Extended Standby					$X^{(2)}$	X	$X^{(2)}$	$X^{(3)}$	X	X			X		X

Fig. 1. AVR Microcontroller Sleep Modes with Corresponding Active Clock Domains, Oscillators, and Wake-up Sources.

To further reduce power consumption:

- ADC (Analog-to-Digital Converter) is disabled, as it is not required during sleep mode.
- Brown-Out Detection (BOD) is disabled, preventing unnecessary power draw when the voltage is stable.

C. Power management: MPU6050

The MPU-6050 is a sensor that combines a 3-axis accelerometer and a 3-axis gyroscope in a single chip, making it ideal for motion tracking and orientation detection. It was preferred over other sensors like GY-61 ADLX335 due to the following reasons.

- I2C interface
- Built in Digital Motion Processor
- Configurable Sensitivity
- Higher 16-bit resolution

For a cattle monitoring system, gyroscope values might not be strictly necessary. Accelerometer values are typically sufficient for most cattle monitoring needs, such as tracking movement, detecting if an animal is lying down or standing up, and monitoring general activity levels. It measures acceleration along the X, Y, and Z axes, which can provide valuable data on the cattle's position and movement. By only using the acceleration value in x, y and z direction, the classifier achieved an accuracy up to 90% [19].

As MPU6050 also allows temperature and gyroscopic measurements which definitely plays a certain part in power consumption, disabling those features will significantly reduce energy consumption.

D. Powering Down Sensors Using MOSFET

To optimize the power efficiency of the system, a low-side MOSFET switching mechanism was employed to physically disconnect the power supply to the MPU6050 (accelerometer and gyroscope) and MLX90614 (infrared temperature sensor) when they are not actively engaged in data acquisition. This method effectively minimizes standby power consumption, which is crucial for energy-sensitive applications.

The microcontroller provides a gate-source voltage (Vgs) of approximately 4V to turn on the power MOSFET (IRFZ44N). While the MOSFET typically requires a higher gate voltage (around 10V) to achieve minimal Rds(on) (8 mΩ) and enter full saturation, a Vgs of 4V is sufficient to overcome the gate threshold voltage, allowing the MOSFET to turn on and establish a low-resistance path between the drain and source [20].

Given that the current drawn by the sensors is very low (typically in the microampere to milliampere range), the power loss due to the MOSFET's Rds(on) is negligible. As a result, there is no need for additional components such as a bootstrapping circuit or gate driver to drive the MOSFET, making this approach both cost-effective and energy-efficient for managing sensor power consumption.
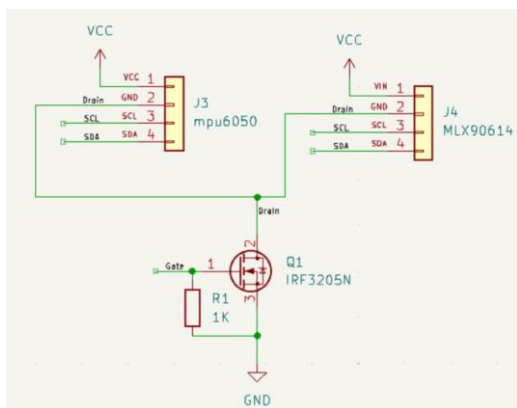

Fig. 2.   Power Control Circuit for MPU6050 and MLX90614 Using an N-Channel MOSFET (IRFZ44N).

E. NRF24L01 low power mode

The data acquired from the MPU6050 and MLX90614 sensors were transmitted wirelessly using the nRF24L01 RF module. The nRF24L01 module, known for its low-power characteristics and reliable data transmission, facilitated the communication between the sensor node and the receiving station.

To further optimize power consumption, the nRF24L01 transmitter was configured to operate in a low-power mode. The transmitter enters sleep mode when not actively transmitting data, thereby reducing the overall energy consumption of the system.

