Sentinel-2 forest fire image segmentation

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Abstract. This report presents a data mining approach for detecting burned areas using pre-fire and post-fire satellite imagery from the Sentinel-2 L2A satellite which were provided in the context of a challenge [4]. The goal of the project is to support local authorities in monitoring and planning the restoration process of forest fire-affected regions in California.
The methodology involves the workflow recommended by the CRISP-DM model, splitting the project in the stages business understanding, data understanding, data preparation, modeling, evaluation and deployment, thus involing agile working. A U-net , a convolutional neural network, was trained with Post-fire images which showed a burned area over 2 percent, using all spectral bands provided by the challange and selected spectral indeces. The results demonstrate the effectiveness of Convolutional Neural Networks in detecting and segmenting burned areas with an Intersection over a union of 0.7603 on the validation data and 0.603 on the test data.

Keywords: Data Analytics · CNN · satellite imagery · segmentation

1 Introduction

Wildfires pose significant challenges to ecosystems, human lives, and infrastructure, making their detection and management crucial for effective crisis response and disaster management. The increasing availability of satellite imagery, such as the data captured by the Sentinel-2 L2A satellite, provides a valuable resource for monitoring and analyzing the impact of forest fires. This report presents a comprehensive data mining approach that utilizes pre-fire and post-fire satellite imagery to detect burned areas in wildfire-affected regions of California. The primary objective of this project is to support local authorities in monitoring the extent of the fire-affected areas and planning the restoration process.

Detecting and accurately segmenting burned areas is a complex task due to the diverse characteristics of wildfire-affected regions. Leveraging binary semantic segmentation techniques, the study aims to differentiate between burned and unburned areas within the satellite imagery. By precisely delineating the boundaries of burned regions, valuable insights can be gained into the spatial extent and severity of the fire's impact. This information enables authorities to prioritize response efforts, allocate resources effectively, and plan for post-fire restoration and rehabilitation.

Ground truth masks, provided by the California Department of Forestry and Fire Protection, serve as reference data for understanding, training and evaluating the models [4]. These masks are meticulously mapped onto the corresponding images, providing reliable annotations for identifying burned areas.

To achieve accurate segmentation of burned areas, machine learning models, particularly Convolutional Neural Networks, which will also be called CNN through the report, are employed. The model is trained using the post-fire imagery, with the ground truth masks serving as the target labels. Through an iterative training process, the model learns to capture the intricate patterns and spectral characteristics indicative of burned regions.

As input for the final model, all spectral bands provided were used. Furthermore the spectral indices NBR, NDMI, NDVI, BSI and NDWI were calculatend and included since they showed to reliably highlight the difference between burned and unburned areas.

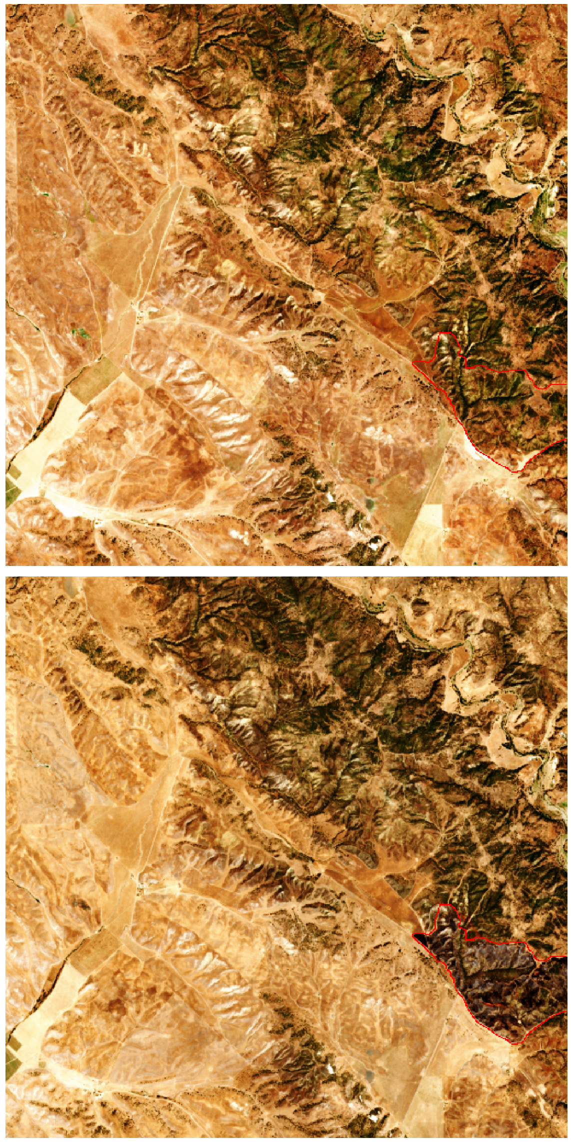
In conclusion, the utilization of post-fire satellite imagery, combined with machine learning techniques, provides a powerful tool for detecting and monitoring burned areas in wildfire-affected regions. The proposed approach contributes to the field of crisis response and disaster management by facilitating the timely and accurate assessment of fire-affected areas, aiding in the planning of restoration processes, and supporting informed decision-making by local authorities. The integration of machine learning models enables a comprehensive understanding of the fire's impact, enhancing the ability to respond effectively to wildfires and mitigate their long-term effects.

