MACHINE LEARNING

M1 PROJECT

LET'S SAVE WILDLIFE !

GROUP n°4

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INTRODUCTION

OUT OF **169 420** SPECIES ASSESSED,

47 187 ARE CLASSIFIED AS THREATENED

Source : latest edition of the IUCN Red List (version 2025.1)

WHAT IS THE PROBLEM ?

NEARLY **50 000 SPECIES** ARE IN DANGER

If we continue on this path, we risk completely destroying our wildlife and ecosystems.

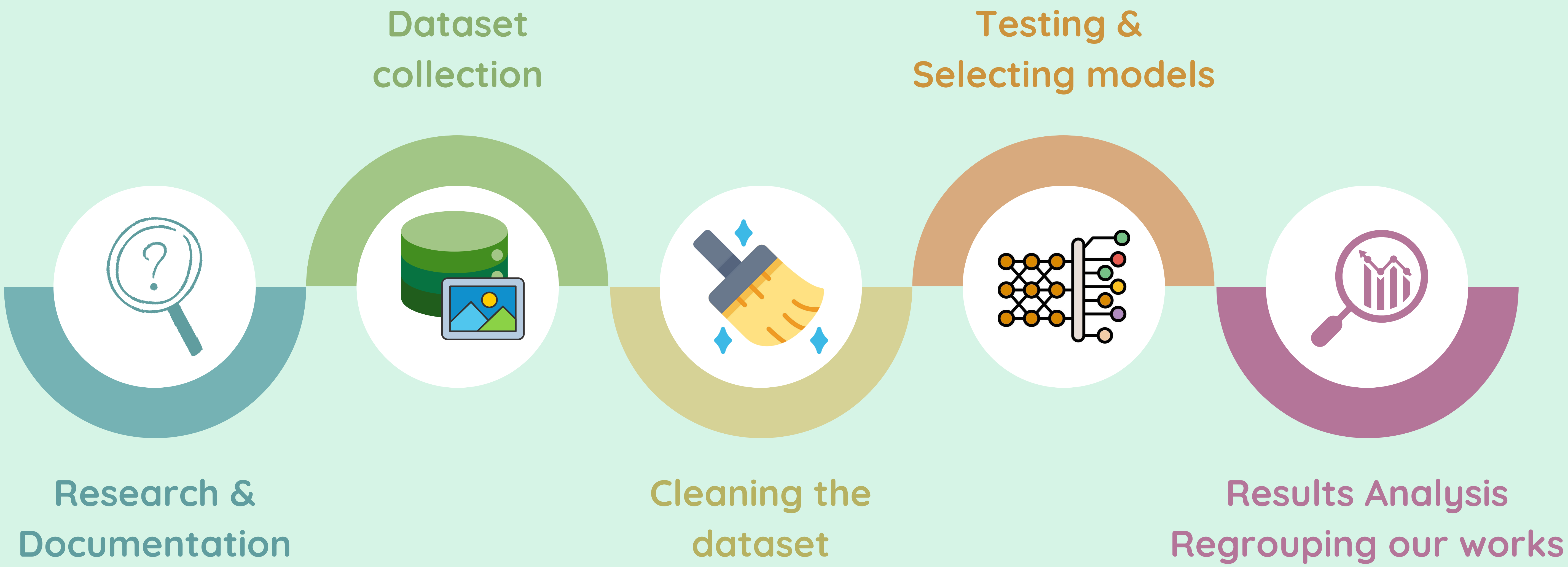
GOALS

- **support** those who are doing their best to **protect wildlife**
- **help monitor** the health of animals.

SCOPE

This **AI** could be **integrated with photographic sensors** to **detect and notify caretakers** about an animal's condition

STEPS TAKEN


Dataset
collection
Testing &
Selecting models
Research &
Documentation
Cleaning the
dataset
Results Analysis
Regrouping our works

TOOLS & TECHNIQUES

TECHNIQUES

Deep Learning with CNNs

applied for image classification

Transfer Learning

using pre-trained models on MobileNetV2

Data Augmentation

to increase dataset diversity and reduce overfitting

TOOLS & TECHNIQUES

MODEL USED

1. Custom CNN
2. MobileNetV2

TOOLS & TECHNIQUES

TOOLS

NumPy

matplotlib

Scikit learn

Streamlit

CHALLENGES

1. Limited Dataset Size

- **Issue :**

  Only 543 images across 2 classes
  → High overfitting risk

Solution :

- Applied data augmentation (rotation, brightness, contrast...)