The transmitted data, including the sensor readings and associated timestamps read from the DS3231 RTC, was received by a corresponding receiver module. Once received, the data was saved to a storage medium for subsequent analysis.

F. Firmware Architecture and Workflow

The data-logger consists of a 3-axis accelerometer for recording acceleration and an NRF module for wireless data transmission. Both modules are integrated into a custom-designed PCB board, which includes all necessary circuitry, such as a low-power switching MOSFET for efficient energy management. The device is powered by a rechargeable 18650 battery cell, ensuring long operational life. A cow-mounted unit and a receiver unit, both equipped with NRF modules, facilitate wireless communication. The cow-mounted device records one data point per minute and transmits the collected data to the receiver every hour. During the intervals between transmissions, the device enters a low-power sleep mode to conserve energy. On the receiver side, an microcontroller paired with an SD card module stores the transmitted data for further analysis. The system operates at a frequency of 100 Hz

during active recording, ensuring high-resolution data collection while maintaining energy efficiency. This setup enables continuous, low-power monitoring of cow activity, making it suitable for long-term use in precision livestock farming.

Fig. 3, illustrates the working logic of a sensor node for cattle monitoring. The system begins operation upon receiving an interrupt from the DS3231 RTC. It powers the MPU6050 (accelerometer) and MLX90614 (temperature sensor) via a MOSFET, collects sensor data along with a timestamp, and then powers the sensors down. If a receiver station is available, the data is transmitted wirelessly; otherwise, it is stored in EEPROM. When a connection becomes available, stored data is sent until the EEPROM is emptied. Finally, the system enters a low-power state by putting the nRF24L01 module into sleep mode and the ATmega328P into power-down mode.
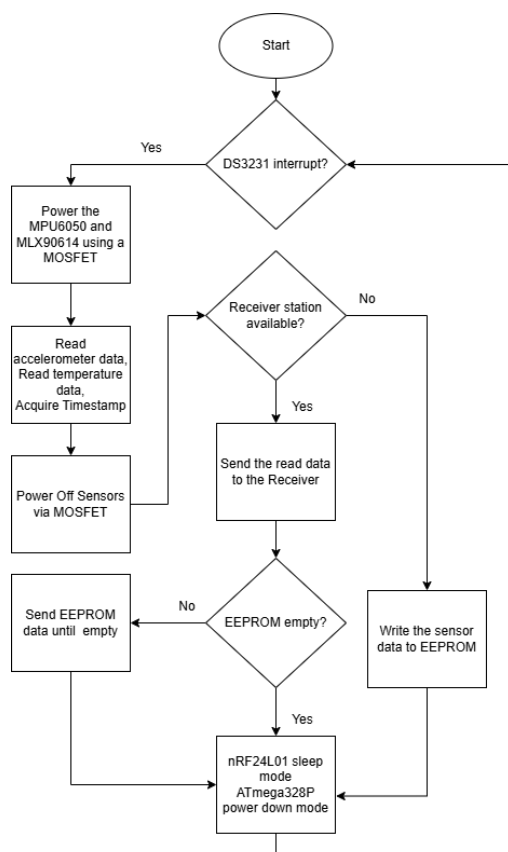

Fig. 3.   Flowchart of the Data Acquisition and Transmission Process

G. Data Collection

Data collection presented significant challenges due to geographical and technological constraints in Nepal. The process began with the installation of the data collection device on the cow, ensuring that the device was well-protected against moisture and potential physical damage caused by the animal's movements (Fig. 4). Special care was taken to securely attach the device in a manner that did not cause discomfort or interfere with the cow's natural behavior. The enclosure for the data logger was 3D-printed using polylactic acid (PLA) material,

chosen for its durability and flexibility. To protect the internal circuitry from mechanical shocks, the enclosure was equipped with shock-absorbing materials. The device was powered by replaceable cell batteries, accessible by opening the enclosure, ensuring ease of maintenance and long-term functionality. A video monitoring system was integrated into the data collection process using CCTV cameras that streamed live footage to Twitch. This video data provided an additional layer of validation by enabling manual annotation and verification of the behavioral data recorded by the device. On the receiver side, an SD card-integrated data logger stored the transmitted data, which was manually retrieved at regular intervals. The dataset comprised three-dimensional acceleration values (X, Y, and Z axes), with notable variations in specific axes corresponding to changes in the cow's posture. This combination of sensor data and video annotation ensured robust and reliable behavioral analysis despite environmental challenges.

