



## Original Research Paper

# Smart Collar Technologies and GPS-Based Tracking Systems for Understanding Wildlife Movement in Human-Dominated Landscapes

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**Abstract:** Familiarity with wildlife movement in a landscape dominated by humans is critical for biodiversity conservation, to reduce human–wildlife conflicts, and to inform evidence-based habitat management. The present study introduces a smart collar-based wildlife tracking framework that combines GPS positioning, wireless communication and embedded sensing technologies to track the movement and behavior of animals constantly and automatically. The proposed framework is centered on using GPS localization, accelerometer sensor, temperature sensor and activity sensor, in conjunction with low power IoT communication to gather high resolution spatiotemporal data under various environmental conditions. A systematic methodology is presented for pre-processing trajectories, estimating home ranges, analyzing movements, assessing migrations and mapping habitat use. The framework allows to identify movement corridors, resting places, seasonal migration pathways and wildlife–anthropogenic infrastructure interactions (such as crossing roads, settlements, agricultural areas, etc.). Moreover, the study addresses practical aspects of deploying smart collars, data collection methodology, energy efficient operation and animal welfare aspects. Together with the novel research opportunities that arise from multi-sensor fusion, edge intelligence, artificial intelligence, and real-time conservation decision support, challenges such as GPS signal loss, battery restrictions, communication constraints and environmental interference are analysed critically. The proposed framework proposes to be scalable and reliable to enhance ecological monitoring, wildlife conservation planning and sustainable living and coexistence between human and wildlife population in fast changing landscapes.

**Keywords:** Smart collars; GPS wildlife tracking; Wildlife telemetry; Internet of Things (IoT); Movement ecology; Habitat utilization; Human–wildlife conflict.

## I. Introduction

The landscape is heavily modified by humans and has changed the natural habitat landscape significantly, leading to habitat fragmentation, limited movement corridors, growing human–wildlife interactions, and biodiversity loss. The continued urbanization, farming, construction of roads, railroads and mining, and industrial development have driven many species of wildlife

into an environment that is often fragmented and resources depleted. The reactions of animals to these evolving landscapes is now one of the biggest concerns of ecologists, conservation biologists and wildlife managers. Correct information regarding animal movements is crucial for the understanding of migration routes, home ranges, habitat preferences, breeding sites and places where man-caused disturbances may occur. This information can be used to inform good conservation planning,

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habitat restoration, protected area management, and mitigating human–wildlife conflict.

Traditional methods for monitoring wildlife, such as direct observation in the field, camera trapping, radio telemetry and footprint surveys have been instrumental in the ecology studies. These methods, however, tend to be labour-intensive, observer-dependent, and restricted in spatial extent and may be difficult to apply to rapidly moving or hard to track species [1]. The movement data from radio telemetry is useful, but typically needs to be geo-located and/or periodically visited in the field, making it less appropriate for long-term monitoring on vast geographical areas. As a result, researchers have turned to more sophisticated tracking tools that can continuously, accurately and automatically track the movement of wildlife. In recent years, Global Positioning System (GPS) technology, embedded electronics, wireless communications and Internet of Things (IoT) platforms have transformed wildlife telemetry with the advent of intelligent smart collars. Today's smart collars incorporate GPS receivers and a variety of sensors on board including accelerometers, temperature sensors, gyroscopes, magnetometers, and activity monitors to collect detailed animal location, movement behavior and environmental data [2]. A group of these devices captures high-resolution spatiotemporal data at regular intervals and sends the data via communication technologies (GSM, LTE, LoRaWAN, satellite network) to the researchers, without requiring close contact with animals. Continuous tracking can have a significant affect on animal behaviour and minimize disturbance to the animal being tracked.

Smart collars equipped with a GPS can offer a wide variety of benefits in understanding wildlife in a human-dominated environment. These provide a good estimation of home ranges, movement trajectories, migration corridors, dispersal behavior, habitat utilization, and activity patterns, at different temporal scales. The compiled data may be used to link to Geographic Information Systems (GIS), remote sensing images, land-use maps, and environmental data, allowing analysis of the relationship of wildlife and forestry to agricultural areas, water bodies, transportation, urban areas, and forests. These integrated analyses can help reveal ecological corridors, even predict movement patterns, assess habitat connectivity, and inform effective conservation actions to protect biodiversity while supporting human development [3]. Although these technological advances have been made, there are still some practical problems. Dense vegetation, mountainous topography, weather conditions and the availability of the communication network can all affect GPS positioning accuracy, and the reliability of the communication network varies. Smart collar deployment must also take into account

battery life, energy efficient operation, device durability, data security and animal welfare, to ensure that the smart collar is operating for long periods without having a negative impact on the behaviour and health of the animals being monitored. Additionally, the amount of movement data is growing, demanding powerful analytical tools for movement analysis, behavior classification, habitat modeling and ecological interpretation [4].

