State of the Art Survey

Detection of Stubble Burning in Upper Punjab Using Remote Sensing and Deep Learning

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Deep Learning

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1.1 Introduction:

Stubble burning is a widespread post-harvest practice in Punjab, Pakistan, and a major contributor to regional air pollution and seasonal smog. Satellite remote sensing has become essential for detecting and monitoring these events, with prior research applying spectral indices (e.g., NBR, NDVI), thermal anomaly detection (MODIS, VIIRS), and, more recently, deep learning-based segmentation models. This survey reviews key methods for stubble burn detection, emphasizing small-scale fires and their impact on air quality. Building on this foundation, our project aims to develop a high-resolution, data-driven model using Sentinel-2 imagery to accurately identify crop field–level burn activity in upper and central Punjab.

1.2 Recent Works:

A. Anand *et al.* [1] presented a fine-tuned deep-learning segmentation model for detecting small-scale agricultural burn areas using high-resolution Sentinel-2 MSI imagery. The model was initially trained on burn data focused on large forest fires and later fine-tuned using hand-annotated Sentinel-2 Level 1C images for a 200 km² region in Punjab. Transfer learning enabled the model to adapt effectively to detecting finer burn patches characteristic of crop residue burning in South Asia. The fine-tuned model outperformed the traditional Normalized Burn Ratio (NBR)-based baseline model. Evaluation metrics included the Jaccard Index and Dice score. This study highlights the value of domain adaptation and high-resolution satellite imagery in improving burn detection performance. It demonstrates the practical benefits of transfer learning in addressing data scarcity in ground-truth-limited regions like Punjab.

Walker [2] reviews key challenges in accurately measuring crop residue burning (CRB) using remote sensing, identifying five main pitfalls: limited spatial and temporal resolution, ill-fitted spectral signals, improper comparison groups, and inadequate accuracy assessment. Using PlanetScope, Sentinel-2, and ground observations, the study shows that brief burns, rapid post-burn changes, and heavy smoke often lead to underestimation. It also finds that standard indices like NDVI and NBR may misclassify tilled fields as burned. The paper underscores the need for rigorous, time-continuous validation—directly motivating our approach using fine-tuned segmentation with high-resolution Sentinel-2 data.

AgriSegNet [3] introduces a deep-learning semantic segmentation framework for detecting farmland anomalies in UAV-acquired imagery to support precision agriculture. It is built on a DeepLabV3+ foundation with a multi-scale hierarchical attention mechanism, which enables the model to learn from images at different resolutions to enhance segmentation accuracy. It was trained on the Agriculture-Vision Challenge dataset and demonstrates strong segmentation performance in complex agricultural scenes. It also incorporates adaptive class-weighted loss with Dice loss to handle class imbalance. Although not designed for fire detection, AgriSegNet demonstrates key design principles such as multi-scale feature fusion and attention, which are highly relevant to stubble burn detection tasks, where small, scattered anomalies must be segmented accurately under varying image conditions.

Chawala and Sandhu [4] developed a remote sensing–GIS approach to quantify the impacts of rice stubble burning and its ambient air quality. Using Landsat 8 OLI images, the authors computed the Normalized Burn Ratio (NBR) index to delineate burned versus unburned areas. By analyzing monthly variations of air pollutants and incorporating wind rose diagrams to assess wind speed and direction, the research demonstrated that stubble-burning episodes correlate with significant spikes in pollutant levels during the burning months. These findings highlight the potential of remote sensing techniques to monitor and guide effective mitigation strategies.

Knopp et al. [5] developed an end-to-end, automated processing chain for rapid burned area mapping using mono-temporal Sentinel-2 imagery. They compiled a novel high-resolution training dataset by integrating burned area masks and used it to train a U-Net–based convolutional neural network for pixel-level segmentation. The authors identified a configuration of spectral band combinations that balanced accuracy and computational efficiency. Notably, the processing chain bypasses extensive preprocessing steps like atmospheric correction and multi-temporal analysis, making it particularly suitable for time-critical applications in fire management. This study demonstrates that deep learning can robustly and rapidly delineate burned areas from a single post-fire Sentinel-2 scene, providing a scalable solution for operational remote sensing of wildfires.

1.3 Datasets:

These are some of the potential datasets we will be using to train our model. In addition to leveraging publicly available datasets like Sentinel-2, MODIS, and VIIRS, our project involves the development of a custom-labeled dataset using Google Earth satellite imagery. This allows us to capture field-level burn events specific to upper Punjab and train high-resolution models tailored to the regional context.

1. MODIS (Moderate Resolution Imaging Spectroradiometer)
2. VIIRS (Visible Infrared Imaging Radiometer Suite)
3. Sentinel-2 (Multispectral Instrument - MSI)
4. PlanetScope (limited due to cost)
5. Agriculture-Vision Challenge Dataset
6. Custom Dataset (Google Earth Engine + Manual Annotation)

1.4 GitHub Repositories:

1. https://github.com/prhuppertz/Burned_Area_Detection
2. https://github.com/hayatkhan8660-maker/Fire_Seg_Dataset
3. GitHub - qubvel-org/segmentation_models.pytorch: Semantic segmentation models with 500+ pretrained convolutional and transformer-based backbones.

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