

Project Name	Project - Jungle Detectives: AI-Powered Image Classification of Wild Big Cats
Team ID	Team-592375
Team members	Syed Mohammad Yasoob Nihar Thampi
Date	18th November 2023

1. INTRODUCTION

1.1 Project Overview

The objective is to create a machine-learning model to accurately classify images of big cat species, including lions, tigers, leopards, cheetahs, and jaguars. The dataset is a curated dataset with 80% training, 10% validation, and 10% testing. Preprocessing includes resizing images, normalizing pixel values, and data augmentation for better generalization. The model architecture is a Convolutional Neural Network (CNN), with a pre-trained CNN architecture as a feature extractor and custom fully connected layers for species classification. The project involves the development of a machine-learning model to classify big cat species images. The model's performance is evaluated using metrics such as accuracy, precision, recall, and F1-score. The validation set is monitored to avoid overfitting. Hyperparameter tuning is performed using grid search or random search, and cross-validation is used to ensure robust hyperparameter selection. Activation maps are used to visualize the image's contribution to predictions, and class activation mapping (CAM) is used to highlight important regions. The model is deployed through serialization, web application development, and API integration. Continuous improvement is achieved through feedback loops, regular retraining, and ethical considerations such as bias mitigation and transparency. The project concludes with a summary of the model's accuracy and potential areas for improvement.

1.2 Purpose

This project aims to create a machine-learning model that accurately classifies images of big cat species using a curated dataset and preprocessing techniques. The model uses Convolutional Neural Network (CNN) architecture and transfer learning to recognize species like lions, tigers, leopards, cheetahs, and jaguars. Standard metrics like accuracy, precision, and recall are used for training and evaluation. The model will be deployed through a user-friendly web application or API, allowing public access for wildlife enthusiasts, researchers, and educators. Ethical considerations, including bias mitigation and transparency, will be addressed to ensure fair predictions. This project contributes to wildlife conservation and research.

2. LITERATURE SURVEY

2.1 Existing problem

The text discusses various studies on the use of deep learning models, particularly convolutional neural networks (CNNs), in species classification and wildlife image classification. It highlights the ImageNet Large Scale Visual Recognition Challenge, which showcases the effectiveness of CNNs in image classification tasks. The paper also explores the application of transfer learning in wildlife image classification, showcasing the potential for similar approaches in the big cat species classification project. The study also discusses the use of machine learning, particularly deep learning, for classifying animal species in camera trap images and its applications in ecological research. The paper introduces Grad-CAM, a technique for generating visual explanations from deep neural networks, providing interpretability to complex models and offering potential applications for the big cat species classification project. The article also discusses the ethical considerations and challenges associated with the use of artificial intelligence in conservation, providing insights into responsible AI practices relevant to the big cat species classification project. Overall, the text provides a comprehensive overview of the potential applications of deep learning in wildlife image classification and conservation.

2.2 References

1. Species Classification and Deep Learning:

Reference: Russakovsky, O., Deng, J., Su, H., Krause, J., Satheesh, S., Ma, S., ... & Fei-Fei, L. (2015). ImageNet Large Scale Visual Recognition Challenge. arXiv preprint arXiv:1409.0575.

2. Transfer Learning in Wildlife Image Classification:

Reference: Norouzzadeh, M. S., Nguyen, A., Kosmala, M., Swanson, A., Palmer, M. S., Packer, C., & Clune, J. (2018). Automatically identifying, counting, and describing wild animals in camera-trap images with deep learning. *Proceedings of the National Academy of Sciences*, 115(25), E5716-E5725.

3. Wildlife Conservation and Machine Learning:

Reference: Tabak, M. A., Norouzzadeh, M. S., Wolfson, D. W., Sweeney, S. J., Vercauteren, K. C., Snow, N. P., ... & White, M. D. (2019). Machine learning to classify animal species in camera trap images: Applications in ecology. *Methods in Ecology and Evolution*, 10(4), 585-590.

4. Interpretability in Deep Learning Models:

Reference: Selvaraju, R. R., Cogswell, M., Das, A., Vedantam, R., Parikh, D., & Batra, D. (2017). Grad-CAM: Visual Explanations from Deep Networks via Gradient-based Localization. In *Proceedings of the IEEE International Conference on Computer Vision (ICCV)*, 2017.