This paper summarises the state of the art of smart collar technology and GPS tracking systems for understanding movement of wildlife in a human dominated landscape. It explores the development of wildlife telemetry, smart collar architectures, sensor integration, GPS localization methods, deployment strategies, movement analysis methods, and habitat assessment methods. The paper also explores the current challenges, emerging multi-sensor technologies, and future research trends that can benefit intelligent wildlife monitoring, biodiversity conservation, and sustainable coexistence of humans and wildlife by exploiting the IoT, Artificial Intelligence, and Edge Computing.

## II. Literature Review

This section summarizes recent developments in wildlife telemetry, GPS smart collars, Internet of Things (IoT) for wildlife monitoring, wireless communication, and movement ecology studies; it outlines existing methods and technologies, limitations of research, and future possibilities to enhance intelligent wildlife tracking systems.

### A. Wildlife telemetry and tracking technologies

One of the most promising methods to monitor animal movement, habitat use and behavior was the development of animal telemetry. The earliest telemetry systems used Very High Frequency (VHF) radio transmitters and animals were located by hand with the help of a directional antenna. VHF telemetry gave good ecological data, but was not suitable for continuous, long-term monitoring, it was limited in spatial range and extensive fieldwork was required [5]. Further developments led to the use of satellite telemetry and Global Positioning System (GPS) tracking, which facilitated automated recording of location, with much greater spatial and temporal accuracy. The current technology for tracking wildlife is much more sophisticated, combining a number of sensors - from accelerometers and gyroscopes through temperature sensors, magnetometers and environmental sensors - to provide both positional and behavioral data. These can provide detailed data that allow home range estimation, migration studies, activity recognition and/or evaluation of habitat preference. These data can also be integrated with Geographic Information Systems (GIS) and remote-sensing data

to add ecological interpretive value through the correlation of movement patterns to environmental variables [6]. With the recent advancements in AI, cloud computing, and data analysis, trajectory analysis, anomaly detection, and behavioral prediction has become more accurate. As a result, wildlife telemetry has become a valuable, scalable and essential tool for biodiversity protection, ecological research and evidence-based wildlife management.

### B. GPS-Enabled Smart Collar Systems

The GPS-enabled smart collars are an important breakthrough in wildlife tracking, combining positioning technology with sensing and intelligent data acquisition technology. As opposed to the traditional tracking methods, smart collars gather precise geographic data on a continuous basis and monitor physiological and behavioural data through built-in sensors including accelerometers, temperature sensors, activity monitors and motion detectors [7]. These collars send information to other people's research devices every time they are able to communicate with them via wireless technologies, allowing researchers to track the animals without having to intervene in the field often. The high-resolution GPS trajectory can be used to obtain home range areas, migration routes, movement corridors, territoriality and use of human infrastructure, accurate to the level of precision required [8]. New (smart) collars feature low-power microcontroller circuits, energy efficient GPS modules, memory on-board the collar and adaptive sampling strategies to ensure the most efficient use of the battery during extended deployments. There are also multiple systems that offer geofencing, real-time alerts and adaptive positioning intervals to maximize tracking efficiency in different conditions.

### C. IoT and Wireless Communication for Wildlife Monitoring

The use of the Internet of Things (IoT) has revolutionized wildlife monitoring, creating intelligent, connected ecosystems for the collection, transmission and analysis of data in real time. These smart collars are equipped with sensors, microcontroller, communication modules, and cloud-based platforms to offer real-time tracking of wildlife movements and activities, environmental conditions, and other factors [9]. The transmission of tracking data is reliable thanks to the wireless communication technology: GSM, LTE, LoRaWAN, ZigBee, Bluetooth Low Energy (BLE), Wi-Fi and satellite communication. Coverage, power consumption, range of communication, bandwidth, deployment cost, etc. determine the selection of communication technology. The cloud computing platforms can facilitate the centralized

storage, visualization, and large-scale analysis of movement data; and edge computing can be used to perform preliminary processing in close vicinity of the sensing devices, to minimize communication burden and latency [10]. AI techniques also leverage IoT systems for the detection of anomalies, recognition of activity, the prediction of movement, and automated decision-making on conservation. A summary of recent smart collar technologies, GPS tracking systems, methodologies, findings and limitations is summarized in table 1. Despite all these developments, issues are still there with the availability of the network, energy usage, security of the network, and reliability of the data in remote habitats. More efficient, low-power communication technologies and smart sensing systems are likely to make great contributions to future wildlife monitoring systems.