2. High Sensitivity to False Positives

- **Issue :**

  High recall but low precision
  → Too many false alarms

Solution :

- Monitored precision and recall to balance predictions

3. Rapid Overfitting on Training Data

- **Issue :**

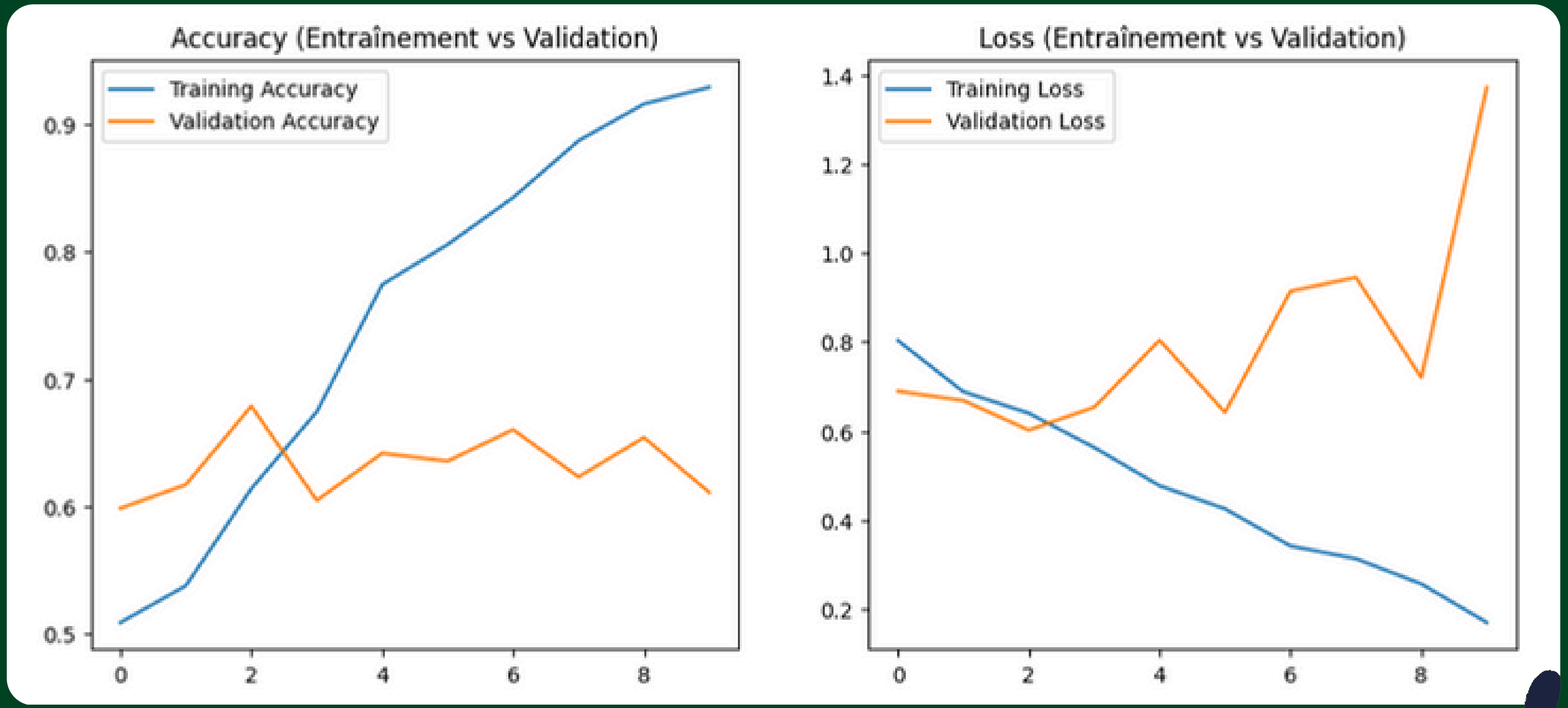
  Validation loss increased early, accuracy dropped

Solution :