5. Ethical Considerations in AI for Conservation:

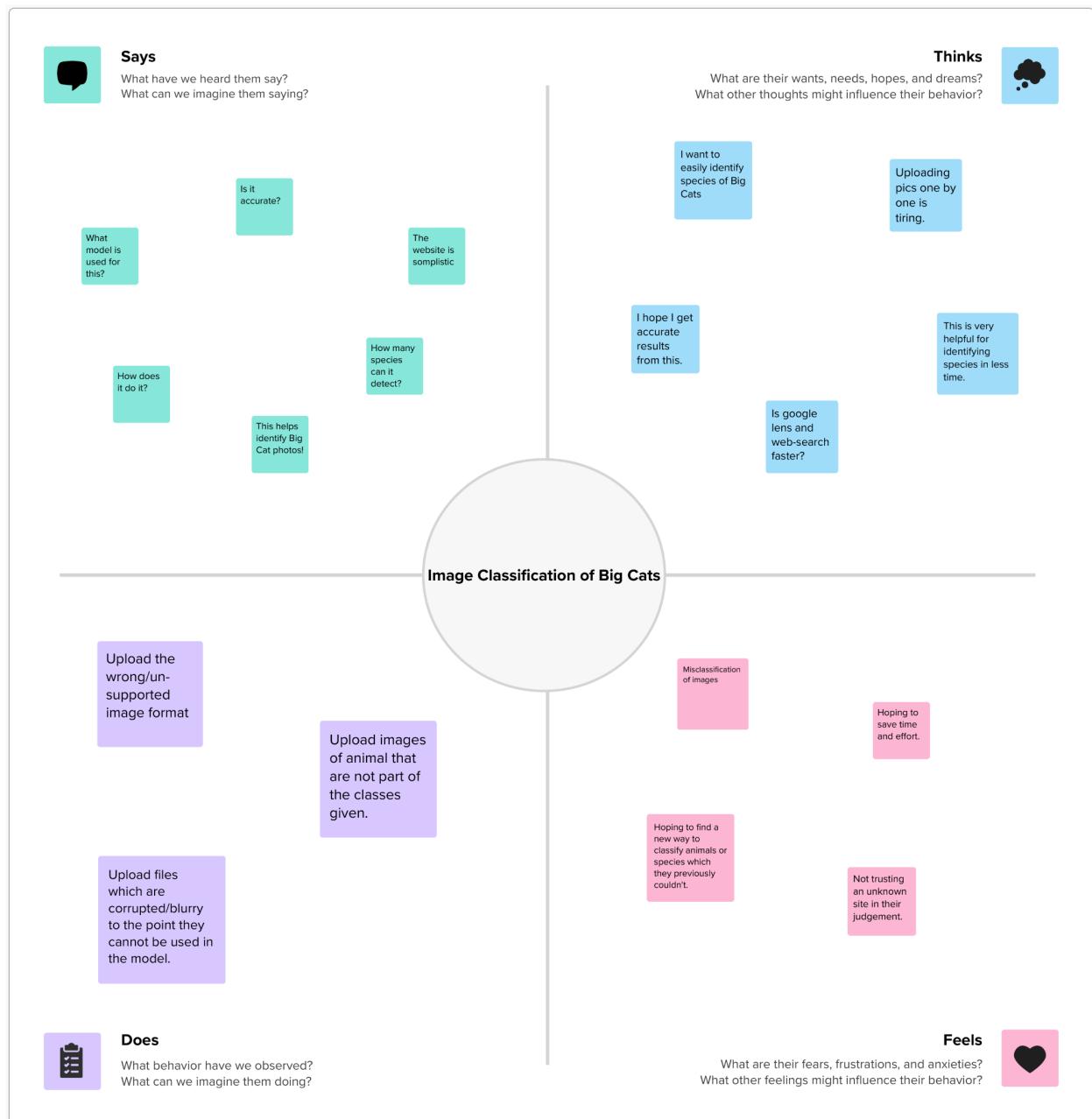
Reference: Dando, M., & McManus, B. (2020). Artificial intelligence, conservation, and the Anthropocene. *Conservation Biology*, 34(1), 245-253.

2.3 Problem Statement Definition

The challenge of efficiently identifying and monitoring big cat species is a significant concern in wildlife conservation and research. Manual species identification is time-consuming, resource-intensive, and prone to human error. A robust, automated solution leveraging machine learning is needed to accurately classify these species from images. The existing gap is the lack of a user-friendly tool that combines advanced image classification techniques with interpretability features. The project aims to develop and deploy a machine learning model that achieves high accuracy in big cat species classification, provides insights into the model's decision-making process, and is accessible to a wide audience. The solution must adhere to ethical standards, ensuring fair and unbiased predictions while safeguarding user privacy. The project aims to bridge this gap by developing a user-friendly and responsible AI solution for automated classification of big cat species from images.