Fig. 4. Wearable Device Attached To The Cow's Neck

H. Data Preprocessing

The raw dataset collected from the sensor devices contained noise, missing values, and irrelevant data points that could potentially impact the analysis. To ensure data quality, preprocessing involved multiple stages:

- Noise Removal: Unwanted fluctuations and erroneous readings were filtered out.

- Handling Missing Values: Incomplete data points were either interpolated or removed.

- Data Consolidation: Multiple datasets collected at different intervals were merged to maintain consistency and completeness. The final preprocessed dataset was stored in CSV format and contained the following key attributes:

  - Acceleration values (X, Y , Z axes) Timestamps (to capture temporal information)

  - Cow ID (to associate data with individual animals)

I. Temporal Data Segmentation

To capture temporal patterns in cow behavior, a sliding window approach was employed. This method segments continuous time-series data into overlapping or non-overlapping windows of fixed duration. Each window encapsulates a sequence of sensor readings, allowing for the identification of behavioral trends over time rather than relying on isolated data points. The sliding window technique is particularly effective in analyzing the dynamic nature of cow activities, such as transitions between standing, sitting, eating, and ruminating. By leveraging this approach, the dataset retains valuable temporal dependencies, enhancing the accuracy of behavioral analysis and pattern recognition.

III. RESULTS

A. Classification

The methodology for analyzing cow behavior involved a systematic pipeline comprising data preprocessing, feature extraction, and classification. The classification process was structured as follows:

1) Model Selection and Justification

A supervised machine learning approach was used to classify cow behaviors into four categories: standing, sitting, walking, and eating. Several classification models were evaluated, including Random Forest, Support Vector Machine (SVM), and XGBoost. XGBoost was chosen due to the following advantages:

- Handles Imbalanced Data Well: Cow behavior data is often skewed, with certain activities (e.g., standing) occurring more frequently than others (e.g., ruminating). XGBoost uses weighted loss functions to mitigate class imbalance.

- Robust Feature Selection: XGBoost automatically determines the most relevant features, improving classification accuracy.

- Fast Training Time: Compared to Random Forest and SVM, XGBoost efficiently processes large datasets while preventing overfitting.

2) Hyperparameter Tuning

To optimize the XGBoost model, a Grid Search with 5-fold Cross-Validation was conducted, testing the following hyperparameters:

- Learning Rate: {0.01, 0.1, 0.2}
- Maximum Depth of Trees: {3, 5, 7}
- Number of Estimators: {100, 300, 500}
- Gamma (min loss reduction required for a split): {0, 0.1, 0.2} The best configuration was found to be:
- Learning Rate: 0.1
- Max Depth: 5
- Number of Estimators: 100
- Gamma: 0.1

