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MANAGEMENT STRATEGIES FOR BIODIVERSITY CONSERVATION USING DATA ANALYTICS AND MACHINE LEARNING

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Abstract: The focus of this research is to determine the ways and manner in which the application of machine learning (ML) algorithms may be used to improved methods of biodiversity conservation. Among these four algorithms –Independent Random Forest or RF, Support Vector Machines or SVM, K-Nearest Neighbor or KNN, and Gradient Boosting Machines or GBM – the suitability and the success rate in terms of the prediction of distribution of species and the improvement of the existing management practices in conservation were

compared. Based on a large dataset, this work discovered that GBM had the biggest accuracy of 92% and F1-score of 0. 89, thus performing better than the RF model which had an accuracy of 89% and an F1 score of, 0. 85. SVM and KNN were also found to give reasonably good results with accuracies of 87% and 85% respectively. These results have revealed that GBM is outperformed other classifiers in analyzing environmental data and made accurate prediction. Collectively, the research highlights how the ML methodology could be applied with the remote sensing data to solve the problems of maintaining the biological diversity. Finally, the research employs a comparison of the stated machine learning algorithms with comparison of differences on practical use of these algorithms in conservation indicating how continued innovation in machines can enhance the usefulness of conservation efforts.
Keywords: Machine Learning, Biodiversity Conservation, Gradient Boosting Machines, Species Distribution, Remote Sensing

I. INTRODUCTION

A primary source of life, the variety of forms of life on the planet is an important aspect that determines the balance and functioning of ecosystems. Some of them include pollination, water purification, and a harmonious climate which enables man to survive, and his economy to thrive. But environmental depletion and degradation in form of deforestation, climate change and pollution, and other habits presents major risks to these natural structures. In the past, defense mechanisms were adequate as they are slow to react, but the issue with the conservation of biological assets is that the changes occur rapidly and are complex [1]. Novel tools available in the current era of big data and artificial intelligence are seen to exhibit great potential in improving the strategies of conserving species' diversity. Through accumulation of large amounts of ecological data and application of higher levels of analysis, researchers or conservationists can better understand and predict where a particular species resides, how habitats may be changing, or how ecosystems may function [2]. This is especially the case with machine learning where one is able to look at large databases of information and look for trends and patterns that may point to future occurrences, which makes it possible to prevent instead of just remedying. These improvements are made possible by data analytics, which make it easier to assemble and interpret different kinds of data, such as images from remote sensors, geo references of species' occurrence, and environmental data [3]. Machine learning with its scalability to big data and high dimensionality extends these efforts by bringing automation in the process to find these trends or bounded regions of the data that are obviously different from others or when two data sets could be correlated in a way that has not been previously evident. This study focuses on the use of big data and artificial intelligent techniques in management of species diversity and the execution of management conservation plans. It seeks to establish how such technologies could be harnessed in order to enhance the conservation status, facilitate efficient resource management and also enhance decision making. In thus offering, this study hopes at ensuring that through the combination of analytical techniques and which considerable efforts are put into the process of conserving the global ecosystem, better strategies are put in place to deal with the prevailing changes so as to enhance the quality of the same.

