École d'ingénieurs
Télécom Physique
Université de Strasbourg
Partenaire stratégique
Institut Mines-Télécom

Satellite Harvest

Generating ground truth data for agricultural remote sensing by coupling satellite and Google Street View imagery

PI10 : PROJECT REVIEW 4

Client : Dr Inbal Becker-Reshef

Supervisor : Mr Josef Wagner
Mr Shabarinath Nair

Mentor : Benoît Lebrun

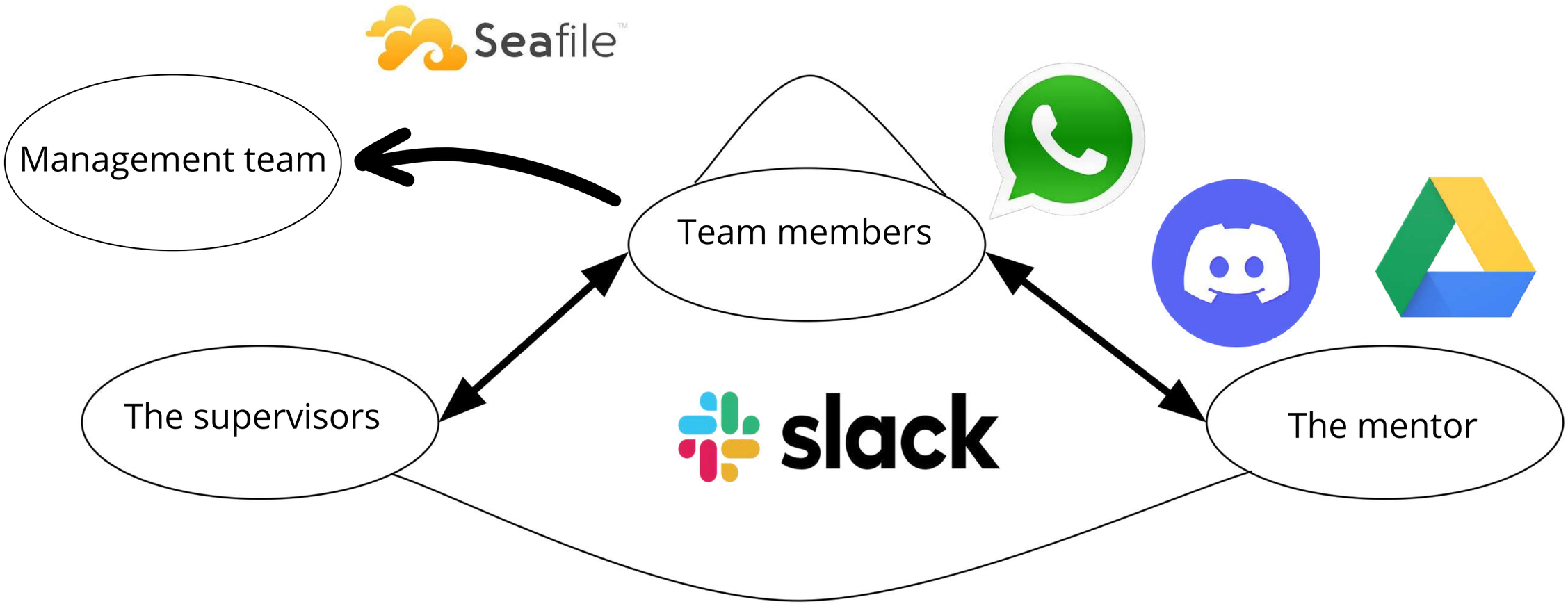
Project manager : Mathys Fillinger

Project members : Boutayna Lakhmi
Martin Fiack
Quentin Duvernay

Table of contents

- Team presentation
- Subject presentation
- Project conception
- Project results
- Project management

Presentation
Communication



Objectives of the project

- A need for ground truth data
- Food security by monitoring crop productivity across the globe
- Address the lack of agricultural data in some countries (Kenya)
- Tremendous amount of data from satellite : WorldView-3 revisit time < 1 day

Deliverables

Type of deliverable	Description
Digital version	A Github repository including : - Commented python codes in English - Trained models with calculated evaluation metrics - Labeled datasets used to train the model - Implementation of the model in France and in Kenya
Documentation	A written report in english
Presentation	A poster A demonstration video

✓

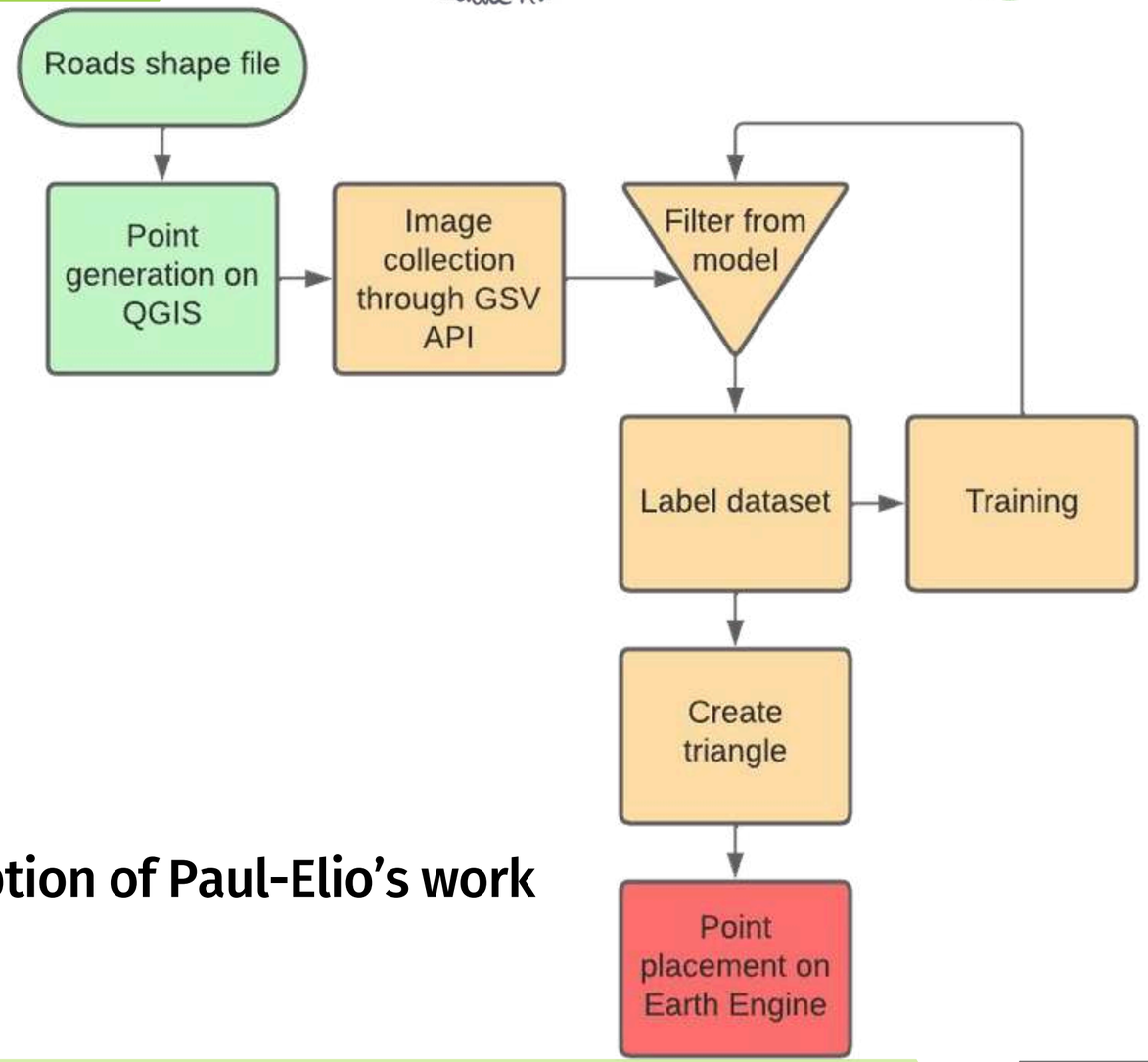
✓

✓

Deliverables table

Initial project status

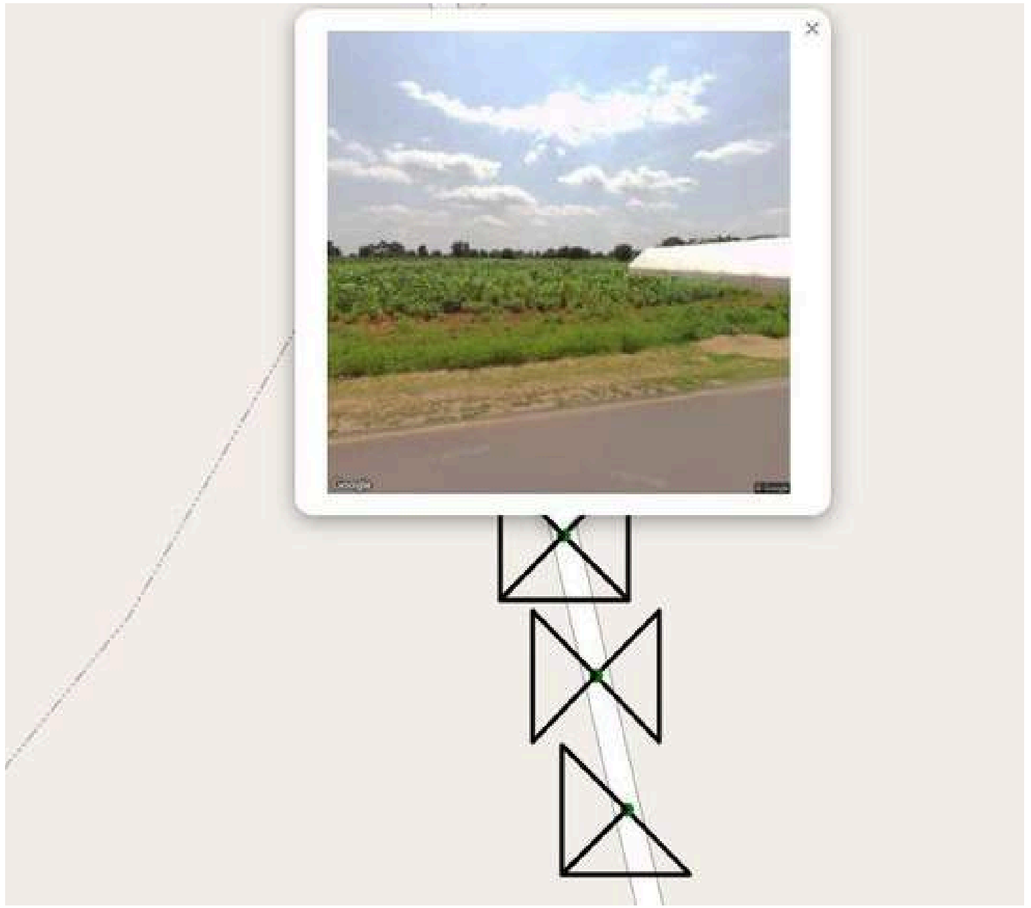
- **Paul-Elio Fresneau's final year internship at Télécom Physique Strasbourg**
- **Binary model : Crop/non-crop**
- **Pipeline of his model**