3. IDEATION & PROPOSED SOLUTION

3.1 Empathy Map Canvas



3.2 Ideation & Brainstorming

The Miro board is organized into four main sections:

- Brainstorm & Idea prioritization:** Contains a template for a brainshop, a key note of brainstorming, and a list of key notes.
- Brainstorm:** A column for generating ideas, with one note: "Design a model to take image as input and classify the images into the given 10 Big Cats species and predict the species as output."
- Prioritize:** A column for prioritizing ideas, with three notes:
 - "Find the suitable type of ML model."
 - "Removal of unsupervised or unnecessary file types."
 - "After deployment, best mechanism to display the input and output."
- After you collaborate:** A column for final actions, with a quick add section and a keep moving forward section containing links to "Miro board", "Open the template", "Continuous deployment now", and "Success, milestones, roadmap & issues".

A central chart titled "Prioritization matrix" plots "Importance" against "Feasibility". It shows a quadrant with four categories:

- High Importance, High Feasibility:** "After deployment, best mechanism to display the input and output."
- High Importance, Low Feasibility:** "Find the suitable type of ML model."
- Low Importance, High Feasibility:** "Removal of unsupervised or unnecessary file types."
- Low Importance, Low Feasibility:** "Find the best way to deploy the model."

4. REQUIREMENT ANALYSIS

4.1 Functional requirement

The functional requirements for the project involve specifying the features are:

1. **Image Upload and Processing:** Requirement: Users should be able to upload images of big cats through the web application. Functionality: The system should preprocess the uploaded images, including resizing and normalization, to prepare them for input into the machine learning model.
2. **Species Classification:** Requirement: The model must accurately classify images into specific big cat species. Functionality: Utilize the trained CNN to predict the species of the uploaded image based on learned features.
3. **User Interface (Web Application):** Requirement: Provide a user-friendly web interface for users to interact with the model. Functionality: Design an intuitive interface allowing users to upload images, receive predictions, and view the results in a clear and understandable format.
4. **Model Deployment:** Requirement: Deploy the trained model for public use. Functionality: Serialize and save the trained model, integrate it into the web application, and ensure seamless deployment on a web server or cloud platform.
5. **Continuous Learning:** Requirement: Enable the model to adapt and improve over time. Functionality: Periodically retrain the model with new data, update the deployed model, and notify users of improvements or changes.

6. Error Handling: Requirement: Handle errors gracefully. Functionality: Implement robust error handling mechanisms to guide users in case of upload failures, processing errors, or other issues.

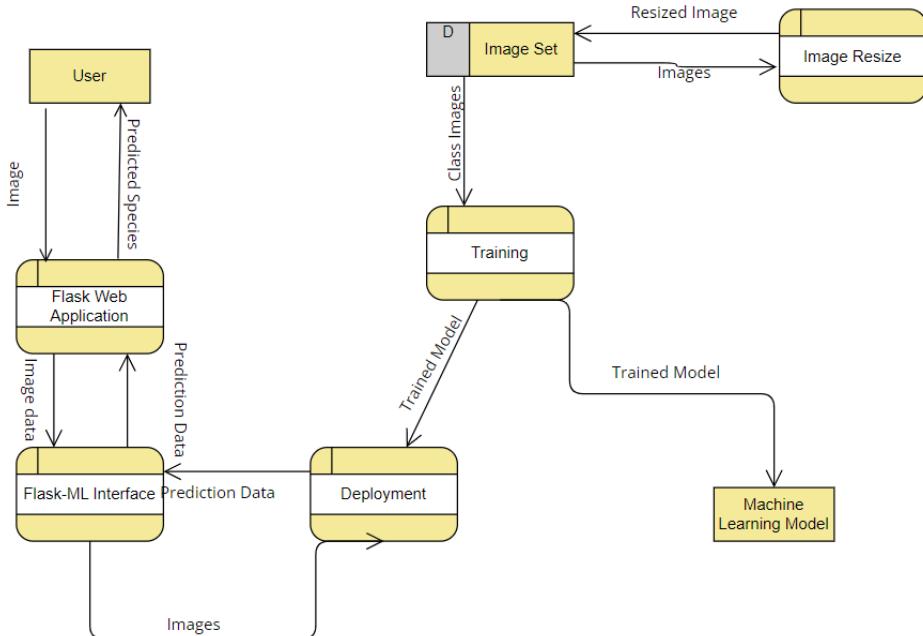
4.2 Non-Functional requirements

Nonfunctional requirements that the system must possess:

1. Performance: Requirement: The model should provide timely responses to user requests. Criteria: Response time for image classification should be within a specified timeframe (e.g., less than 5 seconds).
2. Scalability: Requirement: The system should be scalable to accommodate an increasing number of users and data. Criteria: The web application should handle concurrent user requests and potential increases in the dataset size without significant degradation in performance.
3. Reliability: Requirement: The model should be reliable and available for use. Criteria: The system should have a high availability rate (e.g., 99.9%) and minimal downtime for maintenance.
4. Accuracy: Requirement: The model should achieve a high level of accuracy in species classification. Criteria: The accuracy of the model, measured on the test set, should exceed a specified threshold (e.g., 90%).
5. Interpretability: Requirement: The model's predictions should be interpretable for users. Criteria: Visualization tools for interpreting model decisions should be provided, and users should be able to understand the basis of the classification.
6. Usability: Requirement: The web application should be user-friendly. Criteria: Users should be able to navigate the interface easily, and the process of uploading images and receiving predictions should be intuitive.