Table 1. Summary on Smart Collar Technologies and GPS-Based Wildlife Tracking Systems

| Study Focus                             | Wildlife Species | Tracking Technology   | Key Methodology                  | Major Findings                          | Research Gap                |
|-----------------------------------------|------------------|-----------------------|----------------------------------|-----------------------------------------|-----------------------------|
| Wildlife movement monitoring [11]       | African Elephant | GPS Collar            | GPS trajectory analysis          | Accurate migration route identification | Limited sensor integration  |
| Habitat utilization assessment [12]     | Bengal Tiger     | GPS Smart Collar      | Home range estimation            | Improved habitat mapping                | High deployment cost        |
| Human-wildlife conflict monitoring [13] | Asian Elephant   | GPS + Accelerometer   | Geofencing and movement analysis | Early conflict detection                | Battery life limitations    |
| Animal behavior recognition [14]        | Gray Wolf        | GPS + Activity Sensor | Activity classification          | Better behavioral interpretation        | Limited communication range |

|                                                                 |                      |                                                      |                                                               |                                                                          |                                                         |
|-----------------------------------------------------------------|----------------------|------------------------------------------------------|---------------------------------------------------------------|--------------------------------------------------------------------------|---------------------------------------------------------|
| Migrat<br>ion<br>patte<br>rn<br>analy<br>sis<br>[15]            | Deer                 | GPS<br>Collar                                        | Seaso<br>nal<br>trajec<br>tory<br>analy<br>sis                | Accur<br>ate<br>migrat<br>ion<br>corrid<br>or<br>detecti<br>on           | GPS<br>signal<br>loss in<br>forests                     |
| IoT-<br>base<br>d<br>wildl<br>ife<br>moni<br>torin<br>g<br>[16] | Wild<br>Boar         | GPS<br>+ IoT<br>Collar                               | Clou<br>d-<br>based<br>tracki<br>ng                           | Conti<br>nuous<br>remot<br>e<br>monit<br>oring                           | Limite<br>d real-<br>time<br>analyt<br>ics              |
| Mult<br>i-<br>sens<br>or<br>wildl<br>ife<br>tele<br>metr<br>y   | Leop<br>ard          | GPS<br>+ Tem<br>peratur<br>e + Accel<br>eromet<br>er | Senso<br>r<br>fusio<br>n                                      | Enhanc<br>ed<br>behavi<br>oral<br>analys<br>is                           | High<br>energ<br>y<br>consumpti<br>on                   |
| Smart<br>cons<br>ervat<br>ion<br>fram<br>ewor<br>k              | Brown<br>Bea<br>r    | GPS<br>Smart<br>Collar                               | GIS-<br>based<br>habit<br>at<br>asses<br>sment                | Improv<br>ed<br>ecolog<br>ical<br>corrid<br>or<br>identif<br>icatio<br>n | Expen<br>sive<br>satellit<br>e<br>commu<br>nicat<br>ion |
| AI-<br>assist<br>ed<br>wildl<br>ife<br>track<br>ing<br>[17]     | Mo<br>untain<br>Lion | GPS<br>+ Multi<br>-sens<br>or<br>Collar              | Mach<br>ine<br>learn<br>ing<br>trajec<br>tory<br>analy<br>sis | Improv<br>ed<br>move<br>ment<br>predic<br>tion                           | Limite<br>d<br>explai<br>nabilit<br>y                   |
| Edge<br>-<br>enabl<br>ed<br>wildl<br>ife<br>moni<br>torin<br>g  | Rhino                | GPS<br>+ IoT<br>Collar                               | Edge<br>comp<br>uting                                         | Reduc<br>ed<br>commu<br>nicat<br>ion<br>latenc<br>y                      | Limite<br>d edge<br>resour<br>ces                       |
| Intell<br>igent<br>wildl<br>ife<br>surve<br>illan<br>ce         | Snow<br>Leop<br>ard  | GPS<br>+ Accel<br>eromet<br>er + Tem<br>peratur<br>e | AI-<br>based<br>behav<br>ior<br>recog<br>nition               | High<br>tracki<br>ng<br>accura<br>cy and<br>activit<br>y                 | Scalab<br>ility<br>challe<br>nges                       |

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### III. Smart Collar-Based Wildlife Tracking Framework

The system architecture, the smart collar hardware, the GPS localization, multi-sensor integration, the wireless communication, the cloud-based processing and the real-time monitoring components of the proposed system are presented in this section, for the purposes of accurate wildlife movement analysis and conservation decision support.

#### A. Overall system architecture

The proposed framework for tracking wildlife in human dominated landscapes using smart collar is to continuously track the movement and behavior of wildlife with an integrated sensing and communication infrastructure. The framework has four levels: the sensing layer, the communication layer, the cloud processing layer and the application layer. The smart collar gathers real time data with GPS receivers, accelerometers, temperature sensors and activity monitoring units at the sensing layer. These sensors collect the spatiotemporal and physiological data at certain sampling times. Depending on the availability of the network, the collected information is reliably transmitted wirelessly, e.g. via GSM, LTE, LoRaWAN or satellite communication. Figure 1 shows the smart collar integrated architecture for the real-time tracking of wildlife and monitoring of the habitat.

