**Fire Detection from Landsat-8 Imagery**

**Abstract**wildfire that can spread rapidly and cause significant damage to the ecosystem, wildlife, and human infrastructure. Forest fires can be caused by natural factors such as lightning strikes or by human activities such as campfires, discarded cigarettes, or arson. They can have devastating effects on the environment, including the destruction of trees, vegetation, and habitats for various species. Forest fires also release large amounts of smoke and pollutants into the air, which can have adverse effects on air quality and human health. Firefighters and other emergency personnel work to contain and extinguish forest fires to minimize their impact and protect lives and property. Terrestrial-based systems refer to fire detection systems that are located on land or the Earth's surface, as opposed to being satellite-based or airborne. These systems could include sensors, cameras, or other technologies that are installed on the ground to monitor and detect fire incidents.

**Introduction**

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**Dataset**

The dataset utilized in this research was compiled from Landsat-8 images from South America during the year 2018. The data processing involved handling more than 11,270 thousand images. Among these images, approximately half of them contained active fire pixels. The Landsat-8 sensor characteristics include a spatial resolution of 30 meters, with a panchromatic band offering 15 meters resolution. The radiometric resolution is set at 16 bits, and the sensor has a temporal resolution of 16 days (revisit interval).

The images within the dataset are in georeferenced TIFF (geotiff) format and consist of 10 bands, excluding the 15-meter panchromatic band. To facilitate processing and analysis, the original Landsat-8 scenes, which were large with dimensions of around 7,600 x 7,600 pixels, were cropped into smaller image patches measuring 128 x 128 pixels. A stride overlap of 64 pixels was used both vertically and horizontally to create these patches.

Additionally, the dataset includes binary masks in which the value "True" (1) represents the presence of fire, and "False" (0) indicates the background. These masks were generated based on the conditions established by Schroeder et al. in 2016. The Schroeder conditions were applied to process each image patch. The selection of patches without fire pixels was done randomly from the original images.

Selection of Bands

Band Selection for Fire Detection in Multispectral Images

This research focuses on the selection of bands for fire detection in multispectral images. The dataset used in this study comprises images in the Tiff format, each consisting of 10 bands covering various spectral ranges, including the visible spectrum and infrared. Fire detection methods conventionally rely on thermal and visible spectral bands.

Certain bands show promising results for fire detection Notably, Band 7, representing the Short Wave Infrared 2 (SWIR 2) range from 2.11 to 2.29 µm, Band 6, representing the Short Wave Infrared 1 (SWIR 1) range from 1.57 to 1.65 µm, and Band 2, representing the Blue spectrum from 0.450 to 0.51 µm, are selected. The SWIR region lies just beyond the near-infrared (NIR) region and is characterized by longer wavelengths. This spectral range captures reflected or emitted energy from the Earth's surface and can provide valuable information about the properties like amount thermal radiation, vegetation etc. Anomalously high SWIR reflectance values can indicate the presence of active fires or hotspots.

Contrary to using all ten bands available in the dataset, employing only these three bands for fire detection demonstrated no significant difference in detection accuracy. This finding supports the potential of utilizing a reduced band set to streamline processing while maintaining reliable fire detection capabilities.

The selected bands offer a balance between capturing relevant information for fire detection and reducing computational complexity. As a result, this research presents a promising direction for optimizing fire detection methods in multispectral images by focusing on key spectral bands.

False colouring

The spectral ranges such as SWIR 1 and SWIR 2 cannot be seen. These spectral ranges has to be mapped to certain colours in order to ease detection of features. The bands 7,6 and 2 have been mapped to red,green,blue colours. This technique visualizes the multi-band imagery in a way that is more interpretable to the human eye

U-Net Architecture

U-Net is a convolutional neural network architecture that has shown great performance in various image segmentation tasks, including the detection of fires in satellite or aerial images. In the context of active fire detection, U-Net can be used to accurately segment the regions in an image that contain the fire.

The model is trained to learn the mapping between input images and their corresponding segmentation masks. The output of the U-Net model is a binary mask, where pixels labelled as 1 represent regions containing fire and pixels labelled as 0 represent regions without fire.

Methodology:

The architecture consists of two essential components: the Contracting Path and the Expansive Path. The Contracting Path employs a series of 2D convolutional blocks to gradually extract high-level features from the input image. Each block incorporates a convolutional layer, batch normalization, and ReLU activation to enhance feature representation. A 2x2 MaxPooling operation is applied to reduce spatial dimensions, followed by dropout regularization to mitigate overfitting.

The architecture's effectiveness lies in its compact design, making it suitable for resource-constrained environments. We set the number of filters to a modest value (n\_filters = 16) to reduce model complexity while preserving important features. Additionally, a dropout rate of 0.2 is utilized during training to promote model generalization.

The Expansive Path reconstructs the feature maps using transpose convolutions to perform upsampling. Each upsampled feature map is then concatenated with the corresponding Contracting Path feature map, enabling the network to learn detailed information while retaining global context. Subsequent 2D convolutions with batch normalization and ReLU activation further refine the features.

Evaluation Metric

The Evaluation metric chosen for this model is Intersection over union(IoU).

The IoU metric is one of the commonly used metric to evaluate the fire detection models Intersection over union metric is a good evaluation when dealing with imbalanced classes like fire, where fire pixels might be a small portion of the total image.

References  
[1] Gabriel Henrique de Almeida Pereira, Andre Minoro Fusioka. “Active fire detection in Landsat-8 imagery: A large-scale dataset and a deep-learning study”, ISPRS Journal of Photogrammetry and Remote Sensing,