5. PROJECT DESIGN

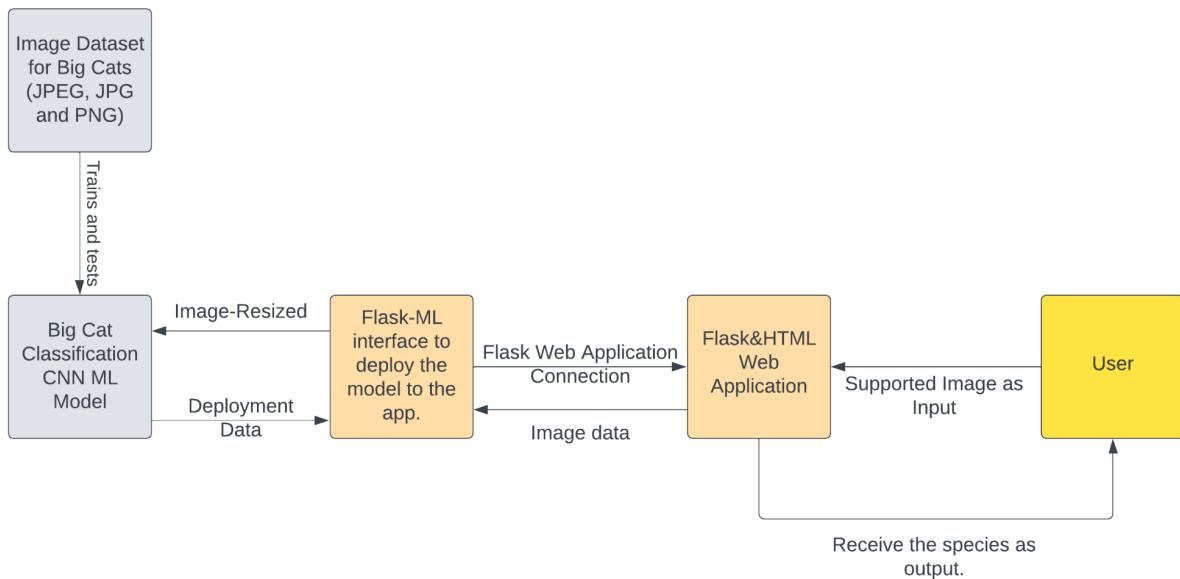
5.1 Data Flow Diagrams & User Stories



User Type	Functional Requirement (Epic)	User/ Administrator Story Number	User Story / Task	Acceptance criteria	Priority	Release
User (Web page user)	Index	USN-1	As a user, I can choose between the home page and the page for predictions	I can access both pages	Medium	Sprint-1
	Upload	USN-2	As a user, I can upload an image of a big cat	The application allows me to select and upload an image, providing feedback on the successful upload	High	Sprint-1

