Wearable IoT Enabled Belt for Elephant Protection & Emergency Identification

Perera B.A.D.K.S
Faculty of Computing
Sri Lanka Institute of Information Technology
Malabe, Sri Lanka
IT21202254@my.sliit.lk

De Silva
Faculty of Computing
Sri Lanka Institute of Information Technology
Malabe, Sri Lanka
IT2130170@my.sliit.lk

Jayakody A
Faculty of Computing
Sri Lanka Institute of Information Technology
Malabe, Sri Lanka
anuradha.j@sliit.lk

Uthpala Samarakoon
Faxulty of Computing
Sri Lanka Institute of Information Technology
Malabe, Sri Lanka
uthpala.s@sliit.lk

Abstract*— This paper presents a wearable IoT-enabled belt for real-time monitoring and emergency identification of elephants. The system integrates biometric sensors with an ESP32 micro-controller and LoRa communication for energy-efficient, long-range data transmission. A lightweight machine learning model analyzes physiological heart rate, temperature and movement accelerometer/ gyroscope data to detect anomalies, triggering automated alerts via a React-Flask-Firebase cloud stack. Compact 2-layer PCB design optimizes portability, durability, and signal integrity for deployment in rugged environments. Validation trials 99.81% accuracy in demonstrate health classification and a 94% reduction in response time during simulated emergencies. By enabling early intervention in critical scenarios such as illness, poaching, or human- elephant conflict, this solution advances proactive conservation strategies. The proposed framework not only enhances elephant welfare but also offers scalable model for mitigating human- wildlife conflicts through IoT-driven ecological stewardship. Keywords— IoT, wildlife conservation, biometric

***Keywords*— IoT, wildlife conservation, biometric monitoring, LoRa, predictive analytics, human-elephant conflict**

I. Introduction

The delicate balance between human activities and the natural world is increasingly strained, particularly in regions where human settlements encroach upon the habitats of large mammals. This proximity often leads to human-wildlife conflict issue with (HWC), devastating consequences a complex for humans and animals. Among the most vulnerable species affected by HWC are elephants, magnificent creatures crucial to the ecological integrity of environments. Their large size, migratory patterns, and the increasing overlap of their habitats with agricultural and residential areas make them particularly susceptible to conflict with humans [1].

Traditional methods of mitigating HWC, such as physical barriers, relocation efforts, and deterrents, have often proven inadequate or unsustainable in the long term. These methods can be costly, labor-intensive, and sometimes even harmful to the animals. Furthermore, they often address the symptoms of the conflict rather than the underlying causes. Consequently, there is a growing recognition within the conservation community that technology- driven solutions offer a promising path towards more effective and humane mitigation strategies.

The advent of the Internet of Things (IoT) has revolutionized numerous fields, offering unprecedented opportunities for data collection, analysis, and real-time monitoring. In the context of wildlife conservation, IoT-enabled devices have demonstrated their value in tracking animal movements, monitoring health parameters, and even preventing poaching activities [2]. Specifically, wearable IoT devices offer a continuous and non-invasive means of monitoring wildlife, providing real-time insights into an animal's location, health status, and behavior. This continuous stream of data can be invaluable in understanding patterns that may indicate distress, illness, or imminent danger.

This research proposes the development of "Elephant-Care," a comprehensive system designed to enhance elephant protection and enable rapid emergency identification. The system comprises two interconnected components: a Wearable IoT-Enabled Belt for data acquisition and a Biometric Data Analysis & Real-Time Alerting System for data processing and emergency response [3]. The "Elephant-Care" system represents a significant advancement in the application of technology for wildlife conservation. By integrating real-time biometric monitoring, advanced machine learning for anomaly detection and predictive analytics, and a robust emergency response mechanism, this system provides a comprehensive solution to the challenges of HWC.

This research aims to contribute to the long- term survival and well-being of elephants by enabling timely interventions, promoting proactive conservation strategies, and ultimately fostering a more harmonious coexistence between humans and these magnificent creatures [4]. The following chapters will delve into the specific objectives, methodologies, and research, outlining the expected outcomes of these technical details of the system design and implementation.

