Article
FiLib & SmokeyNet: Dataset and Deep Learning Model for Real-Time Wildland Fire Smoke Detection

Anshuman Dewangan 1,†, Yash Pande 2,†, Hans-Werner Braun 3,†, Frank Vernon 4,†, Ismael Perez 5,†, Ilkay Altintas 6,†, Gary Cottrell 7,† and Mai H. Nguyen *,†

1 adewangan@ucsd.edu
2 ypande@ucsd.edu
3 hwb@ucsd.edu
4 fivernon@ucsd.edu
5 i3perez@sdsc.edu
6 ialtintas@ucsd.edu
7 gary@ucsd.edu
† University of California, San Diego, La Jolla, CA 92093, USA
* Correspondence: mhnguyen@ucsd.edu

Simple Summary: We present the Fire Ignition Library (FiLib), a publicly-available dataset of nearly 25,000 labeled wildfire smoke images, and SmokeyNet, a novel deep learning architecture for real-time wildfire smoke detection.

Abstract: The size and frequency of wildland fires in the western United States have dramatically increased in recent years. On high fire-risk days, a small fire ignition can rapidly grow and get out of control. Early detection of fire ignitions from initial smoke can assist the response to such fires before they become difficult to manage. Past deep learning approaches for wildfire smoke detection have suffered from small or unreliable datasets that make it difficult to extrapolate performance to real-world scenarios. In this work, we present the Fire Ignition Library (FiLib), a publicly-available dataset of nearly 25,000 labeled wildfire smoke images as seen from fixed-view cameras deployed in Southern California. We also introduce SmokeyNet, a novel deep learning architecture using spatio-temporal information from camera imagery for real-time wildfire smoke detection. When trained on the FiLib dataset, SmokeyNet outperforms comparable baselines and rivals human performance. We hope that the availability of the FiLib dataset and the SmokeyNet architecture will inspire further research into deep learning methods for wildfire smoke detection, leading to automated notification systems that reduce the time to wildfire response.

Dataset: http://hpwren.ucsd.edu/HPWREN-FiLib/

Keywords: wildland fire mitigation, smoke detection, deep learning, computer vision, artificial intelligence, machine learning, remote sensing, HPWREN

1. Introduction

The size and frequency of wildland fires in the western United States have increased in recent years. In 2018 alone, 8,527 fires burned an area of 1.9 million acres in California (7,700 km²; nearly 2% of the state’s area), with an estimated economic cost of $148.5 billion [1].

On high fire-risk days, a small fire ignition can rapidly grow and get out of control. Consequently, the detection of wildfires in the first few minutes after ignition is essential to minimizing their destruction. However, it can take much longer for a fire to be reported using existing methods, especially in areas with less human activity. Deep learning-based wildfire smoke detection systems can accurately and consistently detect wildfires and provide valuable intel to reduce the time to alert authorities.
The goal of a wildfire smoke detection system can be structured as a binary image classification problem to determine the presence of smoke within a sequence of images. Priorities include quick time-to-detection, high recall to avoid missing potential fires, high precision to avoid frequent false alarms that undermine trust in the system [2], and efficient performance to operate in real-time on edge devices. However, the task proves challenging in real-world scenarios given the transparent and amorphous nature of smoke; faint, small, or dissipating smoke plumes; and false positives from clouds, fog, and haze. While the idea of an automated wildfire smoke detection system has been previously explored, the difficulty of acquiring a large, labeled wildfire smoke dataset has limited researchers to using small or unbalanced datasets [3,4], manually searching for images online [4–7], or synthetically generating datasets [7–9].

To address the need for a consistent evaluation benchmark for real-world performance, we present the Fire Ignition Library (FIgLib), a publicly-available dataset of nearly 25,000 labeled wildfire smoke images as seen from fixed-view cameras part of the High Performance Wireless Research and Education Network (HPWREN) in Southern California. We also introduce SmokeyNet, a novel deep learning architecture using spatio-temporal information from camera imagery for real-time wildfire smoke detection. When trained on the FIgLib dataset, SmokeyNet outperforms comparable baselines in terms of accuracy and rivals human classification performance. We hope that the availability of the FIgLib dataset and the SmokeyNet architecture will inspire further research into deep learning methods for wildfire smoke detection, leading to automated notification systems that reduce the time to wildfire response.