B. Sensor Data Analysis and Behavior Visualizations

Fig. 4, depicts the standing behavior of the cow, as captured by the accelerometer data. During standing, the Z-axis acceleration values consistently exceed -1, reflecting the cow's upright posture. The X and Y axes exhibit significant fluctuations due to the cow's natural movements, such as neck rotation (left and right) and minor postural adjustments. These dynamic movements result in variability across all three axes, highlighting the non-static nature of standing behavior. The observed fluctuations underscore the importance of analyzing multi-axis data and temporal patterns to accurately characterize standing and distinguish it from other activities.
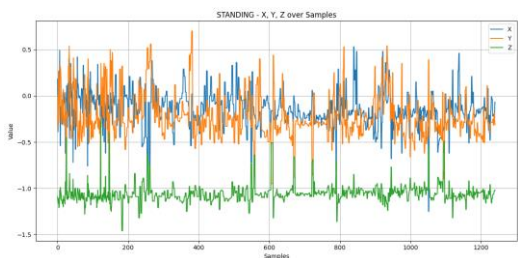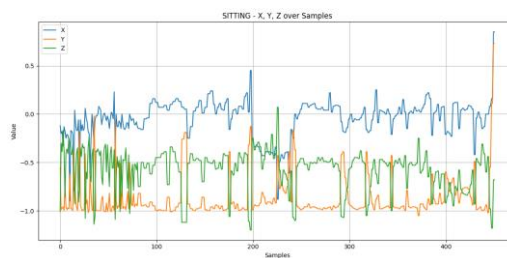
Fig. 5.   Standing Behaviour of The Cow

Fig. 5, illustrates the eating behavior of cows, as captured by the accelerometer data. During eating, the X and Y axes exhibit significant movement, with the Y-axis showing comparatively higher variability. This increased activity in the Y-axis is attributed to the repetitive head and neck movements associated with feeding. In contrast, the Z-axis acceleration values remain relatively stable and resemble those observed during standing behavior, reflecting the cow's upright posture while eating. The distinct patterns in the X and Y axes, combined with the stable Z-axis, provide clear discriminative features for differentiating eating behavior from other activities such as standing.

Fig. 6.   Eating Behaviour of The Cow

Fig. 6, illustrates the sitting behavior of cows, as captured by the accelerometer data. During sitting, the acceleration values for all three axes (X, Y, and Z) consistently fall below the 0 threshold, reflecting the cow's lowered posture. Notably, the Y and Z axes exhibit significant changes compared to other activities, with pronounced variability in their acceleration patterns. These changes are attributed to the cow's body position and movements while transitioning to or maintaining a seated posture. The distinct patterns in the Y and Z axes, combined with the consistent sub-zero values across all axes, provide clear discriminative features for identifying sitting behavior and distinguishing it from other activities such as standing or eating.

Fig. 7.   Sitting Behaviour of The Cow

Fig. 7, depicts the ruminating behavior of the cow, as captured by the accelerometer data. During ruminating, the Z-axis acceleration values fluctuate between negative values , reflecting the rhythmic vertical jaw and neck movements associated with chewing cud. The X-axis remains relatively stable near 0, indicating minimal lateral head movement. In contrast, the Y-axis shows moderate fluctuations, capturing slight forward and backward neck motions. These distinct axis patterns highlight the relatively stationary but active nature of ruminating. The consistent, periodic movements across the Y and Z axes emphasize the value of multi-axis temporal analysis for accurately identifying and differentiating ruminating behavior from othe rcow activities.
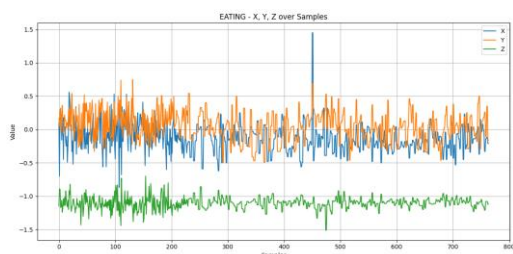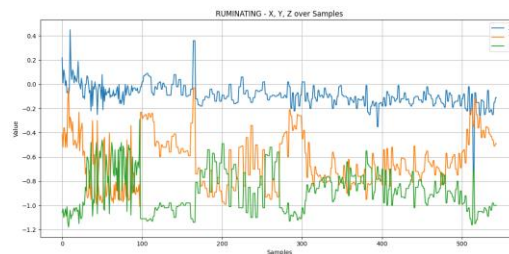

