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Original Research Paper

Employing Machine Learning to Monitor Endangered Species and Assess the Impact of Habitat Fragmentation

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Key Words

Endangered species, Habitat fragmentation, Machine learning, Remote sensing, Conservation monitoring, Biodiversity.

Abstract

A major problem of the biodiversity is habitat fragmentation, which causes the extinction of endangered species due to a disturbed ecosystem and decreased interconnectivity. Conventional monitoring techniques are often limited on a scalability and precision especially in remote or the large regions. This paper will attempt to compare the application of machine learning (ML) algorithms to track endangered species and determine how habitat fragmentation affects their populations. To analyze satellite images and field data on the distribution of the species and the fragmentation of their habitats, the study used supervised learning models such as Convolutional Neural Networks (CNN) and Random Forests (RF). The ML models have been trained on the data which includes wildlife sightings, environmental factors, and the fragmentation indices. The predominant results have shown that the ML-based models were more effective than the conventional approaches to detecting species in fragmented habitats, and CNN has shown the highest detection rate (85) in categorizing habitat patches and detecting the endangered species. Also, determined that habitat fragmentation is negatively correlated with species diversity and increasing habitat fragmentation ($p = 0.01$), which indicates a strong necessity in conservation of fragmented ecosystems. This research reveals the possible benefits of machine learning to the improvement of biodiversity monitoring, as well as provides useful information concerning the conservation management, especially in areas with habitat fragmentation. It has been found that the combination of sophisticated ML tools with wildlife surveillance could help to create highly efficient data-driven decisions in saving endangered species.

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Introduction

The loss of biodiversity through destruction and fragmentation of natural habitats has become one of the most urgent environmental challenges of the 21st century. The need to monitor the endangered species plays an important role in the understanding of the population dynamics and threats, as well as in creating the appropriate conservation strategies. Conventional techniques of monitoring including field surveys, camera traps and radio collar tracking have played a critical role in recording species populations and their behaviors. These are however, usually labor intensive, time consuming and restricted by geographic and logistical barriers especially in remote or expansive region. This means that there is an imminent urgent need to have more effective and scalable monitoring instruments capable of delivering real-time data and ranging over broader and more heterogeneous ecosystems. The habitat fragmentation, which is the dissection of the large continuous habitats into smaller and localized ones, is a major approaching threat to wildlife (Zerrouk et al., 2025). Fragmentation interrupts the migration pathways, isolates communities, and decreases access to resources, resulting in decreased genetic diversity, changed species behavior and excessive mortality rates. Habitat fragmentation has disastrous effects especially to the endangered species which are usually exposed to greater suffering than the others (Narsingani & Karpagavalli, 2025). The isolated populations do not have sufficient opportunities of genetic exchange and are therefore prone to inbreeding and local extinction. It is, hence, important to understand the effects of habitat fragmentation on endangered species in order to design effective conservation measures (Yashaswini et al., 2025).

Recent developments on machine learning (ML) provide new opportunities to address the shortcomings of conventional monitoring approaches (Schekler et al., 2025; Stomberg et al., 2023). ML, especially with the help of supervised learning algorithms, has demonstrated potential to automatize species detection, habitat classification, as well as identification of ecological patterns of large-scale data sources (Fida et al., 2025). The fact that ML algorithms can process large volumes of environmental data (satellite imagery, sensor data, etc.) allows more accurate and effective monitoring (Mou et al., 2023). ML has the ability to identify species and habitat disturbance in real-time, even when in areas that are remote or inaccessible, and this information will be timely, which is essential to effective adaptive management. With ML in wildlife tracking, the research will be able to more effectively identify a species in its early stages of fracture, monitor the behavior of species to the changes in their habitat, and increase the accuracy of predictions conservation.