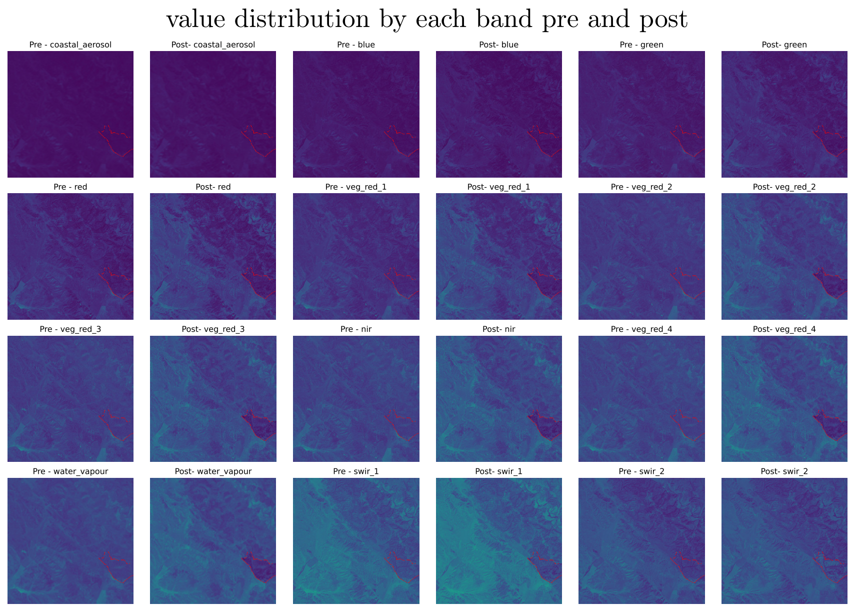
2 Methodology

2.1 The Data

The study's methodological framework relies on the use of the 'California Burned Areas Dataset' [4]. This comprehensive dataset consists of images derived from Sentinel-2 satellites, captured both pre and post-wildfire events. A significant component of the dataset comprises the ground truth masks, supplied by the California Department of Forestry and Fire Protection, meticulously superimposed on the respective images, acting as a benchmark for verifying model predictions.

