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W4

Monitoring biodiversity loss

W4 Lesson 1

Convolutional Neural Networks

AI and Climate Change

DeepLearning.AI

Welcome to Week 4

Explore phase

Researchers and Biologists

Park Staff

Community

Policy Makers

Explore

1. Engage stakeholders ✓
2. Define the problem ✓
3. Determine if AI could add value ✓

"Researchers and conservation biologists need daily information on the number of animals sighted at various locations throughout the Karoo national park in order to monitor trends in biodiversity and animal populations to inform policies that can be enacted to protect and preserve park ecosystems."

Design phase

1. Prototype your solution
2. Ensure data privacy
3. Design the user experience

Snapshot Karoo dataset

Distribution of animals

- gemsbokoryx
- hartebeestred
- kudu
- eland
- baboon
- springbok
- jackalblackbacked
- zebramountain
- steenbok
- birdother
- bustardkori
- duiker
- ostrich

*For more detailed information, check out the **Explore Phase - Exploring the Karoo Image Data***

Snapshot Karoo dataset

*For more detailed information, check out the **Explore Phase - Exploring the Karoo Image Data***

Difficult images

kudu

gemsbokoryx

baboon

Animal labeling from a series of images

baboon

baboon

baboon

Data challenges

MegaDetector

https://github.com/microsoft/CameraTraps/blob/main/megadetector.md

MegaDetector

CPAWS
CANADIAN PARKS AND WILDERNESS SOCIETY
NORTHERN ALBERTA CHAPTER

CONSERVATION X LABS

SMITHSONIAN'S NATIONAL ZOO
& CONSERVATION BIOLOGY INSTITUTE

Snapshot USA

ADEQ
Arizona Department of Environmental Quality

PARQUE NACIONAL SERRA DOS ÓRGÃOS

FELIDAE CONSERVATION FUND

rspb giving nature a home

GOBIERNO DE ESPAÑA
MINISTERIO DE CIENCIA E INNOVACIÓN

Estación Biológica Doñana CSIC

Infraestructuras Científicas y Técnicas Singulares

CZU Czech University of Life Sciences Prague

DC CAT COUNT

U.S. FISH & WILDLIFE SERVICE
DEPARTMENT OF THE INTERIOR

CAMELOT

UNIVERSITY of TASMANIA

UNIVERSITY OF SASKATCHEWAN

WASHINGTON STATE UNIVERSITY

PRIFYSGOL BANGOR UNIVERSITY

UNSW SYDNEY

WOODLAND PARK ZOO

synthetaic

BH LAB

DeepLearning.AI

AI and Climate Change

Convolutional Neural Networks and Pretraining

Neural networks

Neural networks

Neural networks

Computer vision use cases

Model used: YOLOv5, doi.org/10.5281/zenodo.3908559 and pytorch.org

Your project

Animal

No animal

Animal

No animal

Animal

Animal

Animal

Animal

AI and Climate Change

DeepLearning.AI

Biodiversity

MegaDetector

jupyter C2_W4_Lab_1_design_phase_1 Last Checkpoint: 05/10/2023 (autosaved)

File Edit View Insert Cell Kernel Widgets Help Trusted Python 3

Run Code

In [5]:
```
megadetector_result = megadetector.generate_detections_one_image(sample_image, sample_im_file,
print(megadetector_result)
```

```
{'file': './data/bustardkori/KAR_S1_D03_R1_IMAG0111.JPG', 'max_detection_conf': 0.968, 'detec
tions': [{'category': '1', 'conf': 0.968, 'bbox': [0.1999, 0.3542, 0.4015, 0.6153]}]}
```

The resulting output has several fields:

- `file` : the relative path of the input picture.
- `max_detection_conf` : The confidence value of the object that the model is more certain about.
- `detections` : A list containing all detected objects in the picture which confidence is higher than the detection_threshold (0.6 in the examples)

`max_detection_conf` is a confidence level ranging from 0 to 1

- Values close to 0 indicate **low confidence**
- Values close to 1 indicate **high confidence**

DeepLearning.AI

AI and Climate Change

Transfer Learning and Fine Tuning

Computer vision use cases

Additional training

How neural networks “see” images

109	105	100	94	85	79
110	103	96	90	86	87
102	94	89	91	96	102
93	89	89	99	110	116
91	88	93	108	120	123
92	100	108	110	108	109

Color channels

RGB
(22, 9, 0)

RGB
(245, 191, 127)

CNN: Convolution operation

109	105	100	94	85	79
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102	94	89	91	96	102
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Image

*

Convolution

Filter

=

Features
(edges, shapes, ...)

CNN: Convolution operation

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Image

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Convolution

Filter

=

Features
(edges, shapes, ...)

CNN: What do layers learn?

First layer

Deep layers

H. Lee, R. Grosse, R. Ranganath, and A. Y. Ng, in Proceedings of the 26th Annual International Conference on Machine Learning (2009), pp. 609–616.

AI and Climate Change

DeepLearning.AI

Biodiversity

Transfer Learning

AI for Climate Change

DeepLearning.AI

Biodiversity
Design Phase Checkpoint

Design phase checkpoint

- How will you address issues with imbalances, biases, privacy, or other concerns with your data?
- What kind of model will you implement, and how will you measure its performance?
- How will your design address the problem you set out to work on?
- How will the end user interact with your system?

