Deep Learning for Conservation: Classifying Drone Images from Protected Lands

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Image from: https://www.kaggle.com/datasets/irvingvasquez/cactus-aerial-photos

BBC NEWS

Mexico seizes ship carrying 68,000 tonnes of illegal iron

1 May 2014

"Police confiscated an iron ore mining operation belonging to a drugs cartel near Lazaro Cardenas…"

https://www.bbc.com/news/world-latin-america-27233824

REUTERS APRIL 22, 2020 / 10:11 AM / UPDATED 2 YEARS AGO

Mexican crime gangs branching into illegal logging, researchers warn

"..Lack of enforcement due to scant resources and corruption."

VIGIA project

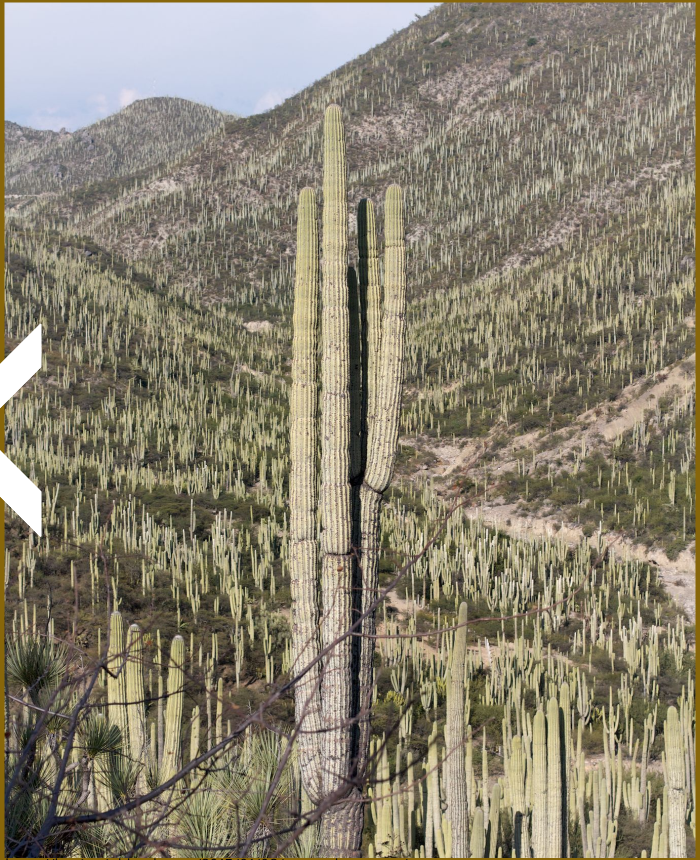
Mexico is rich in biodiversity; however, human activity is degrading these natural areas.

Government efforts to declare natural areas "protected" and surveil them have, so far, been insufficient.

Human monitoring is expensive, limited, and in some areas prone to corruption

Can we develop a system for automatic surveillance of natural areas using artificial intelligence?