Description of Paul-Elio's work

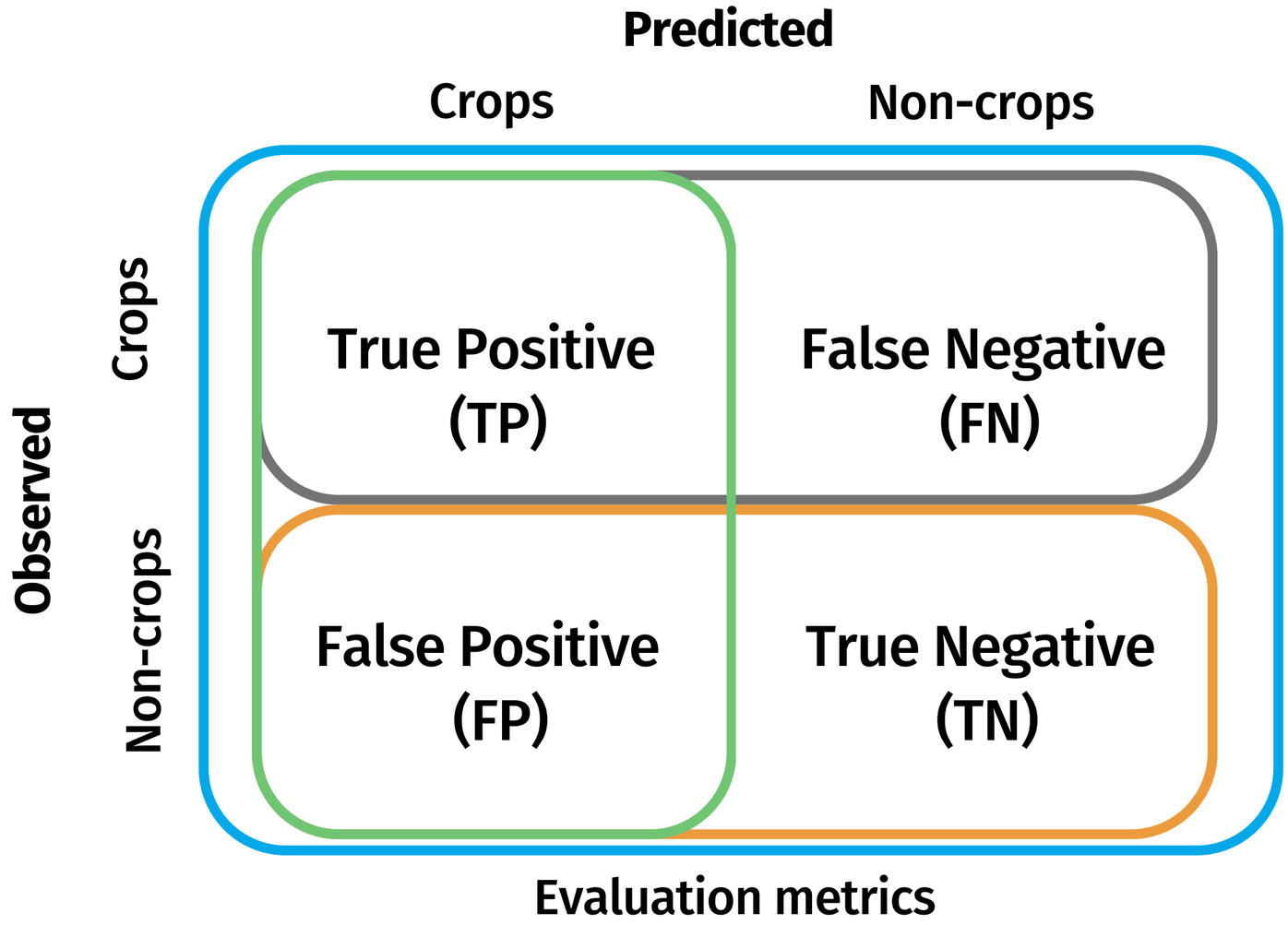
Initial project status

A map with triangles containing a crop with the associated Google Street View image



Final result of Paul-Elio's work

Metrics overview



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

Specificity = TN/(TN+FP)

Precision = TP/(TP+FP)

Recall = TP/(TP+FN)

Specifications

Service function	Expression	Assessment criteria	Level of flexibility
MF1	Reimplement Paul Elio's workflow	precision, memory storage	Precision > 90%
MF2	Match the GSV images with the satellite images	Locate the field spotted on a GSV image, return a data table of GPS coordinates	A point or a full segmentation
MF3	Classify the different types of crops	80%	Optional

✓

✓

Main functions of the specifications

Specifications

Service function	Expression	Assessment criteria	Level of flexibility
CF1	Make a reliable program	Get the evaluation metrics : France precision 90%, Kenya 80%	France +/- 5% Kenya : 75% minimum
CF2	Limited footprint	Memory storage	Limitation : 8Go RAM GPU
CF3	Flexibility of the program	Autonomous program	- Commented program - Less than 3 inputs required from user

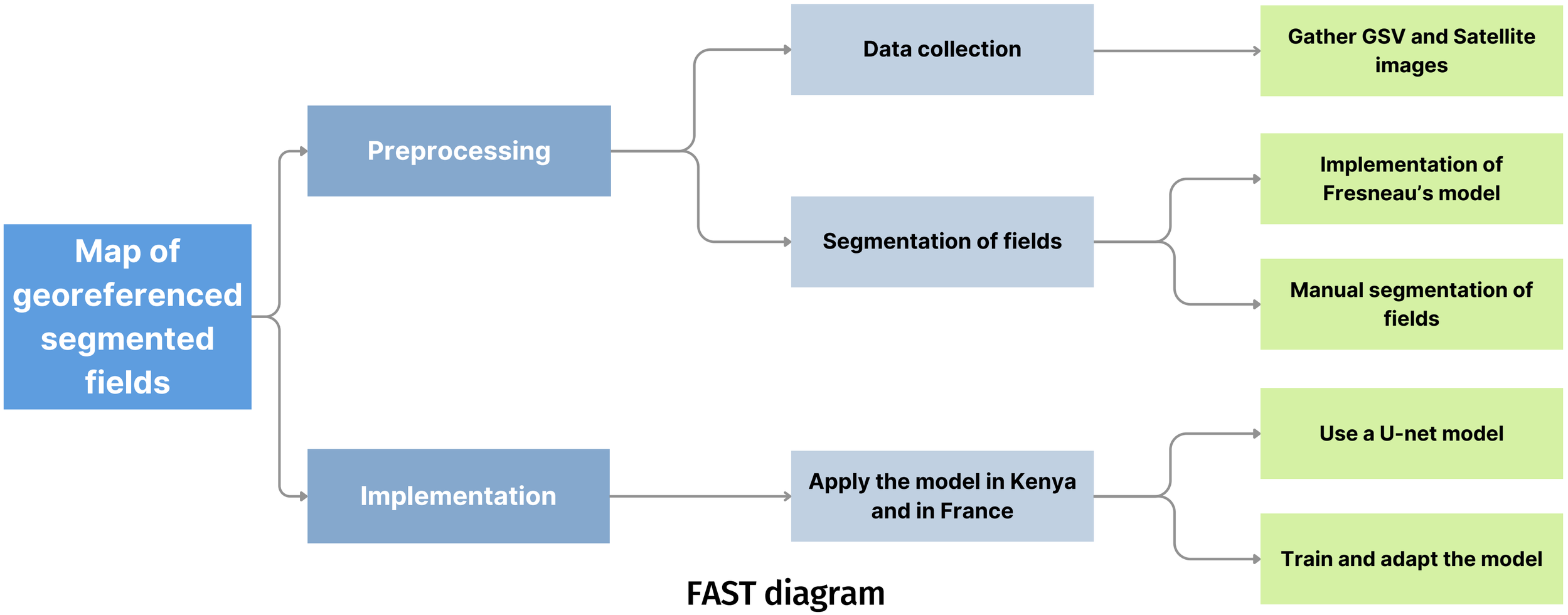
IoU France : 48%
IoU Kenya: 53%

✓

✓

Constraint functions of the specifications

FAST diagram



FAST diagram

Tasks allocation

Completed

In progress

Generating ground truth data for agricultural remote sensing by coupling satellite and Google Street View imagery

- ✓ **Literature review**
  - ✓ Boutayna: **Familiarization with deep learning concepts**
  - ✓ Quentin: **Study of Paul-Elio Fresneau's work**
- ✓ **Field segmentation on satellite images**
  - ✓ Mathys: **Data collection and preprocessing**
  - ✓ Martin: **Model development**
- ✓ **Match GSV images with satellite images**
  - ✓ Quentin: **Work on the current detection model**
  - ✓ Boutayna: **Estimate the precise location of the field**

Tasks allocation

Tasks allocation

Completed

In progress

Field segmentation on satellite images

- **Data collection and preprocessing** ✓
  - Google street view images acquisition ✓
  - Satellite images acquisition ✓
  - Data acquisition ✓
  - Data annotation and labelling ✓
- **Model development:** Implementation in Kenya, then in France ✓
  - U-net architecture design ✓
  - Model training ✓
  - Model evalution and optimization ✓
  - Validation of the model with an example output ✓

