# Assessing the impact of the loss function, architecture and image type for Deep Learning-based wildfire segmentation

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## Motivation

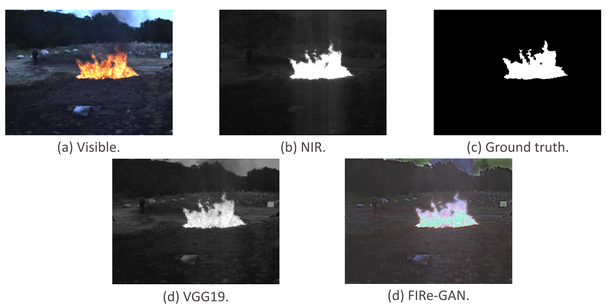
- **Wildfires** have a significant **impact on the environment, properties, and lives**.
- **Wildfire segmentation** is a relevant task to **understand** and **model** events during a **fire**.
- It is **unclear** if the **architecture**, **loss function**, or **image type** has the most **impact** on DL-based **fire segmentation**.

## Goal

- **Evaluate** three SOTA **architectures**, **loss functions**, and four **image types** (**visible**, **near-infrared (NIR)**, and **fused** from two methods) to identify the **parameters** most **relevant** for wildfire **segmentation performance**.
- **Identify** the **best performing** combination and **benchmark** it against **traditional** fire segmentation techniques.

## Dataset

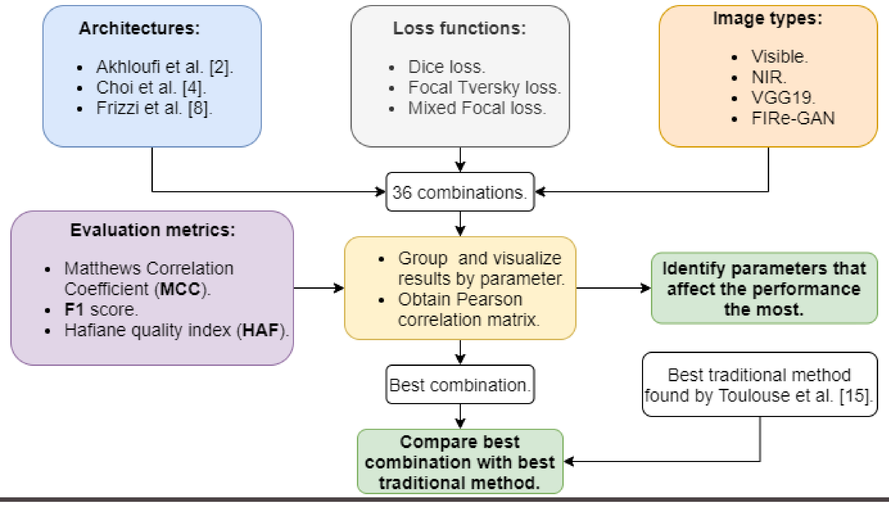
- We use the Corsican Fire Database; 640 visible and NIR image pairs with ground truths for segmentation.
- Visible-NIR fused images obtained through the VGG19 [11] and FIRe-GAN methods [5].



(a) Visible. (b) NIR. (c) Ground truth. (d) VGG19. (d) FIRe-GAN.

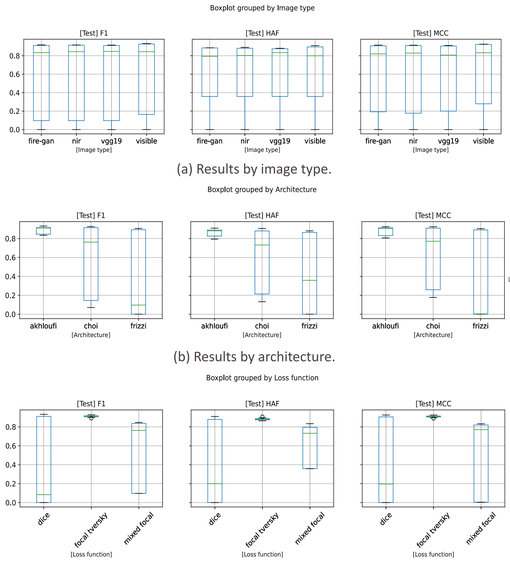
Fig. 1: Sample employed images.

## Methods




## Results

- We present the results for all combinations in Fig. 2 and Fig. 3.

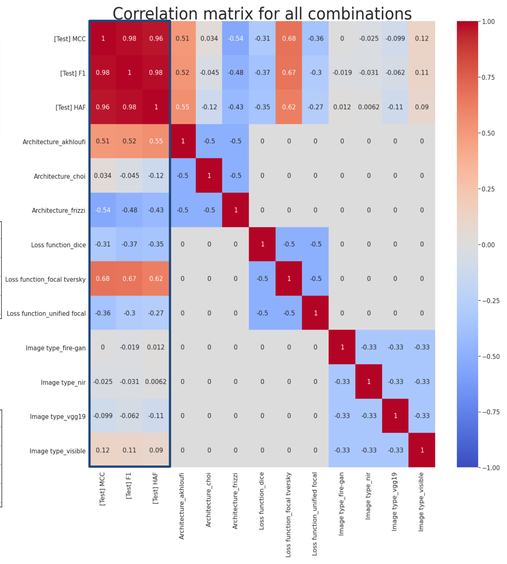



(a) Results by image type.

(b) Results by architecture.

(c) Results by loss function.

Fig. 2: Segmentation results per parameter for all combinations.




- We select the **Akhloufi architecture**, **Focal Tversky loss** and **visible image type** as the **best** combination.
- Table I shows the comparison between said combination and the best traditional method identified by Toulouse et al. [14].

Table I: Comparison between best combination and best traditional method.

| Metric | Method | Value |
|---|---|---|
| MCC | **Akhloufi + F. Tversky + visible** | **0.92** |
| | Phillips et al.[13] | 0.81 |
| F1 | **Akhloufi + F. Tversky + visible** | **0.92** |
| | Phillips et al.[13] | 0.82 |
| HAF | **Akhloufi + F. Tversky + visible** | **0.89** |
| | Phillips et al.[13] | 0.75 |

## Discussion

- The **best combination** clearly **outperforms** the best identified **traditional method**.
- The **Akhloufi architecture** and the **Focal Tversky loss** displayed by far the **most robust results**.
- The **image type** appears to have very **little influence** in the **segmentation performance**.
- The presence of **color** in the **images** shows **little influence** on the **segmentation performance**, in **contrast** to **traditional methods** in which **color** is one of the most **relevant** factors.

## Future work

- **Fused images** may offer a more significant **advantage** for **fire and smoke segmentation**.
- **NIR and fused images** may provide an **advantage** on more **challenging** images (e. g. with more **smoke occlusion**, see Fig. 4).
- **The generation of datasets** with **challenging visible-NIR image pairs**, and with ground truths for **fire and smoke segmentation** is a promising avenue for future work.

Fig. 4: Examples of challenging images with significant smoke occlusion.

## Acknowledgments

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