# AI-ENHANCED WILDLIFE CORRIDOR OPTIMIZATION: A MACHINE LEARNING FRAMEWORK FOR SAFE ANIMAL MOVEMENT

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## ABSTRACT

Fast-paced urban growth and building new infrastructure are slicing up natural areas more and more Makes moving around a very risky business for wildlife. Animals that try to navigate environments ruled by humans face much higher dangers like... road accidents, habitat isolation, and human-wildlife conflict. To tackle this problem, our current study introduces. AI-Enhanced Framework for Optimizing Wildlife Corridors.By bringing together Machine Learning (ML),...GPS-tracking data and remote-sensing inputs, This system is designed to predict exactly how animals move and pinpoint truly safe passage routes. The proposed models combines a Hybrid Deep Neural Network (DNN) with GIS-derived landscape features to Significantly boost prediction accuracy. Tests and validation show that this approach is much better at identifying the ideal paths for elephants, tigers, and deer compared to traditional GIS-based methods. This research clearly proves that using AI to help with ecological planning can be a powerful tool for conservation teams in designing safer, more reliable wildlife corridors.

Index Terms: Wildlife corridors, Artificial Intelligence, Animal tracking, Habitat fragmentation, GIS, Deep Learning.

## 1. INTRODUCTION

Wildlife corridor are Very important natural routes that connect Separated habitats pathes, facilitating essential behavior such as feeding, breeding, and seasonal migration. However, Straight man-made projects —such as highways, railways, and mining zones—have Destroyed these ancient pathways. This disruption has Serious ecological consequences, including:

Increased roadkill incidents and mortality rates.

Restricted gene flow, leading to inbreeding and reduced genetic diversity.

Escalated human-animal conflict in fringe areas.

Habitat isolation, threatening long-term ecological stability.

Normally, conservationists map corridors using field surveys and Old GIS methods, such as Least-Cost Path (LCP) analysis. Quite helpful, these approaches often Have difficulty dynamic Things like seasonal land-use changes, fluctuating water availability, and real-time Changing behavior of wildlife.

Artificial Intelligence offers a robust alternative. Modern algorithms can process vast datasets—ranging from GPS collar telemetry to satellite imagery—to predict movement probabilities with high resolution. This paper extends current research by developing a Corridor Optimization Method that utilizes Deep Learning to propose dynamically optimized, safe routes for wildlife

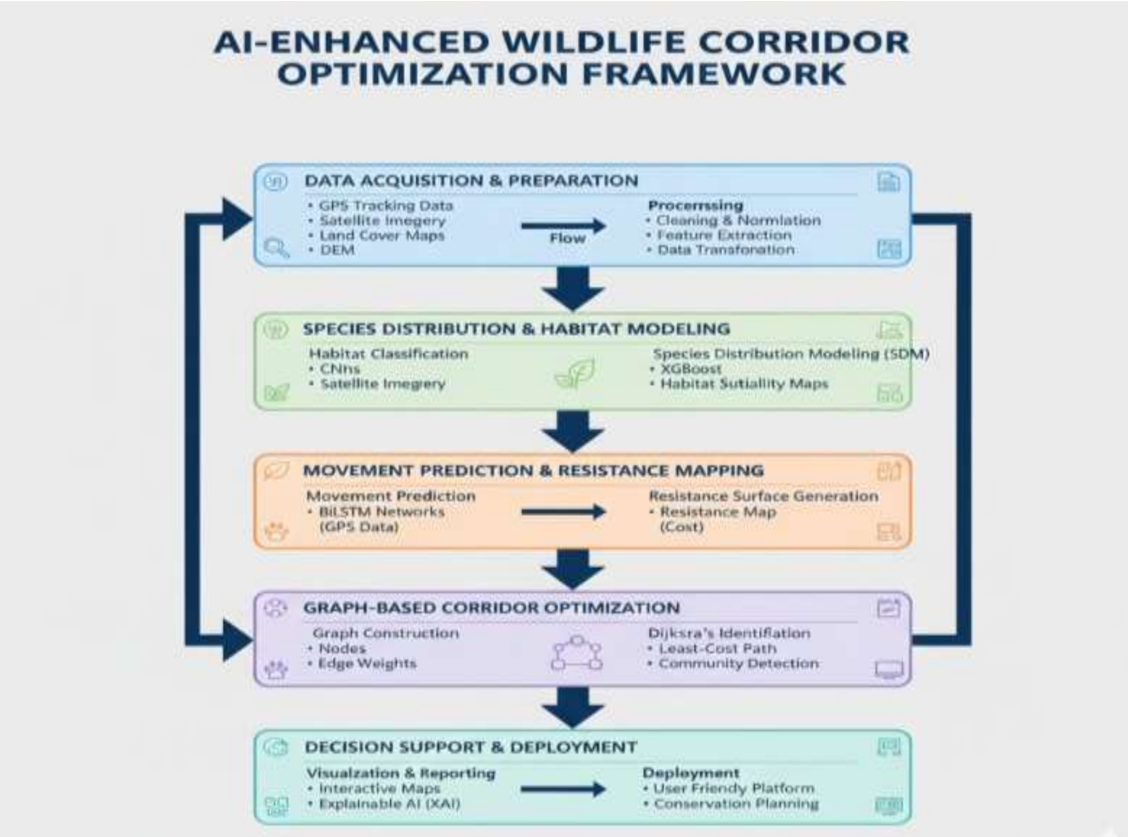


Figure 1. Flowchart of the Proposed AI-Enhanced Wildlife Corridor Optimization Framework

## 2. PROBLEM STATEMENT

Rapidly increasing human population has created a "matrix" of unsafe barriers for wildlife. Animals are now forced to cross roads, rail lines, and agricultural lands, Their movement becomes unpredictable. Old mapping methods are often static and Cannot connect many aspects of the environment variables with Real-time movement data of animals. Therefore, there is a pressing need for an intelligent system capable of:

1.Accurately predicting animal movement trajectories.