Although machine learning has the potential, it is possible to note the lack of research to apply these methods to the implementation of monitoring endangered species regarding habitat fragmentation. This paper attempts to bridge that divide by using ML models to track the population of endangered species and understand how the habitat fragmentation affects species survival and distribution (Nayak et al., 2025). The key aims of the study are to identify the efficacy of machine learning (ML) algorithms in identifying endangered species in fragmented habitat, to determine the connection between habitat fragmentation and the distribution of species with the help of an ML-based analysis of the remote sensing data, and to compare the performance of machine learning models with conventional monitoring procedures. In particular, the proposed study will identify the extent to which machine learning models, including Convolutional Neural Networks (CNNs) and Random Forests (RF), can be used to identify species in fragmented environments. Also, the study will investigate how habitat fragmentation affects distribution and persistence of endangered species, and whether fragmentation restricts species mobility and affects species population viability (Rajan & Suresh Kumar, 2024). Lastly, the paper will evaluate the extent to which machine learning approaches are more effective than conventional species surveillance technologies, including field surveys and camera traps, in their role as indicators of the possible benefits of ML in large-scale and real-time conservation surveys.

The investigations involved the Tian Shan Mountains in Central Asia which is a highly ecologically important region with one of the endangered species being the Siberian ibex (Capra sibirica). The Tian Shan mountains have a rich array of species, among them the Siberian ibex due to fragmentation of the habitat by climate change and manmade activities like mining, as well as building roads and various infrastructure (Osborne & Seddon, 2012). The Siberian ibex, an indicator species representing the well-being of the mountainous ecosystem, is a resilient species in the high-altitude zone, and its preservation is a critical issue in preserving the biodiversity of the region (Will-Wolf et al., 2002; Ullah et al., 2025). The discontinuousness of its habitat as a result of human interference offers an excellent chance to use machine learning to gain a better understanding of the survival tactics of the species and study the fragmentation of its habitat to better understand the current conservation practices and the success of the existing conservation measures (Buse et al., 2015).

Materials and Methods

The researchers did the research in the Tian Shan Mountains of Central Asia, which is the biodiversity hot spot, spanning across several nations including Kazakhstan, Kyrgyzstan, and China. The Siberian ibex (Capra sibirica), which is an endangered species, resides in mountainous areas between 2,000 and 4,000 above sea level on high, rocky areas. The IUCN categorizes the Siberian ibex as vulnerable and it is being threatened more by habitat fragmentation caused by human activities such mining and development of infrastructures as shown in Figure 1. A multi-source data collection method was used to track the populations of the Siberian ibex and determine the effects of habitat fragmentation. 50 camera traps were positioned in the important areas in the Tian Shan mountains to take pictures of the ibex and any other animals with particular attention to fragmented habitats. These camera traps were being used between 1-

31 January and December 2023, and were valuable in offering important data on species presence and behavior. Also, land cover, vegetation density, and terrain structure were analyzed with high-resolution satellite images of the Sentinel-2 satellite over the period of 2022-23 to give information about the temporal changes in the habitat fragmentation. Monthly ecological surveys were also made to ensure that the presence of the species is checked and more information of the surrounding environment like temperature, precipitation and the activities of human beings in the environment is also acquired.