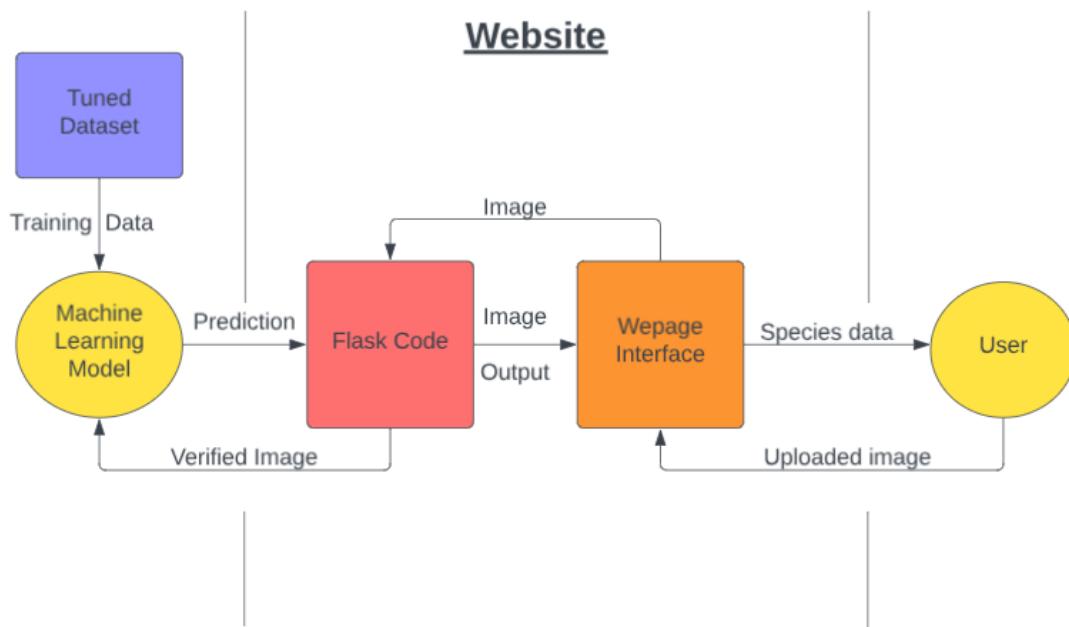
	Species prediction	USN-3	As a user, After uploading the image, I expect the model to predict the species of big cats.	The application displays the predicted species along with a confidence score, allowing me to understand the model's level of certainty.	High	Sprint-1
	Performance	USN-4	As a user, I want quick results without significant delays.	The model provides predictions within 5 seconds of image upload, ensuring a responsive user experience.	Medium	Sprint-1
	User-Friendly Interface	USN-5	As a user, I expect the web application to be easy to use and navigate.	The interface is intuitive, with clear instructions for uploading images, viewing predictions, and accessing interpretation tools.	Low	Sprint-2
Administrator	Model Deployment	ADN-1	As an administrator, I need to deploy the latest version of the trained model.	The system allows me to easily deploy the latest version of the model, ensuring that users have access to the most up-to-date classification capabilities.	High	Sprint-1
	Model Retraining	ADN-2	As an administrator, I want to initiate model retraining with new data.	The admin interface allows me to trigger the retraining process, ensuring that the model adapts to changes in the dataset and maintains high accuracy over time.	Low	Sprint-2

5.2 Solution Architecture



6. PROJECT PLANNING & SCHEDULING

6.1 Technical Architecture



6.2 Sprint Planning & Estimation

Sprint	Functional Requirement (Epic)	User Story Number	User Story / Task	Story Points	Priority	Team Members
Sprint-1	Index	USN-1	As a user, I can choose between the home page and the page for predictions	2	Medium	Syed Mohammad Yasoob Nihar Thampi
Sprint-1	Upload	USN-2	As a user, I can upload an image of a big cat	3	High	Syed Mohammad Yasoob Nihar Thampi
Sprint-1	Species prediction	USN-3	As a user, After uploading the image, I expect the model to predict the species of big cats.	3	High	Syed Mohammad Yasoob Nihar Thampi
Sprint-1	Performance	USN-4	As a user, I want quick results without significant delays.	2	Medium	Syed Mohammad Yasoob Nihar Thampi
Sprint-2	User-Friendly Interface	USN-5	As a user, I expect the web application to be easy to use and navigate.	1	Low	Syed Mohammad Yasoob Nihar Thampi

6.3 Sprint Delivery Schedule

Sprint	Total Story Points	Duration	Sprint Start Date	Sprint End Date (Planned)	Story Points Completed (as on Planned End Date)	Sprint Release Date (Actual)
Sprint-1	10	2 Days	18 Nov 2023	19 Oct 2023	10	19 Oct 2023
Sprint-2	5	1 Days	20 Nov 2023	20 Nov 2023	1	20 Nov 2023

7. CODING & SOLUTION

7.1 Convolutional Neural Network

The Machine Learning model used here is a Convolutional Neural Network. This model runs in a way that different layers are stacked onto each other to form a fully connected neural network. This is a feature that is trained from pictures of big cats, after which the trained model then takes the input image from the user and predicts which big cat it is.

7.2 Flask

The web app integration with feature 1 or the CNN Machine Learning model is done using a Python web app framework called Flask. The Flask file runs on a Python base which runs webpages of HTML and CSS while linking the trained model making a complete web application.

