



Original Research Paper

Deep Learning Mapping of Road Barriers Affecting Wildlife Movement

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Key Words	Abstract
Deep Learning, Wildlife Movement, Road Barriers, Habitat Connectivity, Remote Sensing, Ecological Modelling, Conservation Planning.	Introduction: Expansion and improvement of road infrastructure have substantial impacts on the migration behavior of wildlife in terms of acting as barriers, fragmentation of their habitat and loss of ecological connectivity. Precise delineation of road barriers is critical for effective wildlife corridor design and management. The recent advances in deep learning and remote sensing technology can be exploited to address such challenges. Materials and Methods: A deep learning approach for developing road barrier maps impacting wildlife movements through the use of satellite images, road network information, and observations regarding wildlife movements has been put forth in this study. The gathered data undergo geospatial alignment, enhancement, normalization, and feature extraction processes. The application of a deep learning model using spatial feature analysis for the detection of road barriers, habitat fragmentation assessment, and movement barriers evaluation has been employed. Results and Discussion: The performance of the proposed framework was better than the traditional deep learning algorithms for barrier detection, movement risk prediction, and habitat connectivity assessment. The proposed method had an accuracy of 96.5% in detecting barriers, 94.8% in predicting movement risk, and 93.7% in habitat connectivity assessment, which were superior to CNN, CNN-LSTM, and ResNet50 models. The findings suggest that the model is able to capture complex spatio-ecological interactions related to wildlife movement constraints. Conclusion: The proposed framework is an efficient solution for detecting important road barriers and formulating appropriate wildlife management strategies. The combination of deep learning and geospatial data as well as ecological data helps analyze connectivity of the habitats and formulates necessary mitigation plans.

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Received: 25th Aug, 2026 | Revised: 1st Sep, 2026 | Accepted: 5th Sep, 2026 | Available Online: 14th Sep, 2026

(DOI): 10.70102/AEJ.2026.18.5s.45

Introduction

New studies have shown the relevance of the use of artificial intelligence, geospatial analysis, and intelligent monitoring systems in analyzing the movements of wildlife and addressing ecological challenges. For instance, Bosco and Pavalam (2025) explored human-animal-environmental interactions in pastoral landscapes through geospatial mapping and habitat suitability models, showing how the use of spatial technology is important in studying the spatial patterns of the habitats and movement conditions of wildlife. On the other hand, Gonzalez-Velez et al. (2021) used an artificial intelligence approach that incorporated GIS and multispectral images to predict collision zones between vehicles and wildlife.

Khamchukova et al. (2025) have done an analysis of wildlife crossings and indicated that it is vital to develop sustainable bridge design solutions for minimizing the effect of linear transportation corridors on the movement of animals. The ability of deep learning models in the analysis of complicated environmental patterns was shown by Muralisankar et al. (2025). Additionally, Nandutu, Atemkeng, and Okouma (2022) revealed the possibility of using intelligent systems with sensors and machine learning techniques for timely wildlife monitoring and reduction of the probability of wildlife collisions.

These findings imply that the combination of deep learning, geospatial information, and intelligent sensing technologies may be used effectively for mapping the road barriers and predicting the movement risks.

Literature Review

The recent literature has reviewed how the use of artificial intelligence, geospatial analysis, and machine learning can help in comprehending the issues faced by ecological connectivity and wildlife movement. Pagany & Dorner (2019) have studied the impact of crash barriers and fences on wildlife-vehicle collisions using the techniques of artificial intelligence and GIS. The paper has shown the efficacy of spatial models in analysing the transportation-related impacts on the safety of the animals. Palm et al. (2023) have studied the impact of geographic distance, human footprint, and canopy cover on the grizzly bear genetic connectivity.

Tandi and Mishra (2025) revealed the success of deep learning-based anomaly detection methods for recognizing complex patterns in cyber-physical systems, showing that deep learning approaches could be useful in automation of pattern recognition and risk assessment in general. Yan et al. (2026) proposed a framework for ecological security patterns based on clustering and interpretable machine learning, stressing that the use of explainable AI techniques allows to recognize important ecological areas and to manage landscapes sustainably. Yogamadhavan and Mannayee (2024) analyzed deep convolutional networks for vision-based classification tasks and underlined that deep learning architectures can recognize meaningful features in complex visual images.

Taken together, all those studies show that AI models, GIS analysis, and deep learning approaches help to solve ecological monitoring, assessment of habitat connectivity, and

recognition of environmental risks, making possible advanced road barriers mapping and wildlife movements prediction.

