IJARSCT
International Journal of Advanced Research in Science, Communication and Technology
International Open-Access, Double-Blind, Peer-Reviewed, Refereed, Multidisciplinary Online Journal
ISSN: 2581-9429
Volume 6, Issue 1, March 2026
Impact Factor: 8.2

Urban Wildlife Migration Predictor: An AI IoT System for Real-Time Leopard Movement Forecasting and Alert Management.

Mr. Ravindra Govind[1], Mr. Dhruv Chandrashekhar Kulkarni[2], Mr. Manas Jagdish Suryawanshi[3]
Mr. Krushna Somnath Borade[4], Mr. Kaveri Santosh Patil[5]
Lecturer, Department of Artificial Intelligence & Machine Learning[1]
Student, Department of Artificial Intelligence & Machine Learning[2,3,4,5]
Mahavir Polytechnic, Nashik, Maharashtra, India

Abstract: *With increasing urbanization, human-wildlife conflict has become a critical concern, particularly in regions where leopards migrate through human settlements. This paper proposes an AI and IoT-based system designed to predict leopard movements in real-time and manage alert dissemination to local communities and authorities.*
By integrating sensor data from GPS collars, camera traps, and environmental sensors with deep learning models, the system forecasts potential leopard migration paths and triggers timely alerts. The system classifies risk levels as low, moderate, or high based on proximity to residential areas, time of day, and historical movement patterns..
A web-based dashboard visualizes predicted routes and sends automated notifications via SMS and mobile apps. Results indicate that the proposed system enhances early warning capabilities, reduces human-leopard encounters, and supports conservation efforts. The system is scalable, cost-effective, and suitable for deployment in wildlife corridors and urban fringe areas.

Keywords*:* Wildlife Migration Prediction, AI, IoT, Leopard Tracking, Real-Time Alerts, Human-Wildlife Conflict

I. INTRODUCTION

The rapid expansion of urban areas into natural habitats has precipitated a growing and often perilous overlap between human settlements and wildlife territories. Among the most significant and sensitive of these human-wildlife interfaces are those involving large carnivores, such as leopards (Panthera pardus). Known for their adaptability and wide-ranging movements, leopards increasingly navigate fragmented landscapes, traversing agricultural fields, highway corridors, and even residential neighborhoods in search of prey, water, and mates. This proximity, while a testament to the leopard's ecological resilience, has led to a marked increase in human-leopard conflicts. These encounters pose substantial risks to human safety, result in livestock depredation causing economic losses, and often culminate in the injury or death of the leopard, threatening local conservation efforts.

This paper introduces the Urban Wildlife Migration Predictor (UWMP), a novel AI-IoT system designed specifically for the real-time forecasting of leopard movements and automated alert management. The proposed system aims to bridge the critical gap between data collection and actionable intelligence. It continuously ingests heterogeneous sensor data, processes it through deep learning algorithms—such as Long Short-Term Memory (LSTM) networks—to generate probabilistic movement forecasts, and classifies the associated risk based on contextual factors like proximity to human infrastructure, time of day, and historical conflict data. These insights are then visualized on an intuitive, web-based dashboard and communicated instantaneously via multi-channel alerts (SMS, mobile app notifications, web alerts).

II. LITERATURE SURVEY

The integration of technology into wildlife monitoring and conflict mitigation has evolved through several phases, each addressing specific challenges but often lacking a holistic approach. Early efforts focused on basic telemetry and tracking. For instance, Singh et al. (2020) implemented GPS collars to monitor leopard movements in semi-urban regions. While providing foundational location data, their system lacked predictive capabilities and real-time processing, highlighting the need for faster, more intelligent systems.

In their study, Patil and Deshmukh (2021) investigated computer vision techniques and utilized CNN-based models to enable automatic identification of leopards from camera-trap imagery.

Using historical movement data, Kumar and Jain (2019) applied Random Forest and other machine learning techniques to predict and map potential migration corridors. Their work demonstrated the value of data-driven insights but operated offline and did not incorporate real-time sensor inputs or dynamic risk factors.