Detailed tasks allocation

Tasks allocation

✓ Completed

In progress

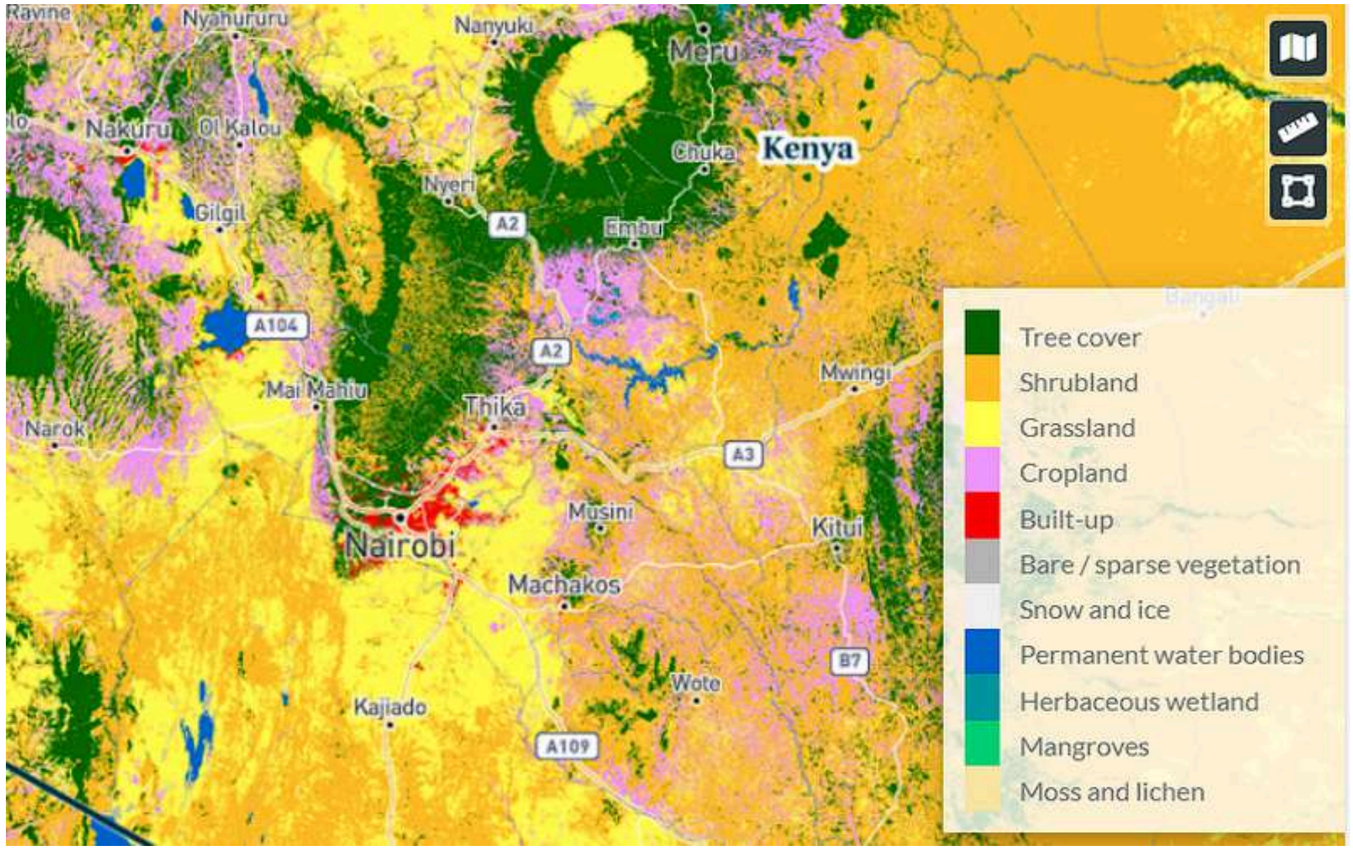
Match GSV images with satellite images

- **Work on the current field detection model** ✓
  - **Enhancing the model** ✓
    - **Optimized code, filtering the data in cities** ✓
    - **Generalizing on all Kenya, instead of just a part (using a bigger training data set)** ✓
  - **Linking the model to our project** ✓
- **Estimate the precise location of the field** ✓
  - **Place a point in the center of each field then locate it** ✓
  - **Final functional, complete github repository** ✓

Our project

Previous model enhancement

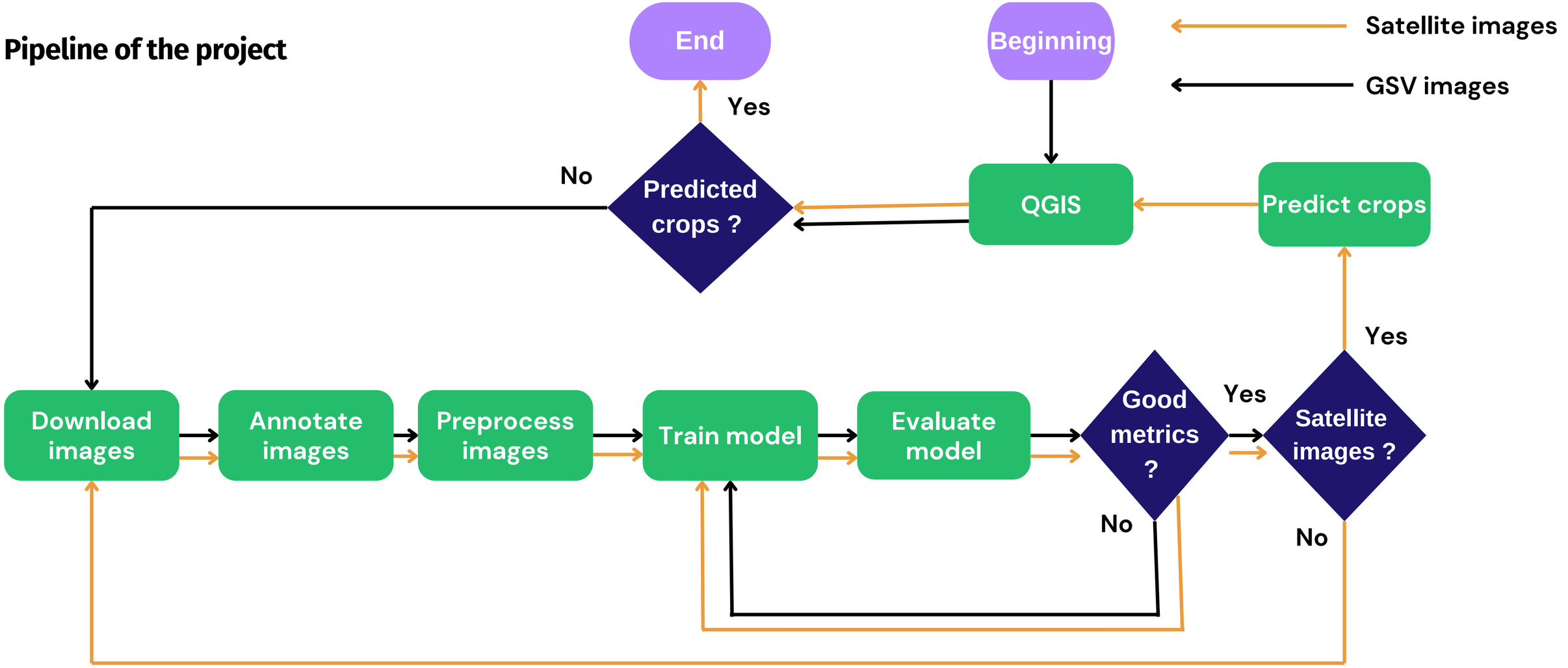
ESA World Cover masks



Our project

The pipeline

Pipeline of the project



Our project

Study areas

Example in 2 countries

In Kenya

-From October to March-

In France

-From March to now-

Our project

Data collection for our detection model in France

Expanded dataset

QGis CSV file

AND

Land Parcel Identification System
csv file

Street View

Process to collect GSV images in France

Our project

Annotation of GSV images

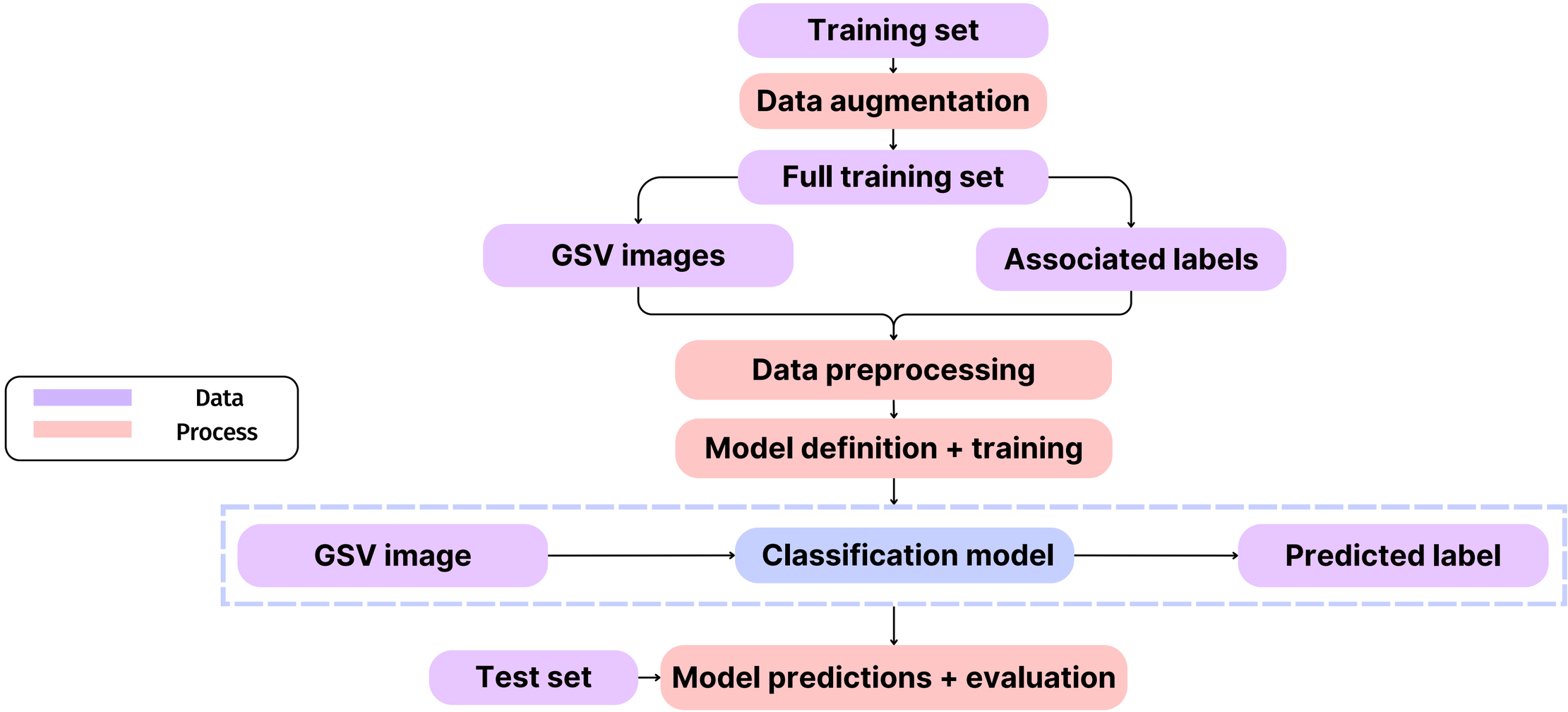
An interface to label our GSV images

	A	B
1	Image	Label
2	gsv_46.5137882814	non_crop
3	gsv_46.5137882814	non_crop
4	gsv_46.6049076201	non_crop
5	gsv_46.6049076201	non_crop
6	gsv_46.6049076201	non_crop
7	gsv_46.6049076201	non_crop
8	gsv_46.6395883033	non_crop
9	gsv_46.6395883033	non_crop
10	gsv_46.6395883033	non_crop
11	gsv_46.6395883033	non_crop
12	gsv_46.6825273756	non_crop
13	gsv_46.6825273756	non_crop
14	gsv_46.6825273756	non_crop
15	gsv_46.6825273756	non_crop
16	gsv_46.7348429031	non_crop
17	gsv_46.7348429031	crop
18	gsv_46.7348429031	crop
19	gsv_46.7348429031	undecided
20	gsv_46.7483335945	non_crop