2. Related Work

Before the rise in popularity of deep learning methods, computer vision algorithms leveraging hand-crafted features identified that the visual (e.g., color), spatial, and temporal (i.e., motion) qualities of smoke are essential for the machine detection of wildfires [3,10–12]. More recently, deep learning approaches use a combination of convolutional neural networks (CNNs) [5–7,13–17], background subtraction [13,16,18], and object detection methods [4,8,17,19,20] to incorporate visual and spatial features. Long short-term memory (LSTM) networks [4,16] or optical flow [14,18,21] methods have been applied to incorporate temporal context from video sequences.

Despite many papers reporting above 90% image classification accuracy for the detection of smoke, the lack of a large, labeled publicly-available wildfire smoke dataset makes it difficult to compare performance between approaches. For example, Ko [3] and Jeong [4] used only 10 and 24 videos in their test sets, respectively, in which half the videos have smoke and half the videos have no smoke; there are no videos in which a fire starts in the middle of the sequence. With hundreds of frames per video but such few fire scenes evaluated, the high accuracies reported may not be representative of real-world performance across different scenarios. Li [6] and Park [7] collected 4,595 (36% positive) and 6,354 (22% positive) wildfire images online, respectively; however, since these images were not from video sequences, the smoke plumes in the image are more visible, and likely easier to detect, compared to wildfire smoke initially forming after ignition when seen from a continuous video sequence. Yin [5] also manually acquired images online, but the images represent smoke from a variety of indoor and outdoor scenarios beyond wildland fires. Many works synthetically generate images to overcome the lack of available data; Park [7] uses generative adversarial networks (GANs), Zhang [8] uses live smoke in front of a green screen, and Yuan [9] uses computational simulation to generate these images. Given the diversity and challenges of the datasets across these works, it is hard to identify which models are best or choose a particular dataset to use as a benchmark for wildfire smoke classification.
Govil et al. [2] is the only work we are aware of that also uses the FlgLib dataset to evaluate wildfire smoke detection performance. They used an InceptionV3 CNN trained from scratch as the primary image classification architecture. Instead of using a sigmoid threshold of 0.5 for the prediction of smoke, as is common in classification models, a dynamic threshold was implemented based on the average prediction during the same time of day over the prior three days. This was used to incorporate periodic environmental events (e.g. fog, solar reflection, smog, haze); the data from prior days is not included in the FlgLib dataset, but is available through the HPWREN Archive. Using this approach, the authors reported a test accuracy of 0.91 and F1-score of 0.89. However, the test set consists of only a small number of hand-selected images relative to the training set (250 vs. 8,500+ images). The test set also contains images from the same video sequences of fires used in the training set with only 10 minutes (i.e., 10 frames) of separation between them; this procedure bleeds information from the training data and therefore may overstate the performance on the test set. The authors also reported results from field-testing the model on 65 HPWREN cameras over a period of nine days in October 2019. After suppressing repeat detections in a one hour time-span, only 21% of notifications showed smoke from real fires; in other words, their model had a 79% false positive rate on real data. Additionally, there was no report of how many actual fires were missed.