—https://jivg.org/research-projects/vigia/



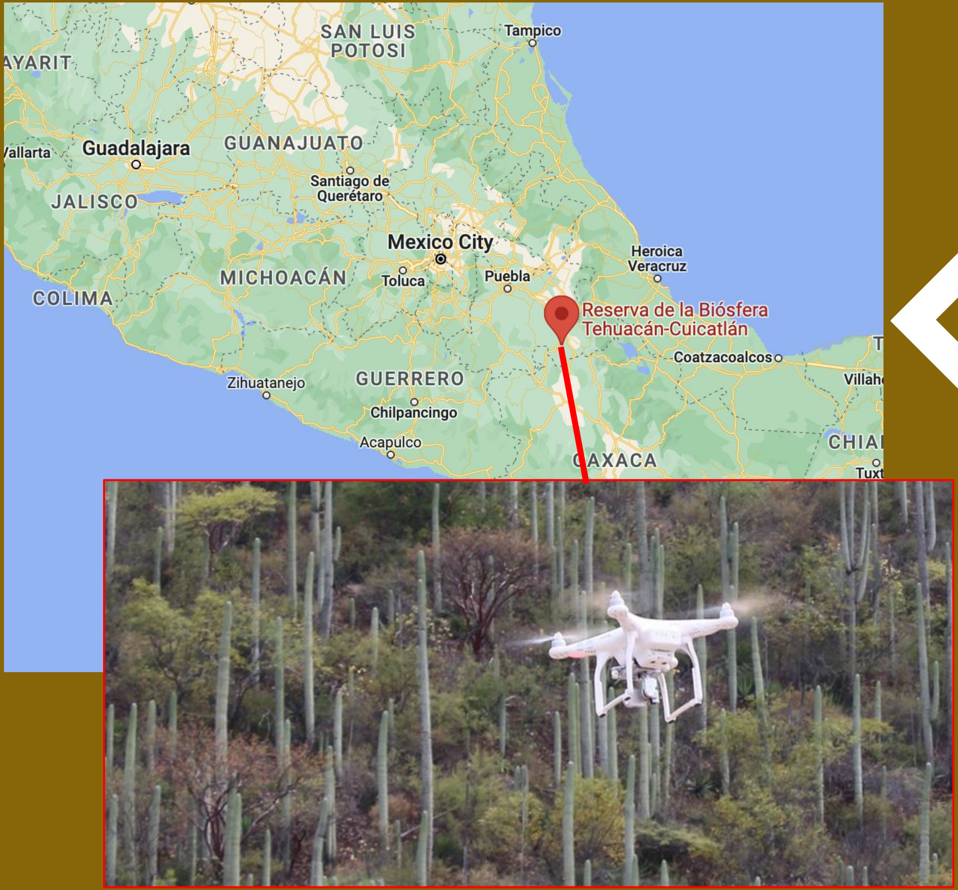
https://benjaminblonder.org/2015/01/08/guess-the-cactus/

Needed Surveillance:

- Detect smoke and fire
- Disrupt illegal hunting
- Prevent illegal logging or mining
- Identify cars/other human activity in protected areas

Research Question:

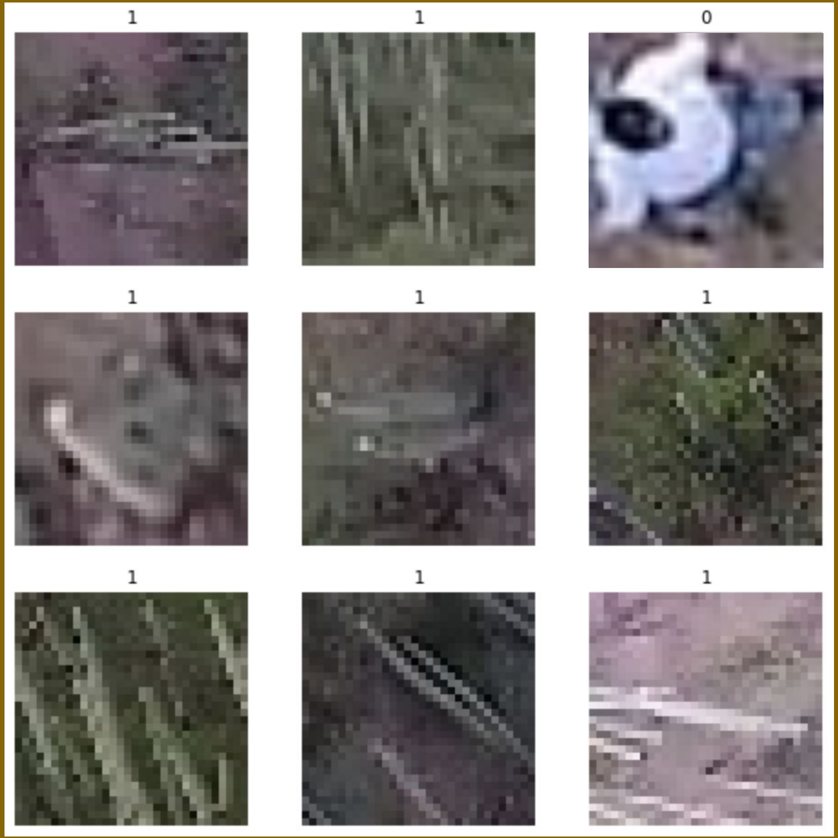
- Can deep learning techniques, applied to small-sized, low-resolution surveillance/drone images, offer reliable image classification for automated monitoring?