A CSV file containing all our labels

Our project

Structure of the detection model



Our project

Results of our detection model in France

Recall	Specificity	Precision	Accuracy
79.2%	98.7%	96.5%	92.7%

Reliable binary classification

Example of images detected as containing crops :

Our project

Data collection in Kenya

Dataset based on previous project

Previous project dataset csv file

Program to list all detected images with a field

Google Maps Static API

Program to collect satellite images through the API

Process to collect satellite images in Kenya

Our project

Data collection in Kenya

Expanded dataset

QGis dataset csv file

Street View

Program to detect crops on GSV images with Google Street View API

Previous project detection model

Google Maps Static API

Program to collect satellite images through the Google Maps Static API

Process to collect more satellite images in Kenya

Our project

Data collection in France

Dataset

QGis csv file

AND

Land Parcel Identification System csv file

Street View

Program to detect crops on GSV images with Google Street View API

Our detection model in France

Google Maps Static API

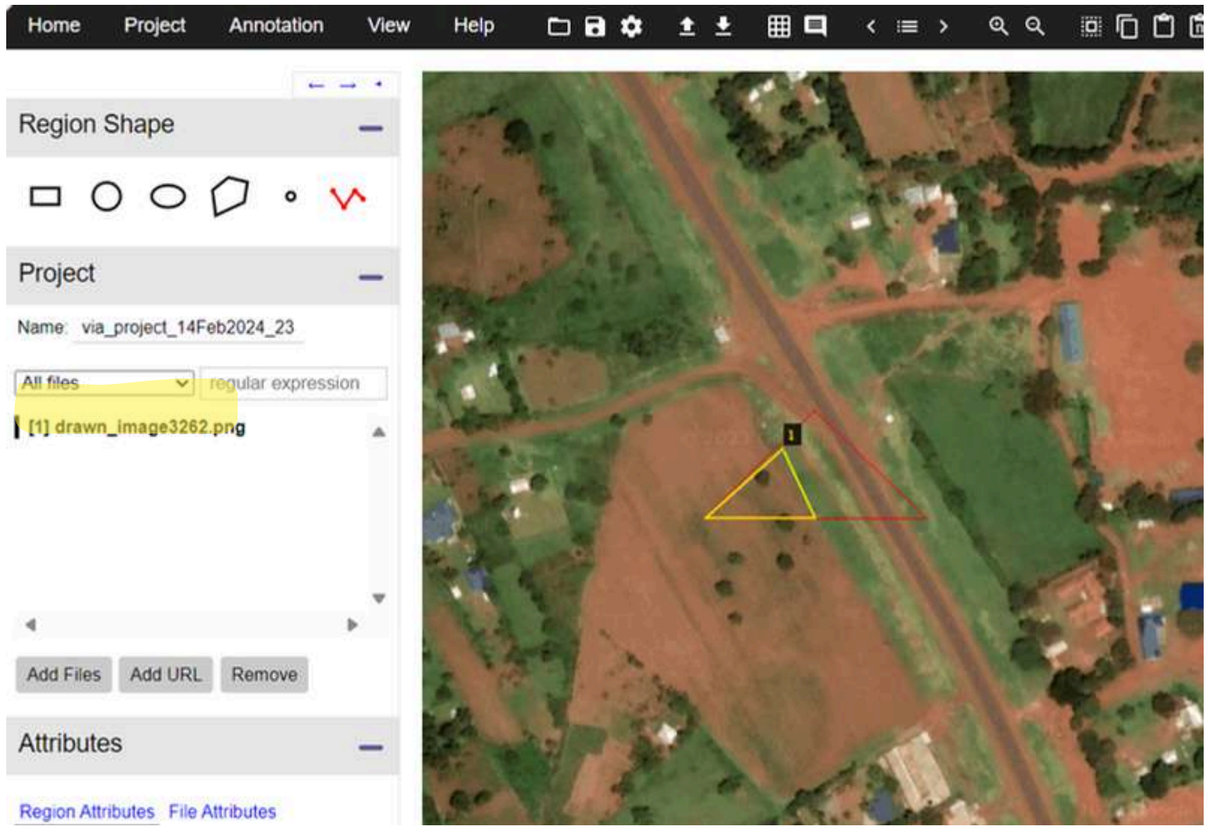
Program to collect satellite images through the Google Maps Static API

