IoT-Driven Livestock Monitoring: Leveraging LoRaWAN for Behavior Analysis and Enhanced Farm Management

Khadijah Febriana, Rahul Thakur and Sudip Roy
Indian Institute of Technology Roorkee, India

Keywords: Livestock Monitoring, IoT, Sensors, LoRaWAN.

Abstract: Cattle play a crucial role in farming by providing essential resources such as milk, meat, leather, and labor, contributing significantly to both economic and social stability in rural areas of India. This work develops an energy-efficient IoT system based on LoRaWAN to monitor and analyze livestock behavior. The system employs an MPU6050 sensor and TTGO T-Beam microcontroller to capture livestock's movement and positional data. This data is continuously transmitted via a mesh network, utilizing The Things Network and ThingSpeak for remote analytics. A neural network with two hidden layers and ReLU activation functions is trained with sparse categorical cross-entropy loss. Validation on a 20% subset of the training data demonstrates high accuracy in classifying complex animal behaviors. Classification results, including F1-scores, precision, and recall metrics, highlight the model's strong capability in behavior differentiation. Overall, this system enhances animal health and welfare, improves farm productivity, promotes environmental sustainability, and strengthens India's food security.

1 INTRODUCTION

The Internet of Things (IoT) is a transformational technology that connects numerous items over Internet networks, allowing for real-time data collection and exchange (Lu et al., 2024). This technology has transformed several industries, particularly agriculture, by driving innovation to improve productivity, resource efficiency, and sustainability. In crop farming, IoT systems monitor crucial characteristics such as temperature, humidity, soil moisture, and nutrient levels to optimize resources and increase yields (Chamara et al., 2022). Similarly, IoT devices provide real-time monitoring of animal behavior, health, and location in cattle farming, giving farmers actionable data to improve herd management and farm productivity (McClune et al., 2014) (Ladha et al., 2013).

Agriculture and livestock production are critical components of India's economy, employing more than half of the population and contributing significantly to the country's GDP. Despite its crucial relevance, the sector faces several obstacles, including the negative consequences of climate change, volatile commodity prices, and limited access to sophisticated technologies. Livestock farmers, in particular, face challenges in successfully monitoring animal health and well-being, preventing strays and theft, and managing their resources. These difficulties are exacerbated in rural settings, where animals frequently graze freely throughout large distances, making them harder to follow and protect. IoT offers a disruptive solution by allowing for real-time monitoring of cattle conditions, detecting behavioral abnormalities, and offering early warnings of health risks (Farooq et al., 2022). This enables farmers to take prompt, proactive steps to improve animal care, cut losses, and improve overall farm management.

While IoT applications in livestock husbandry are still in their early stages in India, its potential to transform traditional techniques is becoming more widely recognized. Farmers can use IoT-based systems to enhance resource utilization, reduce livestock losses, and detect diseases early, supporting efficient and sustainable farming methods. Monitoring animal movements and behavior can provide crucial information about health and welfare. Changes in activity patterns frequently indicate stress, illness, or injury, allowing for early intervention (Atthari, 2017). This is especially critical in rural India, where livestock roam freely and are more likely to get lost or stolen. IoT-enabled tracking solutions can help to reduce these hazards, increase farm security, and boost economic stability in farming communities.

LoRaWAN (Long Range Wide Area Network),

Febriana, K., Thakur, R. and Roy, S.
IoT-Driven Livestock Monitoring: Leveraging LoRaWAN for Behavior Analysis and Enhanced Farm Management.
DOI: 10.5220/0013296600003944
In *Proceedings of the 10th International Conference on Internet of Things, Big Data and Security (IoTBDS 2025)*, pages 273-280
ISBN: 978-989-758-750-4; ISSN: 2184-4976