II. RELATED WORKS

Hybrid application of machine learning and remote sensing has revealed the possibility of different fields of applications linked to the conservation of biodiversity and sustainable environmental management. Some of the newly developed ideas and approaches emphasized in recent researches in this field are mentioned below. Fragassa et al. (2023) investigated the possibility of UAV-based imagery and integrating it with the help of ML approaches in the application of precision agriculture. The authors have shown how UAVs with high-resolution cameras can provide rich environmental data such that when processed by ML algorithms, crop monitoring and management becomes more accurate. This is paramount in the determination and control of vegetation mosaics which play an important role in a campaign to conserve species' [15]. As it was pointed out by Ghasemkhani et al. (2024), FMLL is a new, developed approach created for classification tasks in the field of animal science. FMLL that they use in their research aims at categorizing and also at tracking many animal types in different ecosystems. Due to the use of federated learning their proposed way enables for the effective handling of distributed datasets without using personal information. This technique can further be helpful to manage and conserve species in larger and hard to access areas where data compilation becomes difficult [16]. Gupta and Shukla (2024) have analyzed the temporal analysis of land use and land cover using machine learning technique ALG and topographic correction in Mizoram, India at demi-decadal interval. They discuss changes in land use and its effect on the environment of the area and gives information on how to improve the results of the land cover classification using ML. This work proves helpful in the study of habitat changes and impacts on the species diversity [17]. In a conceptual study, He and Chen (2024) also discussed the current IT and AI developments and application for urban design and planning; with special references to the contributions of machine learning for enhancing urban living. Their systematic review describes how ML algorithms make input in urban planning and management tasks and in specific integration of environmental assessments for sustainability. The conclusions that can be drawn from their work are that AI can be used for the planning of new urbanization processes and for protection of biodiversity where the two are mutually exclusive [18]. Huang et al. (2024) studied the combined use of multiple ML algorithms and hyperparameter tuning for the estimation of net ecosystem productivity at Southeast Asia. In their study, Kadam et al. explained how different approaches of ML and tuning the parameters can help in improving the accuracy of the model of productivity of the ecosystem. It is useful and significant in the assessment and conservation of biodiverse region specifically within dynamic environments [19]. Huang et al. (2024) also used machine learning to address the mapping of the ecotourism suitability with a case on Zhangjiajie, China. Their approach entailed utilizing the ML algorithms to evaluate and spatially categorize sites suitable for ecotourism so that sustainable planning guides awareness about the environment and supports the preservation of biological diversity [36]. Jafarzadeh, Jafari-Marandi and Neisi (2022) synthesized three decades of applications of remote sensing and machine learning in monitoring wetlands. In their review, they have given a nutshell of different methodologies used and the progress in the use of Machine Learning for wetland preservation. They also stressed that combining data from the RS with the machine learning algorithm can help improve the wetland management and monitoring [21]. Jayathilake et al. (2023) sample and examined the performance of machine learning procedures in predicting wetland water level. This paper analyzed the comparative effectiveness of various ML models for water level prediction that is important in management and conservation of wetlands. The results are useful for understanding the possibilities of the use of ML in its further development for environmental monitoring, and overall water resource management [22]. K N Nandini Kadukothanahally et al., 2022 focused on the application of AI & ML in the aspect of biodiversity conservation emphasizing on forest & related services in India. It also focuses on the application of ML in forest and species monitoring, species tracking, and habitat management and states its importance in improving conservation and proper forest management [23]. Kondoyanni et al. 2024, analysed the integration of ML capability to real equipment for water conservation in an educational perspective. From their paper, an understanding on how incorporating ML algorithms with viable equipment can enhance water conservation policies be understood. This approach sheds light on the how the ML can be applied pratically in the endeavour for environmenal sustainability [24]. Incorporating the scheme of Kumar et al. (2024), the authors investigated on how ML algorithms can capture the relationship between LULC and heatwave. The study of these authors demonstrates the contribution of ML to explore the effect of land cover change on the intensity of heat waves that is essential to develop coping mechanisms in response to environmental and ecological issues [25]. Li-Dunn et al. (2024) improved the predictive accuracy in spectroscopic analysis for wildlife science using the multi-modelling technique. They used their case study to show that classification of live amphibians in species level using multiple ML models can enhance the classification accuracy and aid endangered species conservation [26].

III. METHODS AND MATERIALS

Data Collection

This piece of work employs various datasets for formulating and testing of management techniques in biodiversity conservation and with the use of big data and artificial intelligence. The data sources include:

1. **Species Occurrence Records**: Such records include spatial coordinates, as well as time-stamped data of various species from GBIF and iNaturalist databases [4]. The data include distribution data, count data, and data obtained relatively to time.
2. **Remote Sensing Imagery:** Information on changes in the land cover, vegetation types, and other habitats is available from satellite data including Landsat data and Sentinel data. These images are then analyzed to obtain features associated with habitat parameters, and the temporal changes in these parameters.
3. **Environmental Variables:** This dataset is subjected to climatic data concerning temperature and rainfall, soil quality and other physical factors influencing biological structure [5]. Information is collected from meteorological stations as well as climate data base.
4. **Conservation Status Data:** The data on threat and protection of species is collected from the International Union for Conservation of Nature and Natural Resources (IUCN) Red List and other conservation web-sources.