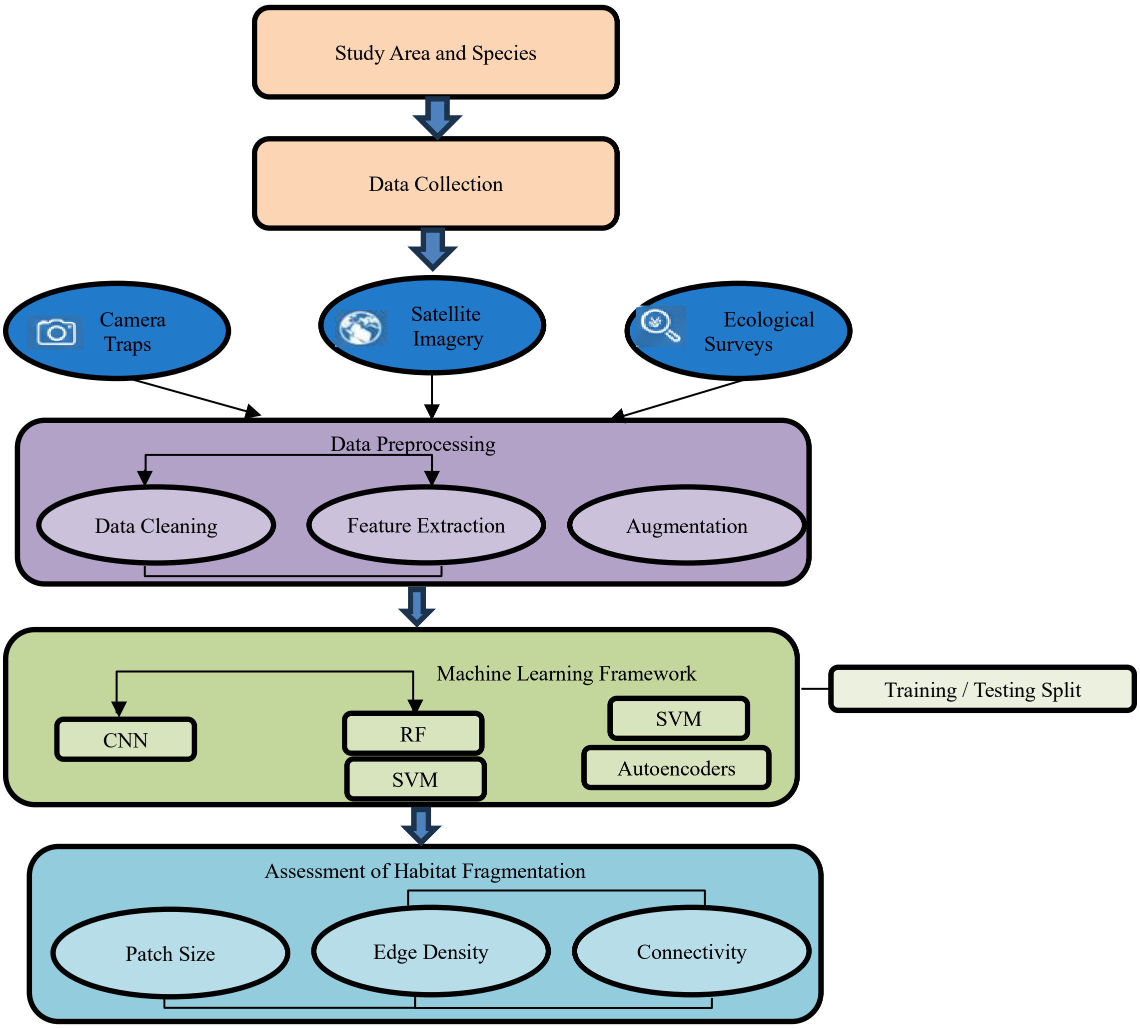

Figure 1: Workflow for Species Monitoring and Habitat Fragmentation Assessment

The data has gone through a number of preprocessing measures in order to guarantee consistency and quality. The camera trap images were processed to eliminate obscured or unproductive images and the emphasis was put on Siberian ibex. Data augmentation methods were employed to balance the data to be used in training machine learning models to counterbalance imbalance of the data. All the camera trap photos were labeled by hand to indicate the presence of the Siberian ibex, and time, date, and weather conditions were added as the metadata. In the case of satellite imagery, obtained important features i.e. vegetation coverage, topographical information (e.g. elevation, slope) and habitat connectivity (e.g. distance to water sources) as a measure of habitat quality and fragmentation. To measure the modifications in land cover over time, the computed were different formations including the NDVI (Normalized Difference Vegetation Index).