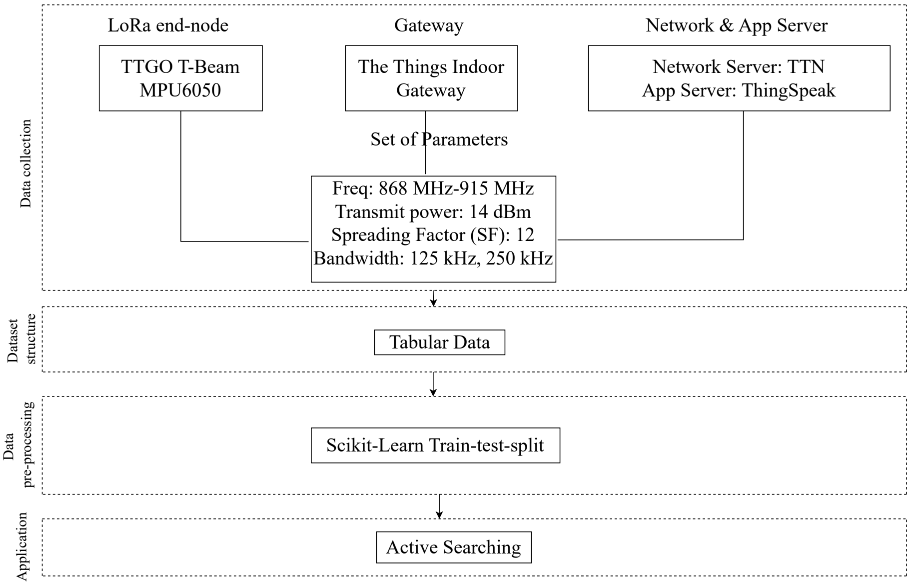


Figure 1: Key Steps in the Proposed Method.

a wireless communication protocol, has emerged as a game changer for IoT applications in remote places, thanks to its long-range, low-power, and cost-effective features. Previous research has demonstrated LoRa's effectiveness in tackling connectivity difficulties in rural areas. (Joshitha et al., 2021) investigated a LoRa-based system for remote data transmission, emphasizing its potential for IoT in locations without standard communication networks. Similarly, (Joshitha et al., 2021) created a long-range tracking device that uses LoRa to ensure independence from third-party networks while lowering operational expenses. These tests demonstrate LoRa's appropriateness for livestock tracking, as it provides dependable, long-distance communication even in resource-constrained environments.

This work's primary IoT-driven livestock monitoring device was the TTGO T-Beam microcontroller. This device integrates LoRa, GPS, WiFi, and an MPU6050 sensor, making it ideal for remote areas with limited connectivity and power supply. The integration of GPS allows exact location tracking, which is critical for animal safety and risk mitigation during free-range grazing (Angriawan and Anugraha, 2019). The WiFi feature enables seamless data transmission to cloud systems, which allows farmers to access real-time information remotely (Mahaputra et al., 2019) (Putra and Romahadi, 2021). Furthermore, the MPU6050 sensor, which can measure acceleration and angular velocity, gives extensive data on animal motions and orientation, allowing the detection of anomalous behavior that may signal distress or disease (Fedorov et al., 2015). This combination of technologies provides India's scalable, efficient, and cost-effective livestock management system.

LoRaWAN is chosen because of its unrivaled benefits in rural and agricultural environments. Its long-range communication capability, low power consumption, and use of unlicensed frequency bands make it perfect for large-scale applications such as livestock tracking (Davcev et al., 2018). LoRaWAN offers a dependable, low-cost alternative to standard communication technologies in areas with limited internet and electricity. Using the TTGO T-Beam, this study intends to address the unique issues that livestock producers in India confront by providing an integrated system to integrate real-time monitoring, location tracking, and behavioral analysis. This technology improves farm management and enables farmers to improve animal care, to cut losses, and to increase economic resilience in order to face the changing agricultural problems.

2 MATERIALS AND METHODS

Our methodology involves a series of key steps: data collection and processing, data enhancement, model implementation, and results analysis. These stages are designed to ensure a comprehensive approach to the system's development and evaluation. Fig. 1 depicts the proposed methodology.

2.1 Data Collection

The primary goal of this data collection is to develop and evaluate a low-cost localization system using the TTGO T-Beam device, equipped with a GPS sensor, MPU6050, and connected to a LoRa Gateway. The dataset collected consists of 1000 data points transmitted over the IN865-867 frequency band, which is specifically suited for LoRaWAN communication in this region. The data collection site is situated on the IIT Roorkee campus in Uttarakhand, India, with coordinates 29°51′52″N, 77°53′47″E.