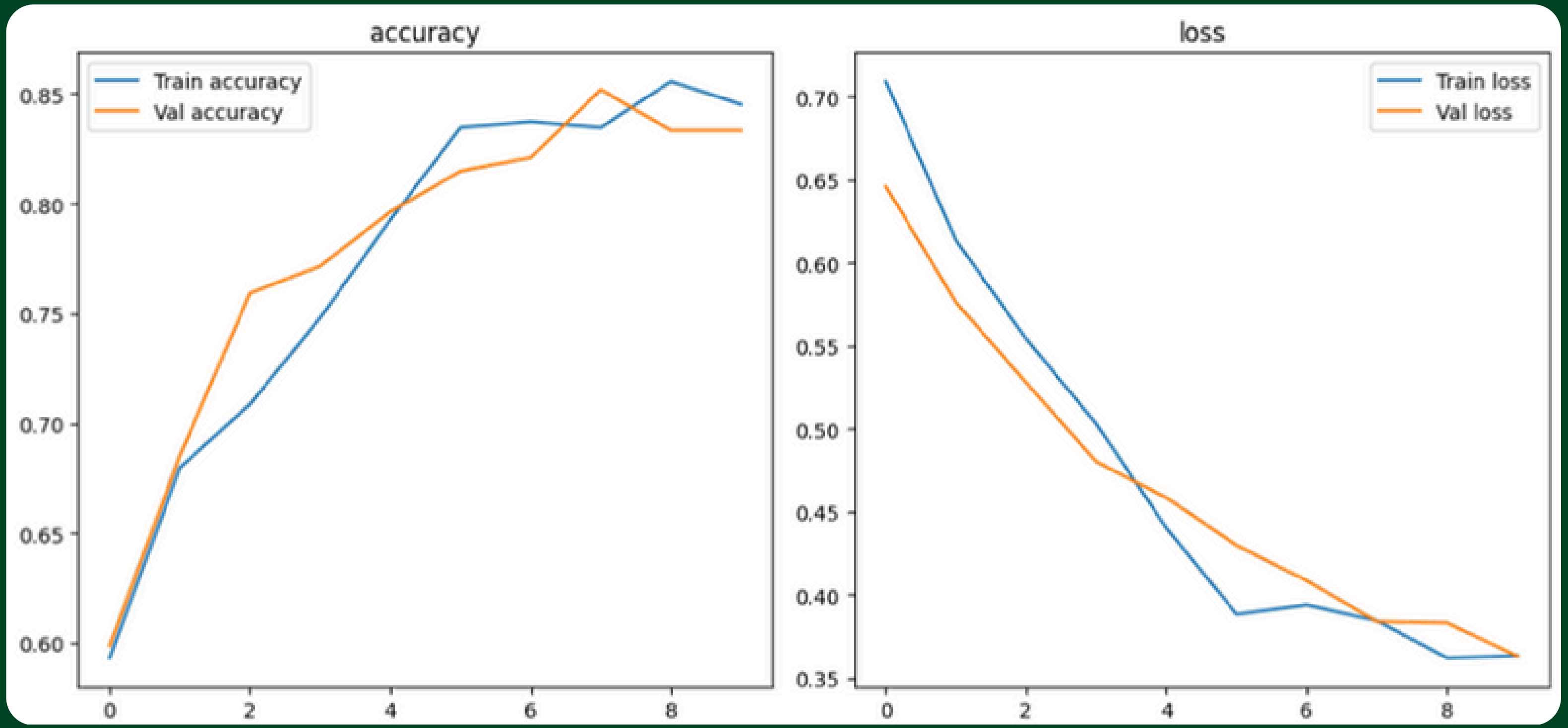
- Added 30% Dropout
- Used EarlyStopping (patience=5)
- Lowered learning rate to 1e-5

TRAINING CURVES

Baseline CNN Model



MobileNetV2 (Transfer Learning Model)