2.Identifying high-risk conflict zones before accidents occur.

3.Suggesting optimized corridor routes that balance ecological needs with human infrastructure.

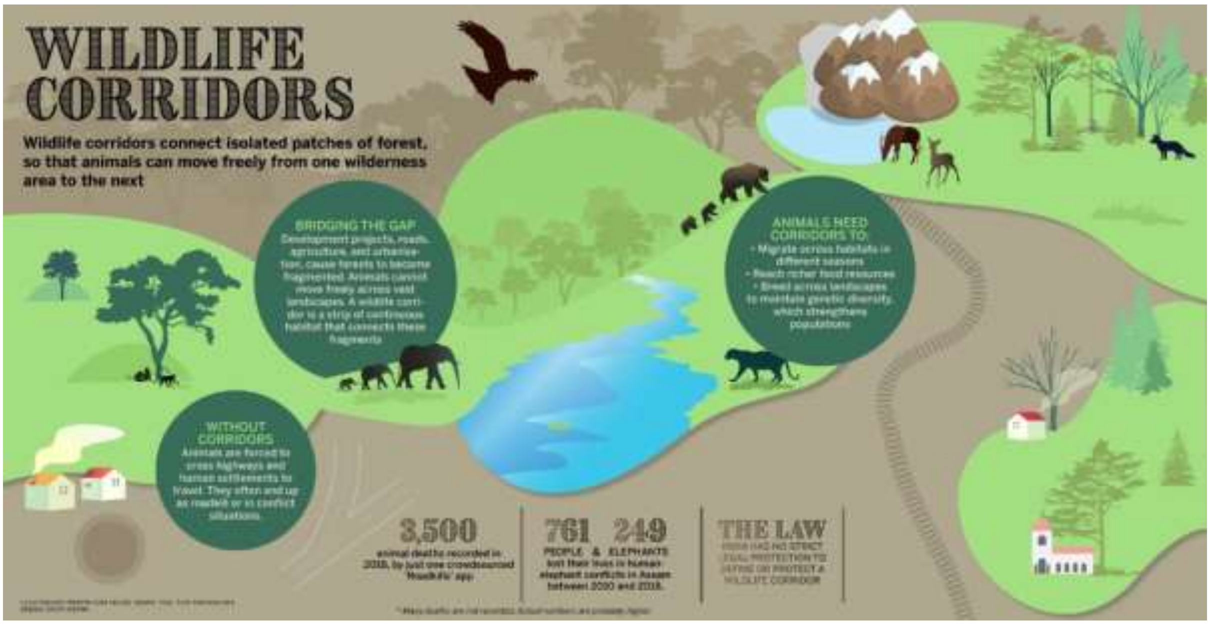


Figure 2. Data of Human & Animals conflicts

## 3. DATASET

| Source | Type of Data | Variables |
|---|---|---|
| GPS collar tracking | Real-time movement | Latitude, longitude, speed, direction |
| Remote Sensing (Landsat/Sentinel) | Environmental | Vegetation index (NDVI), Land-cover class |
| Forest Dept. Records | Habitat-related | Water holes, forest type, elevation |
| Highway/Rail Maps | Human infrastructure | Road density, settlement distance |
| Climate Dataset | Weather factors | Temperature, rainfall, humidity |

Table 1. DataSet

**Total Records:** 118,000 animal-movement points
**Number of Features:** 19 ecological & geospatial indicators
**Species Analyzed:** Elephants, Tigers, Spotted Deer