The IIT Roorkee campus, spanning approximately 1.48 km^2, features a mix of academic buildings, laboratories, dormitories, and extensive green areas, with the majority of the terrain being flat. Despite the overall flatness, the presence of tall buildings and dense vegetation within the campus can significantly impact LoRa signal propagation. These physical structures cause signal blockage, multipath fading, and interference from other wireless communication systems operating in the same frequency band. Such environmental factors limit the effective transmission range of the LoRa signals, particularly when the signals must pass through or around buildings. These challenges highlight the importance of considering the terrain and the potential obstacles when designing and deploying a wireless communication system, as they directly affect signal reliability and the performance of the localization system.

By collecting data in such an environment, we aim to simulate real-world conditions that may be encountered in urban or semi-urban settings, providing valuable insights into the system's ability to overcome these challenges and ensure reliable communication and localization over long distances.

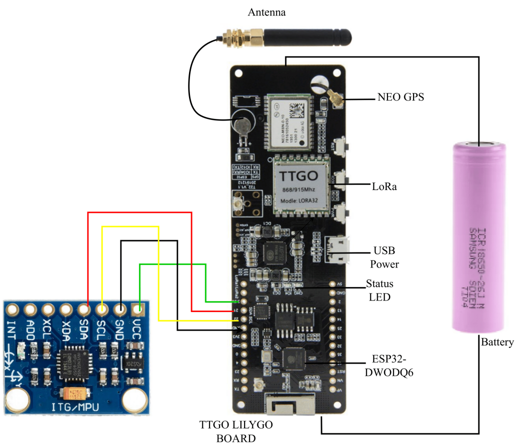


Figure 2: IoT Hardware Prototype.

2.2 Hardware Setup

The hardware setup utilizes a TTGO T-Beam powered by a lithium battery, along with the NEO-6M GPS module and communication options such as WiFi, Bluetooth, and LoRa to build an IoT-based monitoring system (Sugiarto et al., 2023). The TTGO T-Beam serves as the main component for data processing and networking (Sugiarto et al., 2023).

The MPU6050 sensor, connected via I2C, gathers motion and orientation data (acceleration and angular velocity) to measure activities. The LoRa module provides long-range, dependable data transmission in rural locations, with WiFi serving as a backup during LoRa disturbances to improve reliability. WiFi is only enabled in specified situations, such as LoRa transmission failures, firmware updates, or large data transfers. Deep sleep mode on the TTGO T-Beam detects LoRa failures and shuts idle WiFi, boosting energy economy, system stability, and cost savings.

The TTGO T-Beam processes data from the MPU6050 and GPS modules before transmitting it over LoRa to The Things Indoor Gateway, which sends it to the cloud for analysis. This system promotes real-time monitoring with a streamlined configuration, as seen in Fig. 2, Table 1 and Table 2. The TTGO T-Beam is equipped with a Neo-Block based GPS module (usually based on the u-blox NEO-6M chip or similar). Sky conditions, obstructions, and signal interference can affect GPS accuracy. GPS accuracy on the TTGO T-Beam is usually around 2.5 - 5 meters in open conditions with a good signal. At the same time, the MPU6050 sensor resolution for the accelerometer is 16384 LSB/g in the ±2g range, and for the gyroscope, the resolution is 131 LSB/°/ s in the range ±250°/s. Unlike (Islam et al., 2024), which used advanced signal analysis, this work focuses on practical IoT applications for real-time monitoring.

Table 1: Specifications of Node.

Model	**TTGO T-Beam v1.1 ESP32**
ISM bands (MHz)	IN865-867
Semtech	SX1276
Transmit power	20 dBM
SF	7, 12
BW (kHz)	125 kHz, 250 kHz
Power consumption	Active mode (GPS & LoRa transmission): 100-150 mA Idle mode: 10-15 mA Deep sleep mode: 1-2 mA
Weight	52 g

Table 2: Specifications of the Gateway.