Fig. 8.   Ruminating Behaviour of The Cow

Fig. 8, shows the daily activity distribution of the cow over a 3 Energy-Efficient and Affordable Wearable Solution for Cow Behavior Detection Using Machine Learning Day. The cow spent the most time eating (28.9%), followed by standing (29.7%), sitting (23.1%), and ruminating (18.3%).
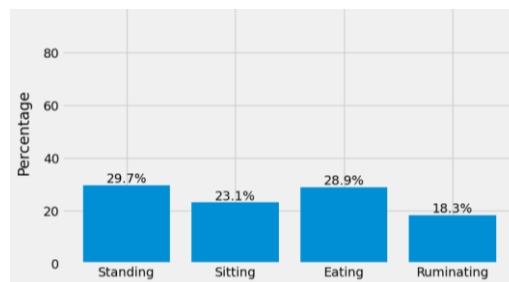

Fig. 9.   Daily Activity Distribution

C. Classification Performance

The performance of XGBoost and Random Forest classifiers was evaluated using precision, recall, and F1-score across four behavioral classes.

For XGBoost, the classifier achieved excellent precision scores of 1.00 for sitting and eating, and 0.95 for ruminating, while precision for standing was slightly lower at 0.76. Recall values were highest for standing (1.00) and ruminating (0.95), followed by sitting (0.83) and eating (0.88). Corresponding F1-scores were 0.90 (sitting), 0.86 (standing), 0.94 (eating), and 0.95 (ruminating).

In comparison, Random Forest yielded similar precision for sitting (1.00) but lower values for standing (0.74), eating (0.88), and ruminating (0.83). Its recall scores were 0.70 (sitting), 0.89 (standing), 0.88 (eating), and 0.95 (ruminating), with respective F1-scores of 0.82, 0.81, 0.88, and 0.88.

Fig. 9, and Fig. 10, illustrate that the confusion matrix for XGBoost and Random Forest respectively which exhibits fewer misclassifications across all behavior classes, particularly for "sitting" and "standing," for XGBoost when compared to Random Forest. This observation is consistent with the higher F1-scores achieved by XGBoost for these behaviors.
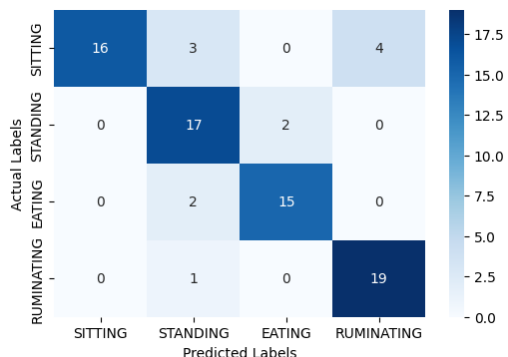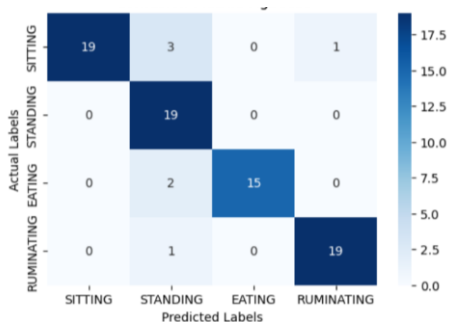

Fig. 10. Confusion Matrix of Random Forest

Fig. 11. Confusion Matrix of XGBoost

D. Fabricated Circuit

The circuit used in this project as shown in Fig. 11, was self-fabricated using a double-sided PCB, which was designed using KiCad. This approach allowed for compact routing and better layout control. The board was manually etched using Ferric Chloride, with top and bottom layers aligned using printed transparencies. Vias were made by drilling holes and connecting layers with soldered jumpers. Key components include the NRF24L01 wireless module, an IRF3205 MOSFET, MPU6050 and a push-button input. Manual soldering was done carefully to ensure reliable connections. This method offered flexibility in design and reduced the cost and time typically needed for prototyping.
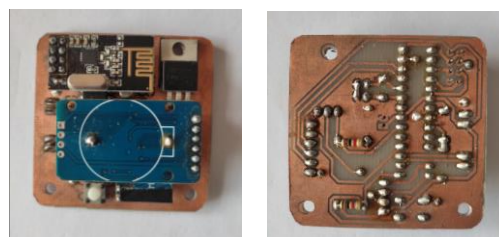