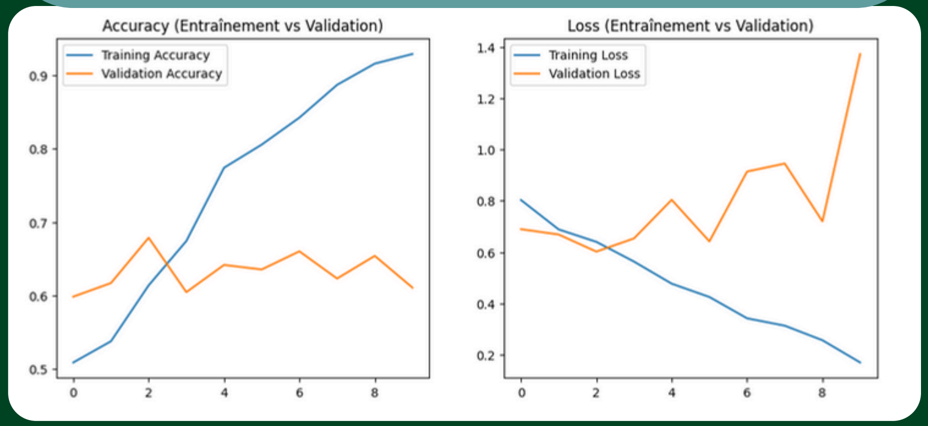
Achieved a final training accuracy of **91.8%**, But only **61.1%** validation accuracy.

Graphs of training and validation accuracy/loss clearly demonstrate the overfitting in the CNN and the stable convergence of the MobileNetV2 model.

This model achieved much better generalization

KEY RESULTS

Baseline CNN Model



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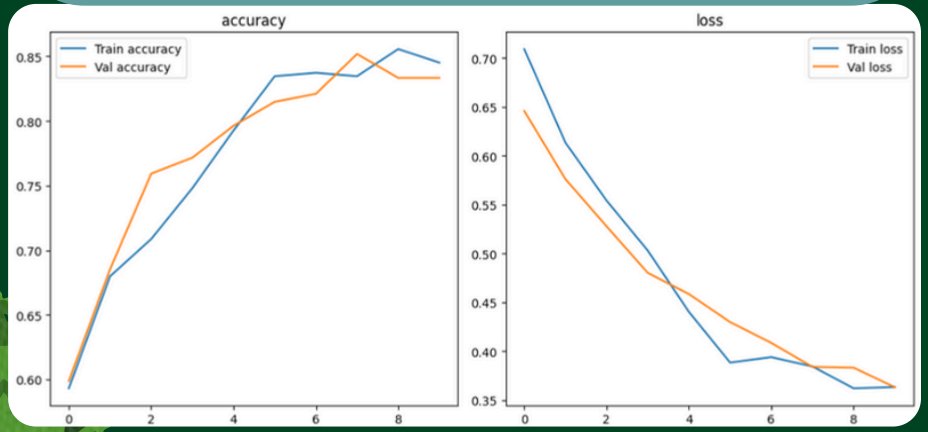

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Classification Report

Class	Precision	Recall	F1-score
Injured	0.93	0.84	0.88
Not Injured	0.87	0.94	0.91