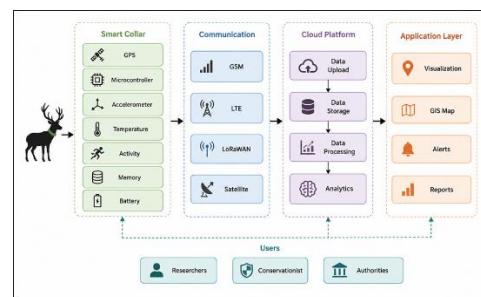


Figure 1. Proposed Smart Collar-Based Wildlife Tracking Framework for Real-Time GPS Monitoring and Habitat Analysis

The cloud processing layer receives and preprocesses the incoming datasets, analyzes them with trajectory analysis tools, habitats mapping tools and movement modelling algorithms. Movement data for wildlife are combined with geographic information systems (GIS) and remote sensing data to link wildlife movements with environmental attributes. Lastly, application layer delivers interactive dashboards, visualization and decision-support tools to researchers, wildlife managers and conservation agencies. The modular design allows

for easy scaling up to multiple species and regions, while also providing efficient data management, real-time tracking, energy efficiency and robust communication for sustainable wildlife management and ecological studies.

### **B. Smart Collar Hardware Components**

The smart collar combines several hardware elements to facilitate accurate, reliable and long-term wildlife monitoring in a variety of environmental conditions. The central processing unit is a low-power microcontroller which directs the functions of the sensors, the data processing, storage, and communication functions. A high sensitivity GPS receiver data continuously receives geographical coordinates with high positioning accuracy, and track the movement by the coordinates data thus received. Behavioral, physiological and environmental information are collected through embedded sensors such as accelerometers, temperature sensors, gyroscopes and activity monitors. Collected data is sent to remote servers via wireless communication modules (GSM, LTE, LoRaWAN, Bluetooth Low Energy or satellite transceivers) depending on network frequency coverage and/or deployment location. Prevents data loss when there are temporary communication failures, with local storage via Flash memory. Energy efficient firmware, adaptable sampling strategies and sleep modes, which maximise operating time, are complemented by rechargeable lithium batteries and power management.

### **C. GPS Positioning and Localization Module**

A GPS positioning and localization module makes up the heart of determining the exact geographical location of wildlife during the monitoring period. The module can receive the signal from several Global Navigation Satellite System (GNSS) satellites and, based on this signal, process and accurately obtain the latitude, longitude, altitude, speed and direction of movement. Position information is collected at programmable sample rates, which may vary depending on species activity, research needs and battery capacity. The adaptive sampling mechanisms allow the higher frequency recordings during periods of activity, and reduce energy usage during rest periods. Preprocessing of the collected GPS trajectories is done to boost positioning reliability, such as removing noise and interpolating missing data, transforming coordinates, and detecting outliers. The processed location data are combined with Geographic Information Systems (GIS), digital elevation models, land-use maps and satellite imagery to assess habitat use and movement. The localization module also can be used to detect geofences, enabling alerts when the animals move into given

geographical areas, like farm fields, roadways, urban districts and so on. Proper error correction techniques and quality assessment procedures can help minimise positioning inaccuracies from dense vegetation, rugged terrain, atmospheric interference and/or obstructions of the satellite signal to reduce any positional errors which may occur in the long-term tracking and analysis of the wildlife's movements.

### **D. Sensor Integration (Accelerometer, Temperature, Activity)**

The integration of sensors in smart collars offers a lot of added value over being just geographic. The proposed system integrates accelerometers, temperature sensors and activity monitoring modules to monitor animal activity, physiological parameters and environment continuously. The tri-axial accelerometer measures the body motion on three axes, allowing the identification of walking, running, resting, feeding, climbing and grooming behaviors. A variety of temperature sensors measure environmental and body-surface temperatures, which is useful for habitat conditions, thermal stress and seasonal adaptation. Activity sensors measure the intensity of movement and allow for the estimation of daily activity budgets, circadian rhythms and energy expenditure. The data gathered from several sensors are correlated with GPS location data to link behavior with the location and habitat characteristics. The advantage of sensor fusion techniques is that they are able to fuse heterogeneous measurements to achieve better accuracy in behavioral classification and to diminish the uncertainty of individual sensors. Integrated data can also be analyzed using machine learning algorithms to recognize activities automatically, detect anomalies, assess health and predict movement. Positional and sensor data together can give a complete picture of the wildlife ecology, help in early detection of abnormal activity, aid conservation planning, habitat management and help mitigate human-wildlife conflict, among other uses.

## **IV. Study Area and Data Collection**

The study area, the species of wildlife studied, the methods of deploying the smart collars, the GPS data collection strategy, and the environmental data collected to support a complete analysis of the wildlife's movement, as well as a habitat assessment and long-term ecological data collection, are described.