Fig. 12. Top and Bottom View of The Circuit

E. Power Consumption

Figure X shows the device's current consumption over time, showcasing powered-on, setup, data collection, sleep, and wake-up phases. During activity (approx. 4 seconds), the device consumes around 11.54 mA (fig. 12), followed by a low-power sleep state (approx. 60 seconds) at ~0.25 mA(fig. 13). This duty-cycled behavior significantly reduces average energy use. The average current per 64-second cycle is$((4s \times 11.54mA) + (60s \times 0.3mA))/64s \approx 1.00mA$. Using two 3200 mAh batteries (totaling 6400 mAh), the estimated Battery Life is 6400mAh / 1.00mA =6400hours ≈266 days.

This result confirms that the system can function for nearly 9 months without recharging or battery replacement, ensuring practical, long-term deployment for livestock monitoring in field conditions.

Fig. 13. Current Consumption of The Device When Powered-ON

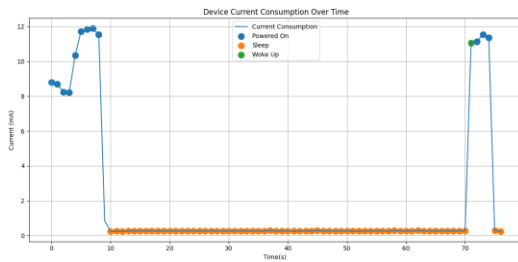Fig. 14. Current Consumption of The Device During Sleep Mode

Fig. 15. Current Consumption of The Device in Milliampere vs Time in Seconds

F. 3D Printed Case

The image shows a 3D-printed enclosure designed to house the PCB. The enclosure was designed using Autodesk Fusion 360 and printed using PLA (Polylactic Acid), a biodegradable and durable thermoplastic well-suited for outdoor and agricultural use. The design contains side openings to attach to a collar, allowing the device to be comfortably worn around a cow's neck. Internally, the enclosure includes space to accommodate two 18650 Li-ion batteries, ensuring extended operational time in the field whereas at the bottom it has a cutout for temperature sensor.
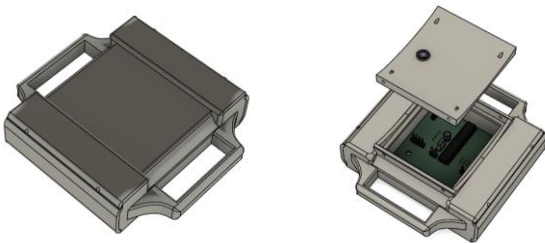

Fig. 16. Top and Bottom View of The Design

G. Cost Breakdown

The table summarizes the cost breakdown of the components used in the proposed wearable cow monitoring device. The total hardware cost amounts to approximately NRs. 3750 (~28 USD), making the system an affordable and cost-effective solution for large-scale deployment in dairy farms. Major components include the ATmega328P microcontroller, MPU6050 accelerometer and gyroscope, MLX90614 infrared temperature sensor, nRF24L01 wireless transceiver, DS3231 real-time clock, IRFZ44N MOSFET for power management, and two 18650 Li-ion batteries. The pricing reflects the feasibility of developing a reliable, energy-efficient, and scalable system without incurring high expenses, making it suitable for both small and large dairy operations.

TABLE II. COMPONENTS AND THEIR PRICES IN NRS

Component	Price (Rs)
ATmega328P	400
MPU6050	250
nRF24L01	350
DS3231	350
IRFZ44N	45
18650 Li-ion Battery	400
PCB and others	800
MLX90614	750
Total	3345

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