Wildlife Tracking and Health Monitoring Using IoT

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Abstract— **This paper presents an IoT-based system for real-time wildlife tracking and health monitoring to support biodiversity conservation efforts. The proposed solution comprises a compact sensor unit mounted on the animal, capable of measuring critical physiological and environmental parameters such as temperature, pulse rate, and GPS location. These data are transmitted over long-range LoRa communication to a receiver module, where they are processed, stored in a cloud database, and visualized through a web-based dashboard.**

The system reduces manual intervention, minimizes disturbance to wildlife, and enables continuous monitoring in remote habitats. To enhance decision-making, a machine learning model is integrated to classify potential health conditions using physiological patterns, enabling early detection of abnormalities and timely intervention. The combination of IoT sensing, cloud analytics, and predictive modeling provides a scalable and reliable framework for modern wildlife conservation.

Index Terms*— *IoT, wildlife tracking, health monitoring, LoRa communication, biodiversity conservation, physiological sensors, machine learning, cloud analytics.

I. INTRODUCTION

Wildlife conservation relies heavily on continuous monitoring of animal movement, behavior, and health. Traditional tools such as radio telemetry and manual field surveys, although widely used, suffer from limitations including restricted range, lack of real-time updates, high maintenance cost, and the inability to capture physiological parameters [1], [13]. These methods often require close human intervention, which can disturb natural animal behavior.

The emergence of Internet of Things (IoT) technologies has significantly advanced wildlife monitoring. IoT systems integrate GPS receivers, biomedical sensors, microcontrollers, and long-range communication modules to provide real-time, non-invasive data collection in remote habitats [2], [3]. Such systems improve tracking accuracy, reduce manual effort, and allow scalable deployment across large conservation areas. This project presents an IoT-enabled system for wildlife tracking and health monitoring. The design incorporates GPS-based location tracking, vital-sign sensors, and LoRa communication for long-range data transmission. Cloud storage ensures persistent access to collected data, supporting remote observation and long-term analysis an approach consistent with modern ecological monitoring solutions [4], [10].

To enhance functionality, a machine learning model is integrated to detect early signs of illness using physiological patterns. Predictive analytics enables timely interventions, helping prevent health deterioration and reducing wildlife mortality [6].

By combining IoT sensing, long-range communication, cloud analytics, and machine learning, the proposed system offers a practical and scalable framework for real-time wildlife conservation and proactive biodiversity management.

II. METHODOLOGY

A. System Overview

The proposed system follows a distributed IoT architecture consisting of an on-animal sensing unit (transmitter) and a base-station processing unit (receiver). At the core of the transmitter unit is the ATmega328U microcontroller, selected for its low power consumption and stable performance in embedded sensing applications criteria well aligned with the requirements of wildlife monitoring deployments [1], [3]. The microcontroller interfaces with multiple physiological and environmental sensors to acquire real-time data from the animal.

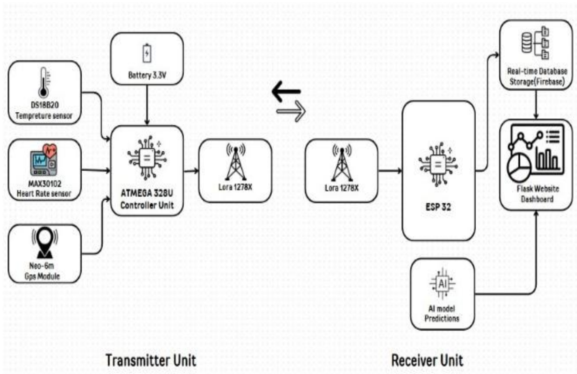

Fig. 1. Functional diagram of the proposed wildlife monitoring system.

Two key health sensors are integrated into the transmitter module. The MAX30102 optical pulse oximeter measures heart rate and blood oxygen saturation, enabling early detection of physiological stress a method widely used in wearable wildlife telemetry systems [4]. The DS18B20 temperature sensor provides accurate body temperature readings, an important indicator of fever, infection, or environmental stress. Both sensors operate over energy-efficient protocols (I2C and 1-Wire), enabling reliable communication with the ATmega328U even under constrained power conditions.

To capture spatial movement, the system incorporates the u-blox NEO-6M GPS module. This device supports GPS and GLONASS constellations, ensuring robust location acquisition in dense forests, mountainous regions, and other challenging terrains an essential requirement for wildlife tracking as documented in [7]. Tracking movement patterns is critical for habitat assessment, behavioral analysis, and monitoring potential human-wildlife conflict zones.