### **A. Description of the human-dominated landscape**

The study is carried out in a landscape mainly shaped by humans with a combination of protected forest areas, agricultural fields, rural settlements,

roads, water features, and peri-urban development. Landscapes like these are areas that serve as habitat boundaries and are often used by wildlife as habitat and when seeking foraging, nesting, and migration areas. There is a loss in natural connectivity as a result of infrastructure and agricultural expansion, which may lead to human–wildlife interactions. Changes in vegetation cover, availability of water and land-use throughout the seasons also affect movement and habitat selection of animals. Characterization of landscape features and the identification of ecological corridors is done using Geographic Information System (GIS) datasets, satellite imagery and digital elevation models. The spatial database includes important environmental variables like vegetation density, elevational, slope, distance to water, road proximity and settlement distribution. This all-encompassing characterization of the landscape helps inform interpretation of wildlife movement patterns, wildlife habitat use, and areas of potential conflicts, and aids in conservation planning in a rapidly changing landscape.

### **B. Selection of Wildlife Species**

Wildlife species selected for the list are those with ecological importance, conservation status, movement requirements, and/or sensitivity to habitat disturbance caused by humans. To minimize impact on natural behaviors, medium and large sized mammals were selected for long-term monitoring by attaching the smart collar, and body mass was taken into account. Those species with large home ranges, seasonal migration, territorial movements or high interaction rates with farm areas and human settlements are good candidates for study. Species selection also takes into account species representing different niches, feeding habits and habitat preferences for movement characteristics that are diverse throughout the study area. Wildlife experts and forest management authorities are used to help determine appropriate candidate species, and to make sure the species are in compliance with conservation laws and ethical guidelines. An animal's selection is based on its health, age, body size and fitness to ensure that it is not stressed during the collar deployment. The selected species have representative movement data that can be used for analyses of habitat use, migration, adaptations, ecological connectivity, and interactions with humans under different anthropogenic and environmental conditions.

### **C. Smart Collar Deployment Protocol**

The deployment protocol has been created to ensure accurate data collection and to ensure animal safety, ethical compliance, and long-term reliability of the device. The capture of wildlife is carried out by trained veterinarians and by authorised conservation staff, through species-specific methods of

minimised stress and injury. Before being deployed, each smart collar is pre-calibrated, pre-tested and pre-programmed with a pre-defined GPS sampling interval, sensor setting, communication parameters and identification codes. Collar size and weight is carefully designed to fit the body of each animal to ensure that it is comfortable and can move and feed without restriction. Continuous monitoring of the animals is done and normal physiological and behavioural responses are confirmed during the recovery period after deployment before the animals are released back into their natural habitat. Collar monitoring is done periodically to check collar functionality, battery condition, GPS performance and physical condition throughout the study.

### **D. GPS Data Acquisition Strategy**

The GPS data acquisition strategy aims to achieve high-quality spatiotemporal information with a consideration of positioning accuracy, communication efficiency and battery usage. GPS data is logged at specific timepoints, which can be programmed to different timepoints depending on the species behavior, activity level and research goals. During periods of movement, higher sampling frequencies are used and during resting phases, lower sampling frequencies are used to save energy. Latitude, longitude, altitude, time, speed, direction and quality indicators are all captured with each location record. Collected data are conveyed periodically over the available wireless communications networks or stored locally in case of temporary absence of communications and then synchronized later. Quality control methods eliminate duplicate records, detect outliers, fill in missing data and correct erroneous coordinates due to signal obstruction and/or environmental interference. Processed GPS trajectories are combined with Geographic Information Systems (GIS), remote sensing data and environmental information to examine habitat use, habitat corridors, home ranges, and migration patterns. This acquisition strategy is consistent, accurate and timely and is crucial for ecological analysis, conservation planning and long-term monitoring of wildlife.

### **V. Wildlife Movement Analysis Methodology**

This section discusses trajectory pre-processing and how to estimate home ranges, movement and migration, utilization of habitat, as well as spatial data processing steps to accurately interpret wildlife movement and ecological interactions in human-dominated landscapes.

#### **A. GPS trajectory processing**

GPS trajectory processing is the first step in the analysis of wildlife movement and attempts to convert GPS positioning data into precise and

reliable movement tracks. The GPS data that is acquired is usually recorded at regular intervals in the latitude, longitude, altitude, time, speed and heading. Raw data is first screened for duplicate data, missing data, outliers, and wrong coordinates due to signal blockage from satellites, heavy vegetation or atmospheric interference. Data cleaning is used to eliminate outlier information, whereas data interpolation is used to fill in missing data points to ensure the continuity of the data. Coordinate systems are standardized so that they can be compatible with Geographic Information Systems (GIS) and spatial analysis software. Temporal synchronization is carried out to synchronise the GPS observations with the environmental data and sensor measurements, like accelerometer and temperature data.