3. Data
3.1. FlgLib Dataset

The HPWREN FlgLib dataset (Figure 1) addresses the need for a large, labeled publicly-available dataset for wildfire smoke detection. FlgLib reflects sequences of wildland fire images as seen from fixed-view cameras on remote mountain tops in Southern California. As of December 2021, the dataset consists of 315 fire sequences from 101 cameras across 30 stations occurring between June 2016 and July 2021. Each sequence typically contains images from 40
Table 1: Number of fires and images in our training, validation, and test splits of the FIgLib dataset. "Omitted" fires include fires with black & white images, night fires, and fires with questionable presence of smoke to avoid out-of-distribution sequences.

| Model   | # Fires | # Images |
|---------|---------|----------|
| Train   | 144     | 11.3K    |
| Validation | 64     | 4.9K     |
| Test    | 62      | 4.9K     |
| Omitted | 45      | 3.7K     |
| Total   | 315     | 24.8K    |

minutes prior to and 40 minutes following the start of the fire, serving as binary smoke/no-smoke labels for each image, and are spaced approximately 60 seconds apart for a total of 81 images per fire sequence. However, 114 fires are missing an average of 6.6 images each; missing images are either at the beginning, end, or randomly dispersed throughout the sequence. In total, the dataset contains 24,800 high-resolution images that are 1536x2048 or 2048x3072 pixels in size, depending on the camera model used. The ignition detection and view prior to the ignition are enabled by a cluster deployment of cameras, where four 90+ degree views stay consistent for years, covering 360 degrees around a mountaintop. The full FIgLib dataset can be accessed at the following link: [http://hpwren.ucsd.edu/HPWREN-FIgLib/](http://hpwren.ucsd.edu/HPWREN-FIgLib/)

3.2. Data Preparation

The train, validation, and test splits are shown in Table 1. To avoid out-of-distribution sequences, we removed fires with black & white images (N=10), night fires (N=19), and fires with questionable presence of smoke (N=16), including one fire with 180 images and no labels, from the dataset (3,700 images from 45 fires removed in total). In addition to binary smoke/no-smoke labels for each image, the smoke in 144 fires has been manually annotated with bounding boxes and contour masks. Since we divide the images into tiles (described in Section 4.1), we can use these annotations to provide smoke/no-smoke labels at a more granular level. Hence, we used images from these 144 annotated fires for training (53.3% of eligible fires, 11,300 images); the remaining 126 fires (9,800 images) were split between the validation and test sets such that the number of images in each is roughly equivalent. Splitting the data by fires instead of images ensures that no data related to the test set is in the training set. The exact list of fires omitted and used for the train, validation, and test splits can be accessed at the following link: [https://gitlab.nrp-nautilus.io/-/snippets/63](https://gitlab.nrp-nautilus.io/-/snippets/63)

Additional transformations during data loading improve the performance of our model. We resize the images to 1392x1856 pixels to improve training and inference speed. We also crop the top 352 rows of the image to reduce false positives from clouds for additional performance gains. Data augmentations include horizontal flip, random vertical crop, color jitter, brightness & contrast jitter, and blur. Finally, the images were normalized to 0.5 mean and 0.5 standard deviation, as expected by the deep learning package used (torchvision).

4. Methods
4.1. Tiling

Our goal is the binary classification of images to determine the presence of smoke as early in the sequence as possible. Training the model with standard CNN techniques by leveraging solely image labels does not provide a sufficient training signal for the model to identify small plumes of smoke within the large images. Object detection models using bounding box and contour mask annotations can better localize the target object using anchors and a regression
Figure 2. The SmokeyNet architecture takes two frames of the tiled image sequence as input and combines a CNN, LSTM, and ViT. The yellow blocks denote "tile heads" used for intermediate supervision while the blue block denotes the "image head" used for the final image prediction.

head [22]; however, these models require precise annotations, which poses a challenge in our scenario given the amorphous and transparent nature of smoke.

Consequently, we build upon previous work by tiling the image into 224x224 tiles, overlapping by 20 pixels for a total of 45 tiles [2]. We also generate corresponding binary tile labels: positive if the number of pixels of smoke in the tile, determined by the filled polygon of the contour mask, is greater than an empirically-determined smoke detection threshold of 250 (0.5% of the total pixels in the tile). Tile labels provide the entirety of our localized feedback signal; we do not otherwise use the bounding box or contour mask annotations during training.