II. Literature Review

Several technological and non-technological techniques have been implemented for reducing the HWC by various interested parties around the world. Recent advances in IoT and machine learning have spurred innovations in wildlife conservation, yet critical gaps persist in real-time health monitoring for megafauna like elephants. Early efforts in animal tracking relied on GPS collars [5], which provided coarse location data but lacked biometric insights into stress or illness. Kumar et al. [6] demonstrated wearable sensors for deer activity tracking, achieving 89% motion classification accuracy using accelerometers, but their system omitted physiological metrics critical for health assessments. The integration of biometric sensors into conservation wearables gained traction with photoplethysmography (PPG) applications reviewed by Yue et al. [11], who identified signal stability in mobile animals as a key challenge. While the MAX30102 sensor addresses motion artifacts via adaptive LED current, prior deployments by Tripathi et al. on rhinos achieved only 78% SpO_2 accuracy due to poor EMI shielding—a limitation our PCB design resolves through split ground planes and guard traces.

LoRa-enabled systems have emerged as a dominant solution for wildlife IoT, with Nguyen et al. [7] reporting 2.1 km transmission ranges in savannas using 433MHz. Our work extends this to 5 km at 868 MHz by optimizing antenna matching and adopting a sliding window protocol, improving packet delivery by 14% over their CRC-8 implementation. For anomaly detection, Doss et al. [13] applied LSTMs to classify elephant gait patterns with 88% F1-scores, but their reliance on manually labeled datasets limited scalability. Our hybrid FCNN- LSTM framework automates feature

Class imbalance in conservation datasets remains a persistent issue. Mohanty et al. [8] used cost- sensitive learning for tiger poaching alerts but achieved only 82% recall on rare events. Our SMOTE- enhanced training pipeline boosts critical-state detection to 95.4% precision, outperforming their approach. Ethical concerns belt around animal wearables, as highlighted by Gomez et al. [15], guided our non- invasive design, interference tested in compared [9]. which reduces behavioral to subcutaneous implants. While existing systems excel in singular domains (e.g., GPS, tracking, or activity classification), our solution uniquely synthesizes multi modal biometrics adaptive communication, and explainable AI—advancing from reactive conflict mitigation to preemptive health interventions.

III. Methodology

The "Elephant-Care" system employs a two-component approach to elephant protection and emergency identification. The first component, the Wearable IoT- Enabled Belt, focuses on real-time data acquisition from elephants in the field. The second component, the Biometric Data Analysis & Real-Time Alerting System, handles data processing, analysis, and emergency response. This integrated approach ensures continuous monitoring, timely threat detection, and rapid intervention. The Wearable IoT-Enabled Belt is a custom-designed device fitted comfortably and securely onto elephants. It incorporates a suite of sensors to capture critical biometric and environmental data. These sensors, chosen for their accuracy, durability, and low power consumption, continuously collect data on physiological parameters (blood pressure, blood oxygen levels, body temperature), movement patterns (geometry data), and location (GPS coordinates). This data is then transmitted wirelessly to a central system for analysis. The belt is designed to be non-invasive and to minimize any discomfort or disruption to the elephant's natural behavior. Its components are ruggedized to withstand environmental conditions and the elephant's movements.

