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A Survey of the Machine Learning Models for Forest Fire Prediction and Detection

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Abstract

Forest fires are a significant threat to the environment, causing ecological damage, economic losses, and posing a threat to human life. Hence, timely detection and prevention of forest fires are critical to minimizing their impact. In this paper, we review the current state-of-the-art methods in forest fire detection and prevention using predictions based on weather conditions and predictions based on forest fire history. In particular, we discuss different Machine Learning (ML) models that have been used for forest fire detection. Further, we present the challenges faced when implementing the ML-based forest fire detection and prevention systems, such as data availability, model prediction errors and processing speed. Finally, we discuss how recent advances in Deep Learning (DL) can be utilized to improve the performance of current fire detection systems.

Keywords

AI, Computer Vision, Deep Learning, Forest Fires, ML, UAV

1. Introduction

Forests play an integral role in maintaining our planet's ecology and carry out a wide range of activities such as carbon sequestration, biodiversity, soil conservation, water regulation, etc., which are vital for the sustenance of life forms on the earth. But due to the frequent recurrence of forest fires, the mere existence of forests is under threat. Forest fires are defined as fires that occur in forests and pose a significant threat to the environment, animals and human lives. Due to the importance of forests for the sustenance of life forms, forest fires are recognized as a significant environmental issue globally. The impacts of forest fires include, but not limited to environmental impacts, economic impacts, impacts on human lives, etc.

The environmental impact of forest fires can be devastating, as they affect the ecological balance of the region, affecting plants, animals, and the soil. Forest fires can sometimes cause irreparable damages, such as reductions in the forest area, and this may, in turn, cause soil erosion, which, in turn, affects vegetation. It takes years for the forest area to recover and as the green cover of the plant is depleted, the amount of air pollution may increase. An increase in the amounts of carbon dioxide, carbon monoxide etc., can further contributes to global warming and climate change. Lastly, let's not undermine the impact of the smoke released into the atmosphere due to the forest fires. Smoke emitted from forest fires will have an impact on human health by inhibiting new health issues and aggravating existing conditions.

On the other hand, forest fires can also have an economic impact. There can be many local and tribal communities whose livelihoods are dependent on the forest vegetation. If a forest fire causes any damage to the forest, all the tribal and local communities will find it difficult to meet their daily needs. Forest fires not only affect local or tribal communities but may disturb economical activities in urban areas. For instance, forest fires can lead to the loss of timber resources, which can cause a lot of damage to the logging industry. In many countries, most of the trade routes are along the forest areas, and damage to these infrastructure resources can impact general transportation and trade as well. Lastly, the tourism industry will also be impacted by forest fires, as the destruction of natural landscapes may not attract tourists anymore.

Not only do they have environmental and economic impacts, but forest fires can also have a significant impact on human life. If forest fires are not controlled, they may spread to residential areas around the forest area, cause property damage, and may result in the loss of human lives. There can be long-lasting health consequences for the people living in the affected region. As mentioned above, the smoke emitted from forest fires will have an impact on human health by inhibiting new health issues and aggravating existing conditions. Infants and elderly people are more vulnerable to the forest smoke emitted.

Overall, the impact caused by the forest fires can be significant to the environment, economy, and human life. It is of vital importance to detect forest fires at the earliest possible opportunity to contain the fire and extinguish it. In this way, we can contain the impacts of forest fires on the environment, economy, and human life.

The rest of the paper is organized as follows. Section II presents an overview of ML techniques for fire detection and how the UAV is used for this purpose. Section III describes how the survey was conducted and presents a review of relevant work. Section IV covers the information about the datasets that are typically used for fire detection. In Section V, the performance and limitation of different ML techniques are presented. Future work and concluding remarks are addressed in Section VI.

2. ML Techniques for the Early Detection of Forest Fires

One of the potential solutions to prevent and contain forest fires could be by leveraging M/DL techniques. Both ML- and DL-based algorithms are gaining prominence as they find a lot of applications in addressing the real-world problems.