Process to collect satellite images in France

Our project

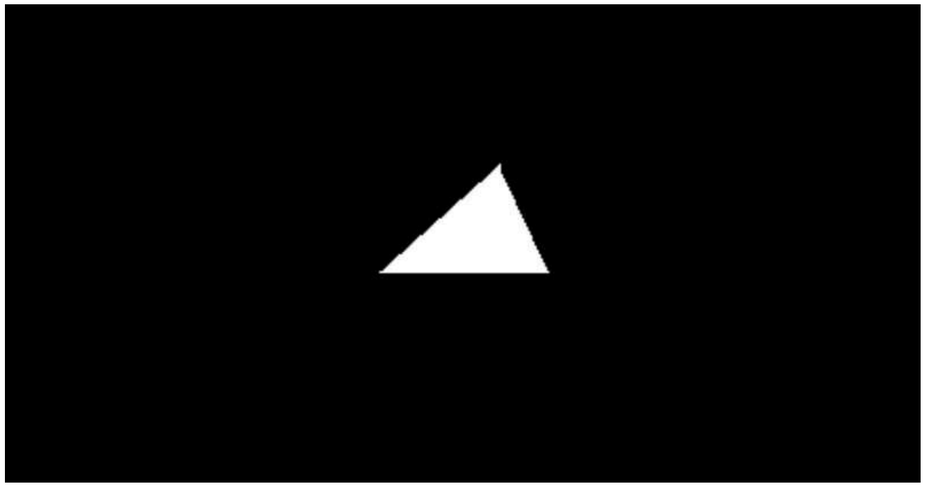
Data annotation

Use of Vgg Image Annotator



Generated mask, then used as input ⟶

Google street view image of the field



Our project

Data storing

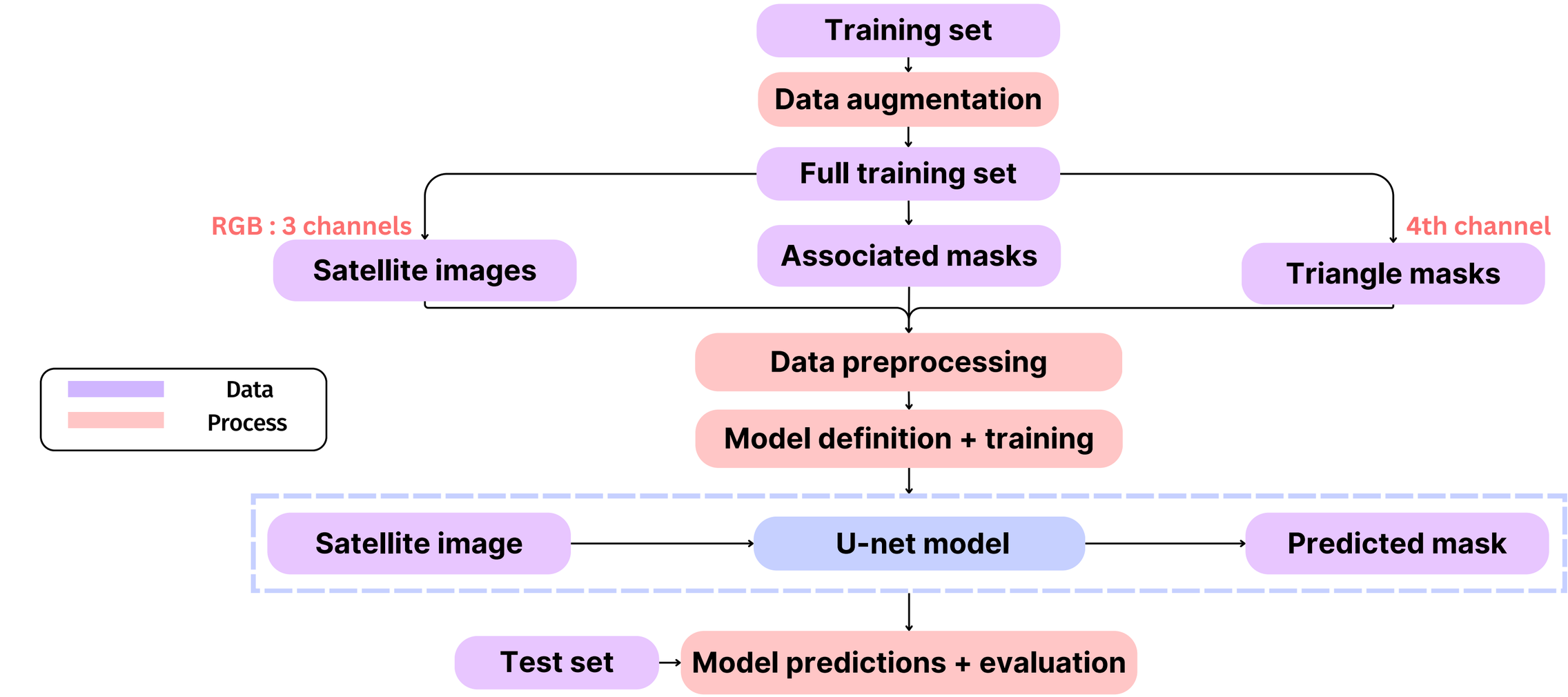
Google Maps Static API

Generation of a dataframe with information about our dataset

id	file_name	type	transforr	latitude	longitude	size	zoom	label	country	orientation	mask	mask_name	triangle_mask_name
1	truncated2!	truncated256_	/	-1.00670	34.170749!	256*256	18	crop	Kenya	West	yes	truncated256_drav	truncated256_mask_tr
2	hflip_trunca	augmented_tr	hflip_	-1.00670	34.170749!	256*256	18	crop	Kenya	West	yes	hflip_truncated256	hflip_truncated256_ma
3	truncated2!	truncated256_	/	0.359044	34.171171;	256*256	18	crop	Kenya	North	yes	truncated256_drav	truncated256_mask_tr
4	bright_trun	augmented_tr	bright_	0.359044	34.171171;	256*256	18	crop	Kenya	North	yes	bright_truncated25	bright_truncated256_n
5	truncated2!	truncated256_	/	0.359044	34.171171;	256*256	18	crop	Kenya	East	no	/	truncated256_mask_tr
6	truncated2!	augmented_tr	zoom_	0.359044	34.171171;	256*256	18	crop	Kenya	East	no	/	zoom_truncated256_n
7	truncated2!	truncated256_	/	0.358986	34.171166!	256*256	18	crop	Kenya	North	yes	truncated256_drav	truncated256_mask_tr
8	bright_trun	augmented_tr	bright_	0.358986	34.171166!	256*256	18	crop	Kenya	North	yes	bright_truncated25	bright_truncated256_n
9	truncated2!	truncated256_	/	0.289139	34.171703-	256*256	18	crop	Kenya	South	yes	truncated256_drav	truncated256_mask_tr
10	zoom_trunc	augmented_tr	zoom_	0.289139	34.171703-	256*256	18	crop	Kenya	South	yes	zoom_truncated25	zoom_truncated256_n
11	truncated2!	truncated256_	/	0.288800	34.171421'	256*256	18	crop	Kenya	North	yes	truncated256_drav	truncated256_mask_tr
12	vflip_trunca	augmented_tr	vflip_	0.288800	34.171421'	256*256	18	crop	Kenya	North	yes	vflip_truncated256	vflip_truncated256_ma

Our project

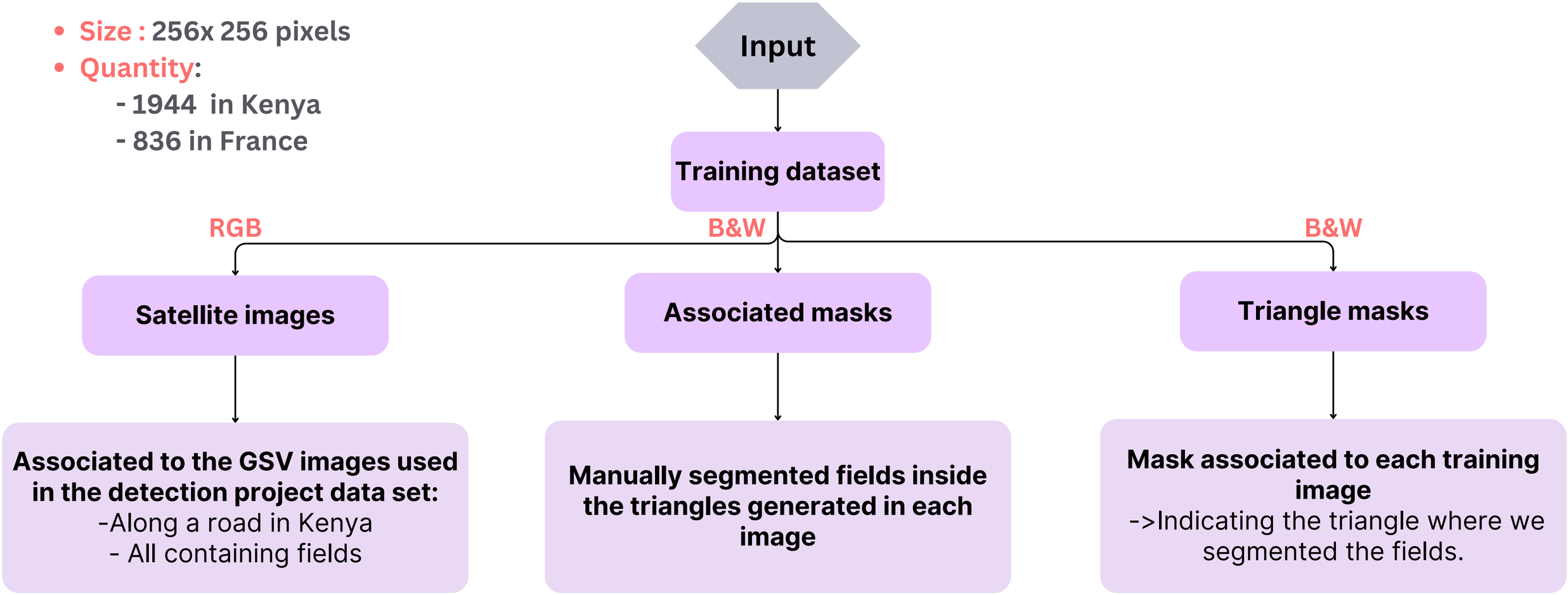
Segmentation model Workflow



Our project

Input

- **Size :** 256x 256 pixels
- **Quantity**:
  - 1944 in Kenya
  - 836 in France

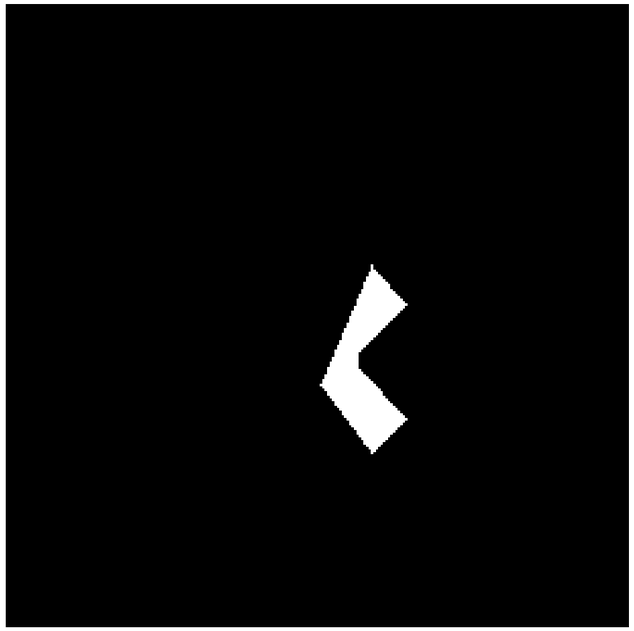


Our project

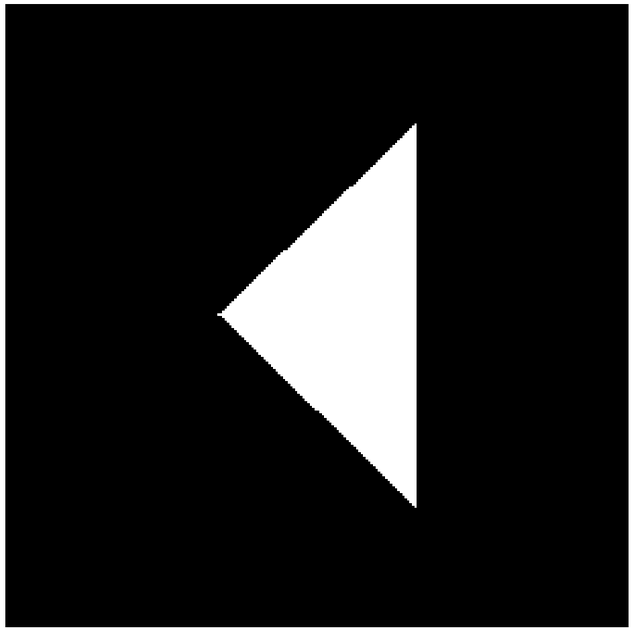
Input

Satellite image

Associated mask



Triangle mask



- **Size :** 256x 256 pixels
  - → U-net layers easier to design when images are a power of 2 in size.
  - → Big enough to fit the triangle
  - → Small enough to require the least memory and computational power.

Our project

Data augmentation

Rotation, flipping, scaling, adjusting brightness, contrast ...

- **Increased dataset size**
- **Improved generalization**
- **Reduced overfitting**
- **Enhanced robustness**

Constraints :

- **Plausible variations**
- **Avoiding artifact introduction**
- **Ensuring quality**