Proposed Methodology

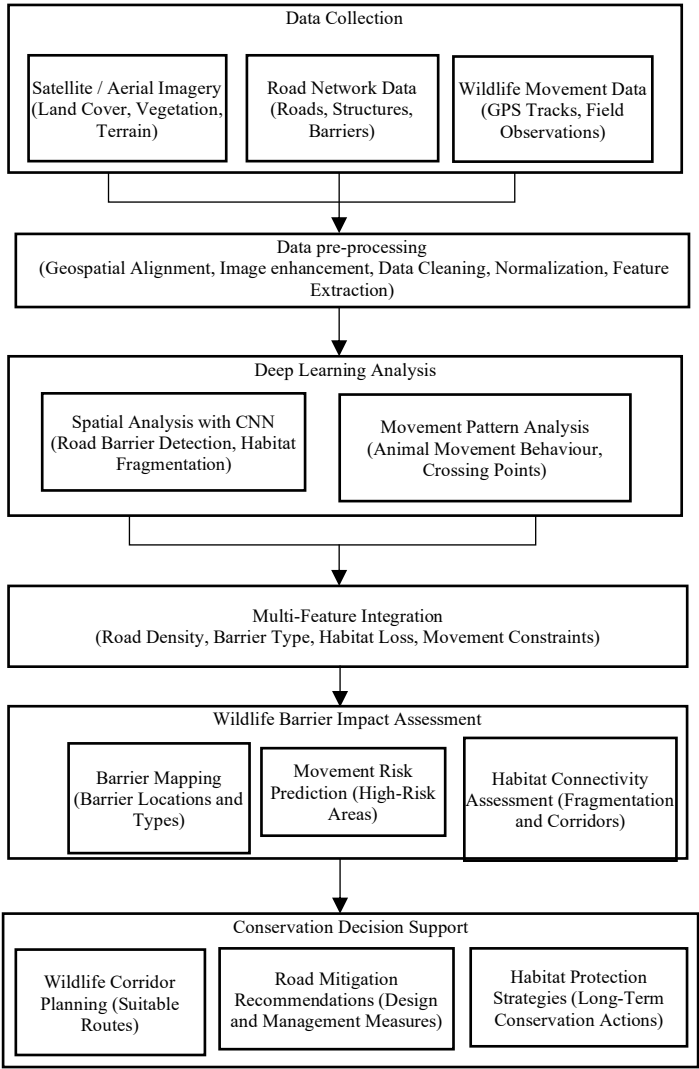


Figure 1: Overall Architecture

Figure 1 provides a framework that incorporates the deep learning approach for analyzing and detecting the road barriers and their impact on wildlife movement patterns. The first step in this framework is the collection of various environmental data sources including satellite imagery, road networks, and movement pattern of wildlife species. These data sources

have the potential to reveal valuable spatial and behavioral data. The collected data is pre-processed in order to enhance consistency in the form of geospatial alignment, image processing, normalization, and feature extraction. This process includes the application of CNN based spatial analysis for detecting road barriers and fragmentation of habitats along with

the analysis of wildlife movement patterns to find crossing behaviors and limitations. These features are used along with other elements including road density, barriers, habitat loss and movement patterns for assessing the overall effect of transportation infrastructure on wildlife movement patterns. This module creates maps of barrier locations, high risk movement zones, and habitat connectivity conditions. It also helps in conservation decisions regarding corridor planning and habitat protection.

Results and Discussion

The effectiveness of the proposed deep learning framework in detecting road barriers, analyzing the constraints in movement of wildlife, and assessing the risks in habitat

connectivity was tested. Barrier detection accuracy, movement risk prediction, and performance in connectivity analysis were some of the elements that were considered during the testing of the model. The model uses the spatial data obtained from satellite images together with other factors.

As evidenced by the findings, the model developed is capable of detecting critical road segments that hinder wildlife movement routes. Spatial analysis using CNN technology was able to detect greater levels of road density, habitat fragmentation, and barrier characteristics based on the environmental information. In addition, movement pattern analysis provided better detection of crossing sites due to variations in wildlife movement patterns.