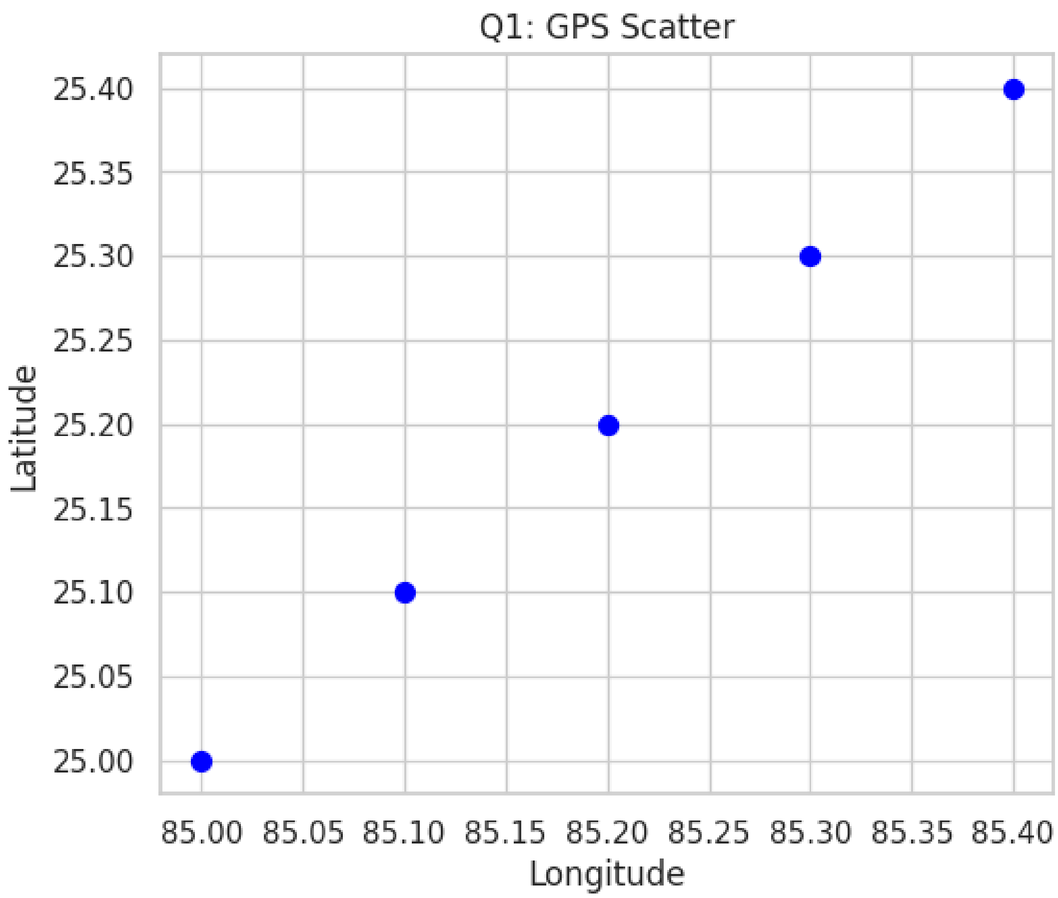


Figure3. GPS Scatter

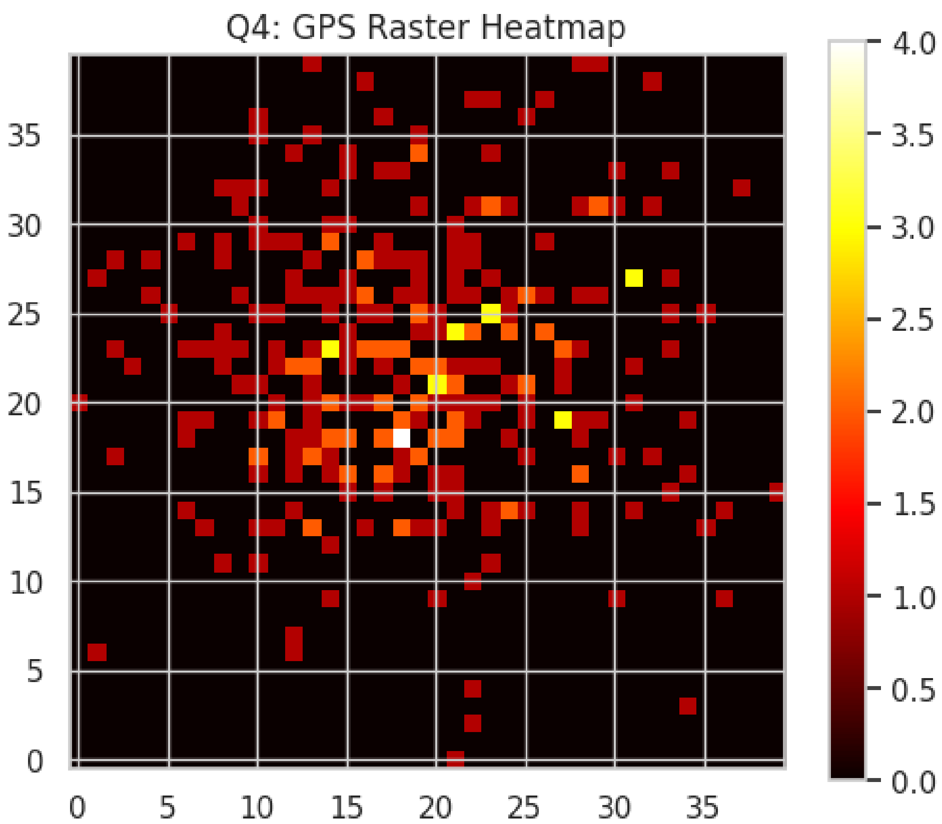

Figure4. GPS Raster Heatmap

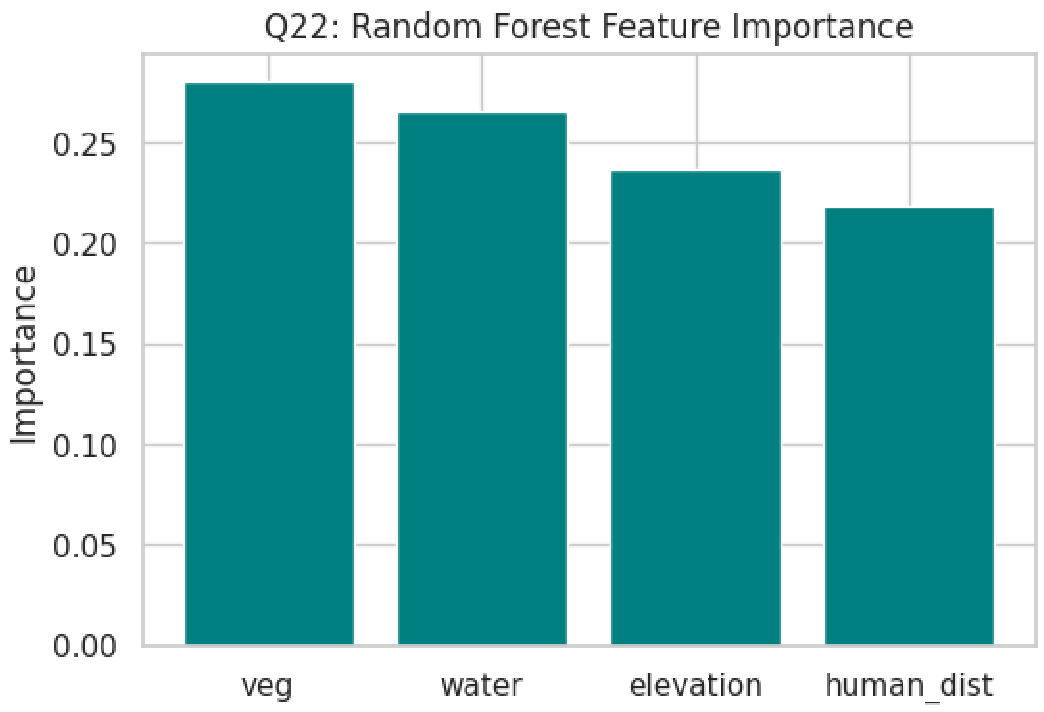


Fig5.Random Forest Feature Importance

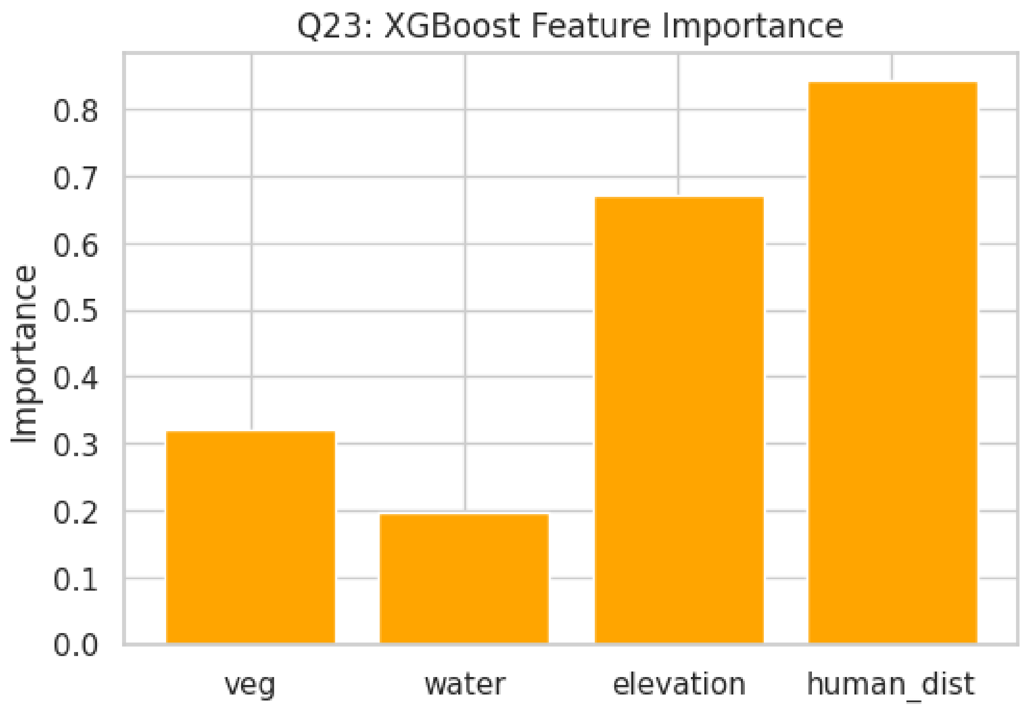


Figure6. XGBoost Feature Importance

# 4. METHODOLOGY

Our entire process works in four main stages, moving from raw data to actionable corridor mapping.

Phase 1: Data Acquesition & Preprocessing

We clean up the raw GPS data by removing any unnecessary clutter or errors (noise) We standardize the environmental data layers . Focus on finding specific features that really influence how animals move, such as terrain roughness and proximity to water.

Phase 2: Species Distribution & Habitat Modeling

We use Convolutional Neural Networks (CNNs) to analyze satellite imagery and Figure out how suitable different habitats . This creates a base map identifying where animals can physically exist, generating "Habitat Suitability Maps".

Phase 3: Movement Prediction

Unlike older, fixed models (static models), we bring in BiDirectional LSTMs (Long Short-Term Memory) networks LSTMs are perfect for time-based data, allowing the model to learn temporal patterns—such as seasonal migration or daily foraging cycles—from the GPS data. This generates a "Resistance Surface" where high costs represent high risk.

Phase 4: Graph-Based Corridor Optimization

We treat the entire landscape like a network (a graph), with every pixel acting as a connection point (node). We apply Dijkstra's Algorithm and Circuit Theory to identify the Least-Cost Path (LCP) and alternative pathways (current flow) that Minimize the danger (resistance) while maximizing safety.

