Forest Fire and Smoke Detection and Classification

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Abstract— Forest fire detection appears to be badly in need since the effects of wildfire are extreme. The traditional methods for smoke detection pose tremendous problems with mixed visuals, the complexity of backgrounds, and poor visibility in the initial stages of fire. In this review paper, the recent progresses of forest fire and smoke detection by deep learning with computer vision are included. The outcomes demonstrated that CNNs and the object detection models, including Faster R-CNN, YOLOv5, and Fire CNN, boost the accuracy in detection and the time to respond. Techniques such as multi-oriented detection, attention mechanisms, and multi-scale fusion of features facilitate the possibility of smoke detection using aspects such as colour, texture, and orientation. Augmenting training data using generative synthetic smoke ensures dependable model performance under a variety of environments. The studies validated the possibility of advanced models for monitoring forest fire in real-time, smoke detection, and indicated that accuracy levels, false alarms, and adaptability could considerably improve in relation to the conventional methods.

Keywords— forest fire; smoke detection, wildfire smoke, fire monitoring,YOLOv5

I. Introduction

Forest fires are among the worst natural phenomena that take a heavy toll on the environment, economy, and society every year. Estimates regarding global losses from forest fires annually vary from $10 billion to $30 billion USD. For instance, in 2020, the California wildfires caused more than $12 billion in insured damages and demolished approximately 4 million acres of land. Besides causing the destruction of ecosystems, forest fires also cause massive pollution to the atmosphere; during peak fire season, wildfire smoke accounts for almost 50% of fine particulate matter in the western United States. The ability to detect smoke early is considered to prompt timely responses to limit the spread of fire, but environmental factors and false-positive rates in conventional systems make the job a challenge. It is improving detection methods for increased accuracy and reliability, using the innovations of modern science.

(a) Economic and Environmental Impact— Forest fires are very costly, both in financial and environmental terms. Estimated annual damages worldwide are in the range of $10 billion to $30 billion. In extreme circumstances such as the California wildfires of 2020, over $12 billion of insurance-covered damages occurred, with around 4 million acres burnt. In addition, the environmental impact can be very disruptive to ecosystems, with pollutants released into the atmosphere. Smoke from the wildfires has added significantly to air quality problems, making up, for example, as much as 50% of fine particulate matter pollution in parts of the U.S. during peak fire season.

(b) Challenges in Smoke Detection— Several environmental factors, such as frequent false positives, make smoke very hard to be detected accurately. For instance, at the wind speeds over 20 mph, the strong winds might blow away the smoke, implying that it cannot be detected in a predictable area. Secondly, in the conditions of foggy weather, reduces visibility up to 50-70 %. This reduces the capability of traditional systems to discern smoke in the surrounding airborne particles. Conventional smoke detection systems have a high rate of false positives up to 20-30% because of the reasons that smoke can appear visually similar to clouds and fog. The systems also receive degraded accuracy, 20-25%, in changing light intensity environments.

(c) Advancements in Smoke Detection Technology— To overcome these detection difficulties, researchers are using advanced technologies such as attention mechanisms and feature extraction techniques to help improve the detection rate by up to 15 percent based on distinguishing smoke from visually similar phenomena. Another enhancement is Mixed-NMS (Non-Maximum Suppression), which has shown significant promise in improving detection confidence on distant fires by up to 12% in controlled experiments.

(d) Use of UAVs for Enhanced Detection— Unmanned Aerial Vehicles (UAVs) with high-resolution cameras and deep learning-based models, including the Convolutional Neural Networks (CNNs), have shown good promise in smoke detection. In fact, UAVs can acquire data in real time and, when appropriately used, perform accurate localization, finding much better precision than static cameras-even in complex terrain-through an improvement of 10-15% in the accuracy of smoke detection. Transfer learning techniques further boost the ability of CNNs in accuracy as they reduce the task requirement of large datasets; in fact, they even go up to 18% improvement when they use a pretrained model on few data.