Design phase checkpoint

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Design phase checkpoint

Images of people and vehicles should be treated as confidential personal information and be identified and deleted as quickly as possible

Checkpoint

- How will you address issues with imbalances, biases, privacy, or other concerns with your data?
- What kind of model will you implement, and how will you measure its performance?
- How will your design address the problem you set out to work on?
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Design phase checkpoint

Checkpoint

Do No Harm

Continue to be mindful of potential concerns that arise in any affected communities.

- How will you address issues with imbalances, biases, privacy, or other concerns with your data?
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Design phase checkpoint

"Researchers and conservation biologists need daily information on the number of animals sighted at various locations throughout the Karoo national park in order to monitor trends in biodiversity and animal populations to inform policies that can be enacted to protect and preserve park ecosystems."

Checkpoint

- How will you address issues with imbalances, biases, privacy, or other concerns with your data? ✓
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W4 Lesson 2

Implementing Model for Detecting and Classifying Animals

AI for Climate Change

DeepLearning.AI

Biodiversity

Implement Phase

AI for Climate Change

DeepLearning.AI

Biodiversity

Project Wrap Up

Implement phase checkpoint

- Is your model performance acceptable?
- Are end users able to successfully use your system?

Evaluate phase

1. Measure project impact
2. Communicate results
3. Determine next steps

Explore phase

Researchers and biologists

Policy makers

Park staff

Local community

Explore

1. Engage stakeholders ✓
2. Define the problem ✓
3. Determine if AI could add value ✓

"Researchers and conservation biologists need daily information on the number of animals sighted at various locations throughout the Karoo national park in order to monitor trends in biodiversity and animal populations to inform policies that can be enacted to protect and preserve park ecosystems."

Karoo dataset

Dataset issues

Kudu

Oryx

Bird

Dataset issues

DeepLearning.AI

AI for Climate Change

Project Spotlight: Tackling Climate Change with Machine Learning – Priya Donti

Emitting sectors

Agriculture
Forestry
Buildings
Transportation
Industry

Stakeholders

Frontline communities
Policymakers
Entrepreneurs
Researchers
Industry
NGOs
Investors

Tools

Engineering
Policy analysis
Social sciences
Machine learning
Operations research
Economics
Natural & physical sciences

Adaptation strategies

Disaster response
Disease monitoring
Ecosystem preservation
Resilient infrastructure

Tackling Climate Change with Machine Learning

David Rolnick[1]*, Priya L. Donti[2], Lynn H. Kaack[3], Kelly Kochanski[4], Alexandre Lacoste[5], Kris Sankaran[6,7], Andrew Slavin Ross[8], Nikola Milojevic-Dupont[9,10], Natasha Jaques[11], Anna Waldman-Brown[11], Alexandra Luccioni[6,7], Tegan Maharaj[6,7], Evan D. Sherwin[2], S. Karthik Mukkavilli[6,7], Konrad P. Kording[1], Carla Gomes[12], Andrew Y. Ng[13], Demis Hassabis[14], John C. Platt[15], Felix Creutzig[9,10], Jennifer Chayes[16], Yoshua Bengio[6,7]

[1]University of Pennsylvania, [2]Carnegie Mellon University, [3]ETH Zürich, [4]University of Colorado Boulder, [5]Element AI, [6]Mila, [7]Université de Montréal, [8]Harvard University, [9]Mercator Research Institute on Global Commons and Climate Change, [10]Technische Universität Berlin, [11]Massachusetts Institute of Technology, [12]Cornell University, [13]Stanford University, [14]DeepMind, [15]Google AI, [16]Microsoft Research

Recurring Themes

- Gathering information

Recurring Themes

- Gathering information
- Forecasting

Recurring Themes

- Gathering information
- Forecasting

Recurring Themes

- Gathering information
- Forecasting
- Optimizing real-world systems

Recurring Themes

- Gathering information
- Forecasting
- Optimizing real-world systems
- Accelerating scientific experimen

Important Considerations

- AI is **not a silver bullet**
- AI is **only one part of the strategy**
- **Collaboration** is key

Climate Change AI

- Digital resources
- Conferences and events
- Funding programs
- Community and newsletter
- Webinar series and virtual happy hours

Climate Change AI

Learn more & join in:

www.climatechange.ai

@ClimateChangeAI

AI for Climate Change

DeepLearning.AI

Week 4 and Course Summary

Temperature is rising

UK Met Office HadCRUT5.0 dataset

The greenhouse effect

Vaclav Smil (2017) & BP Statistical Review of World Energy

Global temperature change 1880-2021

2100 warming projection

1.5°C consistent
+1.3°C

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2100 warming projection

Optimistic scenario
+1.8°C

1.5°C consistent
+1.3°C

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2100 warming projection

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2100 warming projection

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2100 warming projection

achieved through reducing emissions and removing greenhouse gasses from the atmosphere

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Wind power prediction

Baseline:
Moving average

Neural network:
With past data

Neural network:
With wind forecast
(synthetic) data

AI and biodiversity monitoring