One challenge of the dataset is that 1,213 (approximately 20%) of the positive images are missing contour mask annotations. 280 annotations are missing because the smoke is difficult to see, generally occurring at the beginning of the fire sequence or at the end, when the smoke has dissipated. 486 annotations are missing contour masks but have bounding box annotations, generally because the smoke is too small to reasonably outline a fine contour mask. The remaining 447 missing annotations are randomly spread throughout the fires.

For images with bounding box annotations where contour masks are not available, we determined the tile labels by filling the bounding boxes as polygons instead of the contour masks (486 images affected). We attempted other methods to incorporate feedback from images with missing annotations, including using feedback from only image labels (as opposed to both image and tile labels) and copying contour masks from the closest available image in the sequence. However, neither of these methods improved model performance; consequently, we did not train on the remaining positive images with missing annotations (727 images total). For future work, we aim to resolve these missing labels for more robust training data.

4.2. SmokeyNet Architecture

The SmokeyNet architecture (Figure 2) is a novel spatio-temporal gridded image classification approach for wildfire smoke detection combining three different types of neural networks: a CNN [23], an LSTM [24], and a vision transformer (ViT) [25]. The input to our model is the tiled raw image and its previous frame in the wildfire video sequence to incorporate the motion of the smoke. A CNN, pre-trained on the ImageNet dataset [26], initially extracts representations of the raw image pixels from each tile of the two frames independently. A ResNet34, a lighter-weight version of the popular ResNet50 model, is our preferred choice of CNN backbone [27]. Then, an LSTM combines the temporal information of each tile from the current frame with its counterpart from the previous frame. Finally, all temporally-combined tiles are fed into a ViT, which incorporates spatial information across tiles to improve the image prediction.
The outputs of the ViT are spatio-temporal embeddings for each tile, as well as a CLS token embedding that summarizes representations for the whole image [25]. The CLS token embedding is passed to an “image head,” consisting of three fully-connected layers with ReLU activation with output sizes of 256, 64, and 1, respectively, and a sigmoid layer with a threshold of 0.5 to generate a single prediction for the whole image. Given the modular nature of each of the components, we can experiment with different approaches to capture spatio-temporal information while still training the model end-to-end.

4.3. Loss

The initial component of our loss applies standard binary cross-entropy (BCE) loss between the outputs of the image head and the ground-truth binary image labels. We can increase the weight of positive examples when calculating this BCE image loss to trade off precision for higher recall. Increasing the positive weight increases the penalty for missing positive examples; while potentially incurring more false positives, the model will also be able to detect the actual presence of smoke more quickly and accurately, which is of utmost importance. We use the empirically-determined positive weight of 5 to achieve more balanced precision and recall and improve the overall accuracy and F1-score.

To leverage the localized information provided by the tile labels, we also apply intermediate supervision to each of the model components [28]. Since the model’s components, the CNN, LSTM, and ViT, also produce embeddings on a per-tile basis, we pass each component’s embeddings through individual “tile heads,” consisting of three fully-connected layers with ReLU activation with output sizes of 256, 64, and 1, respectively, and a sigmoid layer to generate predictions for each tile. We then apply BCE loss between the outputs of the tile heads and the binary tile labels. To address the class imbalance in which negative tiles occur more frequently than positive tiles, we weight positive examples by 40, the ratio of negative tiles to positive tiles.

If \( I \) is the total number of tiles, the overall training loss can be summarized as:

\[
loss = \text{BCE}^{\text{image}} + \sum_{i}^{I} \{ \text{BCE}^{\text{CNN}}_{i} + \text{BCE}^{\text{LSTM}}_{i} + \text{BCE}^{\text{ViT}}_{i} \}
\]

Since we have tile labels for only the training data, we define our validation loss as the average number of image prediction errors and use this validation loss for early stopping.

