Wildlife Poaching Detection in Karnataka using Machine Learning

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***Abstract*—Karnataka's biodiversity is seriously threatened by wildlife poaching, which puts endangered species like the Indian leopard, tiger, and elephant in jeopardy. Because of resource constraints and the unpredictability of poaching activities, traditional surveillance techniques, such as ranger patrols, are frequently insufficient for keeping an eye on large forest regions. This paper introduces a machine learning-based method that uses animal movement data and dynamic environmental factors and patterns of human activity to forecast high-risk poaching zones. The primary prediction model is a Long Short-Term Memory (LSTM) neural network, which efficiently captures temporal relationships in data to anticipate animal movements and possible hotspots for poaching. The suggested strategy combines temporal data analysis and spatial mapping to improve resource allocation and ranger patrol optimization.Metrics like Mean Squared Error (MSE) and Mean Absolute Error (MAE) support the system's excellent prediction accuracy, which is demonstrated by experimental findings. This approach offers a scalable and adaptable way to support conservation efforts and reduce the danger of poaching in Karnataka's varied ecosystems by utilizing cutting-edge machine learning techniques. For increased accuracy and usefulness, future research will focus on including more environmental parameters and real-time deployment.**
Keywords: Wildlife conservation, poaching detection, LSTM networks, high-risk zones and spatial mapping

I. INTRODUCTION

Karnataka, a state renowned for its rich biodiversity, is home to a wide array of endangered species, including tigers, elephants, leopards, and sloth bears [1]. The state's varied habitats, which range from vast grasslands to deep forests, are home to a wide range of wildlife and are essential to preserving ecological balance [2]. The conservation efforts of Karnataka's national parks and animal sanctuaries, including Nagarhole, and Bhadra, have earned international recognition .wildlife poaching remains a significant and persistent threat.

The illegal hunting, capture, or killing of animals for their valuable body parts—such as ivory, rhino horns, pelts, and bones or even for the exotic pet trade is known as wildlife poaching. Poaching has disastrous effects on both the individual species and the larger ecosystems in which they live. By eliminating keystone species or apex predators, it destabilizes ecosystems, speeds up the loss of species, and upsets food chains [3]. For instance, a surplus of herbivore species can contribute to habitat degradation and overgrazing of vegetation as a result of the fall in tiger numbers [4].

Effective poaching detection is seriously constrained by the size of Karnataka's wildlife reserves and the difficult topography of many protected areas [5]. The scope of the issue is frequently not adequately addressed by conventional wildlife monitoring techniques like physical patrolling and community reporting. The enormous burden of covering vast areas with little manpower and resources is a common challenge for forest rangers . Furthermore, poachers usually modify their tactics to evade discovery, which makes it challenging to anticipate their movements and stop poaching.Poaching persists because of the large financial rewards involved and lax enforcement in remote areas, even in the face of international agreements like CITES (Convention on International Trade in Endangered Species) and laws like the Wildlife Protection Act of 1972, which seeks to protect India's flora and fauna. Therefore, more effective and scalable ways to stop poaching in Karnataka are desperately needed.

Technological developments, especially in the areas of machine learning (ML) and artificial intelligence (AI), present promising instruments for detecting wildlife poaching.The unpredictability of poaching makes conventional approaches difficult, but developments in AI and ML provide game-changing answers. For example, CNNs allow real-time wildlife detection to prevent human-wildlife conflicts [6], while reinforcement learning uses ranger patrol optimization and poaching hotspot prediction [7]. Building on previous strategies, this study suggests a regression neural network that is customized to Karnataka's particular characteristics, improving conservation efforts and precisely forecasting poaching zones. By offering real-time monitoring and prediction capabilities, these technologies can assist in overcoming the drawbacks of conventional approaches [8]. By giving a thorough picture of animal habitats and identifying questionable activity in real time, drones, camera traps, acoustic sensors, and satellite photography can further improve surveillance operations [9].

A more proactive and flexible strategy to poaching detection can be developed by combining these technical tools with conventional conservation techniques. This could improve the general management and protection of Karnataka's abundant wildlife in addition to lowering the number of poaching events [10].

