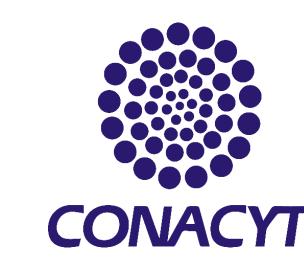
# Deep Learning model for wildfire detection through the fusion of visible and infrared information

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#### Motivation

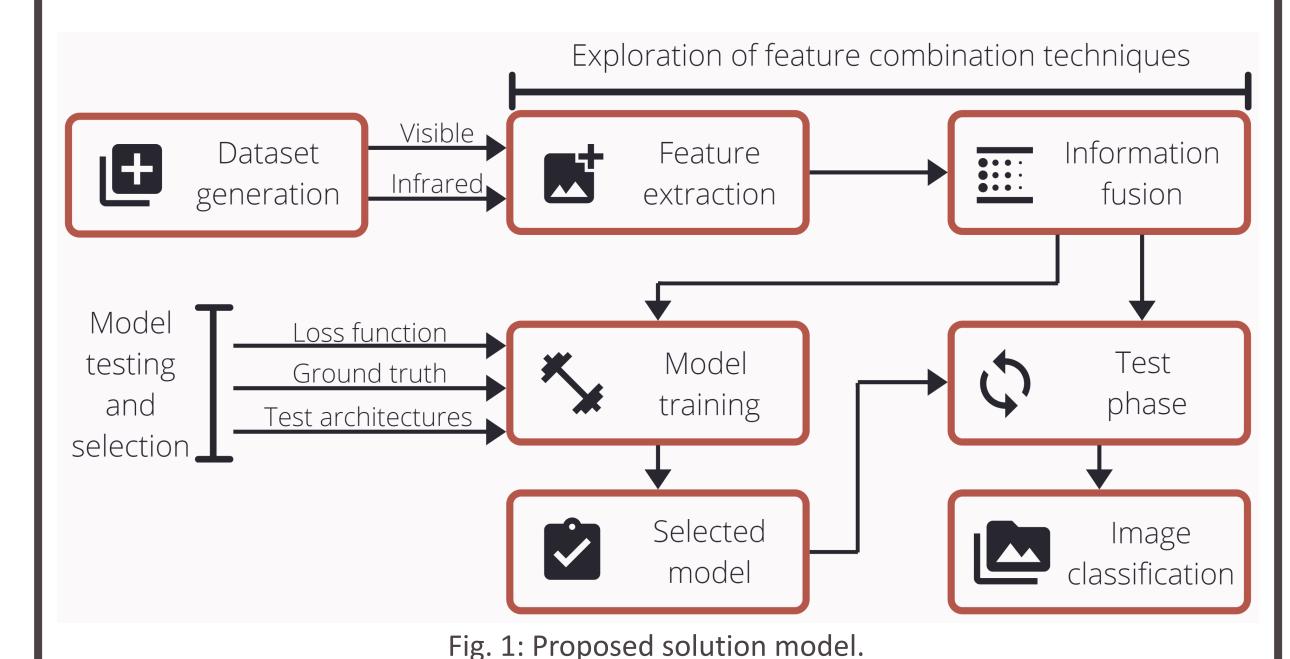
- > Wildfires can get out of control and have a significant impact on the environment, properties, and lives.
- > Early wildfire detection is one of the most relevant aspects to be considered to avoid as much damage as possible.

#### Goal

- > Perform forest fire detection in controlled datasets through a **Deep Learning** (DL) model through the usage of fused visible-infrared information.
- > Obtain a lower false-positive rate when compared to existing techniques.

### Solution model

> Proposed solution model:



We are in the process of implementing, testing and adapting selected information fusion techniques for the task of fire image fusion.