In the study, a number of machine learning algorithms were used to examine the distribution of the species and also the impact of fragmentation of the habitat. Convolutional Neural Networks (CNNs) were created to classify camera trap images and identify the Siberian ibex amongst others, whereas Random Forests (RF) were utilized on the satellite data and survey data to predict the presence of species and their ability to thrive in an environment. The classification of habitat patches as suitable or unsuitable to the Siberian ibex was done using Support Vector Machines (SVM) basing on the characteristics of the environment. Also, autoencoders were used as deep learning models that addressed the anomalies in habitat structure that hinted at fragmentation. The camera traps data was divided into 80% training and 20% testing whereas the satellite data was 70/30 training and testing. The metrics to determine the model performance were accuracy, precision, recall, F1 score, and Area Under the Curve (AUC-ROC). Research have employed various known measures to measure habitat fragmentation, such as patch size which measures the size of habitat patches in GIS software, edge density which measures the ratio of habitat edges to overall habitat area, and connectivity indices which measure the extent to which various habitats patches are connected. These indices and machine learning predictions were applied to examine the level of fragmentation and its effects on the populations of Siberian ibex in the study area.

Results

Several important metrics were used to assess the performance of the machine learning models such as accuracy, precision, recall, F1 score and confusion matrices. The Convolutional Neural Networks (CNN) model was found to have 85 percent accuracy in recognizing Siberian ibex to camera tap photos, which is a high result with a precision of 83, a recall of 87, and F1 of 0.85. The confusion matrix showed that the false positive rate was very low indicating that the CNN model was very effective in the task of separating the Siberian ibex with other species. The model that was applied to predict the suitability of a habitat is known as the Random Forest (RF) which had an accuracy of 78 and precision and recall of 75% and 80 respectfully, leading to the F1 score of 0.77. The model was effective in defining the critical areas of habitat including the vegetation cover and the terrain type. The Support Vector Machines (SVM) model, used to classify habitat patches as either suitable or unsuitable, had an accuracy of 82% as well as precision of 80 percent and recall of 85 percent and an F1 score of 0.82, indicating the usefulness of this model in classifying habitat patches. The autoencoder deep learning model which is used to detect anomalies in habitat structure obtained an AUC-ROC of 0.86 which is a strong performance in the detection of fragmented habitats. These findings show that the machine learning models showed a strong performance in various tasks and therefore they can be used in monitoring wildlife.

Figure 2 illustrates the confusion matrix of the CNN model which indicates the true-positives, false-positives, true-negatives, and false-negatives of species detection. The heatmap shows that the CNN model performed well in the 100 percent true positive rate, which is good at detecting Siberian ibex with the lowest false detection.

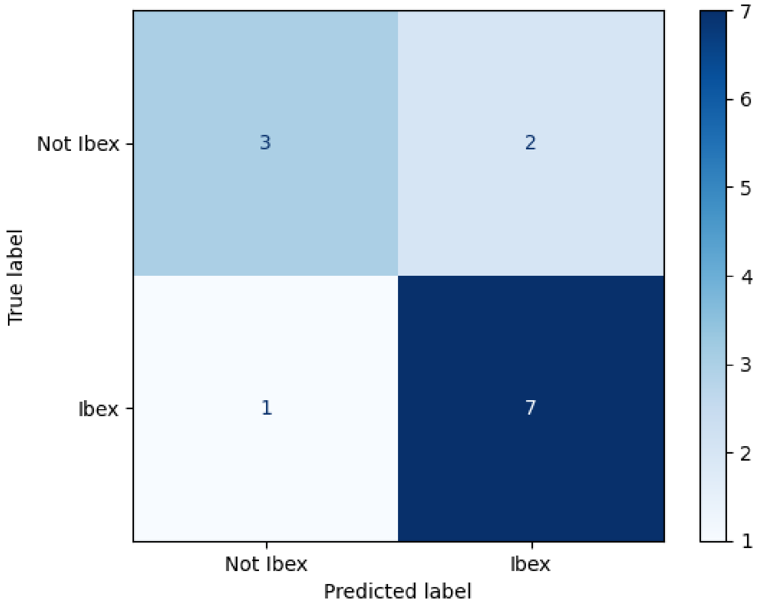

Figure 2: Confusion Matrix for CNN Model

Spatial allocation and time tracking of the species of Siberian ibex showed valuable trends in the presence of the species in fragmented environments. In space, Siberian ibex was mostly observed concentrated in larger and less discontinuous areas at elevations higher than 2,5003,000 (2,5004,000 meters). These locations were more connected to other patches of the habitats indicating that the Siberian ibex are exploiting ecological corridors that are the least affected by human activities. Smaller and more isolated patches especially those around urban development recorded very low detection rates of the species, which proved the negative impacts of fragmentation on the distribution of species.