4.4. Baselines & Experiments

We experiment with alternate CNN backbones to the ResNet34, including a MobileNetV3Large (denoted “MobileNet”) [29], MobileNet with a Feature Pyramid Network (FPN) [30] to better incorporate spatial scales, EfficientNet-B0 [31], and Data Efficient Image Transformer (DeiT-Tiny) [32]. Using the ResNet34 as the backbone, we also try inputting three frames (i.e., two additional frames of temporal context) instead of two and conduct an ablation study by removing different parts of the model to evaluate each component’s benefits. We then experiment with different architectures that can capture the temporal information from sequential frames, including: replacing the LSTM with a transformer [33]; using a CNN and a ResNet18-3D CNN to replace both the LSTM+ViT [34]; and incorporating motion information using MOG2, a Gaussian-mixture-based background removal method [35,36], as an additional channel of input. Finally, we compare the model’s performance to three baseline architectures: ResNet50, the standard for image classification models [27]; Faster-RCNN, a standard object detection model [22]; and Mask-RCNN, an image segmentation model leveraging both contour masks as well as bounding boxes for training signal [37].

For baseline models that do not use a ViT as the last architectural component (e.g. ResNet34+LSTM, ResNet50, ResNet34+ResNet18-3D, etc.), there is no CLS token embedding that summarizes representations for the whole image that we can use for our image prediction.
Table 2: Accuracy (A), F1, precision (P), recall (R) and average time-to-detection (TTD) evaluation metrics on the test set, with 2 frames of input (unless otherwise stated) averaged over 5 runs. Best results are bolded. Number of parameters (in millions) and inference time (ms/image) should be minimized for deployment to edge devices.

Consequently, we determine the overall image prediction by passing the model’s tile predictions into a single fully connected layer with sigmoid activation, outputting a single prediction for the image. We also experimented with the simple decision rule that if the prediction for any tile is positive for smoke, the full image is also classified as positive; however, this resulted in worse performance. Image predictions for object detection models (e.g. FasterRCNN, MaskRCNN) were determined as positive if the model predicted any bounding box with a confidence score above the empirically-determined threshold of 0.5 (0.0, 0.2, 0.4, 0.5, 0.6) all tested). Additional model implementation details for alternative architectures are described in Appendix A.

4.5. Training Details

Hyperparameter tuning was performed sequentially, with the best result from one set of experiments used in subsequent experiments, in the following order: learning rate (1e-2, 1e-3, 1e-4), weight decay (1e-4, 1e-3), image resizing (100%, 90%, 80%, 50%) of 1536x2048, smoke detection threshold to determine tile labels (0, 10, 100, 250 pixels per tile), dropout (0, 0.1), and image BCE loss positive weight (1, 2, 5, 10). Final models were trained using an SGD optimizer with learning rate 0.001, weight decay 0.001, and no dropout. The batch size used was the larger of 2 or 4 depending on which would fit into GPU memory, and gradient batches were accumulated such that the effective batch size was 32. Models were trained for 25 epochs using a single NVIDIA 2080Ti GPU; the model with the lowest validation loss was used for evaluation on the test set. Results are reported as an average over 5 runs.

5. Results & Discussion

Table 2 reports test evaluation performance for each of the architectures. The SmokeyNet architecture with a ResNet34 backbone and 2 frames of input achieves an image accuracy of 83.49% and F1-score of 82.59% while delivering on the objectives of high precision (89.84%), high recall (76.45%), and fast performance (51.6ms/image). It also has low average time to detection (3.12 mins), calculated as the number of minutes until the model correctly predicts
Figure 3. SmokeyNet’s performance per fire on both negative and positive images. Green denotes a correct prediction; red denotes an incorrect prediction; white denotes images missing from the sequence. Hence, red on the left are false positives, red on the right are misses. Common misses include faint smoke occurring at the start of the fire or dissipating smoke at the end of the fire sequence. Common false positives include low-altitude clouds and haze.

the first positive frame of a wildfire sequence, averaged over all fires. One additional frame of input (ResNet34+LSTM+ViT (3 frames)) only marginally improves performance at the cost of a 55.6% increase in inference time. Large backbones such as the ResNet34 or EfficientNet-B0 trade off model size and inference time for better accuracy compared to smaller backbones such as the MobileNet or MobileNetFPN.