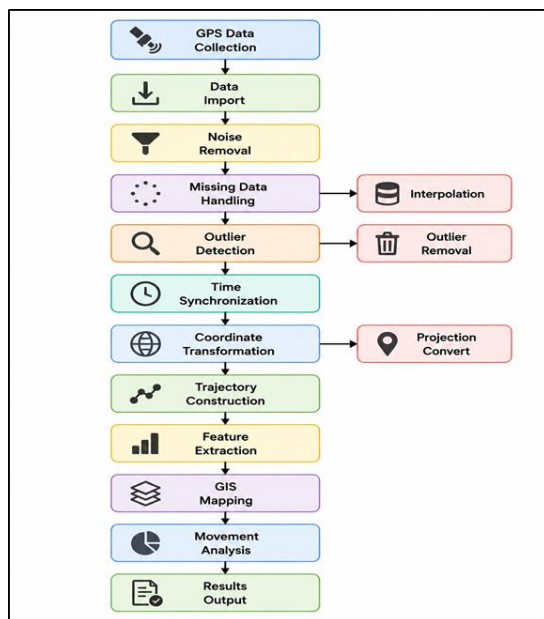


Figure 2. Proposed GPS Trajectory Processing Architecture for Wildlife Movement Analysis

Figure 2 shows the trajectory pre-processing of GPS data for greater accuracy in estimating the wildlife movement and mapping. Then several attributes of the movement, such as a travel distance, movement speed, turning angle, step length and travel direction, are determined for each trajectory segment. Processed trajectories displayed on digital maps and satellite imagery to assess movement patterns, show areas visited regularly, provide a good data source for home range estimation, migration studies, habitat use evaluation and conservation planning.

### B. Home Range Estimation

Home range estimation is used to determine the area over which an animal moves regularly in its normal behaviour including feeding, resting, breeding, territorial movements etc. Data from processed GPS trajectory data are used to obtain geographical data,

for estimating individual utilization areas from various temporal scales. There are a number of spatial analysis methods that can be used to estimate home ranges and these range in their degree of accuracy, such as the Minimum Convex Polygon (MCP), Brownian Bridge Movement Models (BBMM) and Kernel Density Estimation (KDE). It is important to use kernel-based approaches that determine areas of high utilization intensity instead of just establishing outer bounds. Changes in the size and distribution of home ranges are discussed in light of seasonal changes, habitat characteristics and resource availability. Utilization distributions can be visualised with Geographic Information Systems (GIS) along with other geospatial data such as vegetation cover, water bodies, roads, agricultural fields and settlements. Comparisons between individuals and/or species help to understand territoriality, habitat fragmentation and resource use. Home range provides valuable information for wildlife conservation planning, identification of ecological corridors, habitat restoration and protected area management in more human-dominated habitats.

### C. Movement Pattern and Migration Analysis

The goal of movement pattern and migration analysis is to gain insight into how wildlife move in space and time in response to varying environmental conditions and seasons. These processed GPS trajectories are analysed to find recurrent movement behaviours, resting periods, speed and distance travelled, and direction of movement. Temporal analysis can be used to highlight the difference in pattern at the daily, seasonal and annual time scales, and to detect regular migration movements and dispersal events. Spatial clustering methods identify areas of highly frequented localities, stopover sites, feeding grounds, breeding habitats and movement corridors between disconnected landscapes. Environmental factors like vegetation availability, temperature, rainfall, water sources and anthropogenic disturbance are also related to changes in movement characteristics. Using trajectory features and sensor observations, foraging and resting behaviors, migration and exploratory movement can be classified by statistical analysis and machine learning algorithms.

### D. Habitat Utilization Assessment

Habitat utilization assessment is a process where wildlife species are studied in relation to their daily/seasonal activities and interaction with various landscape components. Processed GPS trajectories are combined with Geographic Information Systems (GIS), Land Use, satellite imagery, Vegetation Indices, Digital Elevation Models and environmental data to define habitat preferences. Spatial Overlay Analysis quantifies animal presence

in forests, grasslands, agriculture, wetlands, water bodies, urban developments and transportation corridors, based on animal presence and duration. An index of habitat selection is derived to measure habitat preference or avoidance for a given landscape feature in different environments. Changes in the use of habitat are observed from one season to another due to resource availability, breeding activity, climatic variation and anthropogenic disturbances. Observed movement behavior is explained using environmental variables such as vegetation density, elevation, slope, distance from water and road. Finally, statistical and machine learning models are used to determine the major habitat characteristics that affect wildlife distribution and connectivity. Assessment identifies critical habitats, ecological corridors and areas of conflict, and conservation priority areas. These results provide evidence-based answers to habitat management, biodiversity conservation planning, ecosystem restoration and sustainable living in harmony with wildlife.