Data transmission is facilitated by the SX1278 LoRa module, which employs a long-range, low-power spread-spectrum modulation technique. LoRa is widely adopted in modern ecological IoT deployments due to its multi-kilometer communication capability and resilience to interference [2]. This ensures that collected health and location data can reach the receiver unit even in remote environments with limited network infrastructure.

The functional workflow of the system is illustrated in (Fig. 1). Sensor values are collected and processed by the ATmega328U, encoded into data packets, and transmitted via LoRa. This integrated flow enables real-time monitoring while ensuring modularity for future sensor or hardware expansion. The compact transmitter design minimizes disturbance to the animal and maximizes operational endurance through low power firmware routines.

B. Data Transmission and Cloud Integration

The receiver unit is built around the ESP32-WROOM-32 microcontroller, which receives LoRa packets, validates the payload, and prepares the decoded data for cloud synchronization. The ESP32's integrated Wi-Fi and dual-core architecture make it suitable for high-throughput IoT gateway applications, as shown in other wildlife and livestock monitoring systems [5]. Once received, data is forwarded to a cloud-based Firebase database. This creates a centralized repository for long-term monitoring, multi-user access, and analytics. Cloud storage supports the visualization of historical temperature, heart rate, and GPS trends, aiding in early identification of abnormal behavior or environmental stressors an approach aligned with trends in IoT-enabled ecological research [9].

The cloud platform also enables predictive decision-making by supporting downstream analytics modules, including the machine learning system described in the following sections. Historical trends, seasonal variations, and long-term animal movement patterns can be studied using stored data, enhancing the effectiveness of conservation insights.

Data redundancy and security protocols such as authenticated API calls and dual-stage storage (local ESP32 buffer + cloud) provide robustness against connectivity failures and data loss. This ensures that no critical health or location data is missed during prolonged field deployments. Similar resilient architectures are recommended in wildlife IoT research to maintain monitoring continuity [17]. Overall, the integration of LoRa communication, ESP32-based edge processing, and Firebase cloud infrastructure results in a scalable, energy-efficient, and field-ready methodology for wildlife tracking and health monitoring. It supports real-time observation, long-term analytics, and data-driven conservation strategies.

III. SYSTEM DESIGN

A. Transmitter Side

The transmitter unit serves as the primary data acquisition module, responsible for collecting physiological and positional information from wildlife in real-time. It integrates multiple low-power sensors commonly used in modern wildlife monitoring systems [1], [3]. The overall architecture of the transmitter is shown in (Fig. 2).

Key health parameters are measured using two core sensors: the DS18B20 digital temperature sensor and the MAX30102 optical pulse oximeter. The DS18B20 provides high-accuracy temperature readings, which are essential for detecting deviations associated with fever or environmental stress. Meanwhile, the MAX30102 measures heart rate and blood oxygen saturation, enabling early detection of physiological anomalies an approach consistent with recent IoT-enabled wildlife health systems [4].

For geolocation, the transmitter uses the u-blox NEO-6M GPS module, capable of acquiring signals from both GPS and GLONASS constellations. This ensures reliable location tracking even in forested or mountainous terrains, as demonstrated in prior wildlife telemetry research [7]. The GPS data supports movement analysis, habitat utilization studies, and anti-poaching monitoring.

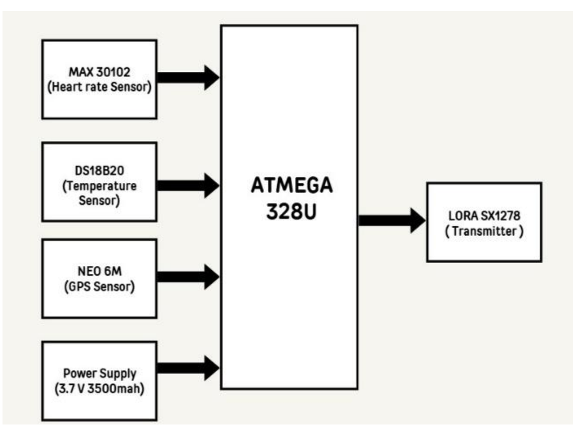

Fig. 2. Block Diagram illustrating the transmitter (animal-side) unit.

The ATmega328 microcontroller functions as the central processor for the transmitter. Selected for its low power consumption and stable embedded performance, it interfaces with the sensors, performs initial data formatting, and prepares packets for wireless transmission.

Communication is provided by the SX1278 LoRa module, which supports long-range, low-bandwidth transmission typically several kilometers with minimal power usage. LoRa has been widely adopted for remote wildlife monitoring because of its resilience to interference and suitability for low-signal, large-area deployments [2]. This ensures stable communication even across dense vegetation or rugged landscapes.