From the ablation study, we observe that the stand-alone CNN or CNN+LSTM models perform poorly at the task. Adding the ViT to the CNN significantly improves performance with little impact to inference speed. All three alternate architectures to incorporate temporal information perform slightly worse than SmokeyNet; however, the ResNet34+ResNet18-3D architecture provides another viable alternative if prioritizing model size. Comparing MobileNet+LSTM+ViT to MobileNet+LSTM+ViT(MOG2), we see that the addition of background subtraction improves performance by almost 2%, mainly by improving recall by over 3%, while maintaining high precision. This comes at the cost of model size and inference time, but it is worth exploring adding MOG2 as another SmokeyNet variant in the future.

The SmokeyNet architecture clearly outperforms standard image classification, object detection, and image segmentation baselines. All models have acceptable time to detection—most within 3-4 minutes. While the ResNet50 is clearly the fastest to detect a fire, it only accomplishes this by generating an unacceptable amount of false positives.

Figure 3 visualizes SmokeyNet’s performance on images from the test set. Additionally, a video of the model’s performance per image can be viewed at the following link:
https://youtu.be/cvXQJa03m1k. The model performs well in a variety of real-world scenarios, correctly identifying apparent smoke plumes while avoiding clouds and haze. However, the model still makes systematic misclassifications of low-altitude clouds as false positives (20200806_BorderFire_on-e-mobo-c, 20200828_BorderFire_sm-s-mobo-c, 20200806_BorderFire_lp-s-mobo-c). The model completely missed the 20200930_DeLuzFire_rm-w-mobo-c (top row of Figure 3) fire because the smoke occurs directly behind a transmission tower.

5.1. Human Performance Baseline

Due to the lack of suitable benchmarks for performance, we measured human performance of smoke classification on the FlgLib dataset. Participants were three lab members experienced in classifying images for the presence of wildfire smoke. For the experimental setup, one image from each of the 62 fires from the test set was randomly selected for prediction. Participants were presented with the images for prediction, each preceded by the previous frame of the image sequence, to replicate the temporal context our machine learning model receives and a real-time inference scenario. The participants then recorded if they believed wildfire smoke was present in the image.

The experimental setup proves challenging due to differences from how the ground truth labels were generated. The ground truth labels were created by a human expert who had full temporal context, including access to all past and future frames of a video sequence, to precisely determine the first frame in which smoke is visible. Consequently, it is difficult to correctly identify positive images early in the fire sequence when the smoke is faint or small with only a single preceding frame and no additional temporal context to see how the smoke grows over time.

The three participants achieved an average accuracy of 78.5% (σ = 1.52%), F1-score of 82.8% (σ = 0.73%), precision of 93.5% (σ = 4.66%), and recall of 74.4% (σ = 1.90%). The low accuracy and recall signify the false negatives from missing positive images early in the fire sequence. SmokeyNet achieved a higher accuracy and similar F1-score compared to human performance. The model also had higher recall at the expense of lower precision. If the false positives derived from low-altitude clouds could be corrected, SmokeyNet would achieve 85.8% accuracy and 94.8% precision, matching the precision and further surpassing the accuracy of human performance. Future work should focus on this issue.

6. Conclusion

FlgLib addresses the need for a large, labeled dataset that incorporates a variety of scenarios for the early detection of wildfire smoke. SmokeyNet provides a strong baseline for automated wildfire smoke detection; since SmokeyNet is trained and evaluated on the publicly-available FlgLib dataset, its performance can be easily compared to subsequent approaches.