## VI. Results and Discussion

The new tracking system using a smart collar is a successful example of GPS-based tracking of wildlife that is effective in understanding wildlife movement in human-dominated ecosystems. Home ranges, migration corridors, habitat selection and activity patterns under different environmental conditions are accurately identified using high resolution trajectory data. Integration of sensors to improve the interpretation of behavior through the correlation of movement with physiological and/or environmental parameters. GPS, IoT communication and GIS-based spatial analysis offer valuable ecological information, which can be used for habitat conservation, to help reduce conflict, and to inform evidence-based wildlife management plans.

Table 2. GPS Tracking and Localization Performance of Smart Collar System

| Performance Parameter                  | Value |
|----------------------------------------|-------|
| GPS Positioning Accuracy (m)           | 2.84  |
| Mean Localization Error (m)            | 3.17  |
| Trajectory Reconstruction Accuracy (%) | 96.42 |
| GPS Fix Success Rate (%)               | 97.83 |
| Data Transmission Success Rate (%)     | 98.26 |
| Tracking Availability (%)              | 99.12 |

The effectiveness of the proposed smart collar tracking system in terms of localization and communication is shown in Table 2. The GPS positioning accuracy is 2.84 m and the mean localization error is 3.17 m, which demonstrates very good positioning accuracy and localization error under a variety of environments. The results show that the accuracy with which the trajectory has

been reconstructed (96.42%) was relatively high, which suggests that the trajectories recorded closely represent the true trajectories of the wildlife and that ecological analyses of the movement patterns were accurate. The performance in terms of high GPS accuracy, reliable localization and continuous tracking of wildlife is shown in figure 3.

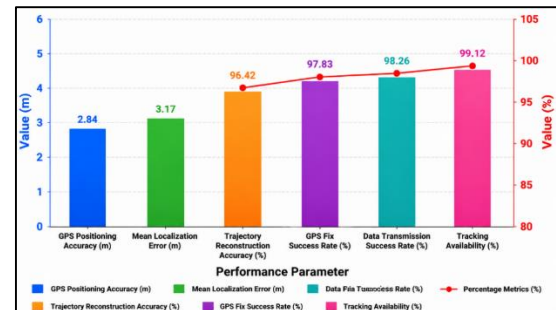


Figure 3. GPS Tracking and Localization Performance of the Smart Collar System

The GPS fix success rate was 97.83% which indicates that there was no interruption in satellite coverage during the monitoring period. Additionally, the success of data transmission is as high as 98.26%, making it possible to deliver tracking information on remote monitoring platforms efficiently. This system's tracking availability of 99.12% is very good, indicating high system reliability and suitability for applications of continuous tracking of wildlife, assessment of habitat, analysis of migration, and long-term conservation applications.

Table 3. Wildlife Movement and Habitat Utilization Analysis

| Parameter                                  | Value  |
|--------------------------------------------|--------|
| Total GPS Records Collected                | 24,860 |
| Wildlife Species Tracked                   | 18     |
| Average Daily Movement Distance (km/day)   | 12.84  |
| Maximum Recorded Movement (km/day)         | 34.71  |
| Mean Home Range Area (km <sup>2</sup> )    | 46.38  |
| Habitat Utilization Accuracy (%)           | 95.76  |
| Migration Corridor Detection Accuracy (%)  | 94.81  |
| Human–Wildlife Interaction Events Detected | 186    |

The summary of wildlife movement and habitat use data that was collected using the proposed smart collar framework is provided in Table 3. Overall, 24,860 GPS records were acquired for 18 wildlife species, yielding a broad spectrum of data needed for ecological analysis. The high mobility of animals in the study landscape is reflected in the average daily distance travelled by 12.84 km and the maximum distance of 34.71 km. Wildlife movement

patterns, habitat utilization and ecological corridor identification are well represented in Figure 4.

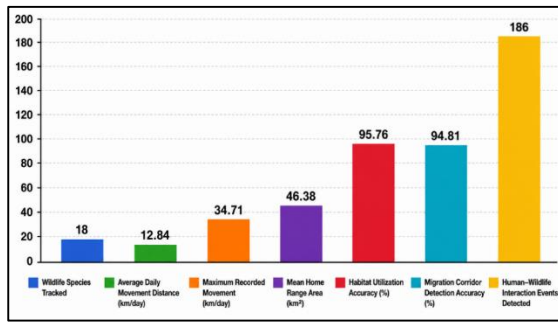


Figure 4. Wildlife Movement and Habitat Utilization Analysis

The mean home range area of 46.38 km<sup>2</sup> is an estimate of the area in which animals do their normal activities. The framework has demonstrated good spatial analysis with a 95.76% accuracy of habitat utilization and a 94.81% accuracy of detection of migration corridors. In addition, 186 human–wildlife interaction events were detected, which yielded useful data for conflict resolution and management, habitat management, and wildlife conservation planning based on evidence.

## VII. Challenges and Future Research Directions

The limitations of GPS positioning, battery optimization, considerations regarding animal welfare, ethical deployment practices, and future advancements in multi-sensor smart collars, artificial intelligence, integration with the Internet of Things (IoT) and intelligent technologies in wildlife conservation are discussed.