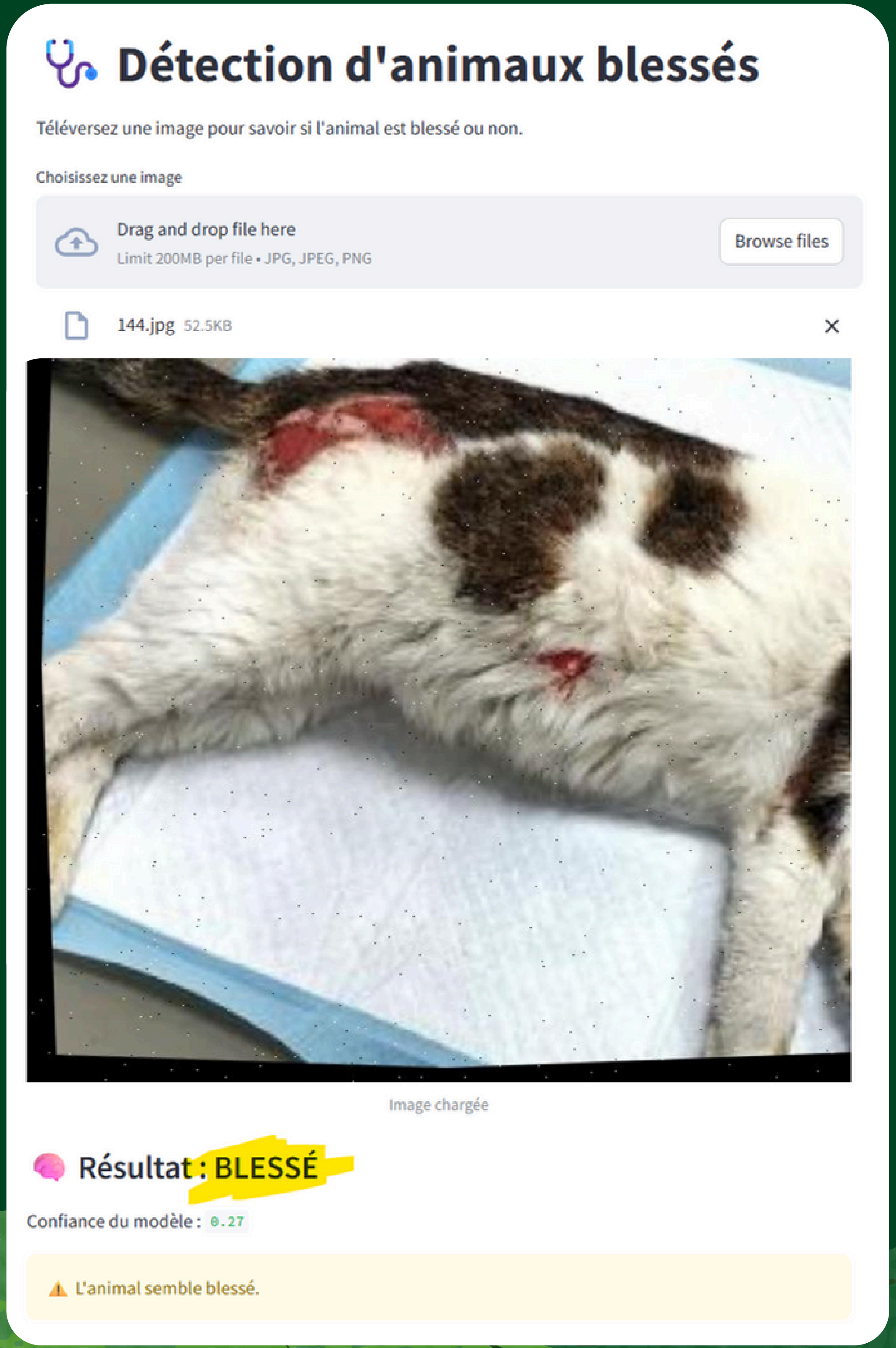
→ **Overall accuracy : 89%**

Analysis

The **CNN model**, despite reaching **high training accuracy**, **failed to generalize well** due to its relatively **shallow architecture** and **limited capacity** to extract complex features.

On the other hand, **MobileNetV2**, benefiting from **transfer learning**, was able to extract rich, **high-level features**, leading to **much higher validation performance**.

OUR SOLUTION : DEMO



Import image

Results

Accuracy

Prediction

NEXT STEPS

Collect More Diverse and Annotated Data

Use **bounding boxes** or **segmentation** masks to train on regions of interest

Object Detection or Segmentation Models

Instead of classifying the entire image, to locate and highlight the specific area of injury, we could use :

object detection

For e.g. :

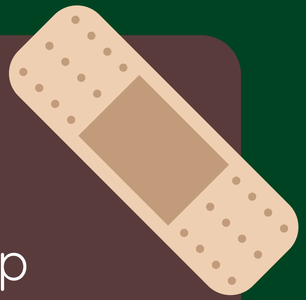
- Faster
- R-CNN
- YOLO

image segmentation

For e.g. :

- U-Net
- Mask
- R-CNN

Multi-label or Hierarchical Classification



Type of injury

- cut, swelling, limp

Severity

- mild, moderate, severe

Body region affected

- limbs, head, torso, etc.

Deploy as a Mobile or Edge Device App

Create a lightweight version of the model to run directly on field devices used in shelters or reserves.

CONCLUSION

Key Points to keep :

Model choice matters

Transfer learning with MobileNetV2 outperformed our custom CNN significantly, especially in generalization.

Overfitting is a real risk

High training accuracy does not guarantee good real-world performance. Monitoring validation metrics is essential.

Data preparation is just as important as modeling

Augmentation, balancing classes, and understanding the dataset's structure had a major impact on the outcomes.

Metric interpretation is crucial

Accuracy alone is not enough. In this case, recall was more important, as missing an injured animal could have critical consequences.

CONCLUSION

Machine learning can contribute meaningfully to animal welfare

With the right tools and approach, we can create real-world applications that aid in wildlife conservation and care.

PARIS PANTHÉON-ASSAS UNIVERSITÉ

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THANK YOU FOR ATTENTION

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Ressources

- Github : See our code
- Streamlit : See our website