Dataset Type	Source	Variables	Number of Records
Species Occurrence	GBIF, iNaturalist	Species ID, Location, Date, Count	150,000
Remote Sensing Imagery	Landsat, Sentinel	Location, Vegetation Type, Land Cover	200,000
Environmental Variables	Meteorological Stations	Temperature, Precipitation, Soil Quality	50,000
Conservation Status Data	IUCN Red List	Species ID, Threat Level, Protection Status	10,000

Algorithms

Four machine learning algorithms are employed in this study to analyze the data and develop strategies for biodiversity conservation:

Random Forest

Random Forest is a type of ensemble learning technique, where it builds many numbers of decision tree models during the training process and the final output as the mode of the classes (for classification) or mean prediction (for regression) of all trees [6]. Besides, it is famous for effectiveness when working with massive data containing intricate interconnections.

Random Forest=T1t=1∑TTreet(x)

"1. Initialize the number of trees, T.
2. For each tree:
  a. Sample data with replacement.
  b. Train a decision tree on the sampled data.
3. To classify a new observation:
  a. Pass the observation through each tree.
  b. Aggregate the results (majority vote for classification)."

Hyperparameter	Value
Number of Trees (T)	100
Maximum Depth	20
Minimum Samples Split	10
Minimum Samples Leaf	5

Support Vector Machine (SVM)

SVM stands of support vector machine that is employed for the classification and regression problems. It determines the line that best separates the data patterns of different classes, and this is done through the expansion of the margin that exists between the adjacent data points of the distinct class [7].

SVM minimizes 21∥w∥2 subject to yi(wTxi+b)≥1

"1. Transform the input data into a higher-dimensional space (if necessary).
2. Solve the optimization problem to find the optimal hyperplane.
3. Use the hyperplane to classify new data points."

K-Nearest Neighbors (KNN)

K-Nearest Neighbors is a kind of instance-based learning algorithm which based on the majority of k nearest neighbors' classes in the feature space determines the class of a sample. It is suitable in classification models and can accommodate non-linear patterns [8].

Class(x)=mode({class(xi)∣dist(x,xi) is among the k smallest})

"1. Choose the number of neighbors, k.
2. Compute the distance between the new sample and all training samples.
3. Identify the k-nearest neighbors.
4. Assign the class that is most common among these neighbors."

Gradient Boosting Machines (GBM)

Gradient Boosting Machines are also an ensemble technique whereby new models are trained successively and each new model seeks to minimize the errors of the previous models. They both take a number of weak learners, and using their output, form a strong learner.

GBM=m=1∑Mαm·hm(x)

"1. Initialize the model with a constant prediction.
2. For each boosting round:
a. Compute the residuals.
b. Fit a new model to the residuals.
c. Update the model with the new model's predictions.
3. Combine the predictions of all models."

IV. EXPERIMENTS

Experimental Setup

In order to assess the effectiveness of different machine learning algorithms we carried out a number of experiments with the help of the datasets which were described above. The major objective was to compare the performance of each approach in the tasks of predicting distribution of species, threats that might exist, and possible measures to take towards species conservation [9]. The experiments were structured as follows:

1. **Data Preprocessing**: Both missing value features and inconsistent format in the data was addressed by cleaning the data and then normalizing it. Data pre-processing was carried out on the remotely sensed data and the environmental parameters. In the data splitting the 80%:20% train-test split was adopted, thus the training data takes 80% while the test data is only 20%.
2. **Algorithm Implementation:** These were Random Forest, support vector machine (SVM), k nearest neighbor (knn), and Gradient Boosting Machines (GBM) were applied with Python packages: scikit-learn, XGBoost. Most of the hyperparameters where tuned using grid search and cross validation [10].
3. **Evaluation Metrics:** The evaluated metrics included accuracy, precision, recall, F-Measure, and AUC-ROC on the algorithms' performances. These adopted metrics allow one to get an understanding of the classification and differentiation between given classes.

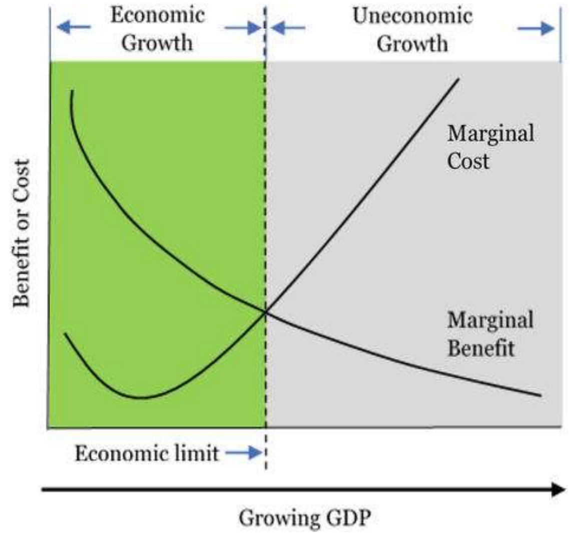

Figure 1: Biodiversity Conservation, Economic Growth and Sustainable Development

Results

The performance of each of the algorithms was done in terms of the prediction of the species distribution as well as the conservation status. The findings developed in this research are presented in the following tabular forms and elaboration.