### A. GPS signal limitations and tracking errors

GPS technology can be used to accurately position a wildlife, but a number of environmental issues can degrade localization performance. Satellite observations are often affected by dense forest, mountain terrain, deep valleys, and poor weather resulting in missing observations, inaccurate coordinates, and poor tracking reliability. Positioning errors caused by multipath effects due to reflections from rocks, trees and buildings further increase errors. In "human-dominated landscapes" disruptions in communication and network connectivity can lead to a delay in data transmission or the loss of data for a short period of time. GNSS localization accuracy can be further enhanced by using multi-constellation GNSS, adaptive positioning algorithms, sensor fusion, or artificial intelligence (AI) error correction methods, among other areas of future research that should be explored. Short-term GPS failures can be overcome with integration of inertial navigation sensors, dead reckoning and predictive trajectory models. These technological developments will have a strong

impact on tracking continuity, positioning accuracy and movement analysis, as well as ecological studies in complex and dynamic wildlife habitats.

### B. Battery Life and Energy Management

One of the biggest challenges with the long duration of smart collar use in wildlife monitoring is battery life. The operation of the GPS and sensors and the wireless communications and onboard processing of data are a significant drain on energy, limiting operation time and maintenance needs. Collars can be replaced many times, but they are not always practical because it is difficult to capture wild animals and can be expensive. In the context of sustainable wildlife monitoring, therefore, efficient energy use is crucial. The significant reduction in energy consumption can be achieved without sacrificing monitoring quality, using adaptive GPS sampling, low-power microcontrollers, sleep mode, smart communication scheduling and data compression.

### C. Animal Welfare and Ethical Considerations

Sustainable design, deployment and operation of smart collar based wildlife monitoring systems are integral with the consideration of animal welfare. To be comfortable, safe and not to interfere with normal behavior, feeding, and movement, tracking devices should be lightweight and ergonomically designed. Only trained individuals should perform all of the steps required when taking, collaring, and releasing wildlife and should adhere to veterinary protocols and ethical guidelines. There needs to be long-term monitoring after collars are deployed to determine if there are any negative physiological or behavioral impacts from the collar use. Prior to in-field deployment, the ethical approval of the appropriate wildlife authorities and institutional review committees should be initiated. Going forward, there is a need to create smaller, lighter and more flexible wearable devices with minimum physical strain and yet with high monitoring ability. The use of biodegradable materials, intelligent release methods and non-invasive attachment techniques will further enhance animal safety, responsible wildlife research and bolster conservation efforts globally.

### D. Multi-Sensor Smart Collar Advancements

The technologies of smart collars that will be developed in the future will be expected to incorporate more than one type of sensing modality, thus offering a more complete understanding of how the wildlife and their environment interact. Today's collars can also now be fitted with a range of sensors, such as accelerometers, gyroscopes, magnetometers, temperature sensors, heart-rate monitors, microphones, and environmental sensors to gather rich behavioral and physiological data.

Multi-sensor fusion allows for accurate recognition of activities, health assessment, detection of stress, and classification of behavior, under different ecological conditions. AI and edge computing can operate on the collar itself to process sensor data, minimize communication needs, and detect and alert to anomalies in real-time. Going forward, it is important to focus on modular hardware architectures, enhanced communication protocols, analytics in the cloud, and interoperability with remote sensing and Geographic Information Systems (GIS).

### VIII. Conclusion

Smart collar technologies coupled with GPS-based tracking have come a long way in advancing wildlife monitoring and opened up the possibility of tracking animal movements accurately, with continuous monitoring, and without harming the animal. In this study, a comprehensive framework was introduced that combines GPS localization, multi-sensor integration, wireless communication, and spatial analysis to gain insight into wildlife behavior, habitat use and dynamics of migration. The methodology proposed allows for accurate trajectory processing, estimation of home range, analysis of movement patterns and habitat assessment, and provide real-time ecological monitoring. Wildlife interactions with fragmented habitats, transportation networks, agricultural areas and urban settlements can be assessed by integrating with Geographic Information Systems (GIS), remote sensing data and environmental variables. The framework further emphasizes the need for energy-efficient smart collars, effective communication systems, and responsible usage practices to guarantee the animals' welfare while monitoring them over the long term. With the GPS signal degradation, battery capacity, and communication restrictions, there are many advances that are expected in future wildlife tracking systems, with continuous improvements in low-power electronics, IoT networks, artificial intelligence and edge computing. In general, the monitoring of biodiversity using smart collars gives valuable scientific evidence for the following purposes: biodiversity conservation, identification of ecological corridors, habitat restoration, and mitigation of human–wildlife conflict. The proposed framework is scalable and practically feasible to assist in sustainable ecosystem management and in the decision-making process of informed conservation, in a rapidly changing landscape.

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