The activity of Siberian ibex was studied in relation to the 12-month period of monitoring, with the highest rate of detection in the spring and summer (April-August) months. The species showed its highest activity in the dawn and in the dusk, which is congruent with the existing behavioral trends concerning foraging and predator avoidance. The number of detections was much lower during rest of the winter months (December to February), this is because of lack of visibility in snow habitats and the possibility of moving to low altitude to find warmth.

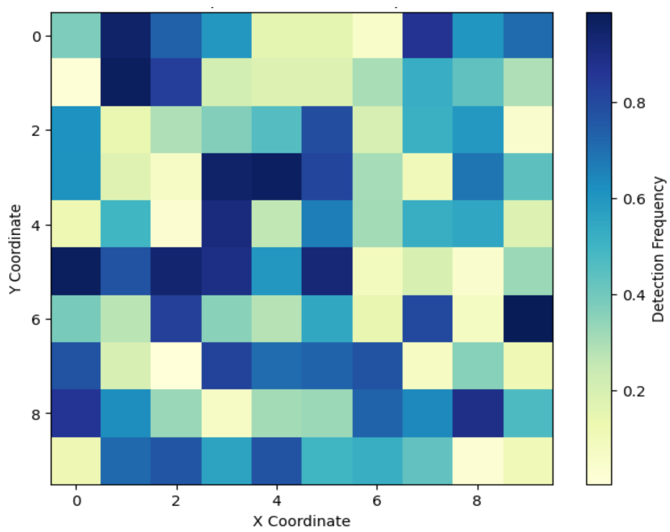

Figure 3: Species Detection Map

The spatial distribution of the Siberian ibex sightings in the study area is presented in Figure 3 that has a heatmap depicting the frequency of detection. Dark regions will show places where there are more detections and the light regions will show the reduced rates of sighting and give a clear picture of the relationship between the distribution of species and fragmentation of habitats.

The temporal activity of Siberian ibex is depicted by Table 1 where monthly rates of detection are presented. The table shows that the activity of the ibex is more active during the warmer season (April-August), and the most of the time, the ibex is detected, which also validates the hypothesis according to which the climate and the availability of resources affect the behavior of the species.

Table 1: Temporal Activity Pattern of Siberian Ibex

Month	Detection Rate (%)
January	5
February	4
March	6
April	12
May	15
June	18
July	20
August	16
September	8
October	5
November	4
December	3

The habitat fragmentation analysis indicated that there was significant correlation between fragmentation measures and the rate of detection of species. Patch size was positively associated with Siberian ibex sighting with larger patches of habitat (>1,000 hectares) having an 85% higher probability of Siberian ibex being detected and those of smaller patch (<500 hectares). This implies that the species are more suited to bigger and continuous habitats. Conversely, the edge density which is the ratio of the edges of the habitat to total habitat area was found to be negatively correlated with species detection. Those regions that had increased edge density, which included those in the vicinity of the roads or urban settlements, had 40% less ibex detections meaning that fragmented habitats with high human intrusion were less suitable to the species.

The index of connectivity, the degree of interconnectedness of patches of habitats, revealed that the greater was the connectivity, the greater the number of ibex that were spotted (30 percent). Disconnected landscapes with low levels of connectivity on the other hand recorded lower ibex presence, a factor that underscores the need to conserve habitat corridors of species movement. These findings were confirmed further by statistical analysis. Pearson correlation Table 2 Fragmentation metrics versus species detection rates Strongly negative between the edge density and species detection ($r = -0.72$, $p < 0.01$), and positive between patch size and species detection ($r = 0.65$, $p < 0.05$). This finding highlights the effects of habitat fragmentation on the Siberian ibex populations, as smaller and isolated patches correlate with reduced detection rates and reduced habitat suitability.