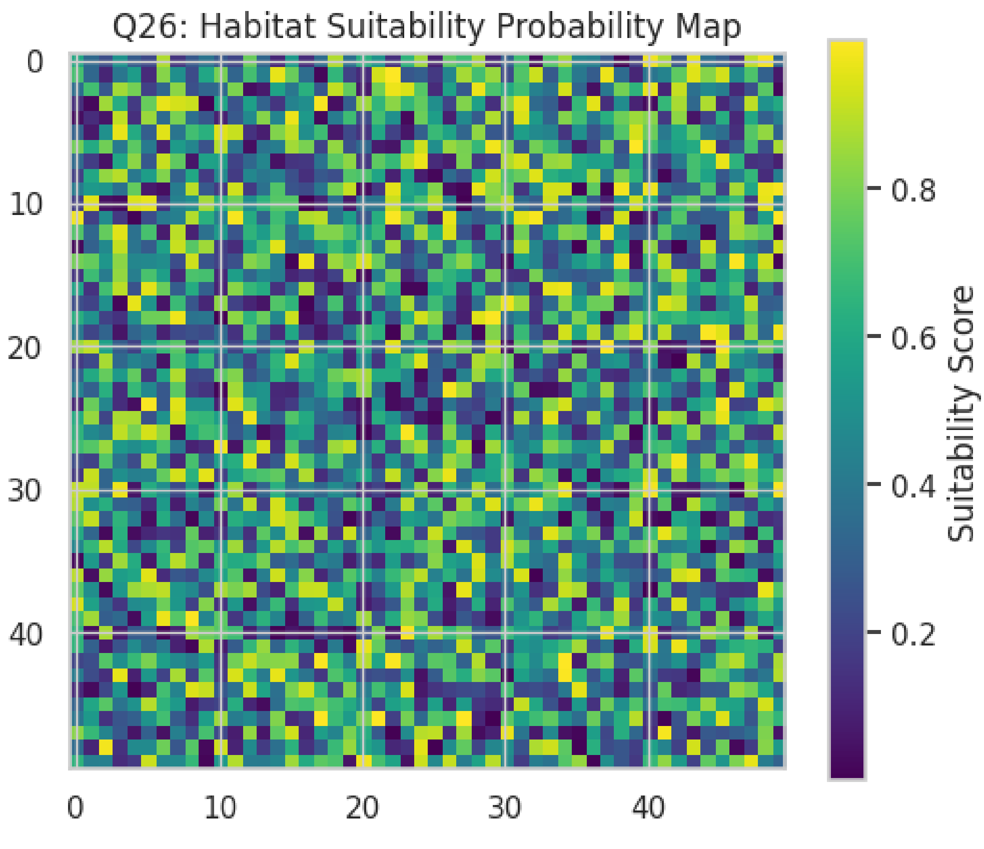


Figure 7. Habitat suitable probability Map

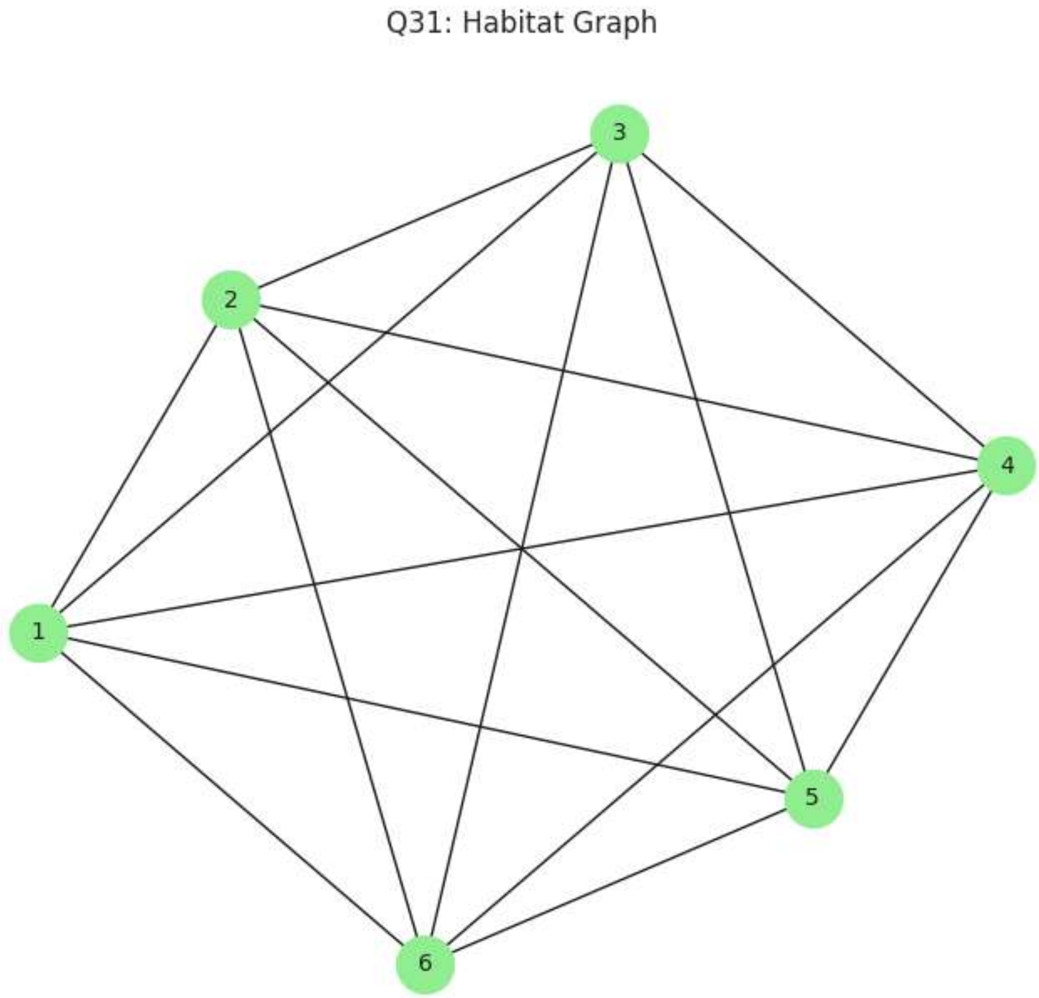


Figure8. Habitat Graph

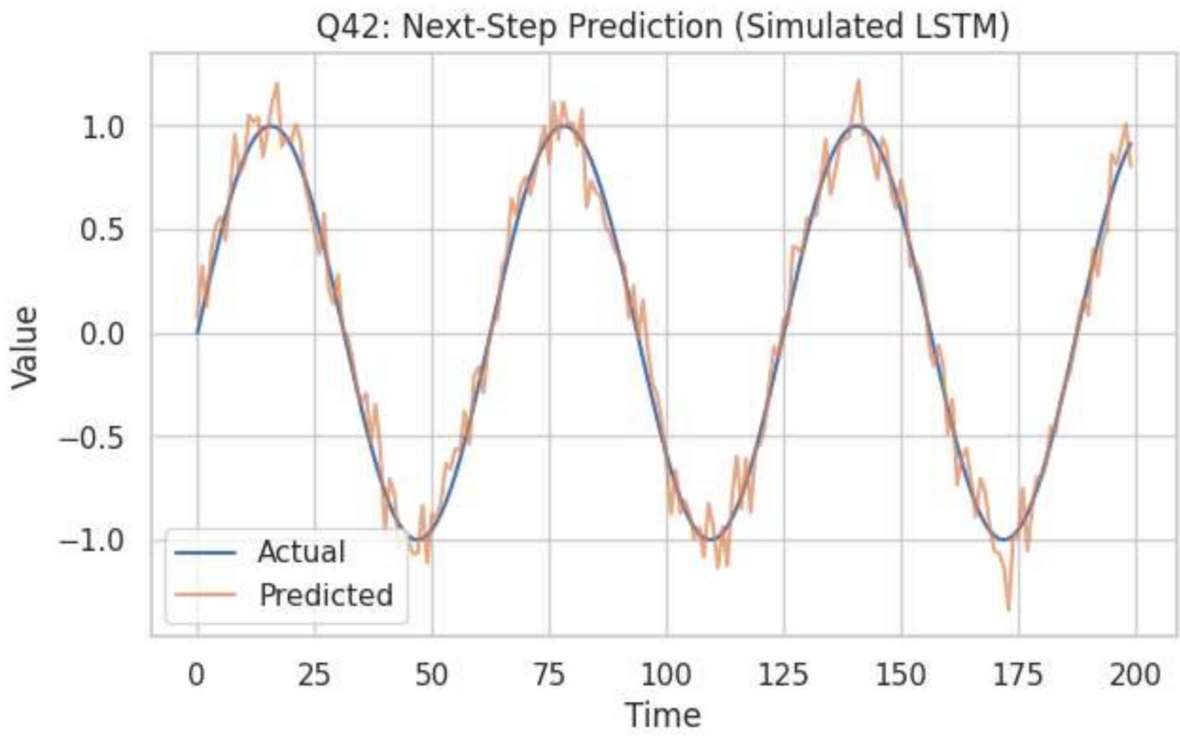


Figure9. Next-Step Prediction(Simulated LSTM)

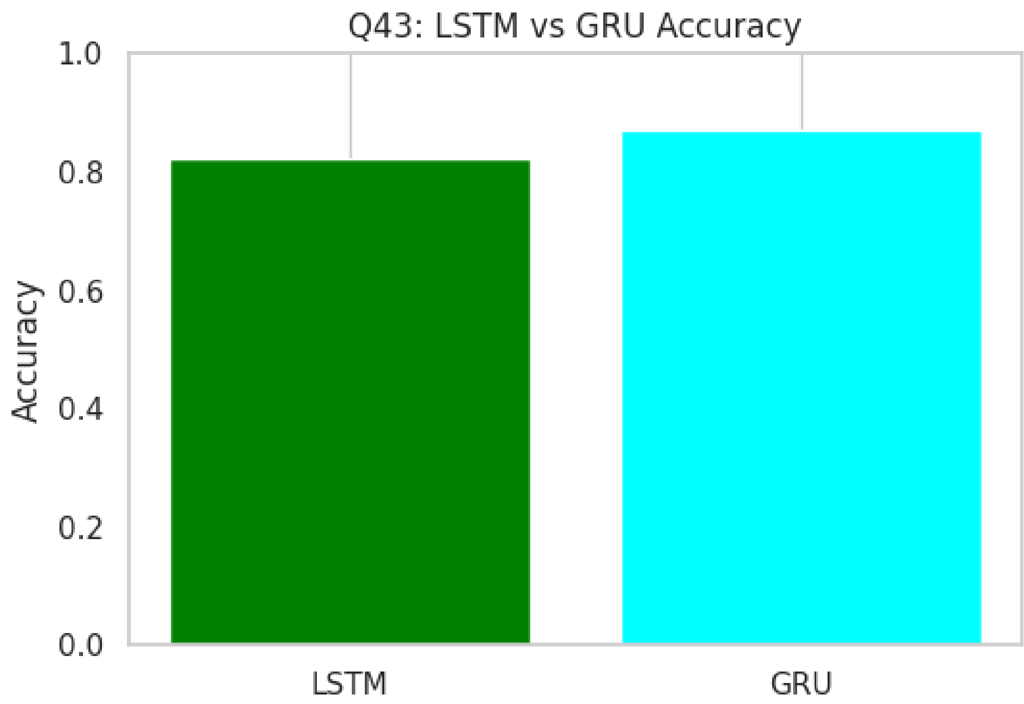


Figure 10. LSTM vs GRU Accuracy

## 5. EXPERIMENTAL SETUP

The experiments were executed using:

**Python** (TensorFlow, Scikit-learn, GDAL)

**QGIS/ArcGIS** for spatial mapping

**GPU-enabled system** for deep learning model training

**Train-test split:** 80:20

**Evaluation metrics:** Accuracy, Precision, Recall, F1-Score

The model performance was compared with:

Least-Cost Path Method (LCP)