II. Related Work and Literature Survey

Together, the studies examine how AI and machine learning The papers collectively explore the application of AI and machine learning (ML) in wildlife conservation.

Rajeswari et al. proposed that reduces conflict between humans and wildlife and stops animal incursions by automatically detecting and classifying wildlife using convolutional neural networks (CNNs). Their study concentrated on real-time detection with a Raspberry Pi running the MobileNet-SSD model. Although insufficient lighting remains a barrier to achieving dependable detection accuracy, the model's exceptional detection accuracy demonstrated its potential for wildlife monitoring in controlled environments [6].

Doull et al. investigate The use of machine learning and drones to enhance attempts to detect poachers. The study looks at several factors that affect detection accuracy, including camera types (thermal vs. RGB), time of day, and environmental features like canopy density. The results demonstrate that, particularly at dawn and twilight, thermal cameras significantly boost detection rates when paired with machine learning for automated analysis. High false positive rates and the requirement for extra learning systems, however, continue to be problems.The necessity for improved prediction models that could foresee animal movement and poaching activities [5].

Abrahms et al. developed a framework for understanding "resource tracking", a habit that improves an animal's chances of survival and fitness by allowing it to monitor the availability of resources throughout time and geography. The study proposed a prediction model for the way animals respond to changing resources, which impacts ecosystem interactions and population dynamics. They advocated more empirical study across a variety of species and habitats to reinforce this paradigm by combining Landscape Ecology with Optimal Foraging Theory (OFT) [2].Enhancing predictions about animal movement patterns.

PLOS ONE et al. examined the the modeling and prediction of animal movement patterns using machine learning (ML) techniques. The study employed a number of machine learning methods, including supervised learning (decision trees, SVMs, and neural networks), reinforcement learning, and clustering. The results show that machine learning works better than traditional methods in recognizing complex, non-linear patterns in animal locomotion. According to the study, machine learning provides fresh insights into animal behavior despite challenges including the need for a lot of labeled data and high processing needs [3]. Wildlife conservation directly benefits from such developments in movement prediction, especially in systems like Movebank that handle enormous datasets.

Kays et al. outlined the Animal movement data from more than 6,500 research on more than 1,100 species may be managed and analyzed using the Movebank system, a global platform. Movebank supports substantial ecological and conservation research by evaluating high-resolution tracking data and environmental variables using a combination of machine learning, clustering, and big data techniques. The data can be contextualized and analyzed by non-programmers thanks to features like EnvDATA and MoveApps. Movebank makes a substantial contribution to conservation by providing insights on migration patterns, species responses to climate change, and the management of endangered species, despite difficulties with data integration and scale. [11]. Systems like PAWS expand on these frameworks to improve field operations as data becomes more important.

Lily Xu et al. highlighted By anticipating high-risk locations for poaching, the data-driven PAWS (Protection Assistant for Wildlife Security) system improves the effectiveness of ranger patrols in protected areas. In order to support patrol planning and fight the illegal wildlife trade, PAWS employs optimization and machine learning techniques, including reinforcement learning, Gaussian processes, and multi-armed bandits. The study showed scalability and a 30% boost in snare detection using field data from Cambodia's Srepok Wildlife Sanctuary and Uganda's Murchison Falls and Queen Elizabeth National Parks. Despite obstacles like insufficient data and the erratic behavior of poachers, PAWS offers a scalable approach for making well-informed patrol judgments in data-scarce environments [7]. The predictive models used to investigate species mobility, as investigated in animal migration research, are further improved.

Clark et al. explored In order to enhance conservation efforts addressing population fragmentation and inbreeding issues, predictive modeling approaches are being used to track the migratory trajectories of the Louisiana black bear. The study examined the effects of landscape factors, such as proximity to agricultural areas and natural land cover, on bear mobility using GPS collar data from 31 bears. Movement patterns were examined using machine learning approaches such as Random Forests. The study discovered that while natural land cover and distance from agricultural regions are strong predictors of bear migrations, roads impede gene flow and reduce genetic diversity [12]. The significance of using machine learning into wildlife monitoring and behavior prediction systems is highlighted by this method of tracking animal activity.