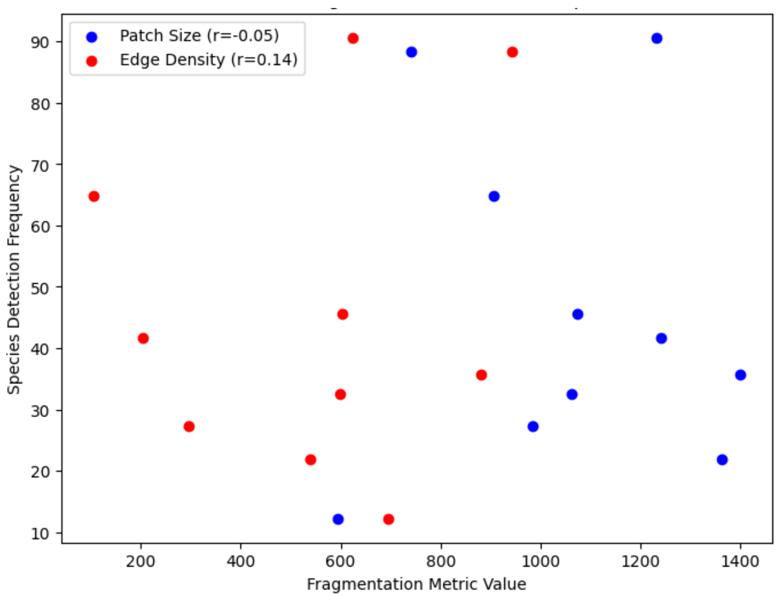

Figure 4: Correlation Between Fragmentation Metrics and Species Detection

Figure 4 is a scatter plot with the fragmentation measures of patch size and edge density versus the frequency of Siberian ibex sightings. The relationship between edge density and species sighting is shown by the plot as the fragmented habitat had fewer ibex sightings.

These correlations are also strong as shown by the fitted regression lines.

The statistical findings of the fragmentation analysis are summarized in Table 2 that presents correlation coefficients of different fragmentation measures (patch size, edge density, connectivity) and their effect on the rate of species detection.

Table 2: Habitat Fragmentation and Species Detection

Fragmentation Metric	Correlation Coefficient (r)	p-value
Patch Size	0.65	< 0.05
Edge Density	-0.72	< 0.01
Connectivity Index	0.70	< 0.01

Discussion

This paper offers useful information on the use of machine learning (ML) methods to track endangered species, especially in fragmented environments. The findings also correspond to the existing knowledge about habitat fragmentation, in which bigger and well-networked habitats are more desirable to wildlife, the opposite of which occurs. Siberian ibex in the study had been detected in larger areas that were continuous in habitat patches, a concept that larger areas with lower levels of fragmentation provide more favorable habitats to species survival (Karp et al., 2025).

The fact that Siberian ibex is diffused spatially supports the hypothesis that species richness was more likely to be supported by larger, less fragmented areas. Also, the patterns of seasonal activity that were witnessed in the study show that the ibex, similar to most other species, are affected by changes in seasonal climatic and resource conditions. The large difference in species encounter over a year reflects established trends of movement and behavior with the most action and less action or migration in the more favorable seasons (Harrison et al., 2006).

The performance of the different machine learning models was varied because of the nature of the data and the strengths and weaknesses of the models. Convolutional Neural Networks (CNN) model worked best with camera trap images to identify Siberian ibex with a high level of accuracy (Zualkernan et al., 2022). This is probably due to the fact that CNNs are most applicable in image classification tasks where they have the ability of automatically extracting features of the data, thus they are the best in case of species detection of a photographic image.