A compact and durable enclosure houses the entire transmitter assembly. Designed for rugged environments, it protects internal components from dust, moisture, and physical impact, similar to other ruggedized IoT collars described in the literature [10]. The hardware implementation is shown in (Fig. 3).

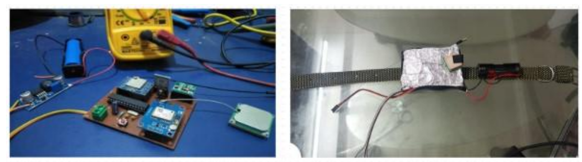

Fig. 3. Physical hardware implementation of the transmitter module.

To maximize battery life, the system incorporates low-power firmware strategies such as sleep modes, reduced sampling frequency when animals are inactive, and optimized sensor polling intervals. These measures extend device longevity—an essential requirement for continuous wildlife monitoring in inaccessible regions. The modular design also supports integration of additional sensors or advanced communication protocols in future iterations.

B. Receiver Side

The receiver module is responsible for collecting, decoding, and forwarding data transmitted by the animal-mounted unit. It acts as the system's gateway for analytics, visualization, and long-term storage. The block diagram of the receiver is shown in (Fig. 4). The module is built around the ESP32 microcontroller, selected for its dual-core architecture, integrated Wi-Fi, and high-throughput handling of concurrent IoT tasks—capabilities that make it well suited for field monitoring applications [5].

LoRa packets from the transmitter are received by an SX1278 module configured in gateway mode. LoRa's robust modulation scheme ensures reliable reception even in complex terrains and low-SNR environments [2]. The ESP32 decodes each packet, verifies its checksum, and extracts the transmitted temperature, heart rate, pulse rate, respiratory rate, and GPS coordinates.

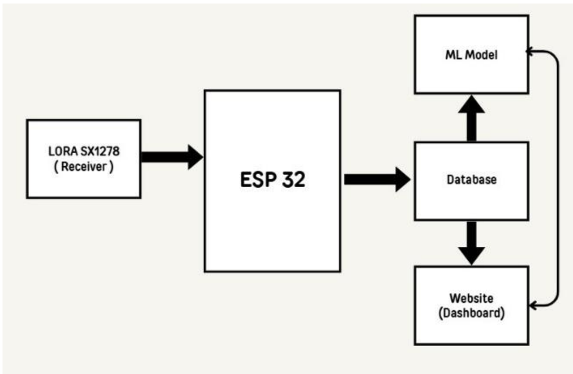

Fig. 4. Block Diagram of the receiver (admin-side) unit.

The processed data is forwarded to a real-time dashboard, enabling conservationists and veterinarians to monitor wildlife health conditions instantly. The dashboard visualizes temperature and heart-rate trends, displays real-time geographic location, and issues alerts for abnormal readings features aligned with other remote-sensing and ecological monitoring systems [9].

To ensure reliability, the receiver uses a dual-storage mechanism. Temporarily, data is cached locally on the ESP32 to maintain operation during network outages. Once connectivity is restored, the data is uploaded to a Firebase cloud database. This cloud-backed approach enables long-term analytics, multi-user collaboration, and seamless integration across research teams [17].

This design allows researchers to perform historical health analysis, identify behavioral anomalies, and track migration or seasonal movement trends. By combining LoRa reception, local buffering, and cloud synchronization, the receiver serves as a scalable and resilient backbone for real-time wildlife monitoring.

C. Software Architecture

The software architecture forms the intelligence layer of the proposed IoT-based wildlife monitoring system. It integrates sensing hardware, cloud infrastructure, predictive machine learning analytics, and a real-time dashboard interface. Similar architectures are increasingly used in modern conservation systems [2], [4] due to their scalability and low operational cost.

1) Data Ingestion and API Layer: The ESP32-WROOM-32 microcontroller transmits sensor readings including temperature, heart rate, pulse rate, respiratory rate, and GPS location through RESTful API calls to a Flask-based server. This ingestion method aligns with lightweight IoT communication standards used in wildlife tracking literature [3], [5]. Each packet is validated for structure and timestamp consistency before processing.

2) Preprocessing and Feature Engineering: Incoming data undergoes standardized preprocessing to ensure consistency with the offline training pipeline. Steps include:

Outlier removal using the interquartile range (IQR) method [13], Standardization with z-score normalization, Median imputation for missing values, SMOTE-based oversampling to correct class imbalance in the training phase, Feature engineering to derive physiological metrics which provide enhanced discriminative capability for disease classification. Such engineered vital-sign features are widely used in biomedical ML systems [6]. (Fig. 5) shows feature-wise relationships between conditions, highlighting separability across the physiological domain.