Model	The Things Indoor Gateway
Frequency	EU868
TX power	20 dBm
Chipset	SX1308
Dimensions	$90 \times 80 \times 40$ mm
LoRaWAN Spec Version	V.1.0.3

2.3 Connection Diagram

This work employs an MPU6050 sensor connected to a TTGO T-Beam board via the Inter-Integrated Circuit (I2C) protocol, a widely used two-wire interface with Serial Clock Line (SCL) and Serial Data Line (SDA). I2C enables multiple devices to connect to a single bus using unique addresses, making it efficient for systems with many peripherals (Nguyen and Dugenske, 2018), (Jouhari et al., 2023). Compared to SPI, I2C uses fewer pins. It offers the flexibility of multiple master-slave configurations, making it an ideal choice for reliable communication between the MPU6050 sensor and the TTGO T-Beam board (Chen and Huang, 2023).

The TTGO T-Beam board also includes a GPS module connecting to the ESP32 microcontroller via the Universal Asynchronous Receiver-Transmitter (UART) protocol. UART is a simple serial communication protocol that sends data between the GPS module and the microcontroller via the TX (transmit) and RX (receive) pins. The GPS module provides critical position data such as latitude, longitude, time, and speed, which the ESP32 processes before transmitting over LoRa or cloud storage. Unlike I2C and SPI, UART does not require a clock signal and instead transfers data at synchronized baud rates (e.g., 9600 or 115200 bps) (Chen and Huang, 2023) (Sharma et al., 2018).

By integrating I2C for sensor connectivity and UART for GPS data sharing, the TTGO T-Beam effectively gathers, processes, and sends data, making it ideal for IoT-based monitoring systems.

2.4 Proposed System Model

We have developed an IoT-based system model that monitors the location and movement of livestock by integrating the MPU6050 sensor with the TTGO T-Beam module. The MPU6050 sensor measures three components of acceleration (Accel x, y, z) and three components of angular velocity (Gyro x, y, z), as shown in Fig. 3. These measurements allow for a detailed analysis of the livestock's movement and orientation, which are critical for understanding their behavior. Additionally, the system collects data on location (latitude and longitude), movement speed, and time, which are essential for tracking the livestock's geographic position and activity patterns. The combination of acceleration and angular velocity data, along with GPS data for location tracking, provides a comprehensive overview of the animal's behavior and movement.

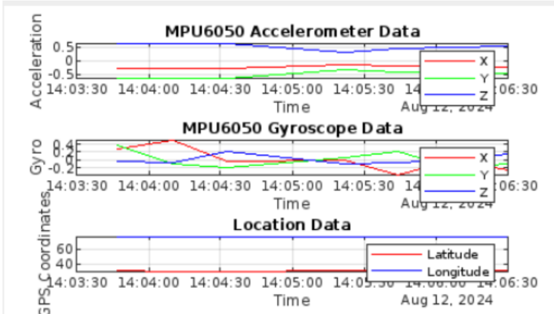
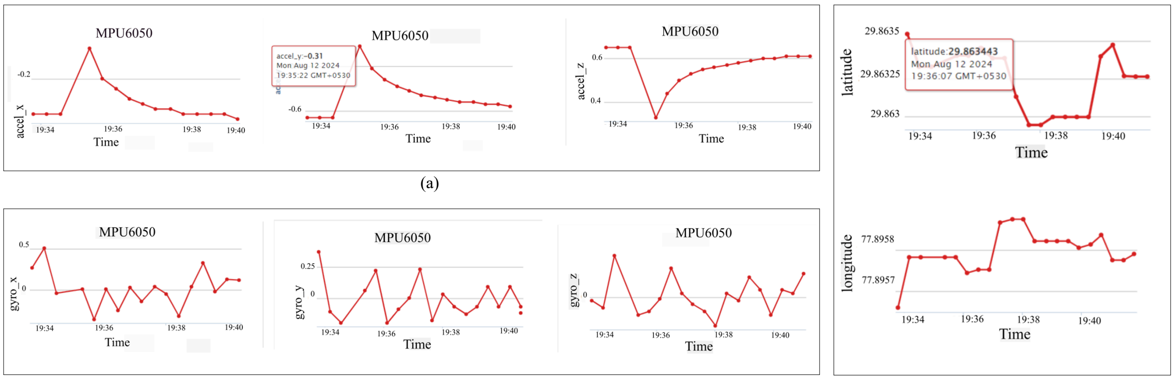


Figure 3: Data Collection for Monitoring and Tracking.