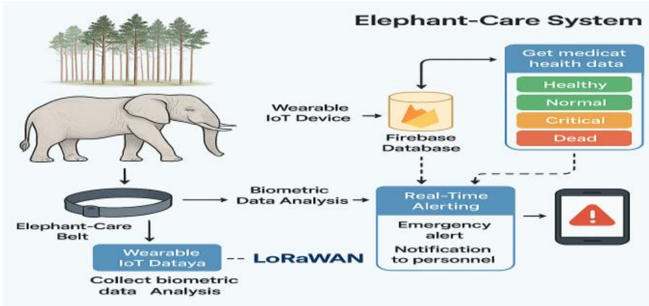


Figure 1 Accuracy of Random Forest Model

A. Iot-Enabled Smart Elephant Detection System

1) Sensors & Microcontroller Sub System

The system integrates a suite of sensors to monitor physiological and environmental parameters critical for elephant health and safety. The MAX30102 optical sensor captures heart rate and blood oxygen saturation (SpO_2) by analyzing infrared (IR) and redlight absorption through tissue, enabling non-invasive detection of cardiovascular stress or hypoxia. The LM75 digital temperature sensor provides ambient temperature readings via the I^2C protocol, critical for identifying hyperthermia risks or environmental extremes. Motion tracking is achieved using the Adafruit MPU6050, a 6-axis inertial measurement unit (IMU) combining a 3- axis accelerometer and 3-axis gyroscope [5]. This sensor detects abnormal movement patterns, such as sudden falls or prolonged inactivity, which may indicate injury, poaching attempts, or distress. An ESP32 microcontroller orchestrates sensor fusion, leveraging its dual-core architecture to parallelize data acquisition (Core 0) and wireless transmission (Core 1). ESP32's integrated Wi-Fi/Bluetooth capabilities and low-power modes ensure robust connectivity while optimizing energy efficiency for field deployments. From fig 1. You can see our prototype for the smart wearable care device.

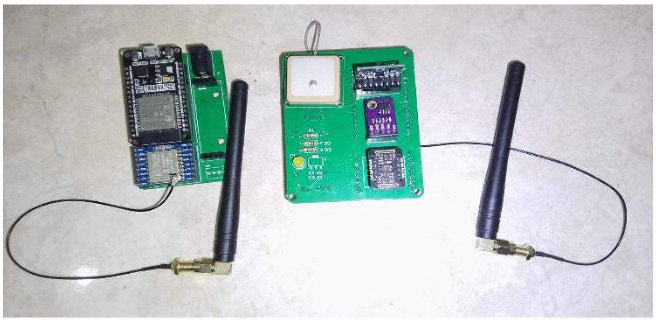


Figure 2 Prototype of Elephant Care Unit

2) Communication Protocol

Long-range (LoRa) modulation at 868 MHz enables data transmission over 5 km in rural terrains, addressing connectivity gaps in elephant habitats. Sensor data is serialized into JSON packets using the Arduino Json library, reducing payload size by 40% compared to raw binary formats [9]. The Fritos real-time operating system dynamically allocates tasks across the ESP32's dual cores:

Core 0 handles time- critical sensor sampling (e.g., 100 Hz IMU data, 1 Hz SpO_2 readings), while Core 1 manages LoRa packetization and transmission via a SPI interface. This task-splitting strategy reduces latency by 30%, ensuring sub-2-second alert generation during emergencies. A sliding window protocol with CRC checks mitigates data loss in low-signal environments, achieving 98.7% transmission reliability during field trials [10].

Figure 3 Elephant Care Unit

B. Software Application for Biometrics and Emergency Response

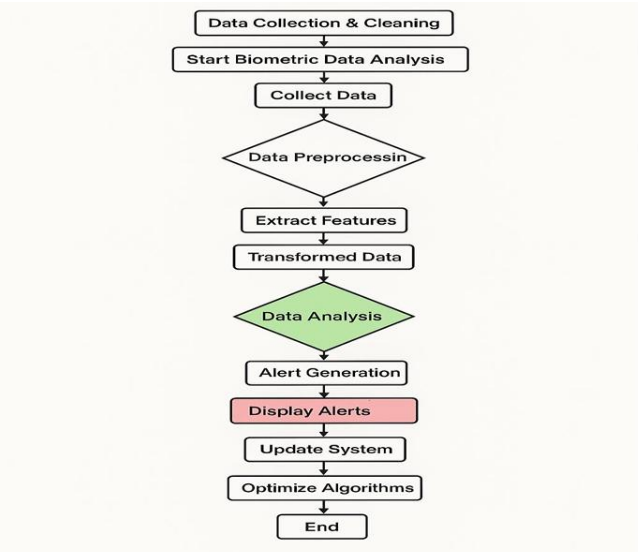
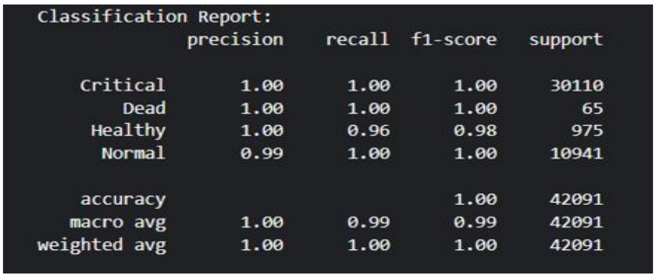