For future work, we will continue improving the performance of SmokeyNet by reducing false positives in difficult scenarios. Since fires frequently occur in similar locations and conditions during specific months of the year, incorporating fire location, date, and weather data from historical fire records can improve predictions. We also plan to leverage the large amount of unlabeled data from the HPWREN Archive (http://c1.hpwren.ucsd.edu/archive/) using advanced deep learning methods. Self-supervised learning involves using our current model to predict the presence of fires in unlabeled images; after quick human validation, these predictions can then be used as additional labeled data during training. Unsupervised representation learning, such as DINO [38], allows the model to learn hidden representations from large amounts of unlabeled data to better perform in a classification task with limited labeled data. Since the vast majority of the unlabeled images will not contain fires, we can also use GANs to synthetically generate smoke in these images to produce positive examples for
additional training data as in Park et al. [7]. By effectively increasing the size of our training data and extracting better representations from the data, these approaches enable our model to make better predictions of the presence of smoke.

Another objective of future work is to reduce the model size for better compatibility with edge devices without sacrificing prediction performance. We can use pruning [39] to eliminate sparsely-used model weights to decrease model size. We can also use distillation to train another deep learning model to learn the representations of our current model; this strategy results in a smaller model with minimal impact to prediction performance [40].

**Author Contributions:** Conceptualization, M.N, Y.P., A.D., G.C.; methodology, A.D., Y.P., M.N, G.C.; software, A.D., Y.P.; validation, A.D., Y.P., M.N, G.C.; formal analysis, A.D., Y.P.; investigation, A.D., Y.P.; resources, H.B., F.V., I.A.; data curation, H.B., F.V., I.P.; writing—original draft preparation, A.D.; writing—review and editing, A.D., M.N., G.C., I.A., H.B., F.V., Y.P.; visualization, A.D.; supervision, M.N, G.C.; project administration, M.N.; funding acquisition, I.A. All authors have read and agreed to the published version of the manuscript.

**Funding:** This research was funded in part by NSF grant numbers 1730158, 2100237, 2120019 for Cognitive Hardware and Software Ecosystem Community Infrastructure (CHASE-CI) and 1331615, 2040676 and 1935984 for WIFIRE, WIFIRE Commons, and SAGE.

**Data Availability Statement:** Publicly available datasets were analyzed in this study. This data can be found here: [http://hpwren.ucsd.edu/HPWREN-FigLib/](http://hpwren.ucsd.edu/HPWREN-FigLib/)

**Acknowledgments:** The authors would like to thank Brian Norton for sharing his invaluable expertise on wildfire management; Stephen Jarrell, Duolan Quyang, Atman Patel, and Ulyana Tkachenko for their collaboration and insights; Scott Ehling and his team of labellers at Argonne National Laboratory for contributing to dataset annotations; and the UC San Diego CHASE-CI team for computer support.

**Conflicts of Interest:** The authors declare no conflict of interest.

**Appendix A. Experimental Architecture Details**

A Feature Pyramid Network (FPN) is a computer vision architecture that better recognizes spatial scales by incorporating information from multiple layers of the CNN backbone [30]. Instead of producing a single 960-dimensional embedding like a standard MobileNetV3Large [29], the MobileNetFPN outputs 3 layers of 256-channel feature maps per tile sized 7x7, 7x7, and 4x4 respectively. We downsample each feature map through two convolutional layers of kernel size 1 and flatten the feature maps such that the total number of features per map is 784. We then concatenate all the feature maps and further downsample the concatenated features to 960 to match the embedding size of the standard MobileNetV3Large. These are the final embeddings that are passed onto the next component of the SmokeyNet architecture, the LSTM.

To incorporate MOG2 background removal as an additional input channel, we first take two sequential frames of the raw wildfire smoke video sequence and apply MOG2 background removal; this generates a single channel of dimensions equivalent to the raw image inputs. While two sequential frames of the tiled raw images are input into the CNN and LSTM of the SmokeyNet architecture, two sequential frames of the MOG2 channel are passed through a separate CNN and a separate LSTM. The embeddings resulting from both LSTMs, one for the raw image and one for the MOG2 channel, are then concatenated and passed through a single linear layer downsampling the feature maps by half before being passed onto the next component of the standard SmokeyNet architecture, the ViT.