As shown in Fig. 3, the GPS data is represented by a red line for latitude and a blue line for longitude, which tracks the livestock's geographic movement over time. This visualization allows for easy tracking of the animal's movement across various terrains, and helps monitor changes in their behavior that may indicate stress, illness, or other significant events. The ability to collect both movement (acceleration and angular velocity) and location data in real-time provides valuable insights into livestock behavior and can aid in early detection of potential issues, improving overall animal welfare and farm management.

The TTGO T-Beam, equipped with a GPS module, serves as the central device in this monitoring system. The data collected by the system, as shown in Fig. 4, is crucial for real-time monitoring and performance analysis of the livestock. The analysis of animal movement patterns, activities, and geographic locations helps farmers make better-informed decisions regarding the care and management of their livestock. The MPU6050 sensor provides detailed movement and orientation data, while the GPS module tracks the geographic location, both of which are essential for accurate monitoring.

This system is specifically designed to operate in rural areas, where cellular network infrastructure may be sparse or non-existent. By utilizing the LoRa communication protocol, the system ensures reliable data transmission over long distances, even in areas with limited connectivity. This capability is critical for monitoring livestock in remote regions, where traditional communication networks may not be available. The ultimate objective of this system is to enable more informed decision-making in livestock manage-



(a) (b) (c)

Figure 4: Data collection over time from (a) Accelerometer, (b) Gyroscope and (c) GPS.

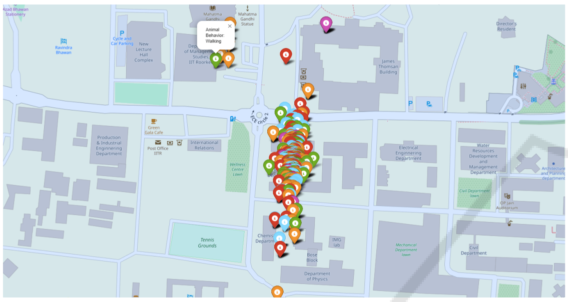


Figure 5: Location Tracking.

ment, enhancing farm productivity, improving animal welfare, and fostering sustainable farming practices. Consistent and accurate monitoring of the animals' movements and behaviors through this system helps ensure that any changes or issues are quickly detected and addressed. This system helps monitor the position of livestock, whether they are moving and in the right group or area or if their position deviates from the range location, as shown in Fig. 5.

2.5 Networking

This system employs LoRaWAN technology for long-range, energy-efficient data communication. TTGO T-Beam devices collect data and transmit it via The Things Indoor Gateway, which connects to the internet through The Things Network (TTN). LoRaWAN's low-power, wide-area capabilities suit rural areas where cellular networks are unreliable or unavailable.

Once data reaches the cloud, it is automatically integrated into ThingSpeak using webhooks. ThingSpeak is a good platform for livestock monitoring with TTGO T-Beam and MPU6050 sensors, including real-time visualization options like movement graphs and GPS mapping. Its MATLAB interoperability allows for sophisticated behavior prediction and anomaly detection analytics. ThingSpeak makes IoT data administration and visualization easier because of its low cost, user-friendly interface, and academic popularity.

ThingSpeak's real-time dashboard allows continuous livestock monitoring by providing graphical data on movement patterns and activity levels. This user-friendly interface makes tracking animal behavior easier and detecting irregularities, both of which are necessary for effective farm management. Figure 6 shows how data flows from the TTGO T-Beam to the cloud for analysis.

The system uses a mesh network architecture as shown in Fig. 7 to improve coverage and dependability in remote regions. According to (Jain et al., 2021), mesh networks provide redundancy by enabling devices to interact directly and take over if a link breaks. This decentralized structure increases data transmission reliability, making the system more durable and resilient for monitoring cattle under difficult conditions.