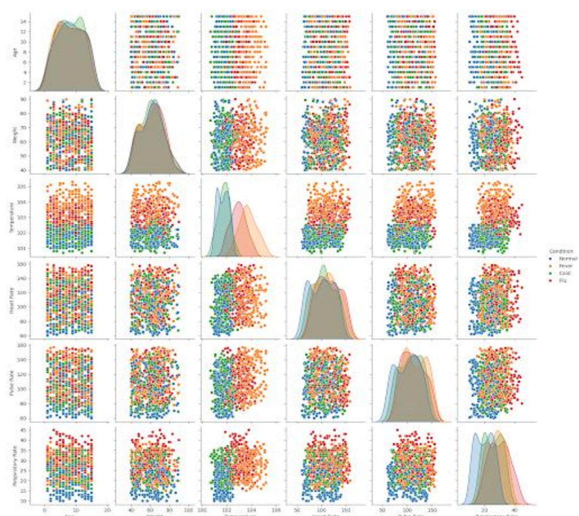

Fig. 5. Feature comparisons for different health conditions.

3) Machine Learning Inference Engine: Several classification algorithms including Logistic Regression, K-Nearest Neighbors, Support Vector Machine, and Decision Tree were evaluated following practices similar to prior wildlife-health ML systems

[7], [10]. As shown in (Fig. 6), the Random Forest classifier achieved the highest accuracy of 91.27%

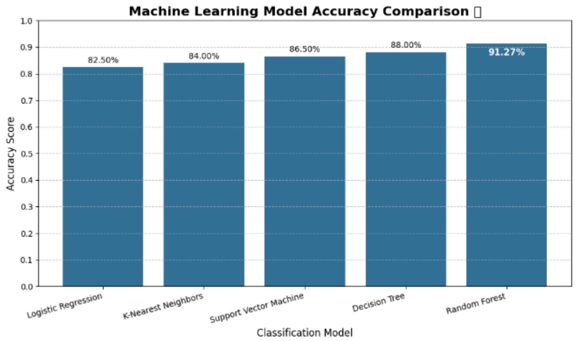

Fig. 6. Comparative accuracy of ML models.

The Random Forest model aggregates predictions from multiple trees and is optimized using multi-class cross-entropy.

This approach improves robustness and reduces variance, which is especially beneficial for noisy wildlife health data [12]. The trained model is serialized using joblib and loaded by the Flask server for real-time inference.

4) Real-Time Alerting and Cloud Synchronization: After classification, the backend generates:

• Predicted health label (Healthy, Cold, Fever, Flu).

• Probability distribution.

• Anomaly/alert flag.

These results are transmitted to a Firebase cloud database, ensuring instant synchronization across devices. Cloud-backed systems are known to enhance accessibility and support multi-user collaboration in conservation environments [17].

5) Dashboard and Visualization Layer: A dynamic web dashboard presents live sensor data, health predictions, and GPS coordinates. The interface (Fig. 7) includes:

• Line charts for temperature, pulse, and respiratory signals,

• Map-based animal location tracking,

• Health risk alerts and probability breakdowns,

• Historical trend analysis sourced from cloud storage.

Fig. 7. Dashboard interface for wildlife monitoring.

This architecture provides a scalable, low-latency decision support system for conservationists, enabling early disease detection and real-time field monitoring, consistent with modern IoT-driven ecological monitoring systems [1], [9].

IV. CONCLUSION

The project titled "Wildlife Tracking and Health Monitoring Using IoT" demonstrates an effective integration of sensing, communication, and analytics technologies to support modern wildlife conservation efforts. The system successfully combines physiological sensors, GPS tracking, and long-range LoRa communication to enable continuous, real-time monitoring of animals in remote habitats. Compared to traditional tracking methods, the proposed IoT architecture offers improved accuracy, lower operational cost, and reduced human intervention.
The inclusion of heart rate and temperature monitoring provides deeper insight into animal health and behavioral changes, enabling early detection of stress or illness. The cloud-based dashboard enhances data accessibility by offering intuitive visualizations of location and health trends, while the machine learning model strengthens decision-making through automated health assessments and predictive analysis.

Overall, this work validates the feasibility and usefulness of IoT-driven wildlife monitoring systems. The modular design supports scalability across species and environments, making it suitable for broader ecological applications. The ability to integrate additional sensors, upgrade communication modules, or incorporate advanced predictive models further enhances the adaptability of the system. As IoT and machine learning technologies continue to advance, the proposed framework can evolve into a more comprehensive and proactive conservation tool. This has the potential to support early disease detection, improve wildlife protection strategies, and provide long-term insights into animal behavior and ecosystem health, ultimately contributing to global biodiversity preservation efforts.

V. ACKNOWLEDGMENT

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