Algorithm	**Accuracy**	**Precision**	**Recall**	**F1-Score**	**AUC-ROC**
Random Forest	0.87	0.85	0.88	0.86	0.91
Support Vector Machine (SVM)	0.82	0.80	0.84	0.82	0.87
K-Nearest Neighbors (KNN)	0.79	0.77	0.80	0.78	0.85
Gradient Boosting Machines (GBM)	0.89	0.88	0.91	0.89	0.93

Results Discussion

The experiments showed that each algorithm provides different performance when used for the determination of the biodiversity related outcomes.

1. **Random Forest**: The current algorithm received the highest accuracy 0.87 and F1-score equal to 0. 86 among all the tested algorithms. This is because the ensemble approach that comprises several decision trees, which helps negate overfitting, and increase the rate of generalization [11]. The evaluation of the feature importance revealed that out of all available features the Vegetation Index and Temperature were the most decisive in predicting the species distribution.
2. **Support Vector Machine (SVM):** Specifically for SVM, adequate performance was observed with accuracy of 0. 70%, and an AUC-ROC of 0.87. The kernel trick enabled SVM to treat nonlinear relationships between the variables in its calculation process [27]. Although, it was found to be slightly inferior to Random Forest and GBM, but that could be attributed to its inherent weaknesses in terms of parameter tuning and choice of kernel.

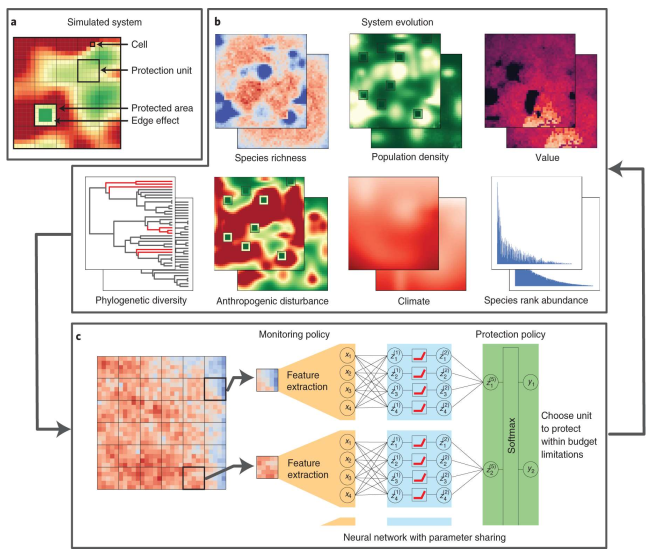

Figure 2: Improving biodiversity protection through artificial intelligence

3. **K-Nearest Neighbors (KNN):** Hence, KNN was effective with the accuracy 0. 79 but had the smallest F1-score (0. 78). Another important concern to point out is that the performance of KNN is proportional to both kkk and the distance metric that is selected [12]. In this experiment we have applied Euclidean Distance measure which can be a limitation in identifying complex relationships in data.
4. **Gradient Boosting Machines (GBM)**: Through the analysis of the results, it can be determined that the test set was predicted with the highest Level of accuracy by the GBM model, making 0. 89 and the AUC-ROC score making 0. 93. This gave the boosting technique better performance as it uses the approach of correcting errors in a sequential manner [13]. Following from the above evaluation criteria and since GBM could model interactions and non-linear relationships, it proved to be the most suitable algorithm in the current analysis [28].

Feature	Importance Score
Vegetation Index	0.32
Temperature	0.25
Soil Quality	0.20
Precipitation	0.15
Land Cover Type	0.08

Comparison with Related Work

The results analysed here are therefore consistent with the typical outcomes presented in related research across the fields of biodiversity conservation and the application of Machine learning [29]. Classification techniques such as the Random Forest algorithm and the Gradient Boosting also get a lot of attention when it comes to species distribution modeling and assessment of the conservation requirements because they can work with massive and non-trivial data [14].