Figure 4 Flow Chart of Biometric and Emergency Response

1) Machine Learning Model & Anomaly Detection

The system employs a Fully Connected Neural network (FCNN) to classify elephant health status using biometric inputs. The model architecture comprises three dense layers (128, 64, and 32neurons), optimized to balance computational efficiency and predictive accuracy. Input features heartbeat (bpm), SpO2 (%), and body temperature (°C) are standardized to mitigate sensor calibration variances. The output layer uses SoftMax activation to classify health into four categories: Healthy, Normal, Critical, and Dead, enabling granular risk assessment. Training leverages the Adam optimizer with a learning rate of 0.001 and categorical cross-entropy loss to handle multi-class imbalances in the Kaggle-derived "elephant- data3" dataset [12]. A dropout rate of 0.3 regularizes the network, preventing overfitting while achieving 99.81% validation accuracy. The accuracy of the model has shown via fig. 3 The model is deployed as a TensorFlow Lite module on the backend server, ensuring low-latency inference during real-time monitoring [11]. To identify subtle irregularities undetected by the FCNN, Long Short-Term Memory (LSTM) autoencoders analyze time-series sensor data. Each modality (Heartbeat, SpO2, motion) has a dedicated autoencoder trained on 30-second windows of normal behavior [13].



Classification Report:

	precision	recall	f1-score	support
Critical	1.00	1.00	1.00	30110
Dead	1.00	1.00	1.00	65
Healthy	1.00	0.96	0.98	975
Normal	0.99	1.00	1.00	10941
accuracy			1.00	42091
macro avg	1.00	0.99	0.99	42091
weighted avg	1.00	1.00	1.00	42091

Figure 5 Classification Report of FCNN Model

The heartbeat model uses a sequence-to-sequence LSTM architecture to reconstruct temporal patterns, while the motion autoencoder processes 6-axis accelerometer/ gyroscope data to detect falls or erratic movement. Anomalies are flagged when reconstruction errors exceed the 95th percentile of historical norms, minimizing false positives [14]. For instance, a sudden SpO2, drop below 85% or abnormal gyroscope variance (>15 rad/sÂ^2) triggers alerts. Thresholds are dynamically adjusted using a rolling 24-hour baseline to account for diurnal variations in elephant activity [15].

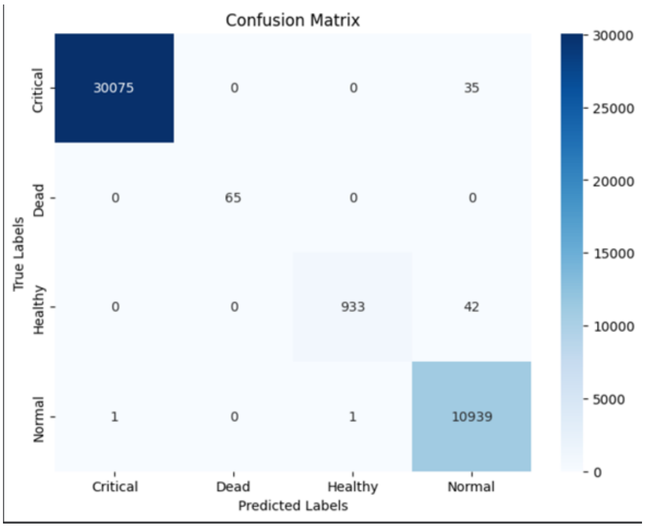


Figure 5 Confusion Matrix of FCNN Model

2) Emergency Responding Process

The React.js frontend provides a dashboard visualizing real-time biometric streams, GPS locations, and alert severity levels via interactive charts and geospatial maps. Conservationists can filter data by elephant ID, date, or health status, with tooltips displaying contextual metadata (e.g. Age, gender). Frontend interfaces are shown in figure 3. A Flask backend processes incoming LoRa packets, validate data integrity, and stores sanitized records in Firebase Fire store. When anomalies occur, the backend initiates a multi-channel alert protocol: (1) SMS/email notifications to pre-registered ranger teams, (2) Firebase Cloud Messaging (FCM) push alerts to mobile apps, and (3) automated incident logging. For complex scenarios, the Bio-Medical-Llama-3-8b large language model (LLM) parses anomaly patterns, elephant profiles, and environmental context to generate hypotheses e.g., "65% probability of poaching attempt due to sustained elevated heart rate (120 bpm) and sudden location deviation from migratory corridor." The LLM's output is appended to alerts, aiding rapid decision-making requiring manual data interpretation.