Table 1: Performance Comparison of Deep Learning Models for Wildlife Barrier Mapping

Model	Barrier Detection Accuracy (%)	Movement Risk Prediction Accuracy (%)	Habitat Connectivity Assessment (%)
CNN	87.4	84.6	82.9
CNN-LSTM	91.2	89.5	87.8
ResNet50	92.8	90.7	89.6
Proposed Deep Learning Framework	96.5	94.8	93.7

From the performance analysis depicted in figure 2 and table 1, it is evident that the deep learning algorithm developed performs better in mapping barriers in terms of accuracy than the traditional approaches. The CNN-based model had an accuracy level of 87.4% for barrier

identification, 84.6% for movement risk prediction, and 82.9% for habitat connectivity assessment, which shows its efficiency in recognizing basic spatial relationships, though poor in understanding complex ecological interactions.

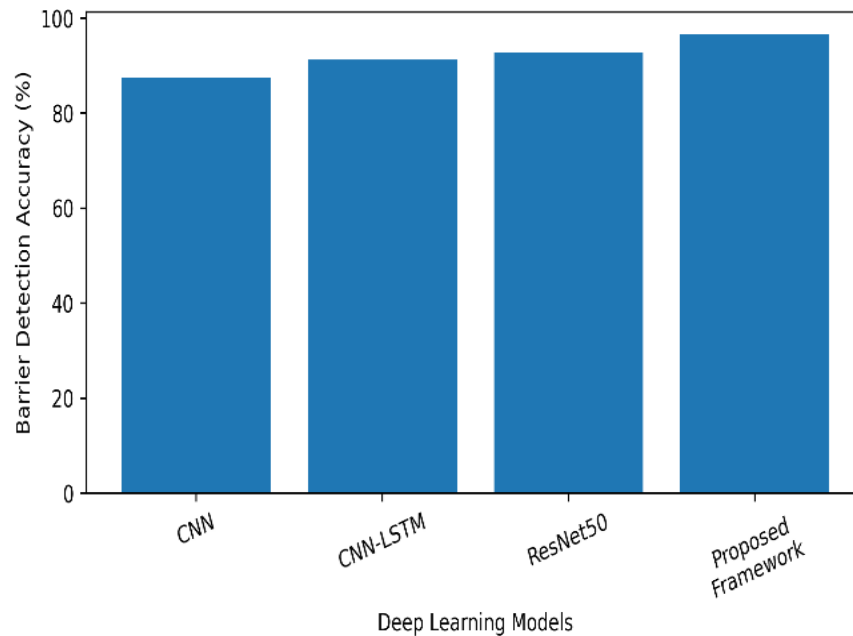


Figure 2: Performance Comparison of Deep Learning Models for Wildlife Barrier Mapping

The CNN-LSTM model enhanced the accuracy of results through the inclusion of temporal sequence learning, resulting in barrier detection accuracy of 91.2%, movement risk prediction accuracy of 89.5%, and habitat connectivity assessment accuracy of 87.8%. Likewise, the use of the ResNet50 model increased the feature extraction ability of the system, leading to 92.8%, 90.7%, and 89.6% accuracy in the three aforementioned tasks, respectively. The proposed model performed significantly better than other baseline models, as it achieved the highest accuracy of 96.5%, 94.8%, and 93.7% for barrier detection, movement risk prediction, and habitat connectivity assessment, respectively. The improvement signifies that the model is able to effectively learn the complex spatial and environmental features involved in the process of barrier detection.

Conclusion

However, construction of roads has been posing major problems in terms of fragmentation of habitat, constriction of movement routes, and increased possibilities of wildlife-vehicle collisions. In this study, a deep learning-driven approach has been proposed for mapping barriers along the road impacting the wildlife movement based on satellite imagery, road network attributes, and wildlife movement data. Such an approach has been able to analyze the spatial and ecological patterns using the deep learning-driven feature extraction method.

According to the evaluation outcomes, the developed model proved to be superior in terms of performance when compared to the current deep learning models, resulting in 96.5% accuracy of barrier detection, 94.8% accuracy of predicting movements risk, and 93.7% accuracy of habitat connectivity assessment. These results suggest that the model is capable of determining

the road segments that disrupt wildlife corridors. Thus, the model offers efficient and reliable ways of planning the preservation efforts of wildlife species through the integration of remote sensing, geospatial analysis, and deep learning techniques. Moreover, the developed framework could be used by wildlife managers and transportation planners for the development of proper mitigations plans, such as wildlife crossings design and other conservation efforts aimed at habitat connectivity improvement. Future studies could consider the inclusion of the data obtained from real-time animal tracking, movement of multiple wildlife species, and environmental factors influenced by the climate change as well as application of explainable artificial intelligence in the development of models.

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