Significance of Image Preprocessing using Colour Filters for Automatic Annotation of Segmentation Models, A Review

Ashwin Rajesh

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I. Introduction

WILDFIRES pose a significant threat to humans, wildlife and the environment alike. Left unchecked, A wildfire can spread rapidly causing large scale destruction to forests & infrastructure, as well as releasing large amounts of pollutants into the atmosphere.

Studies have uncovered very strong associations of wildfire smoke with cardiovascular mortality, asthma hospitalisation and further susceptibility to cardiopulmonary effects in elderly adults. The risk of premature death and respiratory morbidity in the general population are also increased due to wildfilre smoke [1]. Furthermore, ambient air pollution caused by wildfire smoke has been studied to have adverse affects on children, as a result of their developing lungs and inferior nasal deposition [2]. Breathing in wildfire smoke can cause chest pain and tightness, trouble breathing, diziness and other symptoms in children [3].

Wildfires have been consuming increasingly large areas of forest globally in recent years, causing vast amounts of damage to the environment in the form of water & air pollution, climate change and destruction of flora and fauna. Sediment exports in water bodies reportedly may increase by up to 1459 times the unburned amount, drastically degrading water quality in the affected areas. [4]. Emissions of airborne particulate matter from wildfires can significant cause significant disruptions to air pollution mitigation targets set by legislation. [5] shows that in high-fire seasons, pollution levels can reach dangerous levels despite aggressive reduction of anthropogenic emissions. An estimated 97000 km^2 of vegetation was burned in the 2019-2020 Australian bushfires, causing devastating damage to wildlife habitat, with many belonging to species listed at threatened to extinction [6].

Evidently, It has become increasingly crucial to detect wildfires as early as possible to minimize damage to humans and the environment. Current methods of wildfire detection involve three main approaches:

1) Terrestrial sensor nodes, which may be placed at fire-prone locations to detect wildfires through environmental readings.
2) UAVs can be employed to scan large forest areas and inaccessible terrain.
3) Satellite based systems can cover vast areas of land and determine the extent and direction of wildfires.

Despite the various classifications of technologies within wildfire detection, advancements in computer vision object detection has spurred use in terrestrial, aerial as well as satellite systems. [7] explores the feasibility of space-borne fire detection using onboard computer vision to rapidly generate alerts. The traditional method of downloading image data from satellites has too much latency for time-sensitive applications such as fire detection. By examining performance of hardware accelerators for edge computing such as Nvidia Jetson and Movidius Myriad 2, the report found that AI inference on-board the satellite is possible in terms of performance as well as power consumption, allowing for low latency detection of wildfires. [8] details methods to optimise Deep Learning to deal with UAV limitations such as image degredation, small fire size & background complexity. By combining EfficientNet-B5, vision transformers and EfficientSeg convolutional model, an accuracy of 85.12% was obtained, outperforming many state-of-the-art models. [9] proposes a low cost WSN fire detection approach based on YOLO object detection models. The system, named SDFS was trained on a dataset of 26,520 images and achieved a high precision rate of 97.1% for smoke and fire classification.

Due to the importance of computer vision based object detection in wildfire detection, it is imperative that they are as accurate as possible. There are many different techniques to improve the performance of neural networks. Transfer learning is the process of using a model that has been pre-trained on a large dataset and further training and fine tuning it to a specific task. [10] studies the impact of transfer learning on classification by comparing six differnet pre-trained architectures. The models were trained using an open access dataset of 3886 images and found that all six architectures were able to achieve a testing accuracy of above 90% despite a relatively small training dataset. Augmenting data with synthetically generated samples investigated by [11] found that inserting data-space transformations such as warped images provided improved performance and reduced overfitting. [12] proposed an image pre-processing pipeline using advanced

This paper was produced by the IEEE Publication Technology Group. They are in Piscataway, NJ.

Manuscript received April 19, 2021; revised August 16, 2021.

techniques such as HSV filters and corner detection to assist models with classification by eliminating unwanted noise in images. This method has observed to improve fire detection accuracy by 5.5% and smoke detection by 6% in object detection models. Models which allow for finer, more detailed inference called image segmentation models are also improving. These models combine fully convolutional networks with skip architecture to achieve accurate pixel-wise inference of objects [13].

A. Existing Issues

Recent computer vision models are remarkably accurate at wildfire classification. However, they fail to provide any further insights into the state of the wildfire excluding a binary classification. For instance, Knowing the exact shape can be vital information for fire front tracking, which in turn provides valuable insight on which areas the wildfire could spread to. Traditional object detection models fail to capture to the precise dimensions of the fire, as the shape of a fire front is too intricate to be represented by a bounding box. In addition, existing methods of wildfire detection are often performed in remote terrestrial regions, aerially or from space, which will limit the computational power available for running neural networks. Extensively trained Deep neural networks suffer from slower inference, while lightweight shallow networks sacrifice accuracy for prediction speed improvements, therefore limiting the effectiveness of computer vision models in wildfire detection application. Furthermore, existing research regarding methods to track the spread of wildfires is rudimentary. Segmetation models have been under-utilized in wildfire detection applications due to the lack of annotated training data.

This report aims to review methods to enable the tracking and monitoring of wildfires, with a focus on incorporating image segmentation models. Fire detection is currentl carried out through a variety of mediums, such as terrestrial sensor nodes, UAV scanning and satellite based approaches. Observing the literature, it is apparent that computer vision plays a significant role in all systems, Making it important to maximise their efficiency. To this end, methods to automatically annotate image segmentation datasets, including a novel HSV filtering based approach, are examined to determine the ideal way to obtain training data for segmentation models.