3 RESULT ANALYSIS

This work uses temporal data from a GPS module and MPU6050 sensor to track location and movement. The model pipeline classifies livestock behaviors using neural network analysis of multidimensional sensor data such as accelerometer, gyroscope, GPS, and temporal characteristics as shown in the Fig. 4. Following data preprocessing and feature scaling, the neural network, which consists of two hidden layers with ReLU activation, is trained for 100 epochs and verified on a 20% subset of training data to ensure performance stability. The final test accuracy and classification report—which includes precision, recall, and F1-scores for each class—demonstrates the model's ability to distinguish between distinct animal behaviors. High metrics reflect the model's ef-

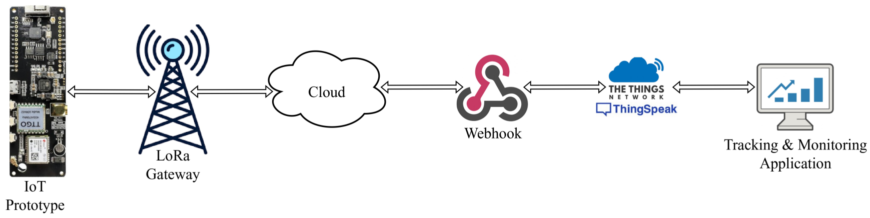


Figure 6: Network Connection for The IoT-based System for Livestock.

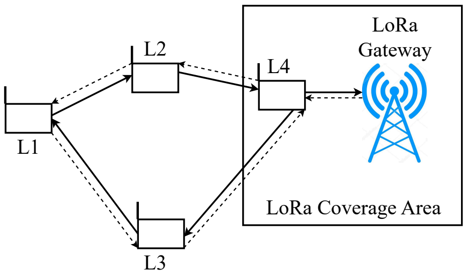


Figure 7: Mesh Network.

ficacy in behavior recognition, but lower scores for certain classes may identify locations where sensor signal overlap or data imbalance affects classification precision. Overall, the results support the model's robustness for animal behavior categorization, while the specific performance metrics provide insights for further improvement in terms of feature representation optimization or dataset diversity enhancement.

From Fig. 8 (a), each line or series of points represents a distinct metric (precision, recall, or F1-score), allowing for an intuitive comparison of how well the model performs in each class. Precision values show the accuracy of positive predictions for each class, indicating how many of the model's positive predictions are right. Recall, on the other hand, measures the model's ability to capture all true positives, indicating how well it recognizes examples of each class. Finally, the F1-score, a balanced measure that combines precision and recall, gives a complete picture of the model's accuracy in each class. Because all metric values are scaled between 0 and 1, with 1 representing the optimum score, the y-axis remains fixed within this range. This arrangement allows us to rapidly identify which courses are tough for the model, as lower points or dips in the line indicate regions where the model may be underperforming.

The training and validation loss curves as illustrated in Fig. 8 (b) provide essential information about the model's learning dynamics and generalization ability. Initially, both training and validation losses are dramatically reduced, indicating effective feature learning and model adaptation to the dataset. However, at epoch 10-15, the validation loss begins to diverge from the training loss, gradually increasing while the training loss decreases. This divergence, which widens the gap between training and validation losses, indicates overfitting. The model appears to be learning specific patterns and noise from training data rather than extracting generalizable characteristics relevant to unseen data, as indicated by the fluctuations and overall increase in validation loss. Early halting, dropout regularization, or weight penalization could all be used to reduce overfitting and improve generalization. Furthermore, extending the dataset or using data augmentation may enhance the model's ability to generalize. This analysis emphasizes the necessity of monitoring loss trends to detect overfitting, which is necessary for deploying robust models in real-world applications.