The Data:

Kaggle dataset

- Tehuacan-Cuicatlan Biosphere Reserve
- Drone aerial images



The Data:

Cactus Aerial Photos

Columnar Cactus (Neobuxbaumia tetetzo)

- 16,138 Cactus images
- 5,366 Non-cactus images
- 80% training, 20% test data

Start with Transfer Learning

MobileNet (trained on ImageNet)

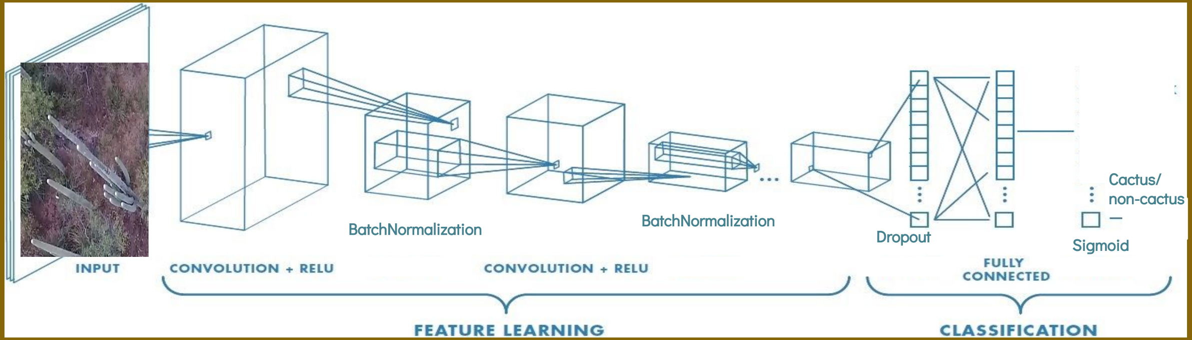
- window_screen: 0.743
- shower_curtain: 0.032
- prison: 0.021
- window_shade: 0.020
- crossword_puzzle: 0.018

Not so helpful... proceed with model building

Data Augmentation

- Random horizontal flip
- Random rotation 0.1
- Random Zoom -0.2-0.3
- Random Contrast 0.2
- Random Brightness 0.2