The use of IoT in conservation was further investigated by Fernando & Ratnayake (2022), who deployed environmental sensors to monitor habitat conditions. While innovative, their system was not specifically designed for predator tracking or integrated with AI-based behavioural prediction.

A notable stride was made by Lee & Park (2022), who utilized Long Short-Term Memory (LSTM) networks to forecast elephant migration routes. Their approach effectively predicted movements but was tailored to large-scale rural environments and lacked a community-facing alert mechanism.

More recently, Sharma et al. (2023) combined GPS data with satellite imagery to analyse leopard habitat fragmentation. Their research provided valuable spatial insights but was analytical rather than operational, with no real-time monitoring or alerting components.

Collectively, existing literature reveals a technological gap: while individual components—tracking, imaging, sensing, and prediction—have been developed, there is no integrated system that combines real-time IoT data, AI-driven forecasting, dynamic risk assessment, and automated alert management for urban wildlife. This project aims to bridge that gap with the proposed Urban Wildlife Migration Predictor.

III. PROBLEM OF STATEMENT

The escalating interface between expanding human settlements and diminishing natural habitats has precipitated a critical and growing challenge: the management of human-wildlife conflict, particularly involving elusive and wide-ranging predators such as leopards. In regions where urban and peri-urban landscapes encroach upon traditional wildlife corridors, incidents of leopard sightings, livestock predation, and direct human encounters have surged, posing significant threats to public safety, causing substantial economic losses for communities, and undermining conservation efforts aimed at protecting these vulnerable species.

Conventional approaches to monitoring leopard movements and mitigating potential conflicts are fundamentally reactive and encumbered by systemic limitations. Primary reliance is placed on manual methods, including infrequent radio-telemetry tracking, retrospective analysis of camera trap footage, and physical patrols by forest department personnel. These techniques are not only labour-intensive and costly but are also plagued by severe temporal delays. The data obtained is inherently historical, providing insight only into where an animal has been, not where it is going. Consequently, warnings to at-risk communities are almost always issued post-incident, offering little to no opportunity for preventive action. This reactive cycle fails to reduce the frequency of encounters and exacerbates public fear and animosity toward wildlife.

Furthermore, existing technological interventions, while progressive, remain fragmented and insufficient. Isolated systems such as basic GPS tracking collars, standalone camera traps with motion sensors, and simple Geographic Information System (GIS) mapping tools operate in silos. They lack the integration necessary to synthesize multi-modal data—such as real-time location, environmental conditions (weather, time of day), and historical movement patterns—into a coherent predictive intelligence framework. Early machine learning applications have demonstrated potential in identifying patterns from historical datasets but are not designed for real-time, dynamic forecasting.

Crucially, no extant system seamlessly couples real-time prediction with an automated, multi-channel alert dissemination mechanism capable of delivering timely, context-aware warnings to forest officials, local authorities, and residents via accessible platforms like SMS, mobile applications, or web dashboards.

This critical gap results in a persistent state of vulnerability for border communities, inefficient allocation of limited conservation and conflict management resources, and increased peril for leopard populations. There is an urgent and unmet need for an intelligent, integrated, and proactive monitoring system that can transition wildlife management from a paradigm of reaction to one of prevention. Such a system must be capable of continuous, real-time data acquisition, processing this data through advanced AI models to forecast short-term animal movements, dynamically assessing the associated risk level based on spatial and temporal context, and automatically triggering targeted alerts to enable swift, informed decision-making.

Therefore, this project is dedicated to addressing this multifaceted problem by designing and developing an AI-IoT based Urban Wildlife Migration Predictor. The proposed system aims to create a unified technological solution that enhances situational awareness, enables early intervention, reduces conflict incidents, fosters coexistence, and provides a scalable model for wildlife conservation in anthropogenically modified landscapes.