Our project

Data augmentation

Original image

Data augmentation

Vertical / horizontal flip

Brightness

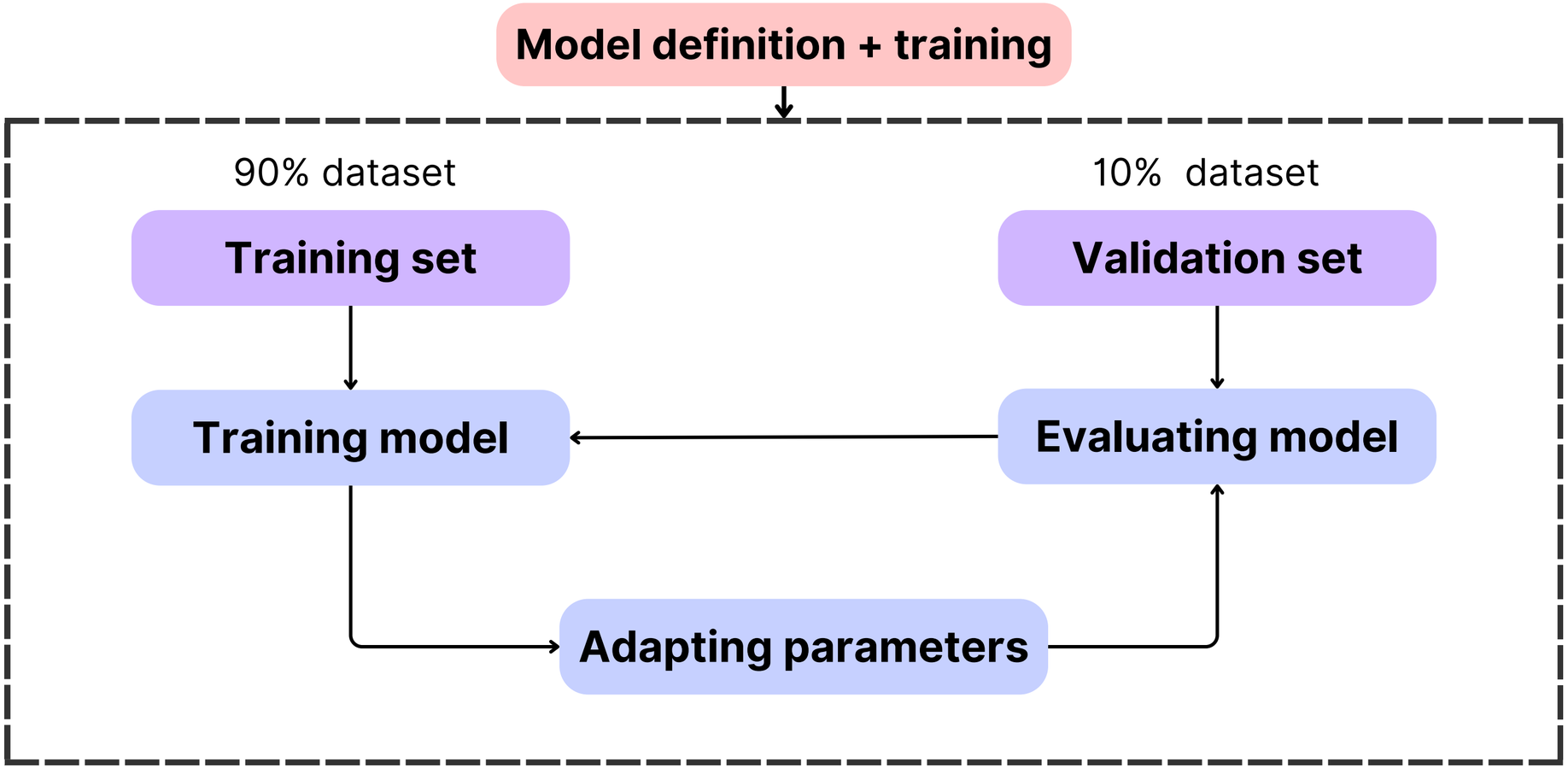
0.7 < factor < 1.7

Zoom in

1.2 < factor < 1.5

Our project

Model definition + training

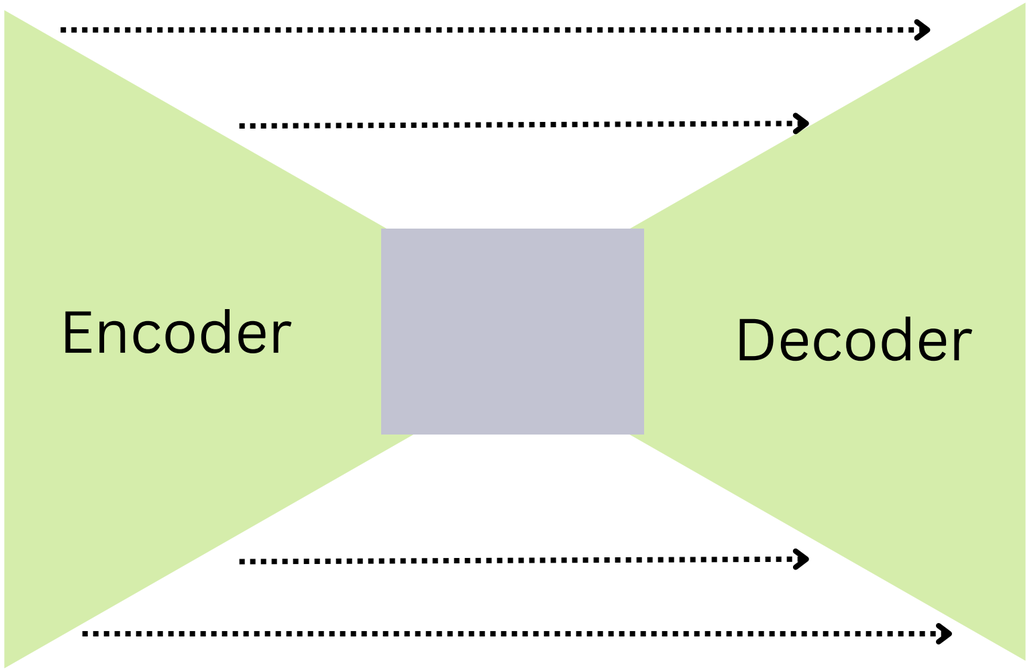


Our project

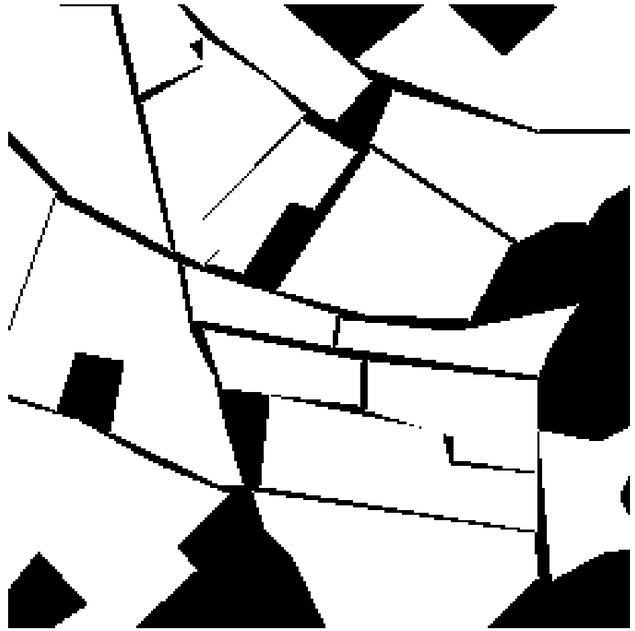
The segmentation model

Input image

U-net convolutional neural network



Predicted mask

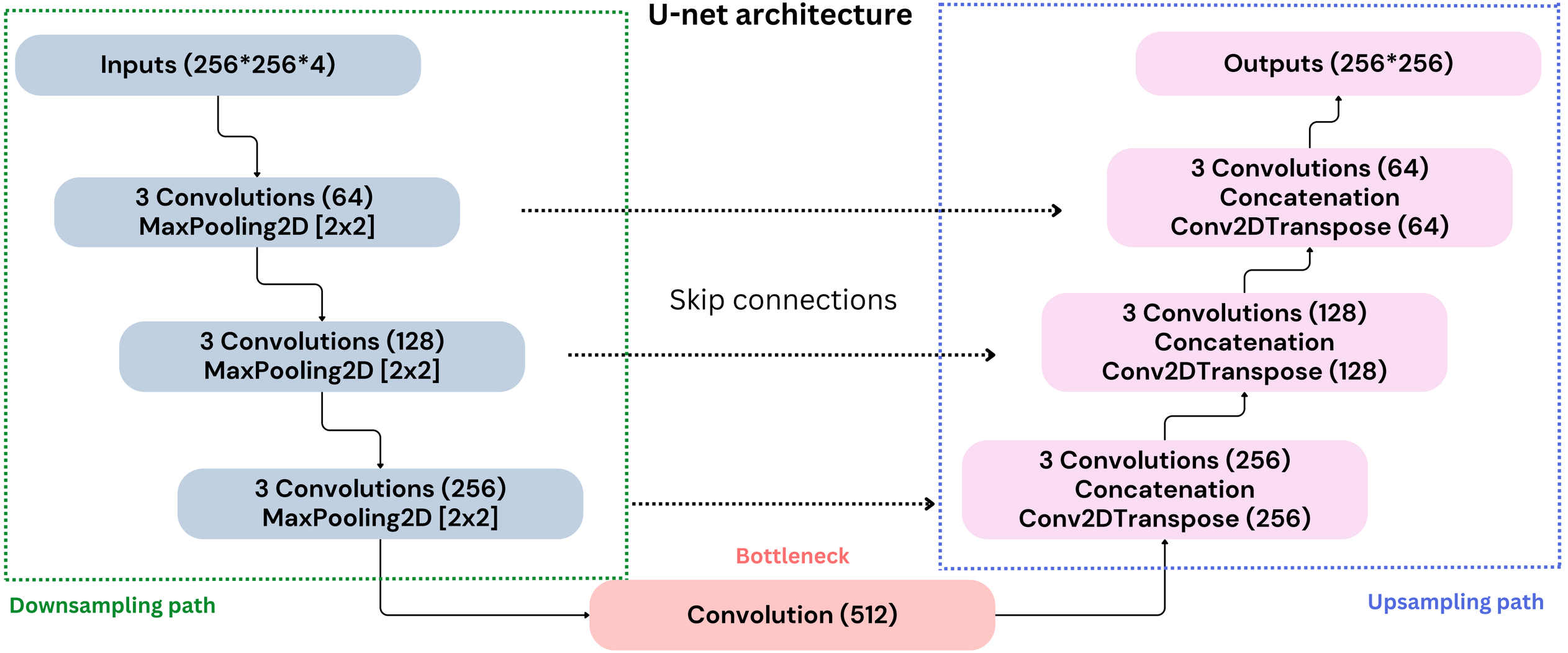


Our project

The segmentation model

HARVEST

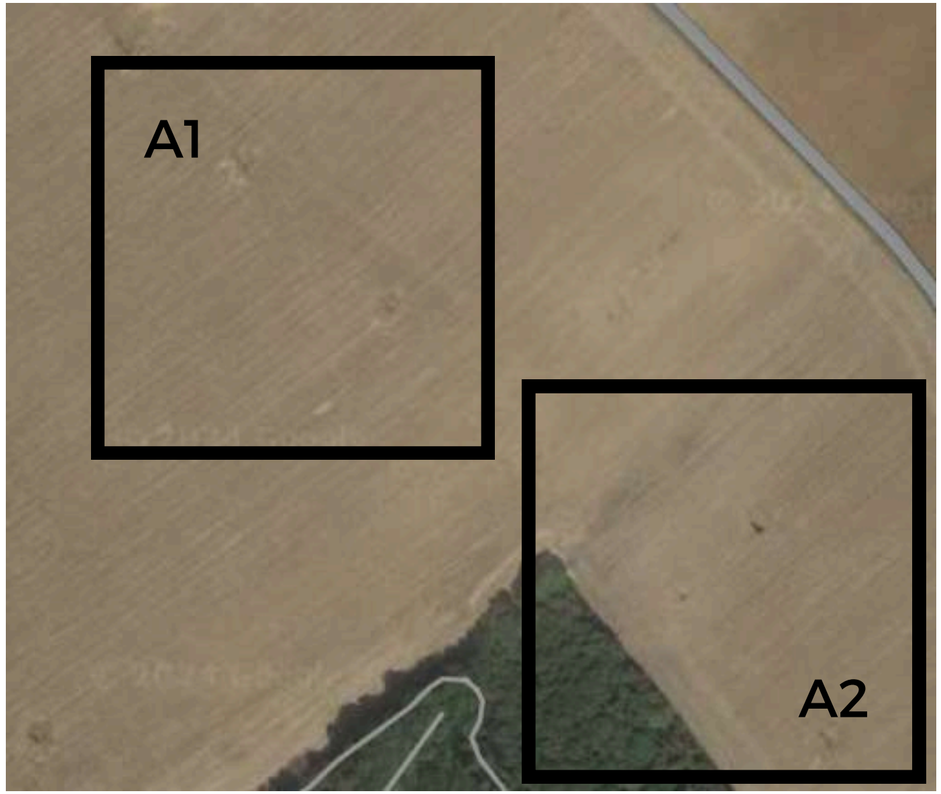
U-net architecture



Our project

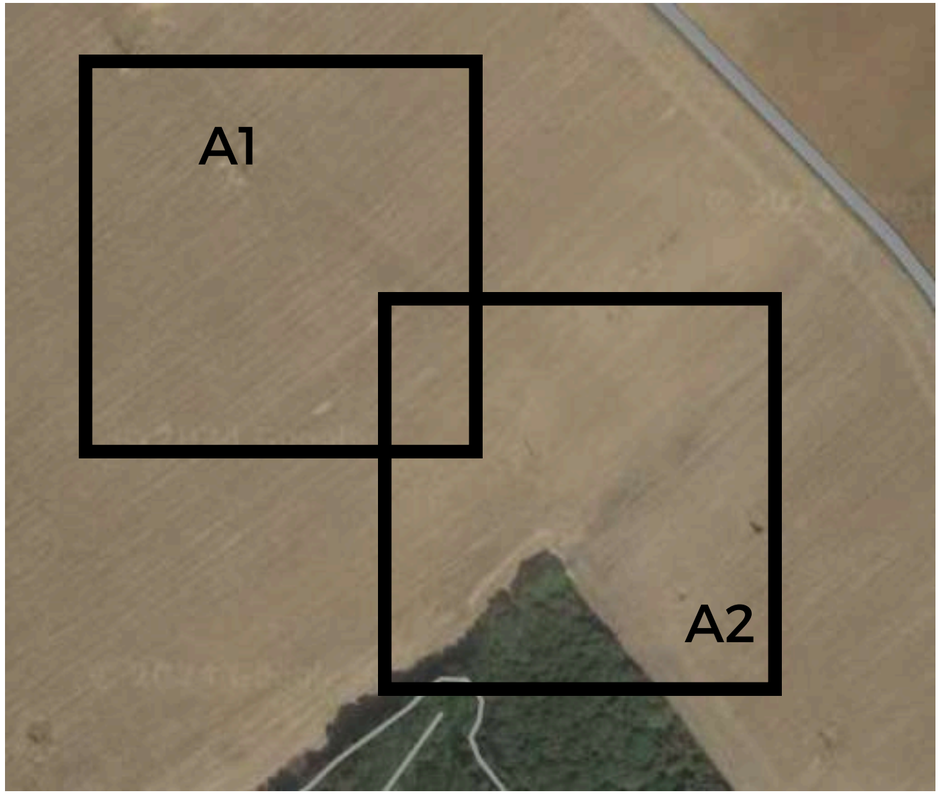
Analysis of results

Intersection Over Union evaluation metric



A1: The prediction by the model

A2: The ground truth



IoU=0

IoU=(A1 ∩ A2) / (A1 ∪ A2)

Our project

Models comparison in Kenya

Models	Inputs	Outputs	IOU	Training time	Insight
Model 1	• 572x572 images • Their associated masks	The predicted masks	–	8 hours	• The model wasn't giving good enough results
Model 2	• 166x166 images • Their associated masks	The predicted masks	–	2 hours	• Smaller size images • The resize function in U-net caused a big loss of information
Model 3	• 256x256 images • Their associated masks • Their associated triangle masks	The predicted masks	22%	8 hours	• Size that fits the U-net better • Added triangle masks • The model is better but not high enough metric
Model 4	• 256x256 images • Their associated masks • Their associated triangle masks	The predicted masks	25%	26 hours	• Doubled out data set using data augmentation • Higher metric

Table of the first models we had trained in Kenya

Our project

Models comparison in Kenya

Models	Inputs	Outputs	IOU	Training time	Insight
Model 5	• 256x256 images • Their associated masks • Their associated triangle masks	The predicted masks	25%	4 hours	• **First use of GPU: significant reduction of training time**