Example Image pre fire and post fire in RGB





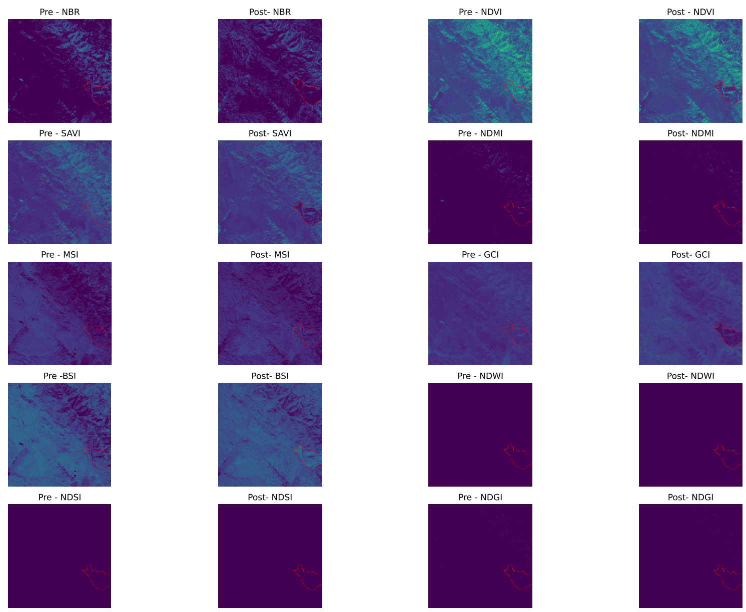
CRISP-DM [1] was used as a guideline to divide the project into the phases business understanding, data understanding, data preparation, modeling, evaluation and deployment. It's a well known standard that provides structure in the process regardless of the field while being agile.

2.2 Buissness and Data Understanding

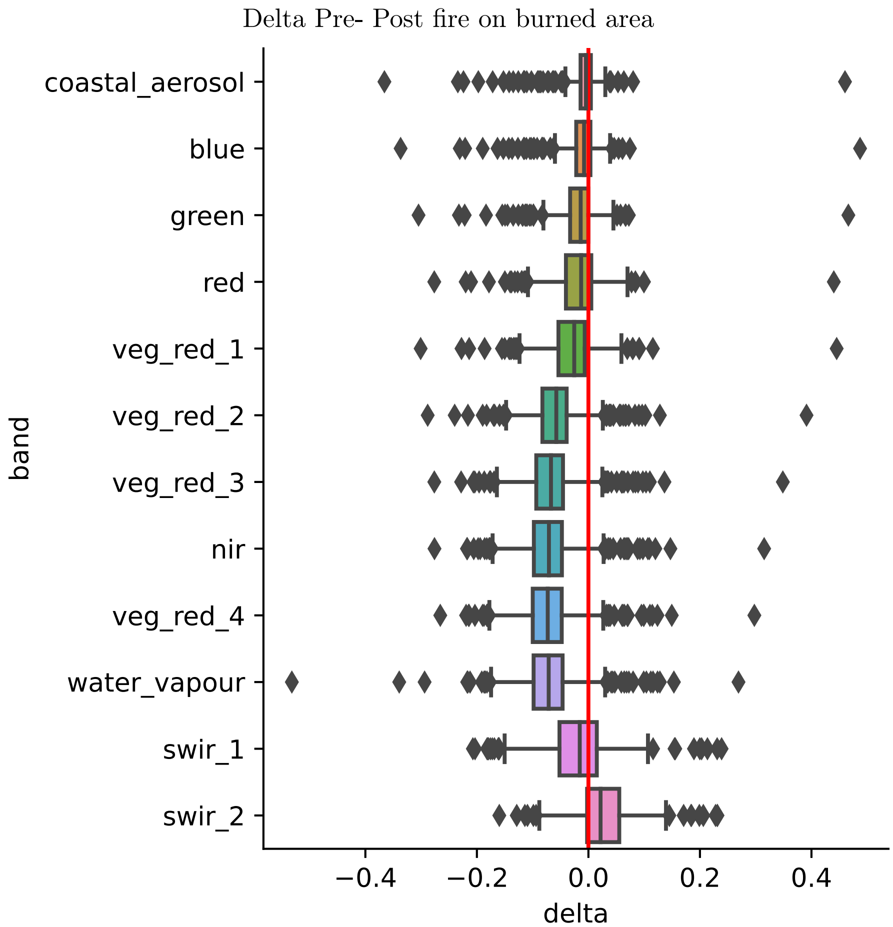
The steps data and business understanding were shaped by research and explorative Data analysis. Several images were chosen randomly to get a vague overview over the given Data.