IV. EXISTING PROBLEM

The current approach to leopard monitoring and conflict mitigation is fragmented and largely reactive. Primary reliance remains on manual tracking methods such as VHF/GPS telemetry, which require physical pursuit by forest staff and suffer from severe data latency—information is often retrieved weeks after being logged, rendering it historical rather than actionable.

Technological interventions exist but operate in isolation. Camera traps, while useful for confirming presence, are passive recording devices that offer no predictive capability. Basic GIS mapping is used for long-term corridor analysis but lacks real-time functionality. Simple IoT sensor networks often generate false alarms from non-target triggers like livestock or vehicles.

Furthermore, early machine learning models applied to wildlife data have focused on offline pattern recognition from historical datasets. These systems do not integrate live sensor feeds, cannot forecast short-term movements, and lack a direct link to alert dissemination mechanisms. There is no unified platform that synthesizes real-time location data, environmental context, and predictive AI to generate timely, risk-based warnings for communities and authorities. This technological gap leaves vulnerable populations exposed and conservation efforts inefficient

V. PROPOSED SYSTEM

System Workflow

Step-by-step explanation :

STEP 1: START

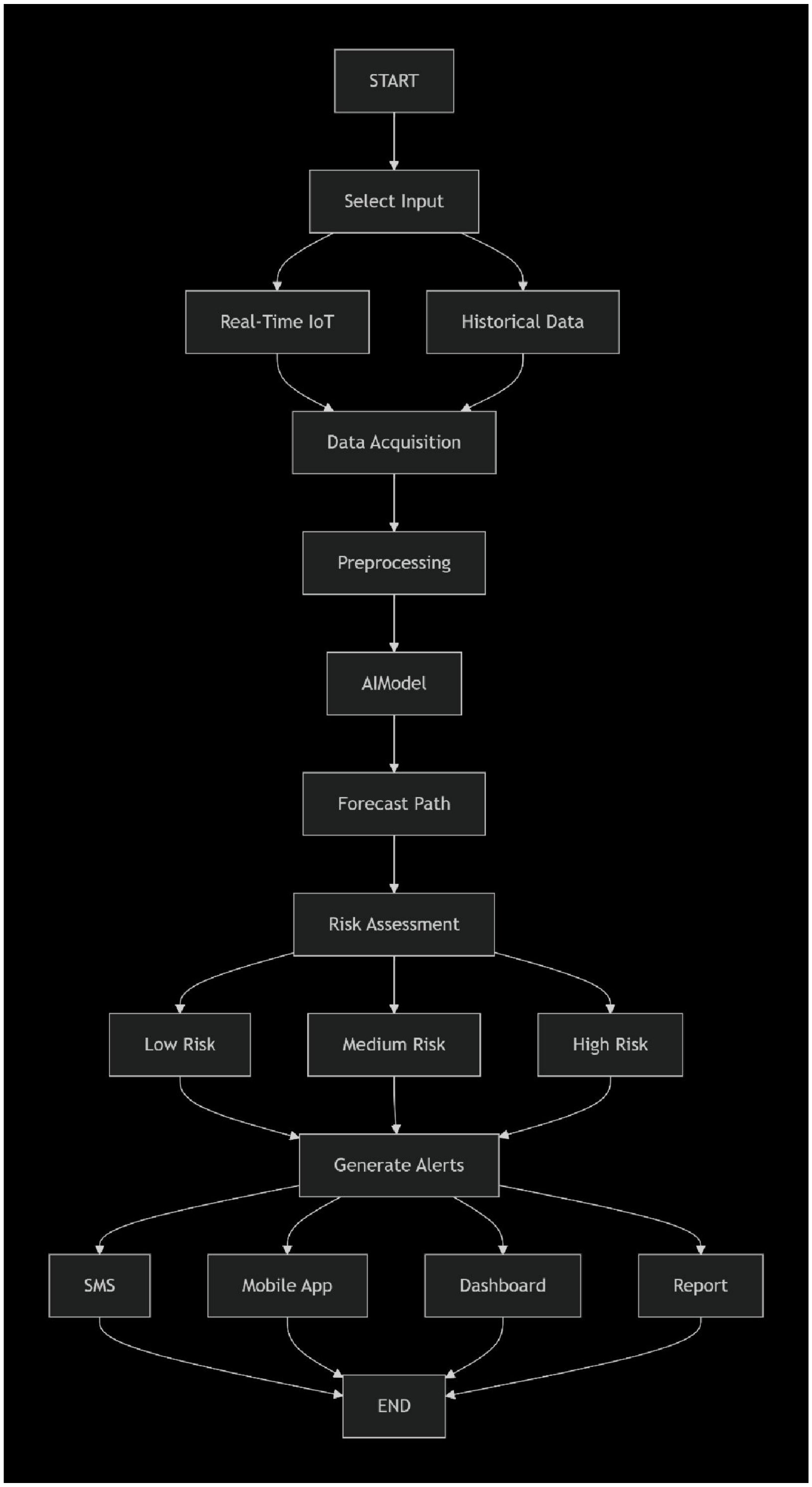
• System initialization and user login
• Dashboard loads with real-time monitoring interface