#### Methods

Pipeline of the proposed system:

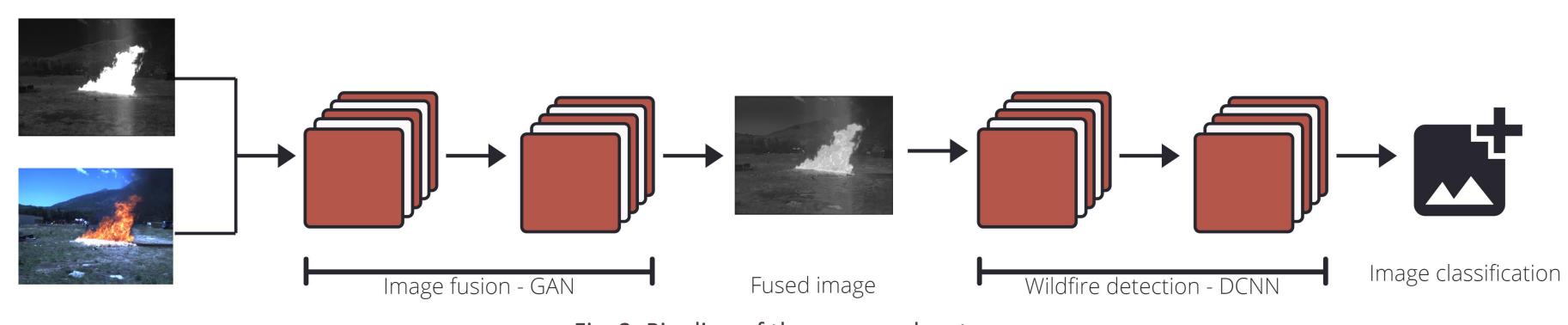


Fig. 2: Pipeline of the proposed system.

> We evaluate the performance of selected image fusion methods [1, 2] on the test set comprised of 640 visible-infrared image pairs of the Corsican Fire Database [3] through the following metrics: image entropy (EN), correlation coefficient (CC), peak signal-to-noise ratio (PSNR) and structural similarity index measure (SSIM).

#### Results

> We present the results for the evaluated methods on Fig. 3.