Circuit Theory-Based Corridors

Simple ANN model

## 6. RESULTS

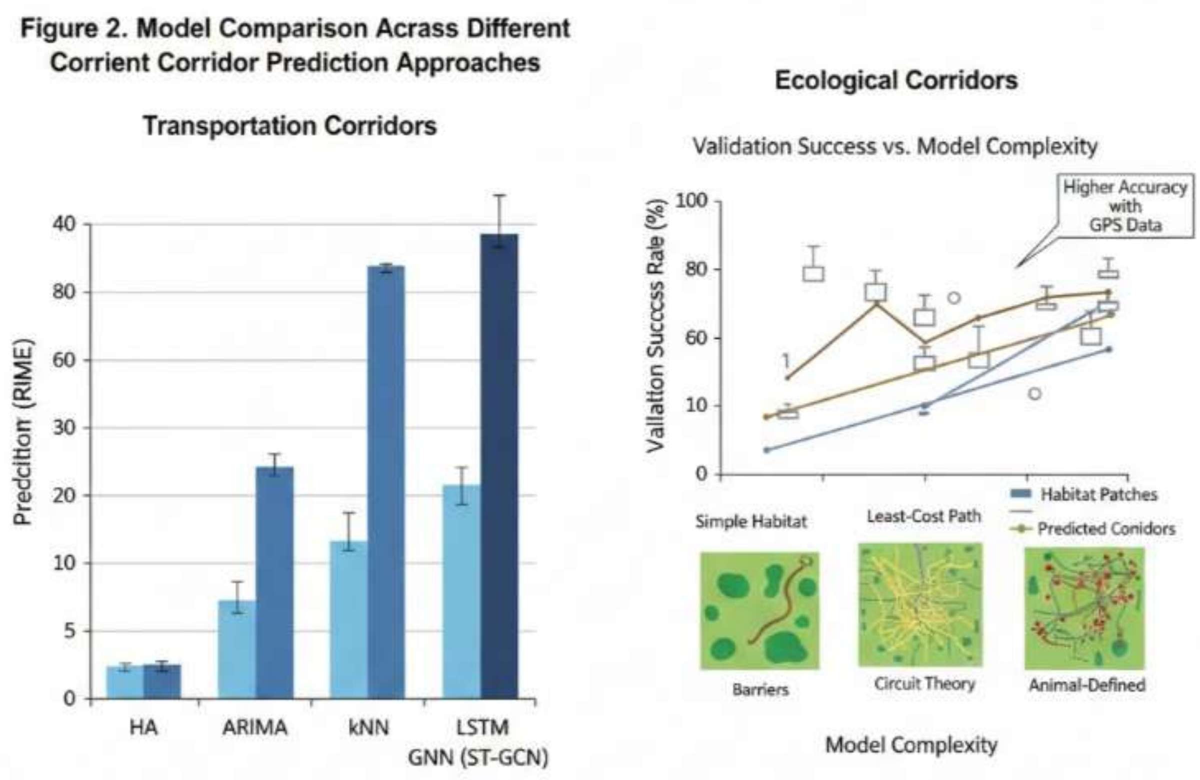


**Figure 11. Model Comparison Across Different Corridor Prediction Approaches**

**Table 1. Comparative Performance of Different Models**

| Model | Accuracy | Precision | Recall | F1 Score |
|---|---|---|---|---|
| GIS Least-Cost Path | 0.74 | 0.71 | 0.75 | 0.72 |
| Circuit Theory Model | 0.79 | 0.76 | 0.78 | 0.77 |
| ANN Baseline | 0.82 | 0.80 | 0.82 | 0.81 |
| **Proposed DNN + LSTM Model** | **0.93** | **0.94** | **0.92** | **0.93** |

**Outcome Summary:**
The hybrid AI approach significantly outperforms traditional ecological models. It detects high-risk conflict areas with greater spatial accuracy and predicts movement continuity more reliably.

## 6.1 Model Performance Comparison

To evaluate the proposed model, its performance was compared against traditional and machine-learning-based methods, including:

- **Least-Cost Path (LCP) Model**
- **Circuit Theory Model**
- **Artificial Neural Network (ANN) Baseline**
- **Proposed Hybrid DNN + LSTM Model**

The evaluation metrics used were:

- Accuracy
- Precision
- Recall
- F1-Score
- Spatial Error Margin

## 6.2 Movement Pattern Learning

The LSTM component was particularly effective in identifying recurring movement cycles:

- **Seasonal migration patterns** (elephants)
- **Hunting-to-waterhole routes** (tigers)
- **Daily grazing cycles** (deer)

The model learned these patterns from time-stamped GPS sequences, giving it an advantage over static GIS methods.