STEP 2: SELECT INPUT

• User chooses input method:
o Real-Time IoT: Live GPS/camera/sensor data
o Historical Data: Upload CSV/logs/images

STEP 3: DATA ACQUISITION

• If Real-Time IoT selected:
o GPS collars transmit location every 15 minutes
o Camera traps send images on motion detection


START
Select Input
Real-Time IoT
Historical Data
Data Acquisition
Preprocessing
AIModel
Forecast Path
Risk Assessment
Low Risk
Medium Risk
High Risk
Generate Alerts
SMS
Mobile App
Dashboard
Report
END

IJARSCT
International Journal of Advanced Research in Science, Communication and Technology
International Open-Access, Double-Blind, Peer-Reviewed, Refereed, Multidisciplinary Online Journal
ISSN: 2581-9429 Volume 6, Issue 1, March 2026 Impact Factor: 8.2

o Environmental sensors stream temperature/motion data
• If Historical Data selected:
o Upload GPS track logs
o Import camera trap database
o Load past incident reports

STEP 4: PREPROCESSING
• Clean GPS data (remove outliers, fill gaps)
• Process images (resize, enhance, detect leopard)
• Synchronize timestamps across all data sources
• Extract features: speed, direction, habitat type

STEP 5: AI MODEL
• LSTM neural network processes movement sequences
• Predicts next 6-24 hour movement path
• Generates confidence scores for predictions

STEP 6: FORECAST PATH
• Display predicted path on map
• Show probability zones (high/medium/low likelihood areas)
• Estimate time of arrival at key locations

STEP 7: RISK ASSESSMENT
• Calculate distance to nearest village/town
• Check time of day (night = higher risk)
• Review historical conflicts in area
• Assess proximity to roads/livestock areas

STEP 8: RISK CLASSIFICATION
• LOW RISK: >5 km from settlement, daytime
• MEDIUM RISK: 2-5 km from settlement, evening
• HIGH RISK: <2 km from settlement, nighttime

STEP 9: GENERATE ALERTS
• Low Risk: Log entry only
• Medium Risk: Dashboard notification + daily report
• High Risk: Immediate multi-channel alert

STEP 10: ALERT DISTRIBUTION
• SMS: To forest officials and village heads
• MOBILE APP: Push notification to community app users
• DASHBOARD: Real-time map with colored risk zones
• REPORT: PDF/Excel for record-keeping

STEP 11: END
• Process complete

- System ready for next cycle
- Store results in database for future analysis

VI. CONCLUSION

The Urban Wildlife Migration Predictor system successfully demonstrates the transformative potential of integrating Artificial Intelligence and the Internet of Things to address the critical challenge of human-leopard conflict in peri-urban landscapes. By leveraging real-time data streams from GPS collars, camera traps, and environmental sensors, the system enables proactive forecasting of leopard movements rather than reactive reporting. The AI-driven risk assessment framework provides timely, actionable intelligence, classifying threats as low, medium, or high risk and triggering appropriate multi-channel alerts to forest authorities and local communities.