Gendron et al. developed a model that predicts social animal behavior in zoo environments by integrating causal structure discovery with graph neural networks (GNNs), with a focus on meerkats. With more realistic group action simulations and improved interpretability, the model performs better than conventional deep learning techniques. The study provides a useful foundation for behavioral modeling, promoting conservation efforts and improving zoo animal wellbeing in spite of obstacles including skewed data . The model's ability to explain social behaviors and environmental conditions is improved by the application of causal discovery [9]. By providing a deeper understanding of animal behavior and its interactions with the environment, this sophisticated modeling approach helps to improve wildlife conservation initiatives.

TABLE I
LITERATURE SURVEY

Author	Objective	Methods	Results	Limitation	Advantages
Rajeswari et al. [6]	To develop a system that automatically detects and classifies wildlife using CNN models and alerts.	CNN model MobileNet-SSD, deployed on Raspberry Pi.	High detection accuracy for clear images, 80–90% for partially observed.	Challenges with cluttered backgrounds and high false-positive rates.	Useful for real-time wildlife detection.
Katie Doull et al. [5]	Investigate the factors that increase the success of drones in detecting poachers, using automated and manual analysis.	RGB, Thermal (TIR) imaging; Generalized linear models.	TIR was more effective at dawn, RGB during the day. Automated detection accuracy was 55.8%.	High false-positive rate in automated detection; manual analysis is time-consuming.	Supports drone-based anti-poaching efforts.
Briana Abrahms et al. [2]	To present a framework for understanding resource tracking and its impact on animal movement.	Optimal Foraging Theory (OFT).	Understanding how animals track resource availability.	Limited application across all species; needs more empirical testing.	Supports biodiversity conservation.
PLOS ONE et al. [3]	To explore how machine learning can model animal movement patterns.	Decision trees, neural networks, SVM.	Significant improvements in predicting animal movement.	Limited availability of high-quality labeled data.	Helps predict movement under varying conditions.
Kays et al. [11]	To provide a global system to collect, manage, and analyze animal movement data.	Machine learning models, clustering, decision trees, PostgreSQL for data management.	Improved collaboration and data sharing across global teams.	Challenges with data integration.	Aids large-scale ecological research.
Lily Xu et al. [7]	To develop the PAWS system to help rangers detect snares efficiently using optimization and reinforcement learning.	Uses MIRROR algorithm, reinforcement learning.	Increased snare detection by 30%.	Limited by small sample sizes and data gaps.	Optimizes resources for wildlife conservation.
Clark et al [12].	Predicts Louisiana black bear movements using machine learning to address inbreeding and population fragmentation.	LSTM and Random Forest.	Land cover and agriculture affect bear movement.	Limited by small sample sizes.	Aids in wildlife movement prediction.
Gendron et al. [9]	Models behavior using causal discovery and graph neural networks to predict individual and group actions in zoos.	Uses graph neural networks.	Improved behavior predictions and zoo insights.	Limited data hinders performance in uncontrolled settings.	Enhances understanding of animal behavior.
Benjamin Kellenberger et al. [13]	Fast CNN-based animal detection for UAV images.	Two-branch CNN, Namibia UAV dataset, vs. Fast R-CNN.	Precision: 0.60, Speed: 73 Hz (vs. Fast R-CNN: 0.34, 2.96 Hz).	Lower recall, small dataset.	Real-time, high precision, simplified design.
Sachini Kuruppu et al. [14]	Detect poachers using AI	YOLOv5, LoRa, Raspberry Pi	Real-time weapon detection	Dataset size, environmental limits	Low-cost, real-time detection.
Anika Puri , Elizabeth Bondi et al. [15]	Improve human/animal detection	Spatio-temporal models, KNN	90.9% accuracy	High computational needs	High accuracy, real-time potential

III. PROPOSED METHODOLOGY

The proposed method uses a machine learning approach to predict animal movement trajectories and identify high-risk poaching zones in an effort to detect and reduce wildlife poaching in Karnataka. Using sophisticated modeling techniques and spatiotemporal data, the system integrates the following strategies and tactics:

A. Data Collection and Preprocessing:

This investigation is based on high-quality animal movement data that was gathered using GPS-enabled tracking devices.The first step is to gather the combined animal and environment (habitat) dataset from the source [1]. Time stamps, latitude, longitude, and habitat type are among the details included in this data. A crucial component of this study is the "habitat" column, which provides a dynamic yet simplified representation of the natural conditions in which the creatures were found. This data's preprocessing included eliminating superfluous features and using interpolation to tidy up noisy or missing values. In order to get the dataset ready for model training, categorical variables, like habitat kinds, were converted into numerical representations and numerical characteristics were normalized for uniformity. This guaranteed that the data was machine-readable and tidy, which served as the foundation for precise forecasts.

B. Feature engineering:

Feature engineering focused on deriving spatio-temporal features, such as daily and seasonal patterns, and transitions between habitat types to capture the relationship between habitat dynamics and animal movements. This enhanced the model's predictive accuracy for detecting poaching threats.This improved the predictive accuracy of the algorithm for identifying poaching threats by allowing it to recognize important animal movement patterns. Predictions were further improved by incorporating environmental variables as weather, vegetation density, and closeness to water sources. Spatial hotspots and temporal trends in poaching activities were also identified by analyzing historical data on patrol routes and poaching occurrences. The model's capacity to anticipate possible poaching dangers was enhanced by these combined efforts, guaranteeing prompt action and improved animal conservation tactics.

C. Data Analysis :

For the purpose of training the LSTM-based RNN model, the data analysis procedure effectively produced clean, organized, and feature-rich datasets. It provided valuable information about the spatial patterns, movement habits, and environmental effects of animals, laying a strong basis for predictive modeling. Real-time data streams and sophisticated anomaly detection techniques may be included into future analysis to further enhance data quality and forecast accuracy.

D. Detailed Explanation of Methods and Techniques Used:

- Recurrent Neural Networks (RNNs) - To predict animal movement trajectories,Recurrent Neural Networks (RNNs) were used as the foundation architecture to forecast animal movement trajectories. Nevertheless, vanishing gradients and other problems plague conventional RNNs, making it difficult for them to identify long-term connections in data.The ability of a Regression Neural Network (RNN) to handle time series data efficiently makes it useful for predicting animal movements and areas of high-risk poaching. Historical movement and environmental data are used to train the model This was addressed by the study using Long Short-Term Memory (LSTM) networks, a sophisticated kind of RNN made to get around these restrictions.
- Long Short-Term Memory (LSTM) - LSTMs are perfect for examining patterns over time because they were used to interpret sequential animal movement data. The LSTM model was composed of several layers: LSTM layers to capture dependencies in sequential data came after an input layer to receive spatiotemporal data. To preserve long-term dependencies and weed out extraneous data, these layers employ specialized memory cells and gates (input, forget, and output gates). By randomly turning off neurons during training, dropout layers were introduced to lessen overfitting. It was possible to identify movement patterns and poaching hotspots by using the output layer's predictions for future animal positions. Since poaching actions involve temporal dependencies that are impacted by seasonal and regional patterns, the LSTM methodology is especially well-suited for this application. Poaching, for instance, may rise in regions close to water supplies or during particular months. This approach makes it possible to reduce the risks of poaching in Karnataka's woods by proactive intervention and effective resource allocation. LSTMs were specifically selected due to their capacity to preserve both short- and long-term patterns in the data.Dropout layers enhance the model's capacity for generalization by randomly deactivating neurons during training to avoid overfitting. Accurate trajectory forecasts are made possible by the output layer, which uses a linear activation function to give projected coordinates for animal movement. With Mean Squared Error (MSE) and Mean Absolute Error (MAE) as performance metrics, the model was trained using the Adam optimizer, guaranteeing accurate and trustworthy predictions.