8. PERFORMANCE TESTING

8.1 Performance Metrics

Accuracy: 0.86

Confusion Matrix:

```
[[4 0 0 0 1 0 0 0 0 0]
 [0 5 0 0 0 0 0 0 0 0]
 [0 0 4 0 1 0 0 0 0 0]
 [0 0 0 5 0 0 0 0 0 0]
 [1 0 0 0 4 0 0 0 0 0]
 [0 0 0 0 0 5 0 0 0 0]
 [1 0 0 1 0 0 2 0 0 1]
 [0 0 0 0 0 0 5 0 0]
 [0 0 0 1 0 0 0 0 4 0]
 [0 0 0 0 0 0 0 0 5]]
```

Classification Report:

	precision	recall	f1-score	support
African Leopard	0.67	0.40	0.50	5
Caracal	1.00	1.00	1.00	5
Cheetah	0.83	1.00	0.91	5
Clouded Leopard	0.83	1.00	0.91	5
Jaguar	0.67	0.80	0.73	5
Lions	1.00	1.00	1.00	5
Ocelot	1.00	0.40	0.57	5
Puma	1.00	1.00	1.00	5
Snow Leopard	0.83	1.00	0.91	5
Tiger	0.83	1.00	0.91	5
accuracy			0.86	50
macro avg	0.87	0.86	0.84	50
weighted avg	0.87	0.86	0.84	50

8.2 Validation Method & Hyperparameter Training

```
vpath=r"C:\Users\nihar\Downloads\new animals\valid"
validation_data= keras.preprocessing.image_dataset_from_directory(
    vpath,
    batch_size = 10,
    image_size =(351,351),

    shuffle = True,
    seed =123,
    validation_split =0.2,
    subset ='validation'
)
```

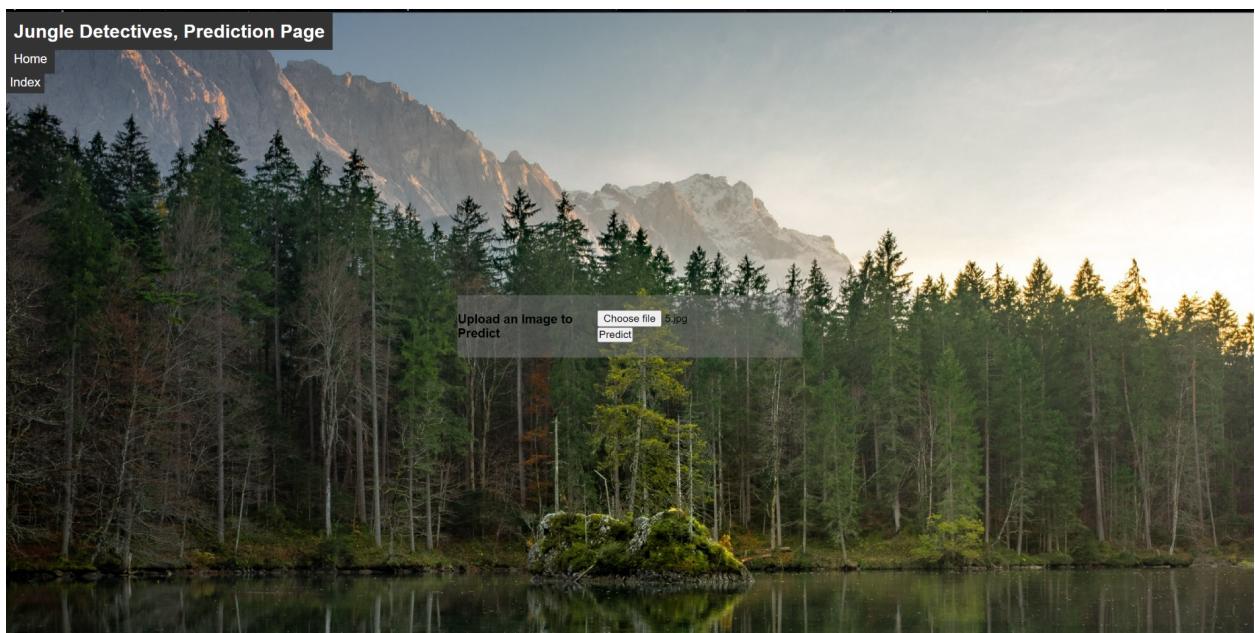
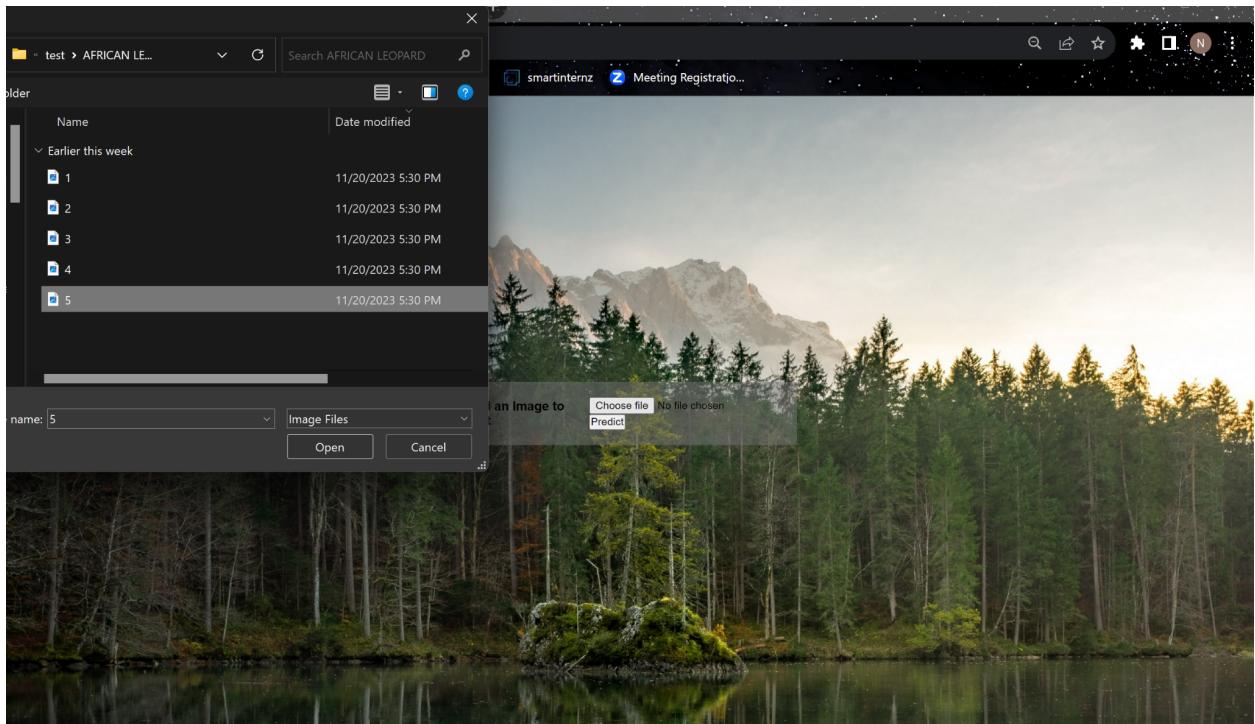
```
Found 50 files belonging to 10 classes.
Using 10 files for validation.
```