Model 6	• 256x256 images • Their associated masks • Their associated triangle masks	The predicted masks	48%	5 hours	• **Tuning hyperparameters of the model (like: learning rate)**
Model 7	• 256x256 images • Their associated masks • Their associated triangle masks	The predicted masks	53%	7 hours	• **Increase of the number of epochs (training iterations)**

Table of the last models we trained in Kenya

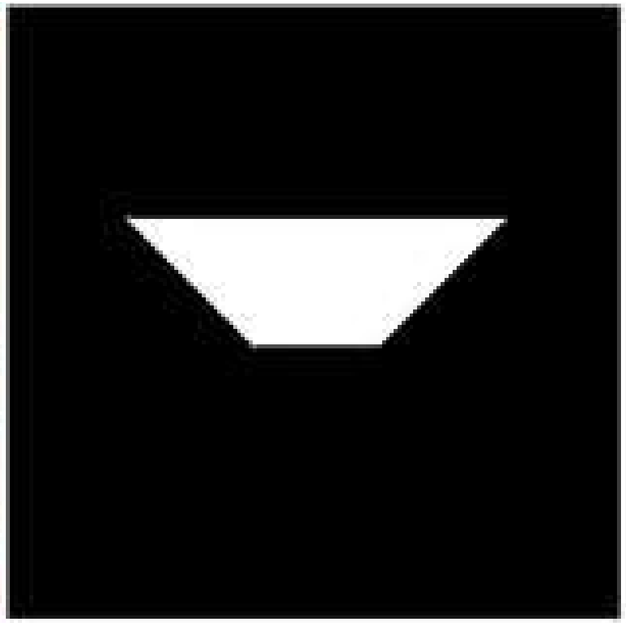
Our project

Metric interpretation in Kenya

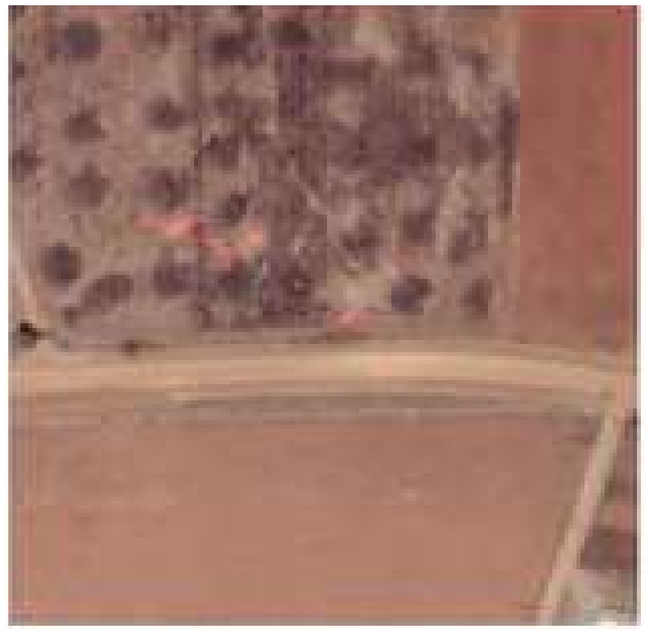
Example output where the model is less effective

Original image

Binary mask



Overlay on original image



Our project

Metric interpretation in Kenya

Example output where the model is effective

Original image

Binary mask

Overlay on original image

Our project

Models comparison in France

Model	Inputs	Outputs	IOU	Training time	Insight
Model 1	• 256x256 images • Their associated masks • Their associated triangle masks	The predicted masks	48%	3 hours	• **Much higher than our first result in Kenya knowing we had less than half the size of the training set used.**
Model 2	• 256x256 images • Their associated masks • Their associated triangle masks	The predicted masks	44%	3 hours	• **We modified the optimizer from Nadam to Adam**
Model 3	• 256x256 images • Their associated masks • Their associated triangle masks	The predicted masks	44%	3 hours	• **Modification of the hyperparameters (number of epochs, patience)**
Model 4	• 256x256 images • Their associated masks • Their associated triangle masks	The predicted masks	46%	3 hours	• **We modified the value of the exponential moving average of the gradients and the value of the exponential moving average of the squared gradient**