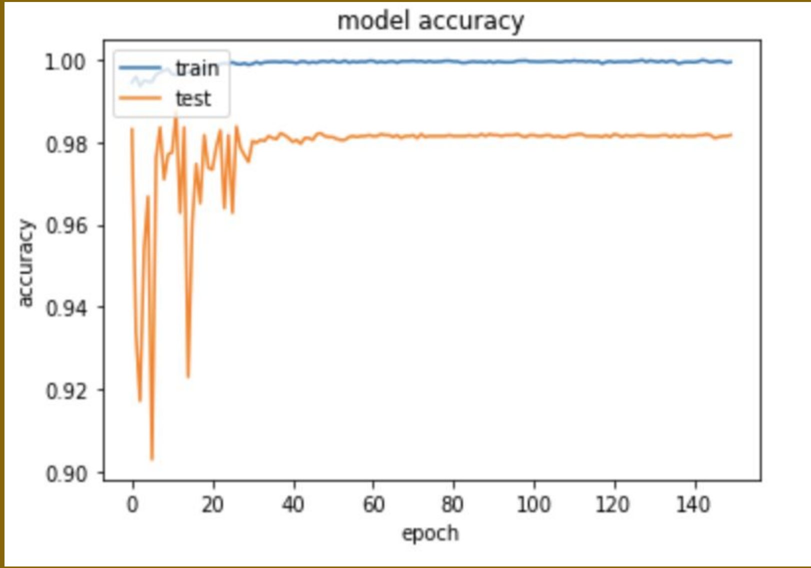
Model Architecture

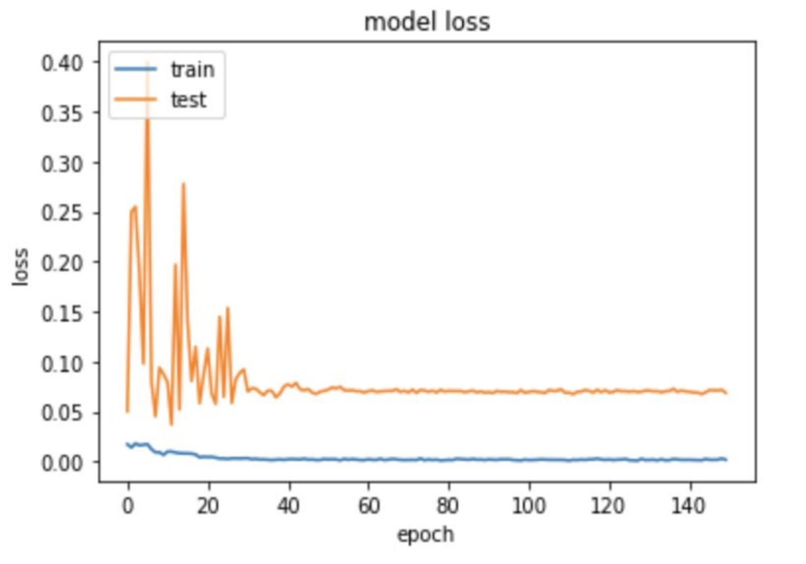


- Adam Optimizer
- Scaled data

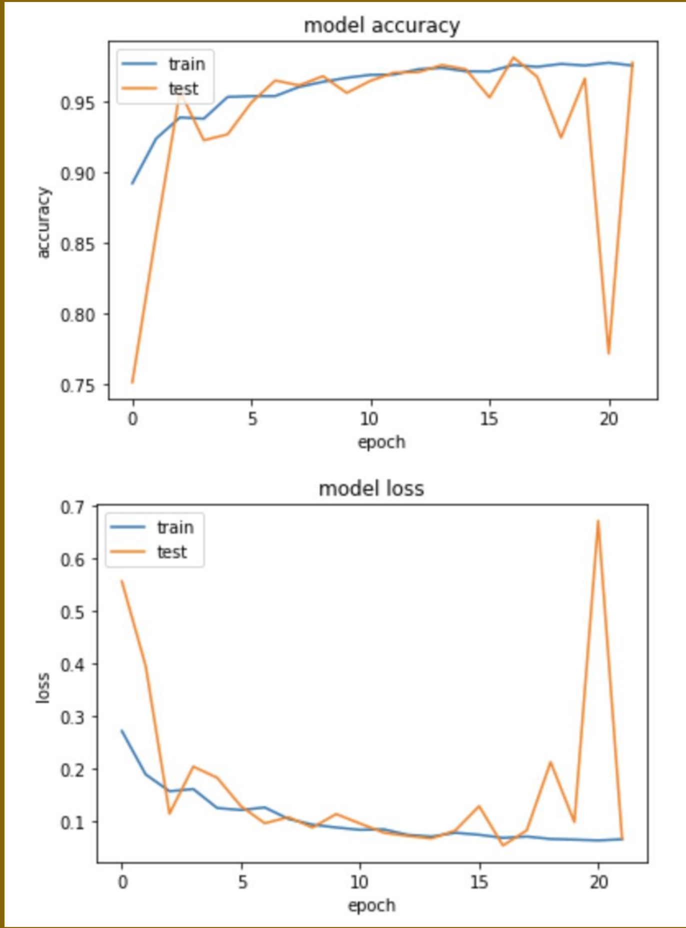
02	11	09	02	02	02
Conv2D	Batch Normalization	Separable Conv2D	Pooling	Dropout	Dense Layer

Early Results: Model Performance is Good, but Overfitting





-Use Fewer Epochs
-Correct overfitting



Improved Fit
Decreased Val_Acc

To remedy overfitting:

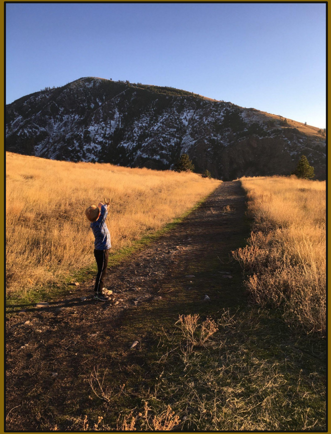
- Increase augmentation,
- Try a different pretrained model/transfer learning
- Try Enhancement learning
- Use k-fold cross optimization
- Use CutMix or MixUp for augmentation
- Retrain on a different training/test split

(Suggestions by Patrick Kalkman on TowardsDataScience)

Results here are fair but model seems not quite stable.
The model early stopping patience 5
Data augmentation was increased compared to previous model.
The previous model had acc = 1 and val_acc = .987
This model has acc = .976 and val_acc = .980

How does the model perform on other images?