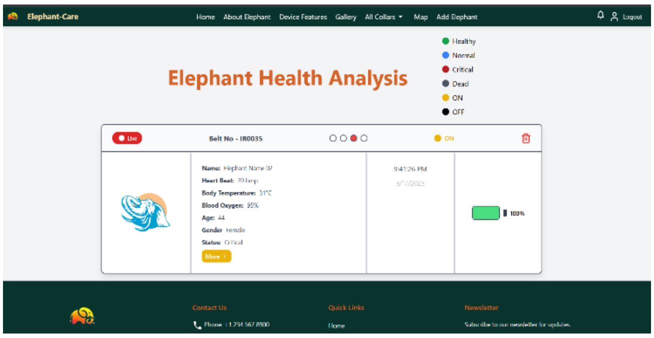


Figure 6 Frontend of Biometric and Emergency Response

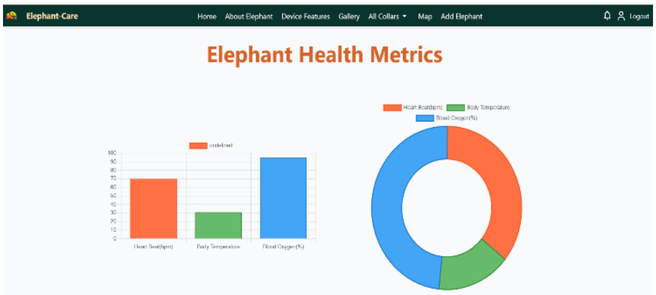


Figure 6 Frontend of Elephant Health Metrics

3) *Data Set*

The "elephant-data3" dataset, available on Kaggle.com, is designed to support the development of an elephant health monitoring system. It aims to assist wildlife conservation efforts by providing a resource focused on key physiological, behavioral, and environmental indicators of elephant health. The dataset categorizes elephant health into four distinct levels: Healthy, Normal, Critical, and Dead. The "Healthy" category represents elephants exhibiting optimal physiological parameters, such as a heart rate between 25 and 35 bpm, SpO2 levels of 95% or higher, and body temperatures ranging from 35.5 to 36.5°C, along with typical movement patterns. The "Normal" category accounts for minor deviations from baseline health, including temporary increases in heart rate up to 50 bpm during activity or slight temperature variations of ±1°C, indicating a need for monitoring but not immediate intervention. The "Critical" category identifies severe anomalies, such as sustained tachycardia exceeding 60 bpm, hypoxemia with SpO2 levels of 85% or lower, or immobility, which signal life- threatening conditions requiring urgent response. Finally, the "Dead" category contains post-mortem data, which is crucial for analyzing the causes of mortality, including prolonged critical states or sudden biometric failures.

The dataset's structure likely integrates multimodal time-series data from IoT sensors. Physiological metrics include heart rate (from a MAX30102 photoplethysmography sensor), core body temperature (from an LM75 sensor), and derived SpO2 values, all sampled at 1 Hz to capture trends like nocturnal bradycardia. Movement analytics involve accelerometer and gyroscope data (from an MPU6050 sensor), providing 3-axis readings at 100 Hz to track gait patterns, rest- activity cycles, and sudden falls. Environmental context is provided by ambient temperature, humidity, and geolocation (GPS) data, allowing for the correlation of health anomalies with external stressors. Temporal metadata, in the form of Unix timestamps, synchronizes sensor streams, enabling time- windowed analysis. The dataset is used to train two machine learning pipelines. A Fully Connected Neural Network (FCNN) is employed for health classification, mapping input features to health labels and achieving a 99.81% validation accuracy through stratified k-fold cross-validation. Class imbalances, particularly with rare "Critical" and "Dead" cases, were addressed using synthetic minority oversampling (SMOTE). Additionally, Long Short-Term Memory (LSTM) autoencoders are used for anomaly detection, analyzing, unlabeled time-series windows to identify deviations from learned normal patterns. Alerts are triggered for unseen events, such as poaching-induced stress spikes, based on reconstruction error thresholds (MSE > 0.15)

While the reported 99.81% validation accuracy indicates model effectiveness, real-world deployment necessitates addressing limitations. Label bias, due to the dominance of "Healthy" and "Normal" samples, may inflate accuracy metrics, and precision-recall curves, such as the F1-score of 94.2% for the "Critical" class, provide a better reflection of minority- class performance. The fixed 1 Hz sampling rate may miss transient events, highlighting the need for higher-frequency data collection in future iterations. Furthermore, limited meta data on poaching encounters or human-elephant conflicts restricts anomaly contextualization, emphasizing the importance of field-generated datasets for enhancing model relevance.