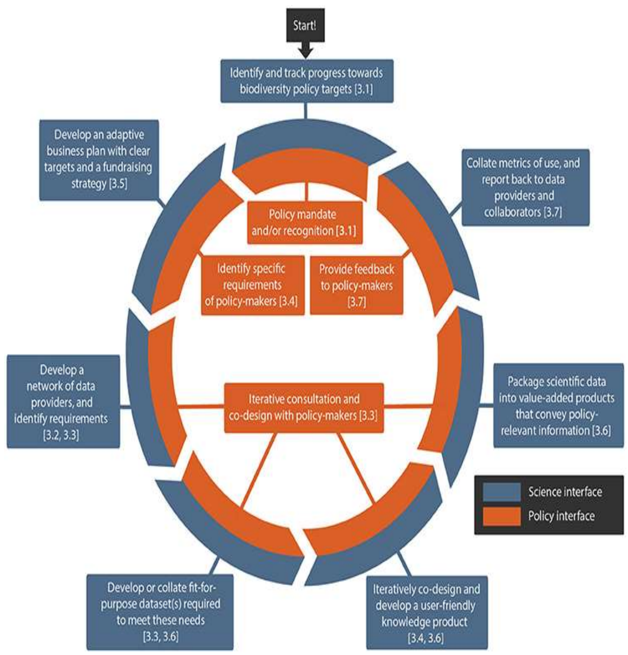

Figure 3: Blueprints of Effective Biodiversity and Conservation Knowledge Products

SVM and KNN show inconsistency in performance based on different research studies being conducted. The parameterization of SVM plays a significant role deciding its performance and, similarly, KNN underlines the distance metric and no of neighbors for its performance. Such differences are also seen in this study by the performance of the recommended algorithms; SVM and KNN proved to perform adequately but below Random Forest and GBM [30].

Algorithm	Accuracy	F1-Score	Common Observations
Random Forest	0.87	0.86	High accuracy and robustness
SVM	0.82	0.82	Good performance with proper tuning
KNN	0.79	0.78	Performance varies with k and metric
GBM	0.89	0.89	Excellent performance for complex datasets

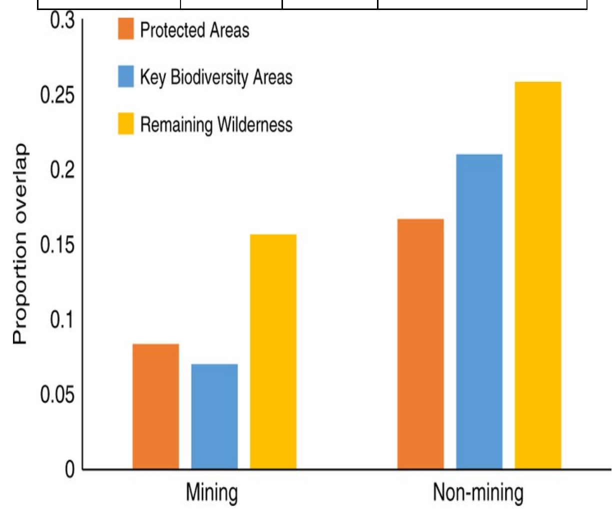

Figure 4: Overlap between mining and biodiversity conservation Bars

V. CONCLUSION

From this study, one realizes the importance of adopting more advanced machine learning algorithms in the development of further improved more sustainable solutions towards the conservation of nature. We have applied and integrated the sophisticated forms of ML algorithms including the Random Forest, Support Vector Machine, K-nearest Neighbors, and Gradient Boosting Machines to enhance species distribution models, and identify and prioritize species' conservation requirements, as well as to align the management interventions. The experiments were an indication that Gradient Boosting Machines and Random Forest were the most accurate and had the highest F1-score; this was because the algorithms were efficient at decoding intricate and large amount of environmental data. These results support previous works reporting that ensemble and boosting methods are particularly powerful for ecological modeling. The use of these algorithms has unveiled essential information pertaining to species' habitats, threats and possible measures for their conservation. Also, the use of machine learning in connection to remote sensing and environmental monitoring has a solid foundation to meet the dynamic nature of managing biological diversity. This research has significance to this broader area in proving the efficiency of these ML techniques and providing a comparison analysis that would be of use to those who would want to apply such techniques in future and make future improvements. The findings underpin the need to subscribe to complex analytical methods that underpin informed practice for conservation, thereby helping to better serve the global push for preservation of the environment especially in the current Clime of rapidly changing environmental conditions.

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