(e) Satellite Imagery for Large-Area Fire Monitoring— One of the fundamental instruments used to observe fires over vast territories is satellite imagery. Such imagery detects smoke plumes through visible and infrared bands. Traditional threshold-based approaches, however, have a drawback in providing false alarms, with an even up-to 30-40% rate induced by environmental variability. Models such as SmokeNet, though, improved detection accuracy so much that false alarm rates came down to about 10-15%. Images captured with a geostationary satellite, such as the Himawari-8 satellite taking images every 10 minutes, allow for near-real-time monitoring of wildfires. FireCNN, a CNN model fine-tuned using Himawari-8 data, improves large-scale wildfire detection by 20-25% in employing multi-scale convolution and residual structures.

(f) Satellite Imagery for Large-Area Fire Monitoring— The key role for early smoke detection, especially before the flames, is played by ground-based video systems. However, video-based approaches have traditionally suffered from problems related to robustness: up to 30% degradation of their accuracy when conditions vary within the environment. Alternative solutions based on CNNs learned with synthetic smoke images will boost detection performances about 15% when compared with traditional approaches. Synthetic smoke data, for instance, has resulted in the increase of model performance by as much as 25% in a low-volume training dataset.

II. RELATED WORK

There are conventional point sensors used in early smoke detection systems that provide poor coverage over large forest areas. Among the trends of climate change and wildfire risks, the efficiency of timely detection to save lives and ecosystems while protecting economies is critical. Advances in deep learning methods for image analysis have brought great promises on detecting wildfires, which include techniques enhancing the speed and accuracy. Besides such innovations, other research works concentrated their focus on real-time detection systems employing UAVs that are equipped with optical and thermal cameras, achieving a detection accuracy up to 99%.

(a) UAVs and Deep Learning Models— Utilizing the deep learning models YOLOv3 and YOLOv5 in tandem with UAVs, also referred to as drones, improves detection accuracy for wildfires to a reasonably estimated 86%. YOLO models employ large datasets, enhance image-based methods, and enable smoke and flame detection better. Several benefits are acquired through UAVs with regard to traditional methods: they can quickly survey large areas and generate high-resolution images at numerous altitudes. This makes them useful for the detection of wildfires in inaccessible regions. Recent developments, like the Swin-YOLOv5 model, have amplified the detection abilities by enhancing average precision up to 4.5%.

(b) Real-Time Detection with UAVs— One other important achievement is represented by the detection systems based on real-time use of UAVs, fitted with optical and thermal cameras. These UAVs have achieved a detection accuracy up to 99%. As they are equipped with both optical and thermal imaging sensors, UAVs can capture high-resolution images that can see the heat signatures from fires in early stages of the fire. This ability to monitor large areas in a timely fashion allows for the detection of fires for useful data for quick response efforts.

(c) Specialized Datasets and Enhanced Models— However, with advanced datasets like NEMO and DeepFire, significant improvement in deep learning models for the detection of wildfires has been observed. In such datasets, images are presented in an intense amount and are detailedly labelled and used for training models like Faster R-CNN and RetinaNet to maximize accuracy at minimal detection time. The challenge remains to differentiate between real fire and optical effects such as bright light or sunset glare. To handle this problem, ensemble learning-based approaches that combine multiple models were considered. For example, the use of the combination of YOLOv5 and EfficientDet achieved an accuracy rating of nearly 79.7%. Recent models like Light-YOLOv4 have focused on network efficiency. It has, therefore, allowed for smoke and flame detection in real-time systems with accuracies up to 86.43%.

(d) Ongoing Challenges and Future Directions— Despite all this progress, an enormous amount of work still has to be put in to create comprehensive solutions for detecting wildfires. Even current systems have problems with detecting fires under complex environmental conditions, especially when lighting changes or weather evolves in one way or another. Another problem is minimizing false positives like those caused by glare or clouds, which might appear like smoke. Although deep learning models have lowered false alarms much more had to be required to advance these systems into anything worthy of the name.