Model: “These are NOT cactus”



CNN: 1.13% likely a cactus
98.87% likely non-cactus

MobileNet:
75% megalith
3% alp
2% stone_wall
1% beacon
1% worm_fence

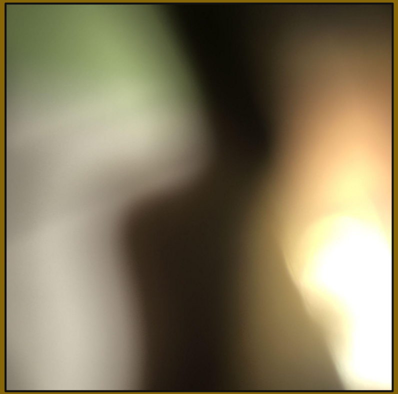
CNN: 0.34% likely a cactus
99.65% likely non-cactus

MobileNet:
22% ant
10% bee
3% sulphur_butterfly
2% fly
2% yellow_lady’s_slipper

CNN: 0.00% likely a cactus
100% likely non-cactus

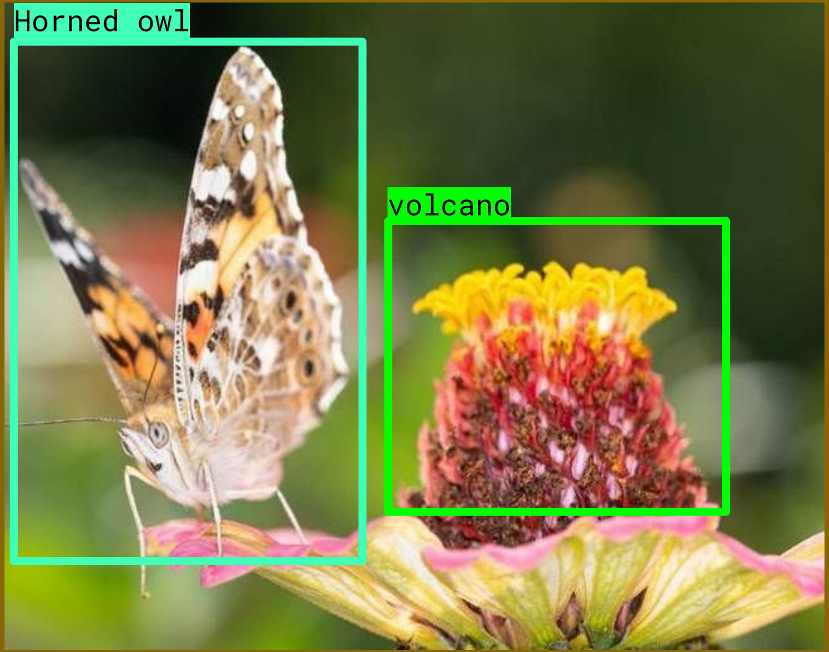
MobileNet:
76% wing
6% volcano
1% airliner
1% missile
1% aircraft carrier

Model: “*Maybe* these are cacti?”



CNN: 9.65% likely a cactus
90.35% likely non-cactus
MobileNet:
68% matchstick
4% spotlight
4% lighter
2% volcano
2% candle

CNN: 10.87% likely a cactus
89.13% likely non-cactus
MobileNet:
22% wall clock
10% analog clock
3% tripod
2% matchstick
2% tarantula



Implications for misclassification

- Flag images that should be cactus but aren't
- Human review flagged images
- False negatives = No major implications

- Misclassification of negative class as positive could reduce effectiveness of security system
- False positives = security threat
- Precision is better metric than accuracy

Next Steps:

Address Overfitting

Domain Adaptation

Residual layer

Transfer Learning

Multiclass Model

Video Analysis

Summary

- **Yes** CNN can offer high performing models on low resolution images
- Transfer learning is not very helpful in this case
- Many models, trained on this data, perform well; fine-tuning improves marginally
- Need for this kind of solution growing
  - fire alert systems
  - security surveillance
  - environmental monitoring

List of references

Used for project info and help with models:

- https://jivg.org/research-projects/vigia/
- https://keras.io/examples/vision/image_classification_from_scratch/
- https://www.kaggle.com/code/twhitehurst3/aerial-cactus-keras-cnn-95-accuracy
- https://ladvien.com/lego-deep-learning-classifier-cnn/

Thank you!

Questions?

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