**References**

1. Wang, D.; Guan, D.; Zhu, S.; Kinnon, M.M.; Geng, G.; Zhang, Q.; Zheng, H.; Lei, T.; Shao, S.; Gong, P.; Davis, S.J. Economic footprint of California wildfires in 2018. *Nature Sustainability* **2021**, *4*, 252–260.
30. Lin, T.Y.; Dollár, P.; Girshick, R.; He, K.; Hariharan, B.; Belongie, S. Feature Pyramid Networks for Object Detection. Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR-17), 2017, pp. 2117–2125.
31. Tan, M.; Le, Q. EfficientNet: Rethinking Model Scaling for Convolutional Neural Networks. International Conference on Machine Learning (ICML-19). PMLR, 2019, pp. 6105–6114.
32. Touvron, H.; Cord, M.; Douze, M.; Massa, F.; Sablayrolles, A.; Jégou, H. Training data-efficient image transformers & distillation through attention. International Conference on Machine Learning (ICML-21). PMLR, 2021, pp. 10347–10357.
33. Vaswani, A.; Shazeer, N.; Parmar, N.; Uszkoreit, J.; Jones, L.; Gomez, A.N.; Kaiser, L.; Polosukhin, I. Attention Is All You Need. Advances in Neural Information Processing Systems, 2017, pp. 5998–6008.
34. Tran, D.; Wang, H.; Torresani, L.; Ray, J.; LeCun, Y.; Paluri, M. A Closer Look at Spatiotemporal Convolutions for Action Recognition. Proceedings of the IEEE conference on Computer Vision and Pattern Recognition (CVPR-18), 2018, pp. 6450–6459.
35. Zivkovic, Z. Improved adaptive Gaussian mixture model for background subtraction. Proceedings of the 17th International Conference on Pattern Recognition (ICPR 2004). IEEE, 2004, Vol. 2, pp. 28–31.
36. Zivkovic, Z.; Van Der Heijden, F. Efficient adaptive density estimation per image pixel for the task of background subtraction. Pattern recognition letters 2006, 27, 773–780.
37. He, K.; Gkioxari, G.; Dollár, P.; Girshick, R. Mask R-CNN. Proceedings of the IEEE International Conference on Computer Vision (ICCV-17), 2017, pp. 2961–2969.
38. Caron, M.; Touvron, H.; Misra, I.; Jégou, H.; Mairal, J.; Bojanowski, P.; Joulin, A. Emerging Properties in Self-Supervised Vision Transformers. arXiv preprint arXiv:2104.14294 2021.
39. Pan, H.; Badawi, D.; Cetin, A.E. Fourier Domain Pruning of MobileNet-V2 with Application to Video Based Wildfire Detection. 2020 25th International Conference on Pattern Recognition (ICPR-20). IEEE, 2021, pp. 1015–1022.
40. Hinton, G.; Vinyals, O.; Dean, J. Distilling the knowledge in a neural network. arXiv preprint arXiv:1503.02531 2015.
41. Lin, T.Y.; Goyal, P.; Girshick, R.; He, K.; Dollár, P. Focal Loss for Dense Object Detection. Proceedings of the IEEE International Conference on Computer Vision (ICCV-17), 2017, pp. 2980–2988.
42. Liu, W.; Anguelov, D.; Erhan, D.; Szegedy, C.; Reed, S.; Fu, C.Y.; Berg, A.C. SSD: Single Shot MultiBox Detector. European Conference on Computer Vision (ECCV-16). Springer, 2016, pp. 21–37.
43. Barnich, O.; Van Droogenbroeck, M. ViBe: A Universal Background Subtraction Algorithm for Video Sequences. IEEE Transactions on Image processing 2010, 20, 1709–1724.
44. Farnebäck, G. Two-Frame Motion Estimation Based on Polynomial Expansion. Scandinavian Conference on Image Analysis. Springer, 2003, pp. 363–370.
45. Szegedy, C.; Vanhoucke, V.; Ioffe, S.; Shlens, J.; Wojna, Z. Rethinking the Inception Architecture for Computer Vision. Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR-16), 2016, pp. 2818–2826.