Specifically, auto annotation using an existing object detection model combined with a prompt based segmentation model such as SAM is compared with creating fire masks using HSV colour filtering. Models are trained with the resulting datasets with identical hyperparameters and training time.

This paper contributes firstly a colour filtering based auto annotation approach which can be used to segment objects with predictable colour characteristics. Secondly, a comparison of automatic annotation methods for fire detection is provided.

Fig. 1: Basic operation of WSNs. Images sourced from Creative Commons, following the guidelines on Attribution 3.0 Unported, CC By 3.0

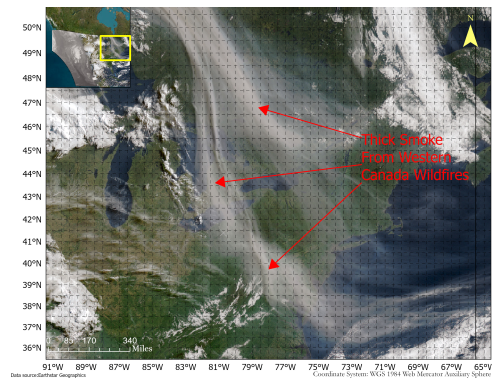

Fig. 2: Satellite Based Wildfire Detection

II. Literature Review

A. Approaches to Fire Detection

Edge computing sensor nodes can be placed at high risk locations that can monitor temperature, humidity and other characteristics of air in the surrounding area. These systems generally use a microcontroller to operate sensors, relying on solar cells for long-term power. By setting up multiple such nodes in different areas forming a Wireless Sensor Network (WSN), the collected sensor data may then be analyzed to determine the locations of fire events [14]. More advance methods of data classification with the use of artificial neural networks boast a high accuracy of >82% with multiple sensors [15]. The low cost of WSN systems has made it an increasingly popular choice for real-time monitoring of forest fires. However, sensor nodes fail to be viable in some situations. Establishing wireless communications for a WSN can prove challenging in rural or untamed areas such as forests [9]. The sensor nodes may also be prone to damage from the wildfire, needing to be replaced in order to continue using the system.

UAVs have seen extensive research for this application, as they provide valuable visual data which can be employed to carry out search and rescue operations, save forest resources, help firefighters navigate efficiently amoung numerous other enhancements. Rather than sending ground crews to monitor hazardous environments, UAVs can drastically reduce the risk to firefighting crews by remotely scanning large amounts of dangerous forest area. However UAVs tend to perform poorly in harsh weather conditions, have limited flight time and require a human operator to have a visual line of sight [16]. These factors combined with expensive operation costs severly limit the effectiveness of UAVs in many circumstances.

Satellite-based fire detection can potentially offer significant advantages over traditional methods due to the vast areas they can monitor. The benefits and limitations of these systems largely depend on the satellite's orbit. Satellites in Sun-Synchronous Orbit (SSO) provide high spatial resolution but revisit the same location only after several days, resulting in low temporal resolution. This delay makes SSO satellites less effective for real-time wildfire detection [7]. In contrast, Geostationary Earth Orbit (GEO) satellites remain fixed over the same region, as their orbital period matches Earth's rotation. Equipped with multispectral imaging sensors, GEO satellites provide continuous monitoring, making them ideal for detecting and tracking fires in real time.

B. Existing Fire Tracking Methods

Recent studies indicate experimentation with data-driven approaches to wildfire tracking. [17] proposes a UAV swarm utilized as a sensor network to keep track of the border region of a wildfire. The UAV team was capable of avoiding collision and maintaining safe distance to the fire level. Another approach proposes the use of a camera attached to a gimbal which surveys the region of interest from a high altitude [18].

C. Image Segmentation Models

A segmentation model partitions an image into multiple segments or image regions, typically used to determine the boundaries of objects in images. As convnets continued improving for whole image classification, progress was being made towards fine-grained inference such as keypoint prediction and local correspondence [13]. A fully convolutional network is used to achieve such a model. Existing models such as AlexNet can be adapdted into a fully convolutional network, then fine tuned to the segmentation task [13]. Such models have been extensively used in medical fields to delineate tumors, organs and tissues [19]. [20] suggests that fully automatic 2D and 3D models show promising results in liver segmentation, however could show improvement in segmenting small structures in high-resolution CT-scans

D. Image Pre-Processing: The HSV Filter

Hue, Saturation, Value (HSV) is a cylindrical-coordinate representation of points in an RGB colour model. It is an alternative representation of the RGB color model that intends to describe colors in a way that is more aligned with human perception. Colour masks can be created by setting upper and lower bounds within the HSV channels. This can then be applied to an image to filter specific tones of colour. A study by [21] utilized HSV thresholding to detect human skin in an image. The process achieved an impressive 99.587% accuracy on natural images under varying light conditions. [12] used a HSV filter in addition to other preprocessing stages to isolate colours of fire in an image to assist object detection models with inference, which resulted in a 5.5% increase in fire detection accuracy. The following bounds were used to preprocess images in the paper:

$$\mathrm{RoI}_{\mathrm{HSV(x,y)}} := \begin{cases} 1, 20 < H(x,y) < 40 \\ \text{ and } 50 < S(x,y) < 255 \\ \text{ and } 50 < V(x,y) < 255 \\ 0, otherwise \end{cases}$$

E. Automatic Annotation

High quality annotated training data is crucial for creating a performant segmentation model. However, manually annotating images requires substantial human effort. As a result, automatic annotation methods have emerged, leveraging pre-trained detection along with prompt based segmentation models to significantly reduce human workload.

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(a) (b)

Fig. 3: Example of Image filtered using the described HSV mask. (a) Original image. (b) Filtered image.

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