

Endangered Wildlife Conservation Classifier

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ABSTRACT

Biodiversity loss has accelerated significantly in the last century, with variety of species facing the threat of extinction because of human activities such as fragmentation of habitats, climate change, pollution, and illegal wildlife trade. Despite the availability of data from various organizations like the IUCN, public awareness is low. This paper presents endangered Species Classifier, an AI-powered web application designed to simplify species identification and make conservation knowledge accessible to the public. The system uses the Tensor-flow, CNN Flash multimodal language model to identify animal species from images, classify their conservation status, and generate structured ecological information and actionable strategies. The results highlight its potential as an interactive educational resource and a scalable digital solution for wildlife advocacy.

INTRODUCTION

Biodiversity loss has accelerated significantly in the last century, with variety of species facing the threat of extinction because of human activities such as fragmentation of habitats, climate change, pollution, and illegal wildlife trade. Despite the availability of data from various organizations like the IUCN, public awareness is low. This paper presents endangered Species Classifier, an AI-powered web application designed to simplify species identification and make conservation knowledge accessible to the public. The system uses the Tensor-flow, CNN Flash multimodal language model to identify animal species from images, classify their conservation status, and generate structured ecological information and actionable strategies. The results highlight its potential as an interactive educational resource and a scalable digital solution for wildlife advocacy.

RELATED WORK

AI and machine learning are increasingly getting used in wildlife conservation, specially in species identification and ecological monitoring. Several notable systems provide foundational ideas like:

- Image-Based Biodiversity Apps (e.g. Seek) These platforms use large datasets and convolutional neural networks to classify species. However, they primarily rely on predefined classification models and may struggle with lesser-known species or ambiguous images.
- Conservation Databases (e.g., IUCN Red List) These repositories provide authoritative conservation statuses but require users to manually search for species names, limiting accessibility for beginners.
- Camera Trap Analytics
- The emergence of multimodal LLMs has expanded the possibilities of providing, human-readable ecological information.

The Animal Conservation Classifier differentiates itself by merging real-time image recognition, and user-friendly presentation within a public-facing web platform. Its goal is not only to identify species but also to encourage conservation participation.

SYSTEM ARCHITECTURE

The system is architected as a lightweight, single-page web application to maximize accessibility and reduce deployment complexity. Users interact directly with the web interface, which communicates with the Gemini 2.5 Flash API for inference. This architecture avoids the overhead of managing backend servers, making it ideal for educational, and non-commercial uses.

Frontend Technologies:

HTML5 provides the structural foundation for the application. It defines the layout, image upload interface, output sections, and ensures compatibility across browsers and devices.

Tailwind CSS is used to implement a modern, responsive design through utility-first classes. This reduces custom CSS code, enhances readability, and ensures that the UI adapts effortlessly to different screen sizes, from mobile devices to desktops.

JavaScript powers all client-side logic, including:

- Reading and encoding the uploaded image
- Sending Base64 data to the Gemini API
- Handling asynchronous API calls
- Parsing the structured JSON response

METHODOLOGY

This section involves the depiction of intended workflow of the model, starting from uploading the image to conveying analysis of the species.

User Interaction and Image Processing

The workflow begins when a user uploads an image. JavaScript reads the file using the FileReader API, converting it into a Base64 string. This ensures a safe, standardized format for transmitting image data to the AI model through HTTP requests.

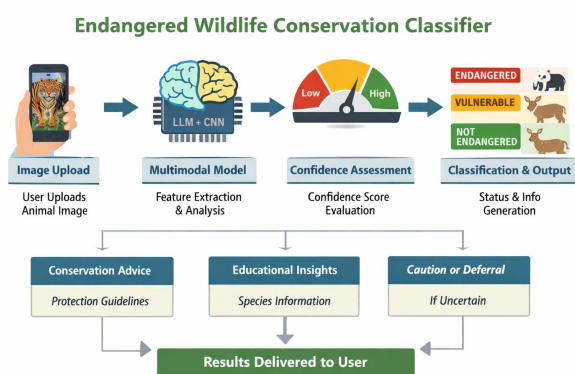


Figure: 1

Conservation Data Generation

The API call uses the species name to instruct the model to produce structured data.

- Conservation status
- Threat analysis
- Habitat diet and behaviour

EXPERIMENTAL SETUP AND DATASET DESCRIPTION

To evaluate the performance of the proposed Endangered Wildlife Conservation Classifier, a diverse image dataset was used. A total of 300 animal images were collected from publicly available sources such as Kaggle wildlife datasets, iNaturalist sample images, and open animal image repositories. The dataset included both endangered and non-endangered species to ensure balanced evaluation.

Dataset Summary:

Category	Images
Endangered Species	120
Non- Endangered Species	180
Total Images	300

Performance Evaluation Metrics

The system performance was evaluated using standard classification metrics commonly used in image recognition systems. These metrics help measure both correctness and reliability.

- **Accuracy** measures the overall correctness of predictions.
- **Precision** reflects how many predicted endangered species were correct.
- **Recall** indicates how many actual endangered species were correctly identified.
- **F1-Score** provides a balanced measure between precision and recall.