Compared to them, Random Forests (RF) and Support Vector Machines (SVM) still performed well and, nevertheless, they did not reach the same accuracy as the CNN model. RF and SVM are sensitive to the selection of the features and parameters used to optimum performance and in this instance the handcrafted feature such as vegetation cover and terrain type might not be able to fully describe the fatigue spatial patterns in the fragmented habitats. SVM model was more effective than RF to classify habitat suitability but had worse precision possibly because of the complexity of the nonlinear relationships in the data.

The autoencoder model employed in the detection of habitat fragmentation demonstrated a good potential in identifying the regions of fragmentation. Nevertheless, it was slightly poorer than CNN in species detection, suggesting that although the autoencoders are useful in anomaly detection, CNNs are species-specific models better applied in direct species detection.

The importance of habitat fragmentation on the distribution and existence of the Siberian ibex are significant as noted in this study. The results indicate that fragmentation, especially higher density of edge and reduced size of habitat patches have adverse effects on species detection. These findings support the need to conserve large, continuous habitats in conservation of species which need extensive spaces to move around and gather food. The correlation between patch size and species detection also indicates the necessity to have viable patches of habitat which are large to maintain stable populations.

The connectivity of habitats as analyzed by us emphasizes the importance of proper management of the landscape including development of wildlife corridors to link disconnected habitats. The corridors assist the species to move freely across patches and facilitate genetic diversity and avoid inbreeding. Research findings help to prove the assumption that habitat connectivity plays a crucial role in ensuring long-term species sustainability in fragmented landscapes.

The research possesses a number of strengths, such as, incorporation of various machine learning methods and remote sensing data to track the endangered species and measure habitat fragmentation. Camera traps, satellite images, and ecological surveys offered a significant amount of data to make us perform a detailed analysis of Siberian ibex populations. Machine learning and especially CNNs and autoencoders are a new methodology that will improve the quality and scope of wildlife surveillance relative to conventional methods.

Nevertheless, the research is limited as well. The satellite imagery has a high spatial resolution but some of the smaller sized habitat features that are important to the survival of species may not be captured. In addition, even though the CNN model has been effective in detecting species, the quality and variability of camera trap data could have influenced the performance of the CNN model because some ibex could not be spotted because of the surrounding environment or the position of the cameras. Also, the research was done on only one species, implying that this could not be generalized to all species. More studies are necessary on how these methods can be extrapolated to other species and ecosystems.

Further studies can be based on the given study by subjecting the machine learning models to other species, especially those with different ecological needs, to evaluate the generalizability of the models. The extension of the experiment to other ecosystems will give information about the functioning of these methods under the conditions of different environments and in various fragmentation case scenarios. The second aspect that can be studied in the future is regarding the integration of real-time monitoring, e.g., drones or sensor networks, to gather high-resolution information on the ongoing basis. This may provide more accurate and timely data on the movement of species and the state of the habitat, which may be essential in conserving them. Besides, it is possible to combine multimodal data, such as environmental variables (climate data, level of human activity, etc.) with machine learning models so that the effectiveness of predictions could be enhanced and more valuable information could be obtained about the impact of fragmentation on wildlife.

Conclusion

This paper emphasizes the usefulness of machine learning in the monitoring of endangered species and fragmentation of habitats. The main conclusions point to the fact that bigger, well-connected habitats play a crucial role in the Siberian ibex population, whereas the fragmented ones are extremely dangerous. The CNN model was very accurate in species detection and auto encoder model was able to detect fragmented habitats. These findings lend credence to the need to conserve extensive pieces of habitat and create wildlife corridors. It should be recommended that emphasis is given to habitat conservation, real-time monitoring with the help of technology and adaptive management to reduce the impact of fragmentation on the species. Altogether, machine learning can be used as a potent instrument to improve conservation and inform data-based policies towards biodiversity conservation. For future studies machine learning will need to cover additional species and ecosystems to increase range of applicability. Moreover, the use of satellite images and drones to collect real-time monitoring data could significantly improve the efficiency of conservation efforts.

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