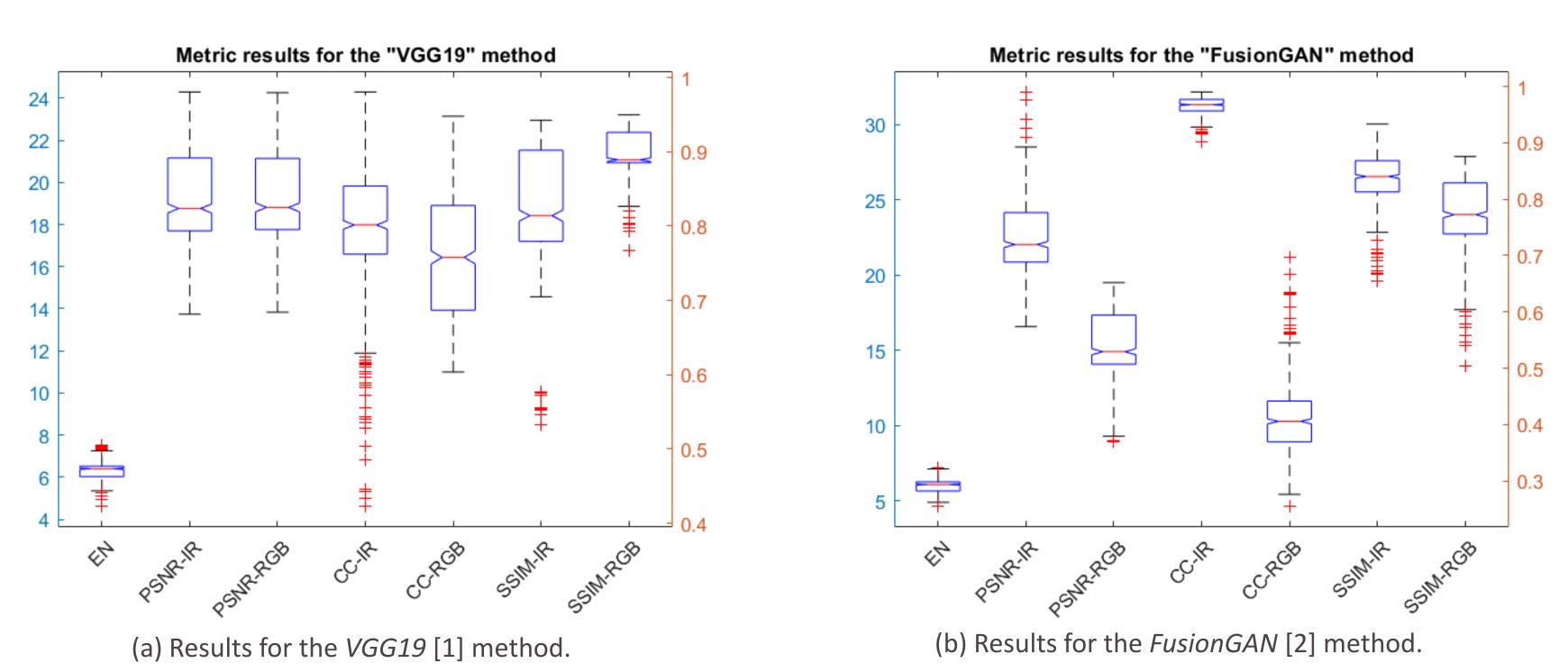


Fig. 3: Performance results for the analyzed image fusion methods.

In Table I we present the average result comparison for the VGG19 [1] and FusionGAN [2] methods.

Metric	VGG19	FusionGAN
EN	6.341551	6.007289
CC-IR-fused	0.797674	0.965768
CC-RGB-fused	0.763721	0.410448
PSNR-IR-fused	19.201477	22.509020
PSNR-RGB-fused	19.225560	15.390010
SSIM-IR-fused	0.833715	0.838937
SSIM-RGB-fused	0.900734	0.778314

Table I: Average results for the analyzed image fusion methods.

# Discussion and future

#### work

- > Both tested models performed well across the evaluated metrics, with the exception of the PSNR score.
- > All tested models implement DL architectures pre-trained on different datasets; the present work serves also as an evaluation of how well these methods can generalize to different domains.
- > We will implement as well the method proposed in [4] and compare it with the two presented methods. The best performing of the three methods [1, 2, 4] will be selected for a transfer learning phase.
- > With the selected model, we will create an augmented fused fire image dataset
- > We will **use** said **dataset** to **train** the to-beimplemented DL model for fire detection, taking as a launching pad the architecture proposed in [5].

#### Reterences

[1] H. Li, X. Wu, and J. Kittler, "Infrared and visible image fusion using a deep learning framework," in 2018 24th International Conference on Pattern Recognition (ICPR), pp. 2705–2710, 2018.

[2] J. Ma, W. Yu, P. Liang, C. Li, and J. Jiang, "Fusiongan: A generative adversarial network for infrared and visible image fusion," *Information Fusion*, vol. 48, pp. 11 – 26, 2019.

[3] T. Toulouse, L. Rossi, A. Campana, T. Celik, and M. A. Akhloufi, "Computer vision for wildfire research: An evolving image dataset for processing and analysis," Fire Safety Journal, vol. 92, pp. 188 – 194, 2017. [4] Y. Zhao, G. Fu, H. Wang, and S. Zhang, "The fusion of unmatched infrared and visible images based on generative adversarial networks," Mathematical Problems in Engineering, vol. 2020,92p. 3739040, Mar

[5] Y. Zhao, J. Ma, X. Li, and J. Zhang, "Saliency detection and deep learning-based wildfire identification in uav imagery," *Sensors*, vol. 18, p. 712, 02 2018

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