Table 1: Previous Research work done in domain of Fire and smoke detection

Reference	Method	Advantage	Outcome	Limitation
Hu, Y., Zhan, J., Zhou, G., Chen, A., Cai, W., Guo, K., Hu, Y., & Li, L. (2024) [1]	Fast forest fire smoke detection using MVMNet	Utilizes deep learning (YOLOv5) for fast and accurate smoke detection in forests	Successfully detects smoke in real-time, improving early fire detection accuracy	Complex backgrounds (e.g., clouds, fog) may still interfere with detection accuracy
Zhang, Q.-x., Lin, G.-h., Zhang, Y.-m., Xu, G., Wang, J.-j. (2017) [2]	Wildland forest fire smoke detection using Faster R-CNN with synthetic smoke images	Uses synthetic data to train models, which improves detection under controlled conditions	Demonstrated good performance in detecting smoke in controlled, synthetic environments	Performance in real-world scenarios with varied environmental conditions was not fully evaluated
Kim, S.-Y., & Muminov, A. (2024) [3]	Forest fire smoke detection using UAV images and deep learning	Uses drone images and deep learning methods to detect smoke and fire	High precision in detecting smoke and fire from aerial views	The effectiveness of detection can be limited by weather conditions and image quality
Ghali, R., Jamal, M., Mseddi, W. S., & Attia, R. (2024) [4]	Review of fire detection and monitoring systems	Comprehensive review of current fire detection technologies	Identifies the strengths and weaknesses of various fire detection methods	Does not propose new models or solutions, limiting its direct application in the field
Hong, Z., Tang, Z., Pan, H., Zhang, Y., Zheng, Z., Zhou, R., Ma,, Y., Han, Y., Wang, J., & Yang, S. (2024) [5]	Active fire detection using CNN and satellite images	Uses CNN to detect fires from satellite images with high precision	Successfully detects active fires using high-resolution satellite data	Requires high-quality satellite images, and detection may be affected by cloud cover or satellite availability

III. COMPARATIVE ANALYSIS

From traditional methods to image-based techniques using deep learning, the evolution of detecting forest fires has been tremendous. Traditional approaches to detecting forest fire, based on either manual patrols or sensor-based approach, make it hard for prompt response since they entail slow response times, high operational costs, and limited coverage; this makes early detection inefficient. Image-based methods, in particular deep learning-based models YOLOv3 and YOLOv5, improve the real-time detection speed with high accuracy due to the considerable large datasets and advanced techniques of data augmentation. The capabilities are successfully enhanced on the use of UAVs with thermal and optical cameras up to the 99% error rate in real-time monitoring. More specifically, ensemble approaches that use a combination of YOLOv5 and other models, such as EfficientDet, present good results, but problems such as smoke vs. fog or glare occur. Although deep learning models greatly improve over more classical approaches, the problem in fine-tuning the detection towards challenging and dynamic forest conditions, specially to distinguish between real fires and non-fire phenomena, remains.

Model	Unique Techniques	Dataset	Accuracy	AP50	FPS	Challenges Addressed
MVMNet	Multi-oriented detection, SoftPool, Mixed-NMS	Forest fire dataset (15,909 images)	88.05%	88.05%	122	Reduces misdetection, missed detection
Faster R-CNN	Synthetic smoke generation, real smoke integration	Custom smoke images	~75-85%	~70-80%	~10-30	Data limitation, reduces manual labeling
YOLOv7	SPPF+, BiFPN, CBAM	Custom smoke dataset	86.4%	83.4%	~50-100	Handles data imbalance, background complexity
FireCNN	Multi-scale convolution, residual structure	Himawari-8 satellite images	35.2% higher than threshold methods	~70-80%	~1-5	Real-time detection on satellite data

IV. CONCLUSION AND FUTURE SCOPE

In conclusion, deep learning-based methods have significantly advanced the field of forest fire smoke detection, offering improved accuracy and speed compared to traditional detection systems. The proposed models, such as MVMNet, Faster R-CNN, YOLOv7, and Fire CNN, demonstrate notable enhancements in detection performance through various innovations like multi-oriented detection, data augmentation, and advanced network architectures. These models tackle key challenges, including data scarcity, misdetection, and overfitting, by utilizing synthetic data, optimizing model structures, and incorporating attention mechanisms. Despite the progress, there remain challenges related to the complexity of real-world forest environments, such as distinguishing smoke from other atmospheric conditions and improving generalization across diverse conditions.

Future research should focus on expanding datasets to include a broader range of environmental scenarios, enhancing image quality, and further developing models that can operate efficiently in real-time. Additionally, the integration of UAVs, satellite imagery, and other sensor technologies could play a crucial role in expanding coverage and enabling more comprehensive fire detection systems. Improving model robustness and efficiency through techniques such as compression and transfer learning could also facilitate deployment in resource-constrained environments, paving the way for more effective and scalable wildfire detection systems.

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