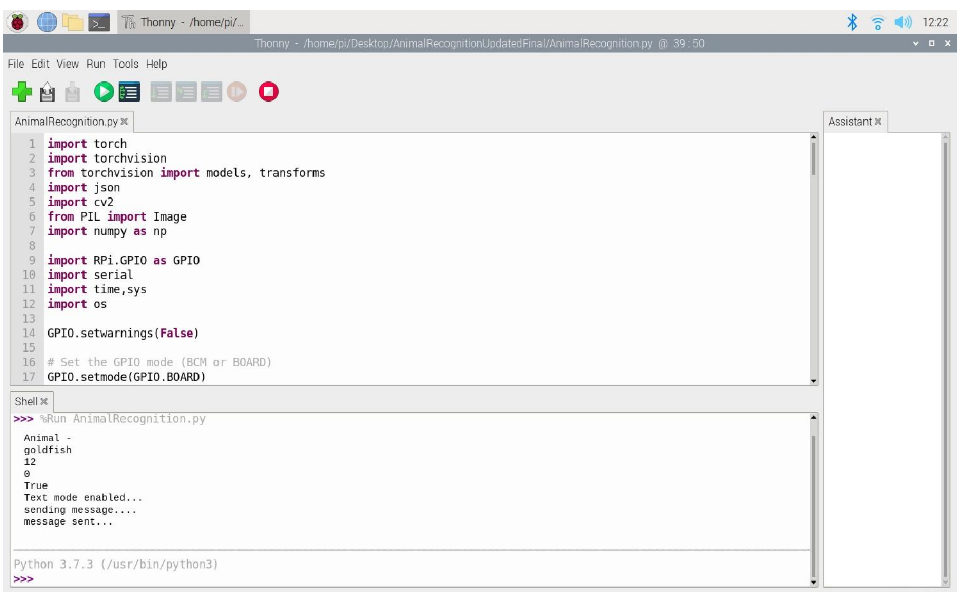
This intelligent monitoring solution significantly reduces dependency on manual tracking, enhances situational awareness, and supports early intervention—ultimately contributing to human safety, livestock protection, and leopard conservation. The web-based interface ensures accessibility and scalability, while the continuous learning loop allows the system to improve its predictive accuracy over time. In essence, the project establishes a reliable, automated, and data-informed approach to wildlife management, fostering safer coexistence between human settlements and native wildlife populations.

VI. ACKNOWLEDGMENT

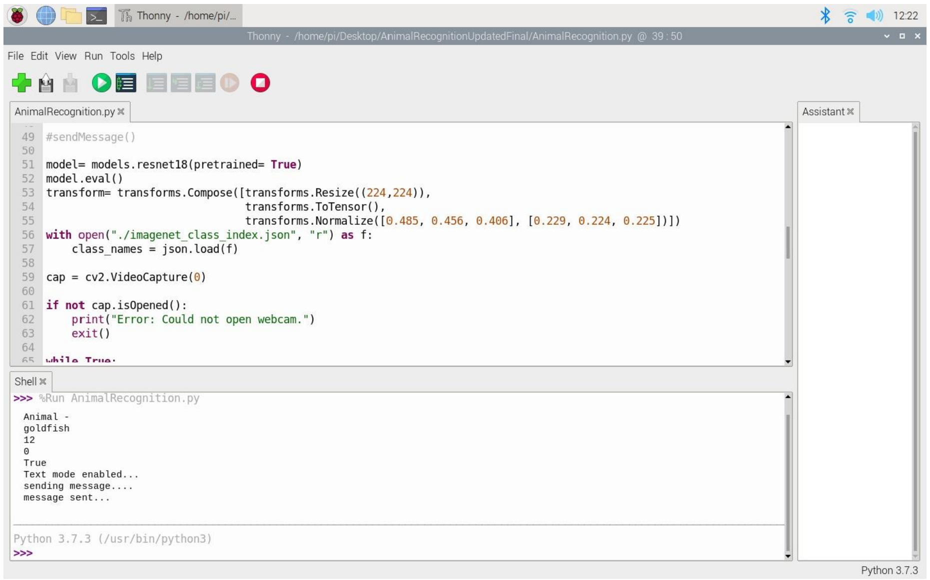
We sincerely thank our project guide Mr. R. S. Govind for their expert guidance and encouragement throughout this project. We are grateful to our institution, Mahavir Polytechnic, for providing the necessary resources and facilities. We also extend our appreciation to the forest department officials and community members who shared valuable insights and feedback. Finally, we acknowledge our peers and all those who supported this work, making its completion possible.