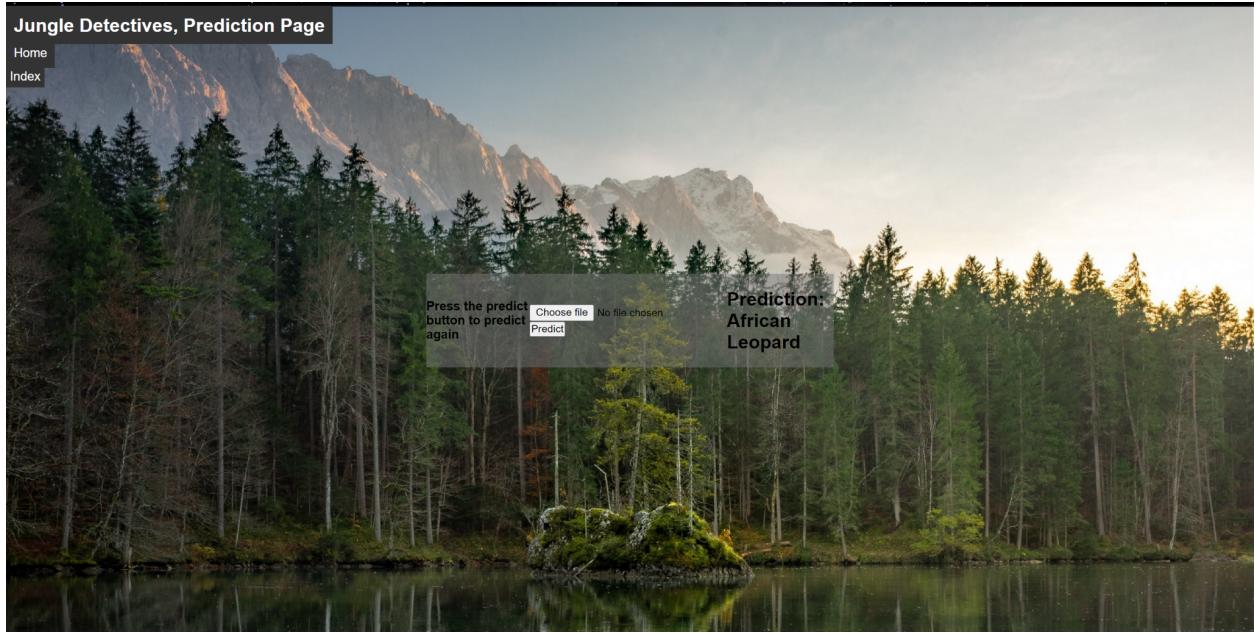
9. RESULTS

9.1 Output Screenshots

```
#####
#testing for ocelot#
#####
from tensorflow.keras.utils import load_img
from tensorflow.keras.utils import img_to_array
img = load_img(r"C:\Users\nihar\Downloads\new animals\test\OCELOT\4.jpg")
img = img.resize((351,351))
x = img_to_array(img)
x = np.expand_dims(x,axis=0)
a = np.argmax(resnet_model.predict(x),axis=1)
class_names = ['African Leopard' , 'Caracal' , 'Cheetah' , 'Clouded leopard' , 'Jaguar' , 'Lions' , 'Ocelot' , 'Puma' , 'Snow Leo
y_pred=resnet_model.predict(x)
class_idx = np.argmax(y_pred,axis=1)[0]
class_name=class_names[class_idx]
print( 'Predicted Class name:' ,class_name)
```







10. ADVANTAGES & DISADVANTAGES

Advantages: The project aims to contribute to wildlife conservation by providing a tool for identifying and monitoring big cat species. It serves as an educational tool for wildlife enthusiasts, students, and educators. The machine learning model automates the process, saving time and resources compared to manual methods. The model's feedback loop and interpretability tools enhance user engagement, promoting better understanding of predictions. The project's focus on continuous learning ensures the model adapts to changes in the dataset and user feedback. The model's public accessibility through a web application fosters widespread interest in wildlife identification. The project also addresses ethical considerations, including bias mitigation and privacy assurances, demonstrating a commitment to responsible AI practices.

Disadvantages: The project faces several challenges, including limited datasets, complex interpretability of deep neural networks, ambiguity in image identification, user feedback variability, deployment and scalability challenges, model maintenance overhead, potential misuse, dependency on user feedback, and model training resource requirements. Limited datasets may hinder the model's generalizability to all big cat species and scenarios. Interpretability may be challenging due to the complexity of deep neural networks and the need for complex visualization tools. Image identification may be ambiguous, leading to misclassifications. User feedback may vary in quality and relevance, making managing and categorizing diverse feedback a complex task.

Deploying and maintaining a machine learning model in a web application may pose challenges related to scalability, performance, and user experience. Regular model updates and maintenance require ongoing effort and resources, including monitoring for biases and ethical considerations. The model's effectiveness depends on user participation, and low user engagement may limit its benefits.

11. CONCLUSION

The Big Cat Species Classification project is a significant advancement in machine learning for wildlife conservation and education. It uses advanced technologies to automate the identification of various big cat species, contributing to the understanding and preservation of wildlife. The project's benefits include potential impact on conservation efforts and an engaging educational resource. Its commitment to continuous improvement and ethical considerations, such as bias mitigation and privacy assurances, reflects a responsible approach to AI deployment in sensitive domains like wildlife conservation. However, the project faces challenges such as dataset limitations, interpretability of complex models, and potential ambiguity in image identification. User engagement, deployment scalability, and ongoing model maintenance are also important considerations. Despite these challenges, the project holds great promise, aligning technological innovation with environmental stewardship. Its user-friendly interface, interpretability tools, and ethical AI practices demonstrate the potential of machine learning in fostering a deeper connection between technology and the natural world.

12. FUTURE SCOPE

The Big Cat Species Classification project is a comprehensive tool for wildlife conservation, research, and public engagement. Its future scope includes enhanced model accuracy, multi-species recognition, real-time monitoring, mobile application integration, multimodal learning, cross-species identification, global collaboration, education and outreach programs, adaptability to climate and environmental changes, integration with conservation databases, blockchain for conservation records, and quantifying population dynamics.

The project aims to refine its model by incorporating state-of-the-art architectures, exploring diverse datasets, and experimenting with advanced training techniques. It also plans to expand its capabilities to recognize and classify multiple species within the same image, facilitating a more comprehensive understanding of the wildlife ecosystem.

Real-time monitoring capabilities could be developed to analyze live video streams, enabling the model to identify and track big cat species in their natural habitats.

A mobile application could be developed to encourage broader participation in citizen science initiatives and wildlife monitoring. Multi-modal learning could involve incorporating audio and behavioral data to enhance the model's understanding of big cat species. Cross-species identification could be expanded to include other wildlife species beyond big cats.

By exploring these future scopes, the Big Cat Species Classification project can become a dynamic and comprehensive tool for wildlife conservation, research, and public engagement.

13. APPENDIX

GitHub: <https://github.com/smarterinternz02/SI-GuidedProject-611952-1700322006.git>

Dataset and model:

https://drive.google.com/drive/folders/1_2CMpH-iE2Rj5yG0AD9UD1EG7HyuR90S?usp=sharing

Project Demo Link: <https://www.youtube.com/watch?v=bQ55bKP8rdY>