Assessing the Impact of the Loss Function, Architecture and Image Type for Deep Learning-Based Wildfire Segmentation

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Abstract

Wildfires stand as one of the most relevant natural disasters worldwide, particularly more so due to the effect of climate change and its impact on various societal and environmental levels. In this regard, a significant amount of research has been done in order to address this issue, with computer vision playing a fundamental role in this regard. In recent years, there has been work pertaining to Deep Learning (DL)-based fire segmentation, showing very promising results. However, it is currently unclear whether the architecture of a model, its loss function, or the image type employed (visible, infrared, or fused) has the most impact on the fire segmentation results. In the present work, we evaluate different combinations of state-of-the-art (SOTA) DL architectures, loss functions, and types of images to identify the parameters most relevant to improve the segmentation results. Finally, we benchmark them to identify the top-performing ones and compare them to traditional fire segmentation techniques. To the best of our knowledge, this is the first work that evaluates the impact of the architecture, loss function, and image type in the performance of DL-based wildfire segmentation models.

1 Poster description

Fire segmentation is of great interest as it represents the first step of several processing stages for both the detection of fire departure and the monitoring and modeling of the fire [4]. The segmentation of fire areas in an image allows us to obtain relevant information regarding its position, rate of spread, height, inclination, surface, and volume [6].

In recent years, Deep Learning (DL) has displayed state-of-the-art performance in different tasks such as image segmentation [13, 3, 16]. Most of the existing DL-based wildfire segmentation methods employ visible images; for the particular context of DL-based wildfire segmentation, it is still unclear if the inclusion of fused information would enable a significant improvement in the fire segmentation performance of a model or if factors such as the architecture and loss function play a more relevant role in the said performance.

In order to investigate these questions, in this work, we train three SOTA DL architectures [2, 4, 8], coupled with three loss functions (Dice [10], Focal Tversky [1], and Unified Focal [15]) and four fire image types (visible, near-infrared (NIR), and fused generated from two methods [11, 5]). Then, we evaluate the resulting thirty-six combinations to assess the impact of each of the mentioned parameters in the wildfire segmentation performance. We use standard metrics to compare the segmented images to their corresponding ground truths to identify the best performing combination. Finally, we employ the Matthews Correlation Coefficient (MCC) [12], the F1 score [7], and the Hafiane quality index (HAF) [9] as in the work by Toulouse et al. [14] to benchmark the best identified combination against the traditional methods evaluated by Toulouse et al. as baselines.

The main contributions of this work are two-fold:

- We perform a comprehensive evaluation of thirty-six combinations of three selected architectures and loss functions, as well as four image types, to assess which of these elements affects wildfire segmentation performance the most, exploring as well the use of attention modules for the particular task of fire segmentation.
- We benchmark the best combination against traditional fire segmentation methods to assess if it provides a significant advantage over them.

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