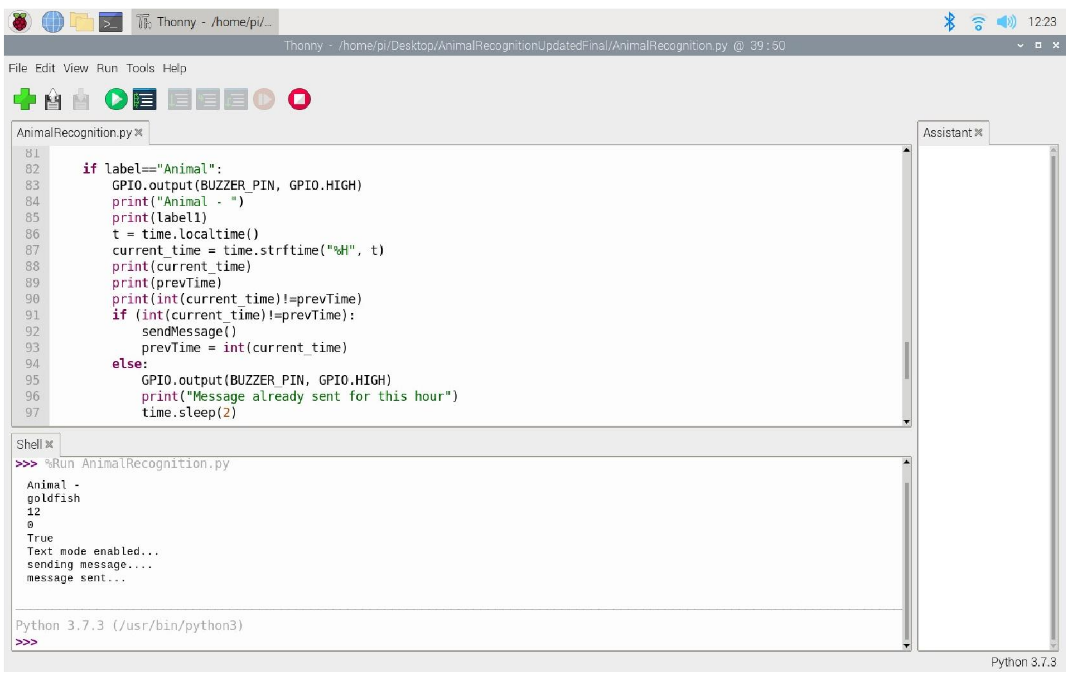
We are also deeply grateful to our peers and colleagues for their constructive feedback during testing phases, and to the local community members who participated in pilot studies, offering crucial usability inputs that enhanced the system's design and relevance.