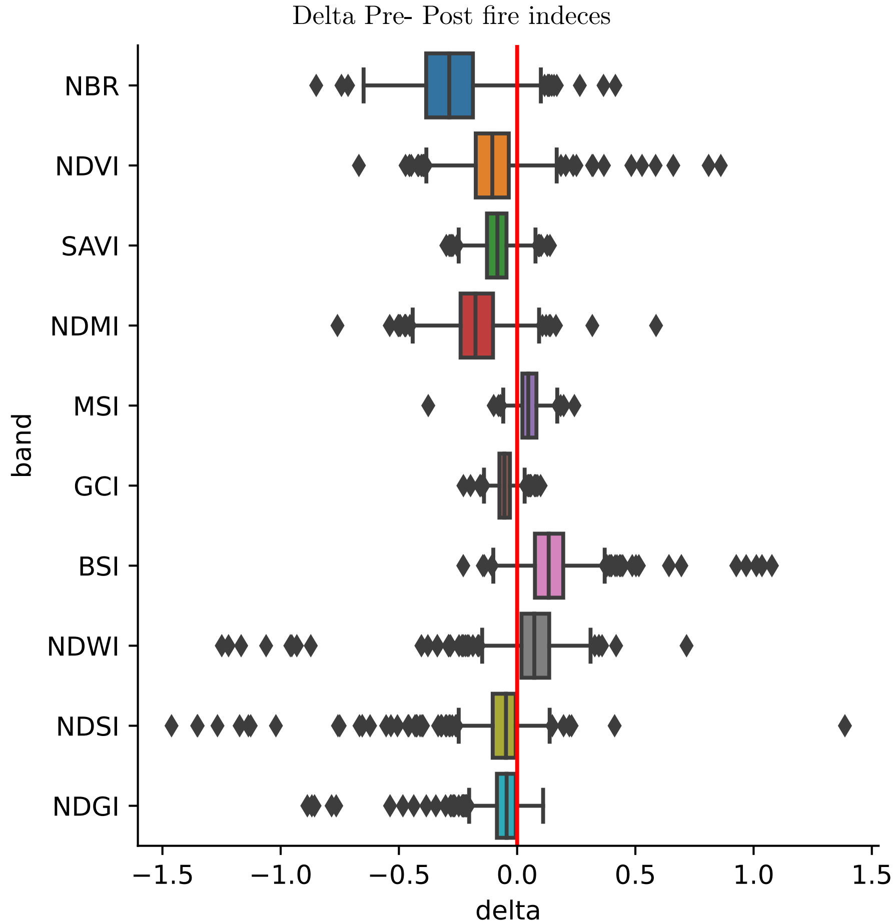
Spectral indeces can be used to analyse and highlight vegetation and water content. It could be assumed that those can assist at correctly identifying post forest fire areas.

Value distribution indeces



In order to meaningfully evaluate which indices are beneficial, the forest fire area in pre and post were compared numerically and the resulting delta is illustrated in the following box-plot. The same was done with the spectral bands as well.

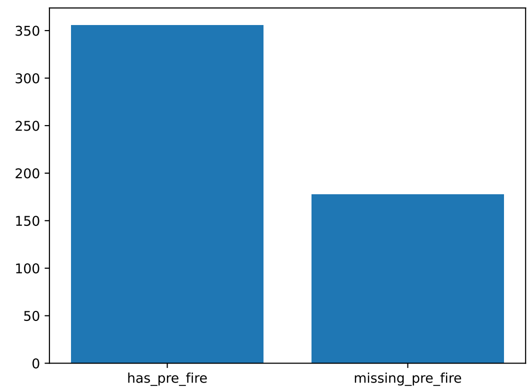

Delta Pre- Post fire on burned area
coastal_aerosol
blue
green
red
veg_red_1
veg_red_2
veg_red_3
nir
veg_red_4
water_vapour
swir_1
swir_2
band
−0.4
−0.2
0.0
0.2
0.4
delta



This insight served as a stating point for choosing hyper parameters for the CNN talked later on in this paper.