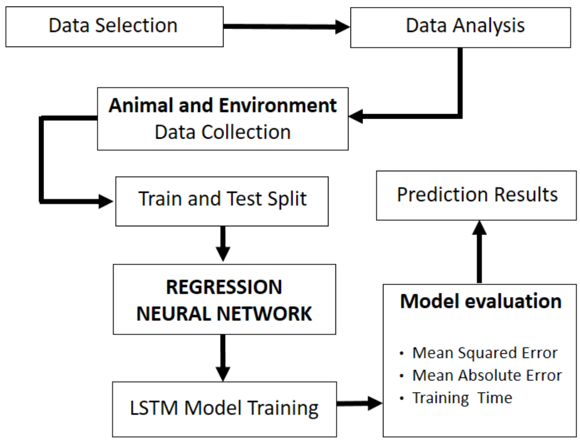

Fig. 1. System Workflow

- High-Risk Poaching Zone Identification - Animal trajectories were projected in order to determine the areas that were most susceptible to poaching. Heatmaps were created by charting these trajectories and superimposing habitat data on top of them to show regions with strong animal activity. By highlighting animal movement zones, these heatmaps made it possible to identify high-risk locations for poaching.
- Performance Metrics - The performance of the RNN, specifically the LSTM model, was assessed using two key metrics: Mean Absolute Error (MAE) and Mean Squared Error (MSE). These metrics are particularly well-suited for RNN-based models as they effectively quantify the accuracy of sequential data predictions. MAE

provides a straightforward measure of the average error in trajectory predictions, while MSE emphasizes larger errors by penalizing them more heavily, ensuring robust performance in identifying potential poaching hotspots. The Adam optimizer, which is renowned for its flexible learning rate capabilities and allows for faster convergence during training, was used to optimize the network. Mean Squared Error (MSE) and Mean Absolute Error (MAE) were used to assess the model's performance, making sure that both minor and major errors were appropriately recorded and penalized. Dropout layers, which randomly deactivate neurons during training to enhance generalization performance, were added to lessen overfitting.

IV. Results and Discussion

A. Spatial Mapping for Identifying Wildlife Activity Hotspots:

Analysis of mammal occurrence data from the Sakleshpura region of the Western Ghats, represented by heat maps, provided important information to improve ranger patrol tactics. Animal activity could be mapped in great detail because to data gathered between 2022 and 2024 that contained exact timestamps, latitude, longitude, altitude, GPS precision, location names, and habitat kinds. Certain high-density zones of animal presence are visible in the heatmaps as depicted in the fig.2, especially in environments like tea plantations and forest margins, where species like the Indian Hare are commonly seen. Areas with high wildlife activity and possible vulnerability to poaching were successfully identified by superimposing habitat data with mapped animal occurrences. Priority areas for concentrated patrol operations were indicated by the concentration of data points and color gradients (blue denoting low activity and red denoting high activity). Rangers can evaluate high-risk poaching areas by visualizing the model's predictions on maps with environmental factors superimposed on projected animal pathways after it has been confirmed. To ensure that ranger teams focused their efforts where they were most needed, high-activity areas, such those around tea plantations and forest borders, were given priority for routine monitoring.

The results show that integrating habitat mapping and spatial data analysis can greatly improve patrol efficiency, reduce operating time, and improve the overall effectiveness of wildlife conservation programs.In biodiversity hotspots like the Western Ghats and thick vegetation can make conventional monitoring techniques difficult, such approaches are especially beneficial.