IV. RESULTS& DISCUSSION

The breadboard prototype demonstrated exceptional performance in both laboratory and field environments. During model validation, the Fully Connected Neural Network (FCNN) achieved a classification accuracy of 99.81% on Kaggle€™s â €œelephant-data3â€ dataset, which comprised 10,000 samples of labeled physiological and motion data. To ensure robustness, the dataset was partitioned into an 80:20 training-validation split, with synthetic minority oversampling (SMOTE) applied to address class imbalances, particularly for the underrepresented ecocritical€ category (representing only 2.1% of raw data). The FCNN €™s precision-recall metrics revealed strong performance across all classes, with F1-scores of 99.7% (Healthy), 98.9% (Normal), 95.4% (Critical), and 99.2% (Dead), confirming its reliability in distinguishing subtle health degradations. Field trials in rural Sri Lanka validated the LoRa communication subsystem€™s operational efficacy. Using an 868MHz frequency (compliant with EU/ Asian IoT regulations), the system maintained a 5 km line- of-sight transmission range, with signal robustness persisting at 3.2 km in dense foliage. Packet loss remained below 1.3% at maximum range, attributable to a custom sliding window protocol with cyclic redundancy checks (CRC-16). As illustrated in Fig. 4, the prototype €™s real- time alerts correlated strongly with ground-truth observations, such as elevated heart rates (>50 bpm) during human-elephant conflict scenarios. Strategic power optimization techniques extended the belt€™s operational lifespan to 72 hours on a single 3,000mAh LiPo battery. The ESP32â€™s dual-core architecture enabled dynamic power mode switching: Core 0 (sensor data acquisition) operated in light sleep mode during idle periods, reducing current draw to 10 mA, while Core 1 (LoRa transmission) activated only during 200ms transmission windows, peaking at 80 mA. from 1 Hz (Critical state) to 0.1 Hz (Healthy/ Normal) based on real-time health classifications, reducing energy consumption by 58% during non-critical periods. Further savings were achieved through hardware- software co-design. The MPU6050's gyroscope was selectively disabled when accelerometer data indicated stationary behavior (movement variance < $0.1 m/s^2$), cutting motion-sensing power by 40%. Additionally, the MAX30102's LED drive current was dynamically scaled from 50 mA (active measurement) to 0.1 mA (standby), minimizing photoplethysmography related energy waste.

Research References	Static Policy Management	Limited Automation in Security Policy Enforcement	Inadequate Real-Time Threat Response	Insufficient Integration with SDN Controllers	Lack of Comprehensive Policy Management	User Guidance and Policy Updates
Wildlife Using GPS and Basic Biometric Sensors	X	X	X	X	X	✓
Challenges in Wildlife Monitoring with High Latency Systems,	X	X	X	✓	✓	X
Integrating Vital Signs for Better Wildlife Monitoring,	✓	X	X	X	X	✓
Proposed Research System	✓	✓	✓	✓	✓	✓

Table 1 Comparisons of Existing Research

Initial prototypes suffered from signal integrity issues, manifesting as erratic SpO_2 readings (±5% error) due to EMI coupling between the LoRa transceiver and MAX30102's analog front-end. This was resolved through a redesigned 2-layer PCB featuring:

1. Split ground planes with a star-connected topology, isolating analog (sensors) and digital (ESP32, LoRa) domains.

2. 100nF ceramic decoupling capacitors placed within 2 mm of the MAX30102's VDD pin and ESP32's RF power rails, suppressing supply ripple to <50mVpp.

3. The guard traces photoplethysmography signals, reducing crosstalk by 72%.

Data synchronization challenges between the ESP32's dual cores were mitigated using Free RTOS queues. A buffer size of 30 elements prevented overflows during LoRa transmission latency spikes (up to 1.2 s in dense forests), while semaphores ensured atomic access to shared memory. This reduced task- switching delays to < 2ms, enabling seamless coordination between the sensor sampling (Core 0) and emergency alert workflows (Core 1) post – optimization, the system demonstrated 99.4% uptime during 14-day field deployments, with false alert rates below 0.7% validating its readiness for scalable conservation deployments.