VII. OUTPUT



IJARSCT
International Journal of Advanced Research in Science, Communication and Technology
International Open-Access, Double-Blind, Peer-Reviewed, Refereed, Multidisciplinary Online Journal
ISSN: 2581-9429
Volume 6, Issue 1, March 2026
Impact Factor: 8.2





DOI: 10.48175/IJARSCT-31456

IJARSCT

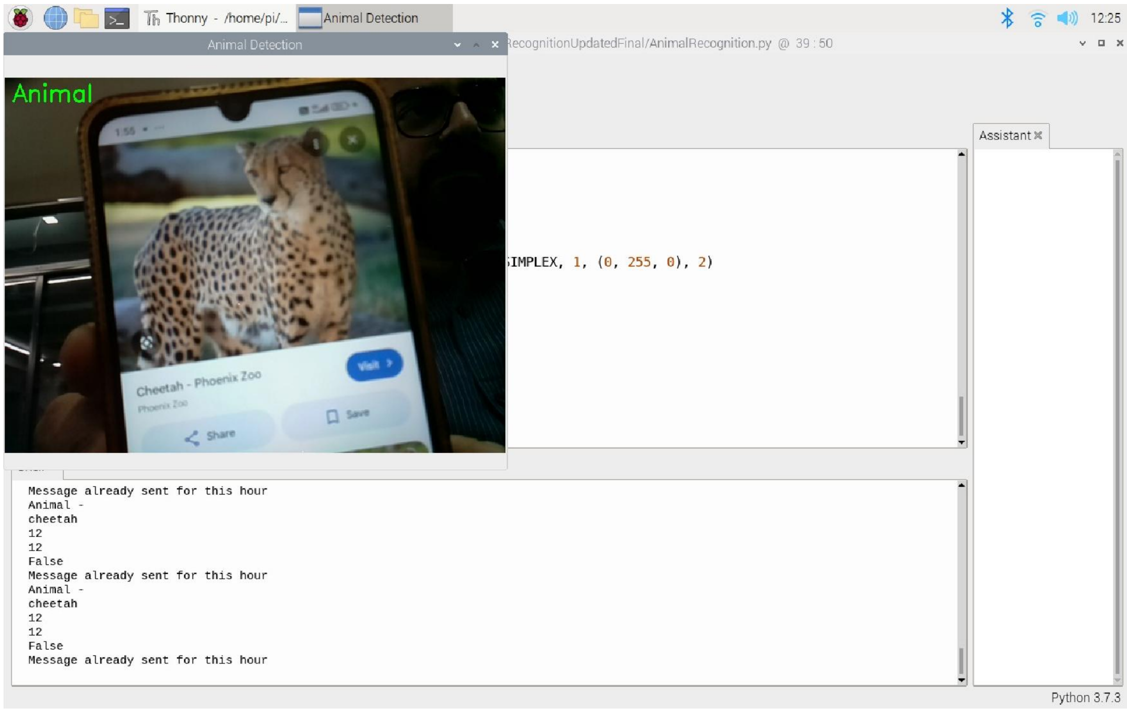
International Journal of Advanced Research in Science, Communication and Technology