The sparse categorical cross-entropy loss function, which is used in the model's training phase, calculates the difference between the model's projected probability for the true class and the actual class label. The loss for a single data point is as in the Eqn 1:

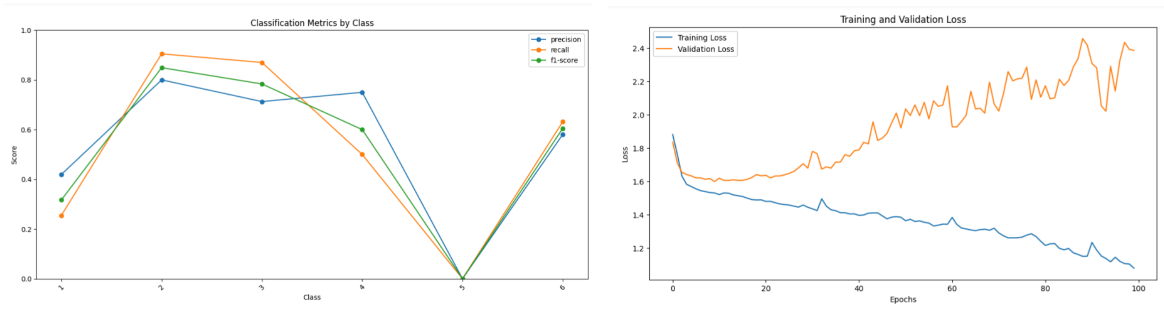
$$L = -\log(p_y) \tag{1}$$

where p_y represents the expected probability of the true class y, and y represents the instance. For a dataset with several samples and classes, the average sparse categorical cross-entropy loss over all instances is given by Eqn 2:

$$Loss = -\frac{1}{N}\sum_{i=1}^{N}\log(p_{y_i}^{(i)}) \tag{2}$$

where N is the total number of samples in the dataset, and $p_{y_i}^{(i)}$ is the estimated probability of the correct class y_i for the i-th sample. In this case, for each data instance, the model generates a probability distribution across all potential classes. The sparse categorical cross-entropy loss function penalizes the model according to how far the predicted probability for the true class deviates from 1. The closer $p_{y_i}^{(i)}$ is to one for the correct class, the lower the loss for that instance.

The loss function encourages the model to provide a high probability to the correct class and a low probability to the incorrect class. During training, the model's weights are modified to reduce the average loss across all occurrences, enhancing the model's ability to predict the proper class label. The



(a) Classification

(b) Training & Validation Loss

Figure 8: (a) Classification Metrics and (b) Training and Validation Loss.

training and validation loss curves in Fig. 8(a) reflect the sparse categorical cross-entropy loss estimated at each epoch. The training loss steadily drops as the model optimizes to better suit the training data, however the validation loss gradually increases after a certain point, indicating probable overfitting. By decreasing this loss function, the model increases classification performance until it begins to memorize the training data as evident from the rising validation loss.

4 CONCLUSIONS

In this paper, we have designed an IoT-based system that can effectively track and monitor livestock animals, ensuring low power consumption and long-distance communication capabilities. Hence, this system is suitable for remote areas with limited cellular network access. Such real-time monitoring systems can prevent theft and loss of livestock animals, which are common issues in livestock farming. This system can help identify the specific activities based on the behavior and movement patterns of the animals by analyzing the GPS, accelerator, and gyroscope data. Future enhancements of this system could involve improving the range and quality of LoRa signals in challenging environments like dense forests. Optimizing the power consumption for better battery life and incorporating additional sensors to monitor animal health and environmental conditions could further enhance the capabilities of the proposed system. Applying machine learning-based techniques to analyze large datasets may provide valuable insights into the movement of livestock animals and their health conditions. Moreover, features like voice commands or automated report generation will improve the user interaction and decision-making process in the next versions of the system in the future.

ACKNOWLEDGEMENTS

This work was partially supported by the Doctoral Fellowship in India (DIA) program of the Ministry of Education, Government of India.

REFERENCES

Angriawan, R. and Anugraha, N. (2019). Sistem Pelacak Lokasi Sapi dengan Sistem Komunikasi LoRa. *Inspiration: Jurnal Teknologi Informasi dan Komunikasi*, 9(1):33–39.

Atthari, A. (2017). Sistem Tracking Position Berdasarkan Titik Koordinat GPS Menggunakan Smartphone. *Jurnal Infomedia: Teknik Informatika, Multimedia, dan Jaringan*, 2(1):2549–1180.