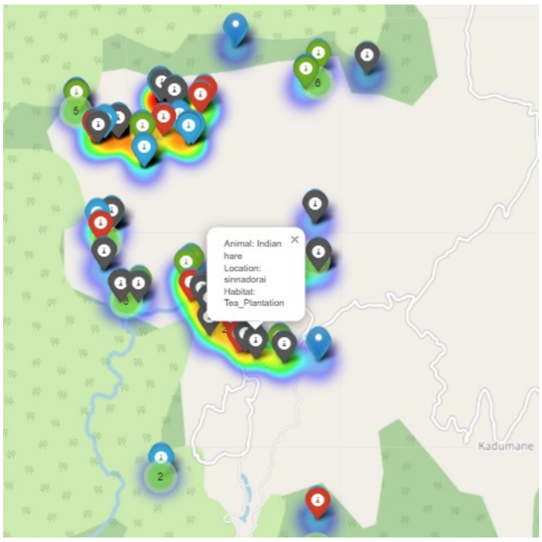

Fig. 2. Heatmap of Indian animal sightings across habitats

- Training and Validation Loss (MSE) - One important performance indicator for assessing the predictive accuracy of the LSTM-based Regression Neural Network (RNN) is the Mean Squared Error (MSE) loss. Significant early prediction mistakes were indicated by the MSE loss, which began the training process at a comparatively high value of roughly 0.26. The loss values steadily stabilized as training went on, and by the conclusion of 50 epochs, the training and validation MSE losses had converged to roughly 0.03.The model successfully minimized the squared prediction errors and captured the underlying patterns in the temporal data, resulting in a final stabilized MSE loss value of 0.03.

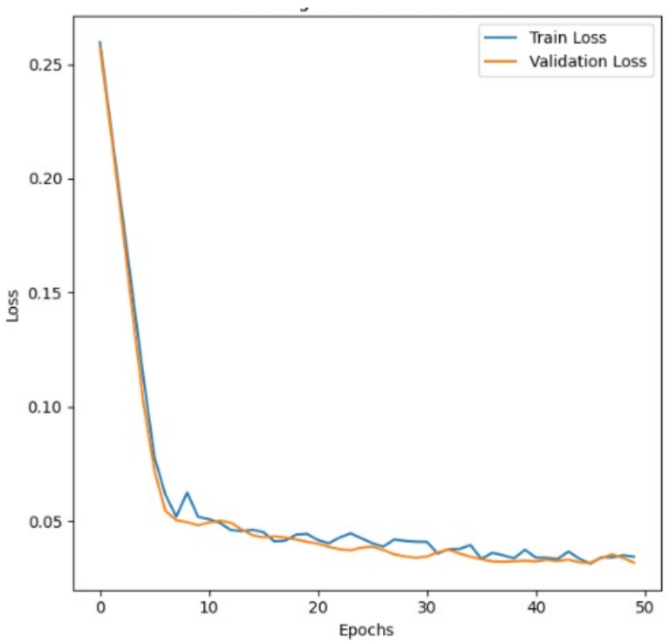

Fig. 3. Mean Squared Error (MSE)

B. Performance and Accuracy:

Mean Squared Error (MSE) and Mean Absolute Error (MAE) were the two main metrics used to assess the performance of the LSTM-based Regression Neural Network (RNN), offering information on the precision and dependability of the model's trajectory predictions for animal motions.

- Training and Validation Mean Absolute Error (MAE) - A significant performance indicator for evaluating the LSTM-based Regression Neural Network's (RNN) predicted accuracy is the Mean Absolute Error (MAE). The MAE value at the beginning of training was noticeably high, at about 0.46, suggesting significant initial prediction errors in the estimation of animal movement trajectories. But since the model quickly picked up useful temporal patterns from the sample, the MAE significantly decreased throughout the first ten epochs. Both the training and validation MAE curves stabilized as training went on, with the validation MAE obtaining a little lower value of about 0.13 and the final training MAE reaching about 0.15. The model successfully avoided overfitting and showed high generalization abilities on unseen data, as indicated by the small gap between these two curves.