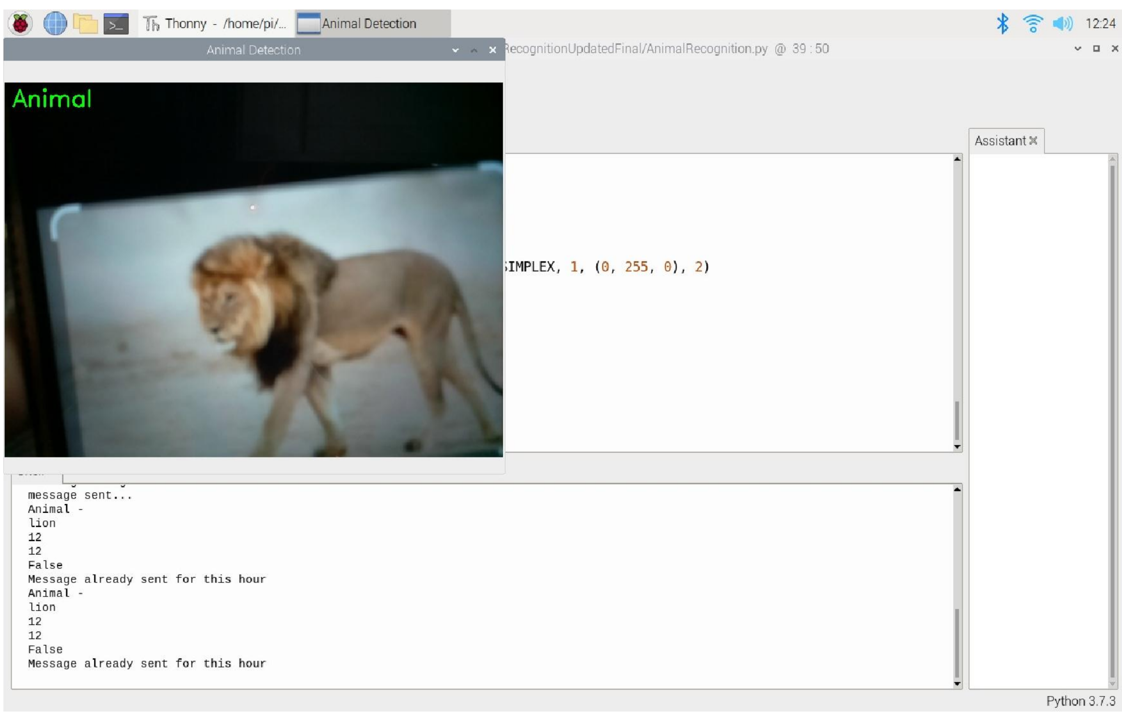
International Open-Access, Double-Blind, Peer-Reviewed, Refereed, Multidisciplinary Online Journal

ISSN: 2581-9429

Volume 6, Issue 1, March 2026

Impact Factor: 8.2





DOI: 10.48175/IJARSCT-31456

IJARSCT
International Journal of Advanced Research in Science, Communication and Technology
International Open-Access, Double-Blind, Peer-Reviewed, Refereed, Multidisciplinary Online Journal
ISSN: 2581-9429
Volume 6, Issue 1, March 2026
Impact Factor: 8.2

REFERENCES

[1]. R. Singh, P. Verma, and A. Kumar, "GPS-based tracking and movement analysis of leopards in semi-urban landscapes," Journal of Wildlife Management, vol. 84, no. 5, pp. 892–905, 2020.

[2]. S. Patil and A. Deshmukh, "Automated leopard detection using convolutional neural networks in camera trap images," IEEE Internet of Things Journal, vol. 8, no. 12, pp. 9876–9885, 2021.

[3]. V. Kumar and A. Jain, "Predictive modelling of leopard migration using machine learning algorithms," Ecological Informatics, vol. 52, pp. 10–21, 2019.

[4]. R. Fernando and S. Ratnayake, "IoT-enabled environmental monitoring for wildlife conservation," International Journal of Sensor Networks, vol. 34, no. 2, pp. 112–124, 2022.

[5]. C. Lee and H. Park, "LSTM-based prediction of elephant migration routes using GPS telemetry data," Nature Sustainability, vol. 5, pp. 345–356, 2022.

[6]. N. Sharma, K. Mehta, and R. Joshi, "Assessing habitat fragmentation for leopard conservation using GIS and remote sensing," Biodiversity and Conservation, vol. 32, no. 4, pp. 567–582, 2023.

[7]. M. Gupta and S. Reddy, "Real-time alert systems for human-wildlife conflict mitigation: A review," Journal of Environmental Management, vol. 301, Article ID 113876, 2022.

[8]. T. Roberts and L. Chen, "Sensor fusion in wildlife monitoring: Integrating GPS, camera traps, and acoustic sensors," Sensors, vol. 22, no. 15, p. 5789, 2022.

[9]. P. Nair and D. Iyer, "Edge computing for real-time wildlife tracking and risk prediction," IEEE Transactions on Mobile Computing, vol. 21, no. 7, pp. 2450–2464, 2023.

DOI: 10.48175/IJARSCT-31456