Chamara, N., Islam, M. D., Bai, G. F., Shi, Y., and Ge, Y. (2022). Ag-iot for crop and environment monitoring: Past, present, and future. *Agricultural systems*, 203:103497.

Chen, J. and Huang, S. (2023). Analysis and Comparison of UART, SPI and I2C. In *2023 IEEE 2nd International Conference on Electrical Engineering, Big Data and Algorithms (EEBDA)*, pages 272–276.

Davcev, D., Mitreski, K., Trajkovic, S., Nikolovski, V., and Koteli, N. (2018). Iot agriculture system based on lorawan. In *2018 14th IEEE International Workshop on Factory Communication Systems (WFCS)*, pages 1–4.

Farooq, M. S., Sohail, O. O., Abid, A., and Rasheed, S. (2022). A survey on the role of iot in agriculture for the implementation of smart livestock environment. *IEEE Access*, 10:9483–9505.

Fedorov, D., Ivoilov, A. Y., Zhmud, V., and Trubin, V. (2015). Using of measuring system mpu6050 for the determination of the angular velocities and linear accelerations. *Automatics & Software Enginery*, 11(1):75–80.

Islam, K. Z., Murray, D., Diepeveen, D., Jones, M. G., and Sohel, F. (2024). Lora localisation using single mobile gateway. *Computer Communications*, 219:182–193.

Jain, B., Trivedi, K., Agarwal, S., and Thakur, R. (2021). MeshSOS: An IoT Based Emergency Response System. In *HICSS*, pages 1–10.

Joshitha, C., Kanakaraja, P., Bhavani, M. D., Raman, Y. N. V., and Sravani, T. (2021). LoRaWAN Based Cattle Monitoring Smart System. In *ICEES*, pages 548–552.

Jouhari, M., Saeed, N., Alouini, M.-S., and Amhoud, E. M. (2023). A survey on scalable lorawan for massive iot: Recent advances, potentials, and challenges. *IEEE Communications Surveys & Tutorials*, 25(3):1841–1876.

Ladha, C., Hammerla, N., Hughes, E., Olivier, P., and Ploetz, T. (2013). Dog's life: wearable activity recognition for dogs. In *Proceedings of the 2013 ACM international joint conference on Pervasive and ubiquitous computing*, pages 415–418.

Lu, J., Li, W., Sun, J., Xiao, R., and Liao, B. (2024). Secure and Real-Time Traceable Data Sharing in Cloud-Assisted IoT. *IEEE Internet of Things Journal*, 11(4):6521–6536.

Mahaputra, I., Agung, I., and Jasa, L. (2019). Rancang Bangun Sistem Keamanan Sepeda Motor dengan GPS Tracker Berbasis Mikrokontroler dan Aplikasi Android. *Majalah Ilmiah Teknologi Elektro*, 18(3):361–368.

McClune, D. W., Marks, N. J., Wilson, R. P., Houghton, J. D., Montgomery, I. W., McGowan, N. E., Gormley, E., and Scantlebury, M. (2014). Tri-axial accelerometers quantify behaviour in the eurasian badger (meles meles): towards an automated interpretation of field data. *Animal Biotelemetry*, 2:1–6.

Nguyen, V. and Dugenske, A. (2018). An I2C Based Architecture for Monitoring Legacy Manufacturing Equipment. *Manufacturing Letters*, 15:67–70.

Putra, A. and Romahadi, D. (2021). Sistem Keamanan Sepeda Motor Berbasis Internet Of Things (Iot) Dengan Smartphone Menggunakan Nodemcu. *Jurnal Teknologi Terpadu*, 9(1):77–87.

Sharma, R., Pandey, B., Jha, V., Saurabh, S., and Dabas, S. (2018). Input–output standard-based energy efficient uart design on 90ánm fpga. In *System and Architecture: Proceedings of CSI 2015*, pages 139–150.

Sugiarto, E., Suhendi, A., Abdussalam, M. Y., Husniah, Z. A., and Lestari, A. P. (2023). Prototype design of a fishing boat safety monitoring system using lora and microsensor devices. *JMECS (Journal of Measurements, Electronics, Communications, and Systems)*, 10(2):77–85.