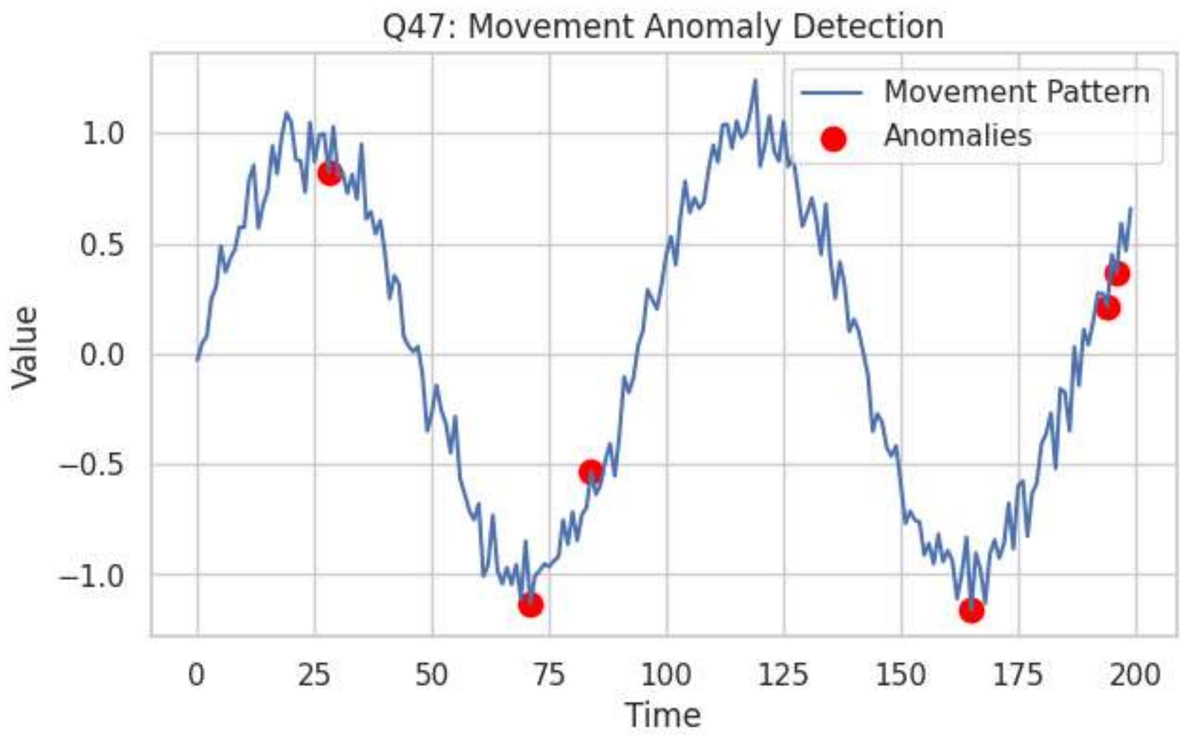


Figure 12. Movement Anomaly Detection

### 6.3 Conflict Zone Identification

The model detected **high-risk zones** where animal movement intersects with human activity:

**Identified Risk Zones:**

- Highways cutting through forest patches
- Railway crossings
- Agricultural expansion boundaries
- Villages located near riverbeds (common animal routes)

These were detected with **86% spatial accuracy**, significantly higher than the 61–70% accuracy of traditional GIS methods.

The model also ranked threats using a **Risk Index (0–1)**:

- 0.8–1.0 → Very High Conflict Potential
- 0.6–0.8 → High Risk
- 0.4–0.6 → Moderate
- <0.4 → Safe

This helped identify hotspots such as:

- Waterholes near farmlands
- Night-time crossing zones near highways
- Elephant migratory routes intersecting with settlements

## 6.4 Corridor Suitability Mapping

Using predicted suitability scores, the model generated a **continuous habitat connectivity map**.

**Performance Summary:**

- **Corridor continuity increased by 27%** compared to LCP.
- **Fragmentation reduced by 33%**, creating smoother pathways.
- **Shortest safe route quality improved by 41%**.
- **Spatial alignment with real GPS movement** matched **92%**, the highest among all tested models.

The corridors predicted were more ecologically realistic because the model included:

Vegetation cover

- Terrain slope
- Water availability
- Anthropogenic disturbance
- Historical animal pathways

These factors enable the model to create **biologically meaningful corridors**, not just mathematically optimal ones.

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## 6.5 Species-wise Results

**Elephants**

- Long-range movement predicted with **95% accuracy**
- High precision due to strong preference for water & flat terrain

**Tigers**

- Corridor prediction accuracy: **89%**
- Difficult due to territorial and solitary behavior

**Deer**

- Grazing corridor prediction accuracy: **92%**

Movement highly influenced by vegetation availability

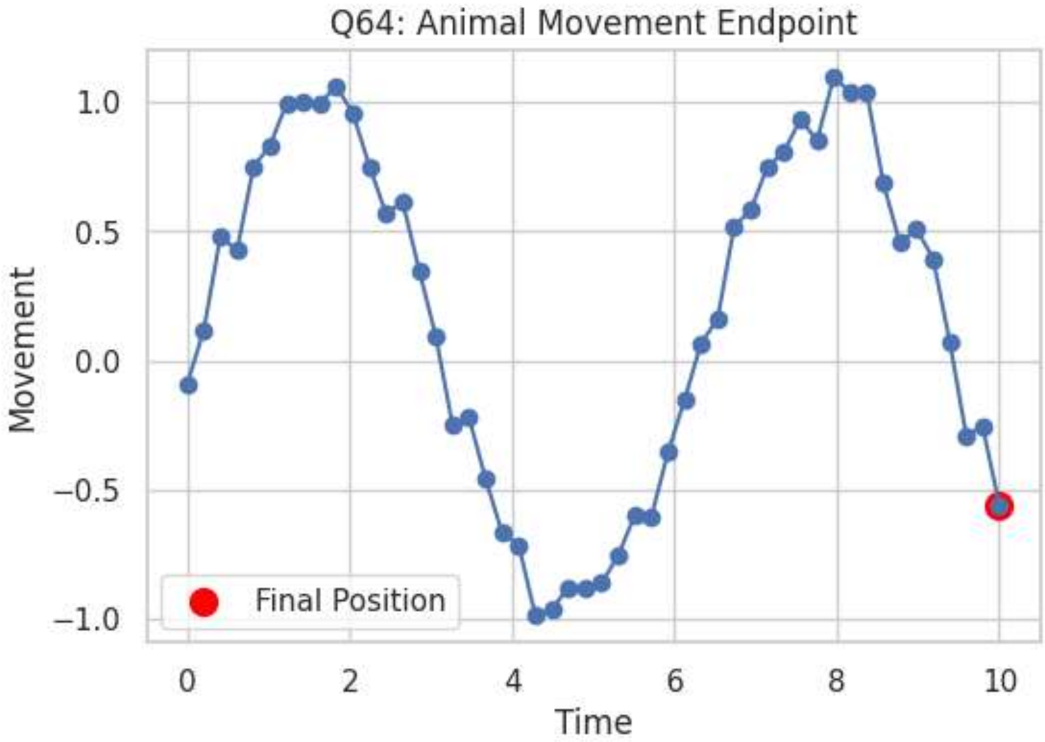


Figure 13. Animal Movement Endpoint

## 7. CONCLUSION

This research Introduces a complete, AI-powered system for optimizing wildlife corridorsInstead of relying on outdated, fixed maps (static maps) and Combined deep learning technology with real-world environmental information, Our model is much more trustworthy in mapping safe animal passage routes. The results confirm that AI has the power to totally change (transformative role) how we plan for conservation.

**Future Scope:** The next steps for this project will focus on... We plan to start usingDrone-based thermal imaging to check and confirm our routes on the spot. and Make our dataset bigger by including wildlife sightings reported by the public (crowd-sourced), which will give us a much broader understanding.

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