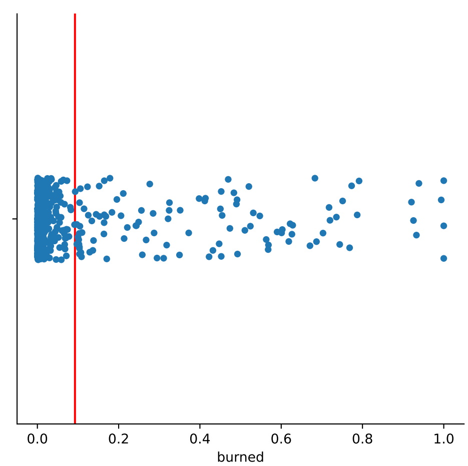
2.3 Data Preparation

During the explorative Data analysis it was also crucial to understand the quality of the data. In many cases the pre fire image was missing.

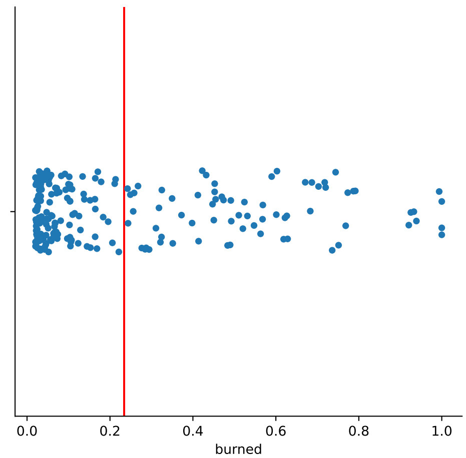


Missing pre fire imagery

Also most post fire images showed relative small burned areas so the mean size of all burned areas was 9%



Excluding the images which showed a relative burned area of 2% made the mean go up to 23%



By removing the data with the smallest mask, the Neuronal network gets exposed to larger masks and its expected that larger masks will be predicted, especially because the amount of data is relatively small.

2.4 Modeling

For training Pytorch Lighning was used in an overall unstructured trial and error manner. All hyper-parameters for every model trained were the same except for the inputs, pre fire data used, batch size and data preparation applied. The batch size has been increased to 5, the maximum memory capacity for the GPU used. Since this paper revolves around a classification problem of the computer vision domain the UNet model was chosen. UNet was developed for biomedical picture segmentation and suitable for this use case. [2] Additionally it seemed a popular choice. For the same reason the dice loss function as well as the weights of imagenet have been implemented because they have been developed for image segmentation as well.[3] The constant learning rate of 0.00025 was chosen due to the fear of overfitting. As encoder resnet34 was used.

The most significant results of trial and error model training can be seen below :

ID	Inputs	best IOU(epoch)	Batch size	use prefire	data preparation
14	band 1-12	0.465 (4)	4	True	False
19	band 1-12; NBR, NDMI, NDVI, BSI, NDWI	0.528 (28)	5	True	False
30	band 1-12; NBR, NDMI, NDVI, BSI, NDWI	0.733 (27)	5	False	True
37	band 1-12; NBR, NDVI, GNDVI, EVI, AVI, SAVI, NDMI, MSI, GCI, BSI, NDWI, NDGI	0.616 (22)	5	False	True

3 Result

After various training and testing it has become clear that choosing too many inputs like in attempt 37 models tend to perform less accurate. When on the other hand including 12 bands perform even worse, which may also be a side effect of the implementation of the missing data preparation and the inclusion of pre fire footage. The optimum was reached during the 30th attempt in the 27th epoch with an IOU score of 73.3%.

4 Discussion

It has not become clear what effect the data preparation had compared to the inclusion of a different set of inputs. Potentially the model would have been even more precise if that clarified. It should be assumed that according to the human readable differences between the bands, attempt 30 has the right combination of inputs and necessary data preparation step. Speaking of which, it has been attempted to filter datasets which have too many missing data points. Although the python dataframe to track these inconsistencies has been constructed it did not make it into the end result. It is to be expected to improve the results through more accurate rather than incomplete data. Another hypothesis is that further improvements could have been made if the hyperparameter optimization was automated to tweak the models accuracy about a few percent.

Nonetheless every neuronal network benefits from more data to learn from. Based on these results, CNNs could reliably segment forest fires on satellite imagery, requiring only well labeled post-fire imagery. This could mean a satellite does not have to be at the same spot twice in order to detect burned soil.

References

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