**Wildfire Detection System using Deep Learning**

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***Abstract:*** *- Wildfire spread rapidly and cause significant damage to the ecosystem, wildlife, and human infrastructure. They can have devastating effects on the environment, including the destruction of trees, vegetation, and habitats for various species. Early detections of forest fires can reduce the amount damage and time. Traditional fire detection methods often rely on ground-based observations or human reporting, which may be limited in scope and response time. Satellite imagery offers a valuable alternative for fire detection, enabling large-scale coverage and rapid identification of fire incidents. However, interpreting multispectral satellite data is complex due to the presence of various spectral bands, atmospheric effects, and other environmental factors. This paper addresses the challenge of detecting the forest fires from the satellite images using U-Net architecture which enables faster inference on large-scale datasets, making it well-suited for real-time fire monitoring applications. Moreover, the model's capability to analyze multispectral data allows it to capture unique fire characteristics that are not readily apparent in traditional visual or infrared imagery.*

**1. INTRODUCTION:**

Wildfire detection systems are designed to detect and send an alert to the officials to the place where the wildfire took place. This detection system is basically created to prevent the escalation of fire and reduce destruction. There are many types of wildfire detection systems like Satellite-based systems, ground-based-based systems, and drone-based systems.

The Satellite-based wildfire detection system is used to notice and monitor wildfires from space. This system uses data from sensors on satellites to detect changes in temperature and other environmental conditions that may indicate the presence of a wildfire. This information then can be used to help the firefighters and other emergency responders to quickly locate and respond.

**Literature review**

According to the paper published Gabriel Henrique [1]a very huge dataset for Active Fire Dataset containing image patches of 256 x 256 pixels was considered. The dataset was extracted from Landsat-8 images. The images are 16-bit TIFF images, excluding the images which are sensitive to all the visible colours of the spectrum with 30m of spatial resolution. U-Net Architecture was used for segmenting the image and Intersection over Union (IoU) of 80.7% was achieved.

According to Periara el at. [3] fire pixel ratio was used in the research. Ratio of a fire pixel refers to the proportion of a given pixel that is on fire compared to the total area of the pixel. In wildfire detection, the ratio of a fire pixel is an important parameter that can help to estimate the severity and intensity of the fire.

The ratio of a fire pixel is typically measured using spectral data from remote sensing instruments, such as satellite or aerial sensors. These sensors capture multispectral or hyperspectral images of the fire scene, which contain information about the reflectance or radiance of the different spectral bands.

In the paper by Rostami[4]. To calculate the ratio of a fire pixel, the spectral values of the pixel in the infrared or thermal bands are compared with the values in the visible or near-infrared bands. The infrared or thermal bands are sensitive to the heat emitted by the fire, while the visible or near-infrared bands are less affected by the fire and reflect the background features, such as vegetation or soil.

In a study by Sudha et al. and Murugan et al.[13], Support vector machines find hyperplanes that separate data points into respective classes of Fire or No Fire classes. SVMs are good with data that is not regularly distributed and has unknown distributions.

In a study by Mahdi et al. [5], CNN have been found to be better for better segmentation outcomes. The SWIR (Short wave infrared) sensor data was used to check for identifying the sudden change in the thermal data. Generative adversarial network were used for creating additional images from main Dataset. The general methods like flipping were also used for Data Augmentation[11]

The abrupt change in Vegetation of area can also be considered for better detection of fires. As per Pietrabissa [8] using Vegetation index along with the reflectance values of the places can improve the detection of fires. The encoder-decoder CNN architecture was used which also acts similar to that of a U-Net Architecture.

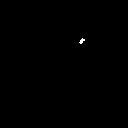
**2. METHODOLOGY**

**Data collection and Data processing**

The dataset utilized in this research was compiled from Landsat-8 Satellite images from South America during the year 2018. The data processing involved handling more than 11,270 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 [2]. The Schroeder conditions were applied to process each image patch. The selection of patches without fire pixels was done randomly from the original images. The figure 1 represents the original images with their corresponding binary mask in which the presence of fire pixel is 1 and non-fire pixel as 0.