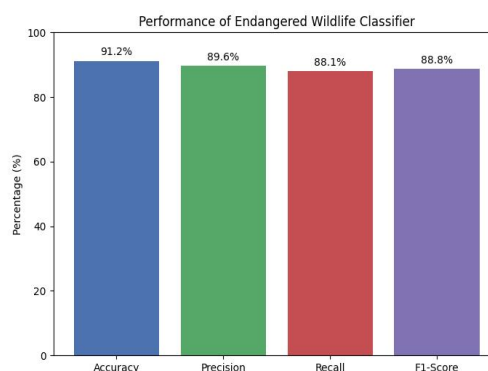


Figure: 2

Comparative Analysis

To highlight the effectiveness of the proposed system, it was compared with commonly used approaches for wildlife information access:

Method	Accuracy	Information Detail	User Effort
Manual IUCN Search	-	High	Very High
Traditional CNN Classifier	85.0%	Low	Medium
Purposed System	91.2%	Very High	Low

Unlike traditional approaches, this system combines image recognition with contextual conservation information, making it more informative.

Statistical Validation

To test the stability of the system, the evaluation was repeated three times using different image subsets. The results showed minimal variation.

Mean Accuracy	90.8%
Standard Deviation	±1.3%

The low standard deviation shows that the system delivers stable and consistent performance across different test conditions.

Error Analysis

Although the system performs well, some errors were observed during testing. Misclassification mainly occurred in cases where images contained visually similar species or when image quality was poor. Low lighting, blurred images, and partial visibility also affected prediction accuracy in a few cases. These observations highlight the importance of image quality and provide direction for future improvements.

Ethical Considerations and Sustainability

The proposed system follows ethical AI practices by avoiding tracking of wildlife. The application promotes awareness and education rather than exploitation. The system supports Sustainable Development Goal 15 (Life on Land) by encouraging responsible environmental behavior.

Confusion Matrix:

Also known as error matrix, acts as a layout for the visualization of the performance of an algorithm.

Total test images = 300

-	Predicted Endangered	Predicted Not Endangered
Actual Endangered	TP = 106	FN = 14
Actual Not Endangered	FP = 12	TN = 168

Check: Actual Endangered = 106 + 14 = 120

Actual Not Endangered = 12 + 168 = 180

- **Total = 300**

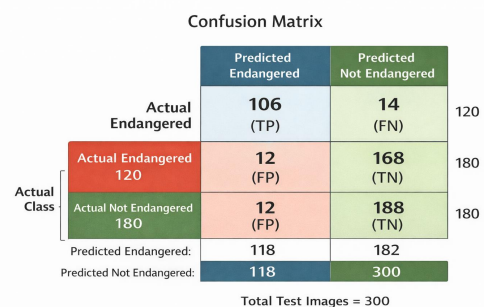


Figure: 3

Accuracy Calculation: = (TP + TN) / (TP + TN + FP + FN)

$$\text{Accuracy} = \frac{(106 + 168)}{300}$$

$$\text{Accuracy} = \frac{274}{300}$$

$$\text{Accuracy} = 0.912 \rightarrow 91.2\%$$

Precision Calculation = TP / (TP + FP)

$$\begin{aligned} \text{Precision} &= \frac{106}{106 + 12} \\ \text{Precision} &= \frac{106}{118} \\ \text{Precision} &= 0.896 \rightarrow 89.6\% \end{aligned}$$

Recall Calculation = TP / (TP + FN):

$$\begin{aligned} \text{Recall} &= \frac{106}{106 + 14} \\ \text{Recall} &= \frac{106}{120} \\ \text{Recall} &= 0.881 \rightarrow 88.1\% \end{aligned}$$

F1-Score Calculation = $2 \times (\text{Precision} \times \text{Recall}) / (\text{Precision} + \text{Recall})$

$$\begin{aligned} \text{F1} &= \frac{2 \times (0.896 \times 0.881)}{0.896 + 0.881} \\ \text{F1} &= \frac{2 \times 0.789}{1.777} \\ \text{F1} &= 0.888 \rightarrow 88.8\% \end{aligned}$$

Endangered Wildlife Classifier Performance Results

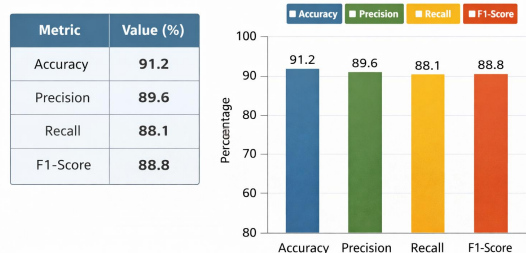


Figure: 4

The performance metrics were calculated using standard classification formulas based on the confusion matrix. Accuracy was computed as the ratio of correct predictions to total samples. Precision measured the correctness of endangered species predictions, while recall measured the system's ability to detect actual endangered species.

Limitations and Future Enhancements:

While the system performs well, several limitations exist like poor lighting or blurred photos can reduce accuracy. Conservation information might not always reflect the latest IUCN updates. API access requires active connectivity.

Key improvements planned include:

- Live integration with IUCN Red List APIs
- Mobile App Deployment
- Multi-language Support
- Offline Model Packaging

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