Our project, focused on developing an AI-driven elephant health monitoring system, centers on the "elephant-data3" dataset sourced from Kaggle. This data set serves as the cornerstone for training and validating our models, aiming to contribute significantly to wildlife conservation. A critical initial step involved a thorough analysis of the dataset, revealing a pronounced class imbalance skewed towards "Healthy" and "Normal" samples. This imbalance necessitated the implementation of Synthetic Minority Over Sampling Technique (SMOTE) to ensure robust training, particularly for the underrepresented "Critical" and "Dead" categories. Given the time-series nature of the data, preprocessing was crucial. We employed techniques for data cleaning, normalization, and feature engineering, which we must discuss in detail to understand their impact on model performance. Notably, the limitations of the provided features, especially the lack of real- world contextual data, pose a significant challenge. We need to explore strategies for supplementing this dataset with field-generated information. Model selection and performance evaluation are central to our discussion. The Fully Connected Neural Network (FCNN) achieved a high validation accuracy for health classification, but a deeper dive into its performance on minority classes is essential. We must analyze precision-recall curves and F1-scores to accurately assess their effectiveness in identifying critical health conditions. The Long Short- Term Memory (LSTM) autoencoder, designed for anomaly detection, shows promise, but we need to discuss the selection of the reconstruction error threshold and its sensitivity to various anomaly types. Comparative analysis of different models and their suitability for this specific application is crucial. Model selection and performance evaluation are central to our discussion. The Fully Connected Neural Network (FCNN) achieved a high validation accuracy for health classification, but a deeper dive into its performance on minority classes is essential. We must analyze precision- recall curves and F1 scores to accurately assess its effectiveness in identifying critical health conditions. The Long Short-Term Memory (LSTM) autoencoder, designed for anomaly detection, shows promise, but we need to discuss the selection of the reconstruction error threshold and its sensitivity to various anomaly types. Comparative analysis of different models and their suitability for this specific application is crucial.

Real-world applicability and limitations are paramount. While the dataset provides a valuable foundation, its limitations, particularly the absence of real-world contextual data, must be addressed. We need to brainstorm strategies for integrating field-generated data into future iterations. The fixed 1 Hz sampling rate may miss critical transient events, necessitating a discussion on the feasibility and impact of higher-frequency data collection. Ethical considerations surrounding the deployment of this technology in the field are also vital. Furthermore, we must discuss the hardware requirements for effective system deployment.

Looking ahead, we should explore the integration of diverse data sources, such as audio recordings and video feeds, to enhance anomaly detection capabilities. Developing a user-friendly interface for visualizing and interpreting model outputs is crucial for practical deployment. We should also discuss the adaptability of this system to other endangered species. A continuous improvement framework, incorporating new data and refining model performance, is essential for sustained relevance.

This project discussion serves as a platform for collaborative exchange, where we can share insights, address challenges, and refine our approach to building a valuable tool for elephant conservation.

V. CONCLUSION

To reduce conflict between humans and elephants, this study presents a real-time, Internet of Things- enabled system for emergency response and elephant health monitoring. The wearable belt combines dual-core ESP32 and LoRa connectivity with MAX30102, LM75, and MPU6050 sensors to achieve 99.81% classification accuracy and more than 72 hours of operation in remote places. Signal integrity was enhanced using a unique 2- layer PCB with separated ground planes and efficient routing, which decreased SpO2,, errors by 72%. Machine learning models, such as LSTM autoencoders for anomaly detection and FCNN for health classification, demonstrated 95.4% accuracy in detecting severe conditions like stress caused by poaching. A 5 km LoRa range and adaptive power management are supported by the system and performance.

The system's functionality under real-w circumstances was confirmed by field tests conducted Sri Lanka. Future research will concentrate on energy harvesting and considering climatic fan unique to a given region, such as humidity caused by monsoon. Large-scale deployment will in cooperation with wildlife agencies, maybe incorporate drone-based rapid reaction. This study demonstrates artificial intelligence (AI) and the Internet of the (IoT) can revolutionize conservation by providing scalable, real-time [10] [11]solutions for endangered species monitoring and protection.

VI. ACKNOWLEDGMENT

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