Original Image Ground truth  

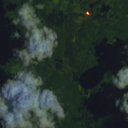
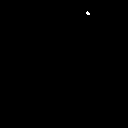
 

Fig. 1. The original images with their corresponding masks

**Selection of Bands**

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.

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. 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**

False colour is a method where specific spectral bands or combinations of bands are assigned to the red, green, and blue (RGB) channels, creating a synthetic colour image. Unlike traditional RGB representations, false colour goes beyond the visible spectrum, revealing hidden features and phenomena that may not be apparent in conventional imagery.

The spectral ranges such as SWIR 1 and SWIR 2 do not lie in the visible spectral range. 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 general structure of U-Net contains a Contracting path and 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 MaxPooling operation is applied to reduce spatial dimensions, followed by dropout regularization to mitigate overfitting.

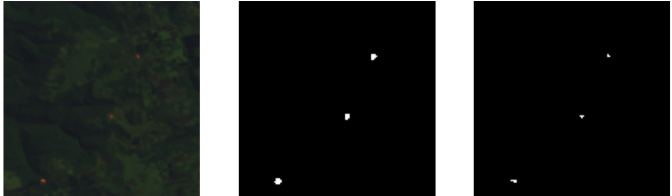
The Expansive Path reconstructs the feature maps using transpose convolutions to perform upsampling. Each upsampled feature map is then concatenated with the corresponding Contracting Path feature map, enabling the network to learn detailed information while retaining global context. Subsequent 2D convolutions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

The final pixels values are mapped to 1 and 0 by thresholding. Most fire detection techniques use a threshold of 0.5 which has also been used as the standard threshold in the design of this network

**Training and Testing**

The Dataset on whole has 11,270 images. The data was split into 7:1:2 ratio for training, validation and testing. The generated false coloured images were used as input for the network and corresponding binary masks for the images acted as ground truth. The whole network was trained on 10 epochs. The output of the network on various sample images is in fig 2

Original Predicted Ground truth





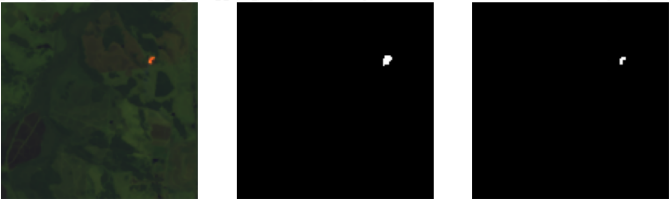


Fig. 2. Original images with their corresponding predicted output and ground truth

**Evaluation Metrics**

One of the challenges in evaluating the models which work on fire detection in satellite images is the presence of exceedingly a greater number of non-fire pixels compared to fire pixels. The Intersection over Union (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 This metric is generally used to give importance to the amount of overlap between the predicted output and ground truth.

**3.RESULTS**

In many fire detection methods, particular attention is paid to abrupt variations in reflectance and unusual thermal radiation patterns, as these characteristics help identify the location of a fire. By adjusting the number of filters and the size of windows used in the process of convolution, a comparison can be drawn between the fire-affected pixels and the surrounding neighbourhood pixels. As a result, various window sizes for convolution have been carefully selected. Different variation of the network.

**Table of Results**

|  |  |  |  |
| --- | --- | --- | --- |
| Network | No of filters | Window size of filter | Intersection over union (IoU) |
| Fully convolutional Network | 4 | (3,3) | 45.2 |
| Fully convolutional Network | 16 | (3,3) | 47.8 |
| U-Net | 4 | (3,3) | 50 |
| U-Net | 8 | (3,3),(5,5) | 52 |
| U-Net | 16 | (3,3),(5,5) | 55 |
| U-Net | 16 | (3,3) | 61 |

**Conclusion**

The U-Net Architecture has been found effective in identifying the fires with using lesser bands as input also while being efficient and fast enough to be used in real time fire detection system. Filter size of 3 was found to be more effective in highlighting the forest fires compared to other filter sizes. The research also falls in line with the previous research which used SWIR bands (only 3 bands) as input instead of using all the 10 bands in the Landsat 8 image dataset.

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