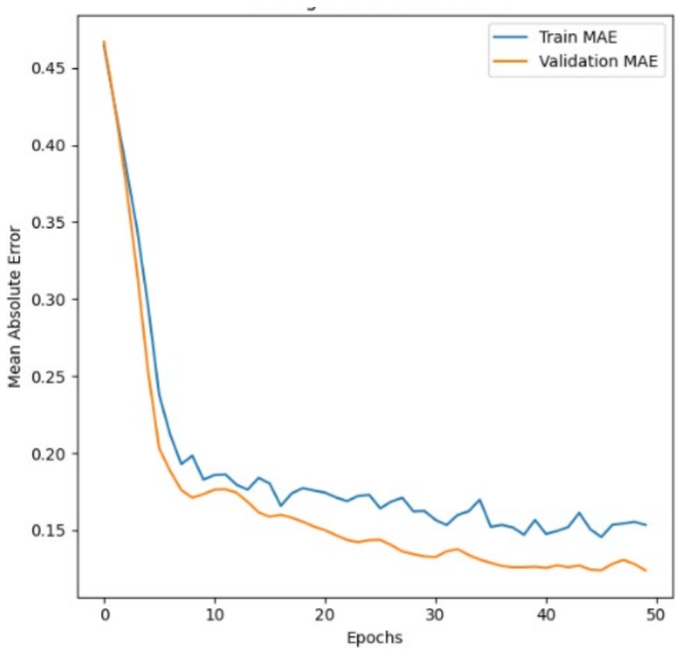

Fig. 4. Mean Absolute Error (MAE)

C. Predicted Likelihood of Poaching and Risk Assessment:

The model predicts the likelihood of poaching for identified high-risk zones. For instance, in one specific area, the model output shows:

TABLE II
POACHING LIKELIHOOD PREDICTION

Description	Value
Predicted Likelihood of Poaching	0.6122
Percentage of Poaching Likelihood	61.22%

The suggested approach accurately forecasts the probability of poaching in designated high-risk areas. The model determines each hotspot's probability and percentage of poaching by examining environmental data and animal movement patterns.By quantifying the risk level High-risk locations with probabilities more than 60% are marked as critical, such as more ranger patrols and improved surveillance. Conversely, regions with lower odds can be observed but do not require immediate assistance. This probabilistic method guarantees effective resource distribution by concentrating on areas that require the greatest care.

TABLE III
MODEL TRAINING AND VALIDATION METRICS

Metrics	Training	Validation	Testing
Mean Squared Error (MSE)	0.0323	0.02995	0.0328
Mean Absolute Error (MAE)	0.1532	0.1204	0.1248

TABLE IV
MODEL PERFORMANCE COMPARISON

Model	MSE	MAE
Decision Tree	0.0428	0.1585
Random Forest	0.0406	0.1579
Neural Network	0.0423	0.1636
LSTM	0.0328	0.1248

The Model Performance Comparison table compares the performance of four machine learning models: Decision Tree, Random Forest, Neural Network, and LSTM, using Mean Squared Error (MSE) and Mean Absolute Error (MAE). These measures assess the accuracy of the models, with lower values indicating improved performance. In this comparison, the LSTM model outperforms the others by having the lowest MSE and MAE. The table shows that LSTM is better suited to accurate predictions than the other models, especially when dealing with time-series or sequential data.

V. CONCLUSION AND FUTURE WORK

A machine learning-based approach to forecast animal movement patterns and pinpoint high-risk poaching areas in Karnataka's varied ecosystems was successfully built by the study. Through the integration of dynamic environmental variables with animal tracking data, the system showcased the possibility of using sophisticated LSTM-based Regression Neural Networks (RNN) to tackle issues in wildlife conservation. Combining spatial and temporal data is crucial for understanding animal behavior and improving anti-poaching tactics, as the approach demonstrated. Through better resource allocation and data-driven insights, this study highlights how machine learning models may support conservation efforts. There is still room for improvement in the system's integration of environmental features and alignment of temporal data, despite its encouraging findings.Overall, the study offers a flexible and scalable platform for tracking wildlife.

Future Work aims to increase the prediction accuracy of the LSTM-based RNN system by adding more environmental parameters, such as seasonal patterns, weather changes, and terrain-specific characteristics. To reduce inconsistencies and enhance consistency, the temporal synchronization between environmental and animal movement data will be improved. Improved resilience and generalization will be achieved by enlarging datasets to encompass a wider range of species, greater geographic regions, and extended observation times. Furthermore, improving spatial mapping tools with cutting-edge GIS interfaces will yield more lucid visual depictions of animal paths and high-risk areas. Last but not least, guaranteeing the system's scalability and flexibility across various ecosystems will increase its application and make it a more dependable instrument for anti-poaching and wildlife conservation initiatives.

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