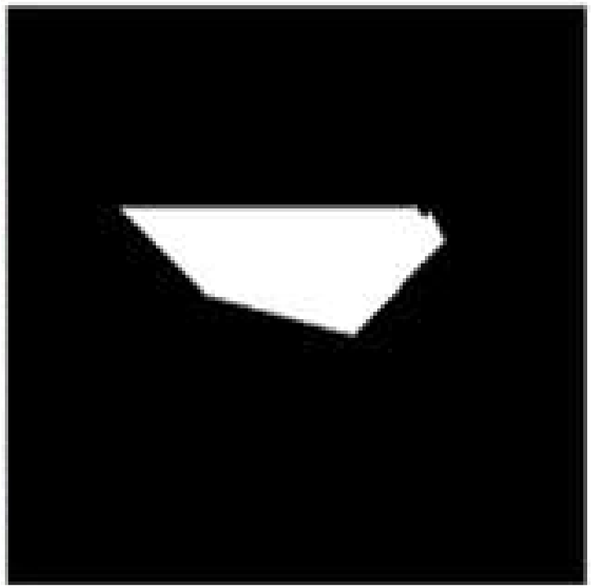
Our project

Metric interpretation in France

Example output where the model is less effective

Original image

Binary mask



Overlay on original image

Our project

Metric interpretation in France

Example output where the model is effective

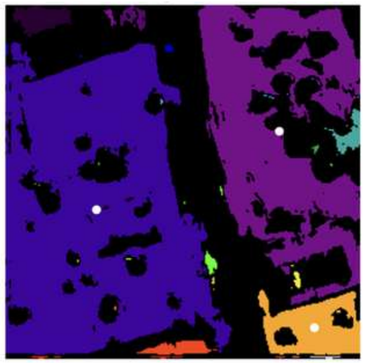
Original image

Binary mask

Overlay on original image

Our project

Center of the predicted crops

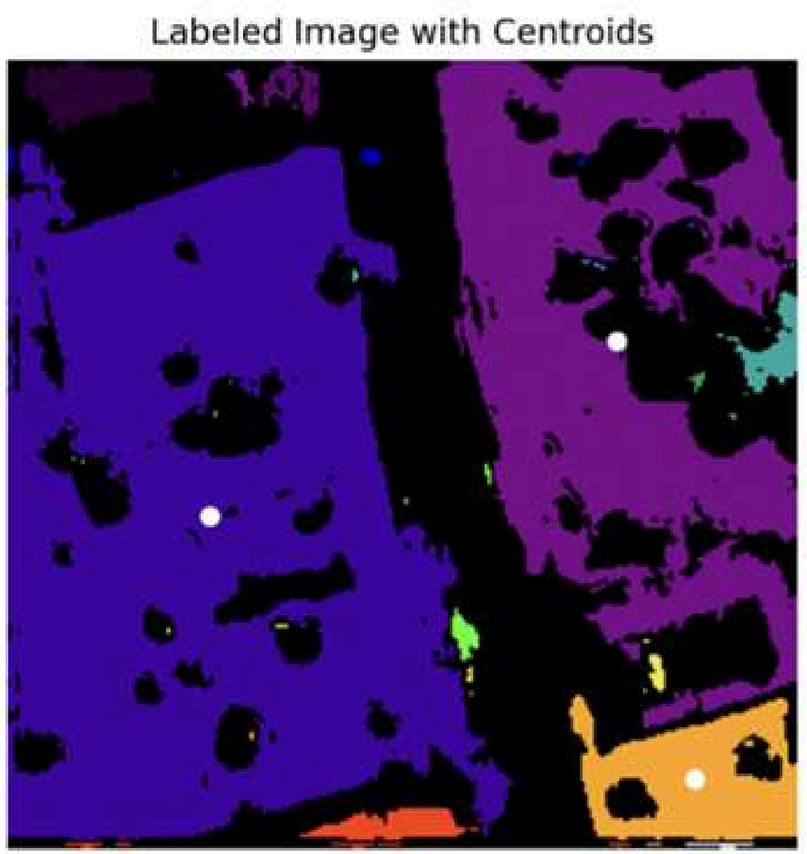


1. Process the model prediction to identify distinct regions.
2. Calculate their centroids in pixel coordinates.
3. Convert these into geographic coordinates using GPS mapping and a calculated ground resolution.
4. Display results

Our project

Center of the predicted crops

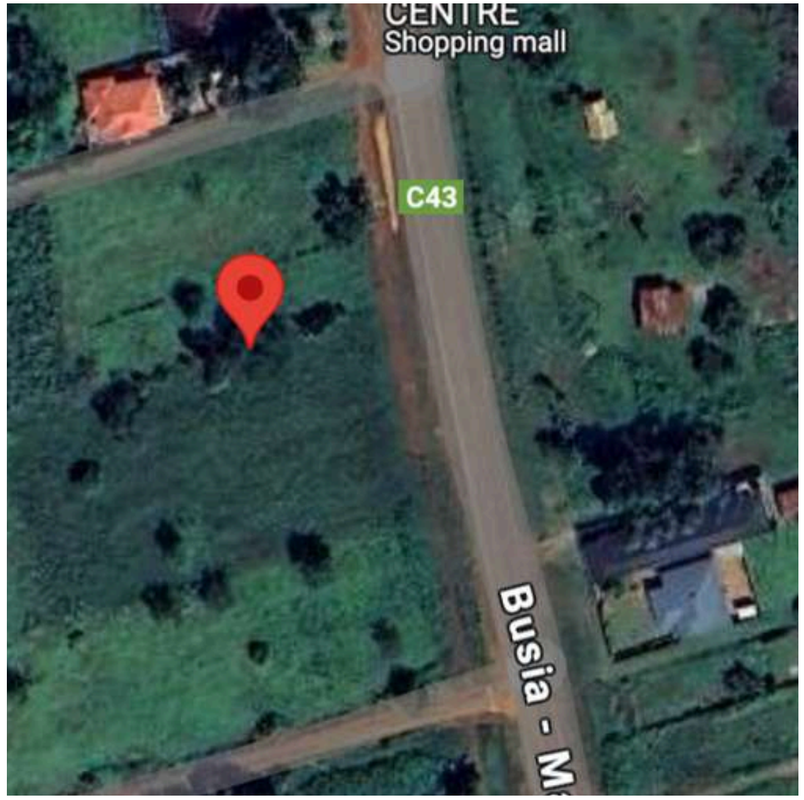
Example output of the program



Our project

Center of the predicted crops

The GPS coordinates in Google maps



The output of our program on the image

Amelioration points

Model optimization

- Increase the quantity and diversity of the dataset.
- Experiment with different architectures or customize the U-net with additional layers, skip connections etc
- Further hyperparameter tuning: learning rate, batch size, or optimizer choice.

Hardware upgrade

- Using more powerful computers in order to:

- Accelerate the training time

- Allow for more complex models or larger batches

École d'ingénieurs
Télécom Physique
Université de Strasbourg
Partenaire stratégique
Institut Mines-Télécom

Poster of the project

Satellite Harvest

HARVEST

Project pipeline

Initial project status : Field detection model

Binary classification model for Google Street View images to indicate if they contain fields or not, trained in Kenya, that we later retrained in France.

Field segmentation model using U-net CNN

- Data collection, annotation and preprocessing.
- Implemention of a U-net CNN to segment fields within satellite images.
- Model training, evaluation and refinement.

Georeferencing the detected fields

Development of a program that identifies the centroid within each segmented field and calculates the corresponding GPS coordinates for precise geolocalization.

Results

Example output of segmentation

Original image

Overlay on original image

The image on the right illustrates the results after applying our model, with the segmented fields highlighted in red, indicating the model's predictions.

IoU metric: overlap between the predicted segmentation and the ground truth.
IoU obtained=53%

Field Geolocation

Original image

Field centroid

The program delineates fields in images using our model, marks each field's center, and outputs a CSV file with these centers' GPS coordinates.

image	region_id	latitude	longitude
satellite_image9318.png	1	0.20182522125682067	34.19720215638781

Project management
Estimated budget

			Total price(€)		
Salaries	**Amount(h)**	**Price each (€**	**Projected**	**Current**	**% completed**
TPS Engineer	600,00	40,00 €	24 000,00 €	24 000,00 €	100,00%
Supervisors	120,00	60,00 €	7 200,00 €	7 200,00 €	100,00%
Mentor	40,00	40,00 €	1 600,00 €	1 600,00 €	100,00%
Management team	50,00	60,00 €	3 000,00 €	3 000,00 €	100,00%
Salaries total			**35 800,00 €**	**35 800,00 €**	**100,00%**
Operating Costs	**Amount(nb)**	**Price each (€)**	**Projected**	**Current**	**% completed**
Rents and insurance			1 000,00 €	1 000,00 €	100,00%
Personal computers	4,00	222,00 €	888,00 €	888,00 €	100,00%
Total operating Costs			**1 888,00 €**	**1 888,00 €**	**100,00%**
Total costs			37 688,00 €	37 688,00 €	100,00%

Estimated budget

Project management
Completed tasks

✓ Completed ⟳ In progress

We are just on time

TASK TITLE	SEPTEMBER				OCTOBER				NOVEMBER				December				
	W 36	W 37	W 38	W 39	W 40	W 41	W 42	W 43	W 44	W 45	W 46	W 47	W 48	W 49	W 50	W 51	W 52
Getting a handle on the topic																	
Familiarization with AI concepts	✓																
Working on the existing model	✓																
Data collection of satellite images in Kenya	✓																
Choosing the adecquate model for segmentation	✓																
Data annotation in Kenya	✓																
Documentation																	
State of the art	✓																
Researching evaluation metrics	✓																

Schedule

Project management
Completed tasks

✓ Completed ⟳ In progress

We are just on time

TASK TITLE	JANUARY				FEBRUARY				MARCH					APRIL			
	W 1	W 2	W 3	W 4	W 5	W 6	W 7	W 8	W 9	W 10	W 11	W 12	W 13	W 14	W 15	W 16	W 17
Conceptualization																	
Develop the segmentation model in Kenya	✓																
Provide GPS coordinates for recognized fields	✓																
Data collection of GSV and satellite images in France	✓																
Annotation of GSV and satellite images in France	✓																
Develop the segmentation model in France	✓																
Testing and improvement																	
Evaluate the models' metrics	✓																
Optimize models' efficency	✓																
Finalization and complete GitHub repository	✓																

Schedule

R4

Project management
Risks analysis

RI: Risk Indicator

PO: Probability of Occurence

RC: Resolution Capability

I: Impact on the project

$$RI = \frac{I \times PO}{RC}$$

	Low	Medium	High
Probability	1	3	9
Impact	1	3	9
Resolution Capability	1	3	9
Risk Indicator	1	3 and 9	27 and 81

Scale of risks gravity

Project management
Risks analysis

$$RI = \frac{I \times PO}{RC}$$

Reference point	Risk	Probability	Impact	Resolution Capability	Risk Indicator
1.1	Exceed the memory	High (PO=9)	Medium (I=3)	Use an external hard drive (RC=9)	Medium (RI=3)
1.2	Loss of files	Low (PO=1)	High (I=9)	Archive files on Google Drive and on Seafile (RC=3)	Medium (RI=3)
1.3	Slow program execution	High (PO=9)	Medium (I=3)	Work on GPU instead of CPU (RC=3)	Medium (RI=9)
1.4	Exceed the maximum of free images	Low (PO=1)	Low (I=1)	Create an Excel document and a python script to count downloaded images (RC=1)	Low (RI=1)

Technical risks table

Project management
Risks analysis

$$RI = \frac{I \times PO}{RC}$$

Reference point	Risk	Probability	Impact	Resolution Capability	Risk Indicator
2.1	Be overwhelmed by the courses	High (PO=9)	Medium (I=3)	Respect the schedule and work during extracurricular hours (RC=9)	Medium (RI=3)
2.2	Different timetables due to our chosen option	High (PO=9)	Low (I=1)	Virtual meeting or meeting after courses (RC=3)	Medium (RI=3)

Environmental risks table

Project management
Risks analysis

$$RI = \frac{I \times PO}{RC}$$

Reference point	Risk	Probability	Impact	Resolution Capability	Risk Indicator
3.1	Lose connection with our client	Low (PO=1)	High (I=9)	Communicate regularly with our supervisors (RC=3)	Medium (RI=3)
3.2	Lose a member	Low (PO=1)	High (I=9)	Restart all the organization of the project (RC=1)	Medium (RI=9)
3.3	Lose motivation	Medium (PO=3)	Medium (I=3)	Organize team buildings (RC=3)	Medium (RI=3)

Relational risks table

Conclusion

Project management

- Monthly reports
- Meeting reports
- Public and technical reports
- Human and technical assessment
- Schedule
- Budget
- Poster / Video

Technical aspects

- Deploying a pipeline from binary field detection to field localisation in : Kenya and France
- Implementing a segmentation model
- Implementing a program to localise the segmented fields

Overlay on test image

Binary thresholded mask

Thank you for your attention !