In addition to being effective in solving real-world problems in various domains such as healthcare, finance, transportation, marketing and advertising etc., ML/DL are finding application in early detecting of forest fires. Techniques such as Computer vision, ML algorithms and Long Short-Term Memory (LSTM) based models are being leveraged to detect and prevent the spread of forest fires.

Computer vision is a field of computer science that enables computers to learn the contents of images, such as identifying and understanding the objects and people in images and videos, etc. [1]. The Computer Vision field is about enabling computers to perceive the way humans look and understand objects or entities in real-time [1]. Computer vision involves the use of ML algorithms to analyze images and videos. These algorithms are trained using large amounts of annotated image data. The main tasks of Computer Vision are four as summarized below:

2.1. Image Classification

The image classification task is about identifying the class to which an object belongs [2]. For instance, consider an image dataset of a forest fire that includes various elements such as fire, trees, grass, etc. The task of the image classification model is to correctly identify the fire present in a given image. **Figure 1** captures an example of image classification where the ML model classified the object in an image as fire.

2.2. Object Detection

Object detection tasks deal with localizing a specific region of interest in an image and classifying this region like a typical image classifier [3]. Further, an image may contain more than one region of interest, pointing to different objects present in the image. This means that the object detection task is a more advanced version of the image classification problem. **Figure 2** demonstrates the

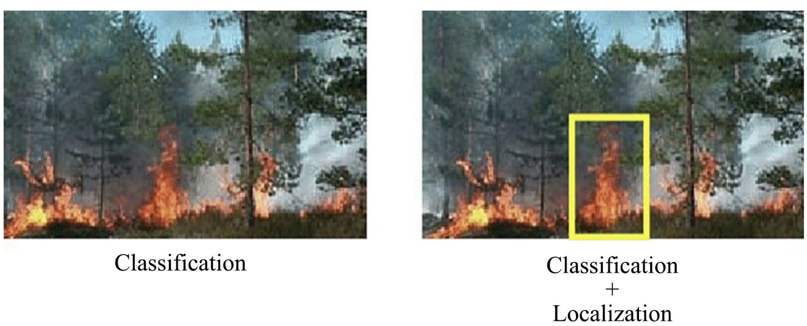

Figure 1. An example of image classification of forest fire.

Figure 2. Demonstrating the technique of object detection during forest fire.

application of an object detection algorithm based on YOLO v3. YOLO (You Only Look Once) is one of the popular object detection models known for its speed and accuracy. Since its inception in 2016, YOLO has undergone several revisions, with the latest being YOLO v7 [3]. As of writing this paper, YOLO v8 had just been released and was gaining rapid interest among researchers and ML enthusiasts. **Figure 3** demonstrates the process of forest fire detection using UAV and YOLOv3.C.

2.3. Semantic Segmentation

Semantic segmentation means the identification of similar objects in an image that belong to the same class at the pixel level [2]. Semantic segmentation algorithms identify similar objects in an image and color them in the same way to emphasize that they belong to the same class.

2.4. Instance Segmentation

The instance segmentation task is about recognizing the different instances given in the image and their boundaries at the deep pixel level. **Figure 4** demonstrate the tasks of semantic segmentation during a forest fire.

In addition to the utilization of computer vision techniques, classical ML technologies such as logistic regression, support vector machine-based classifiers, decision tree classifiers, and random forest classifiers are widely useful in classifying whether there is a fire or not, given the input dataset. These datasets are typically comprised of smoke or fire detection, and temperature detection sensors. In addition to the classical ML algorithms, DL methodologies such as Recurrent Neural Networks (RNN) and Long Short-Term Memory (LSTM) networks are also useful in classifying fires and non-fire scenes.

2.5. The Use of UAVs

Unmanned Aerial Vehicles (UAVs), also known as drones, have become increasingly popular in recent years for a variety of applications, including forest fire detection. Given the fact that UAVs can be equipped with a range of sensors (*i.e.* cameras, infrared sensors, gas sensors), combined with their agility and remote controllability, make them an effective tool for monitoring forests and detecting fires quickly.

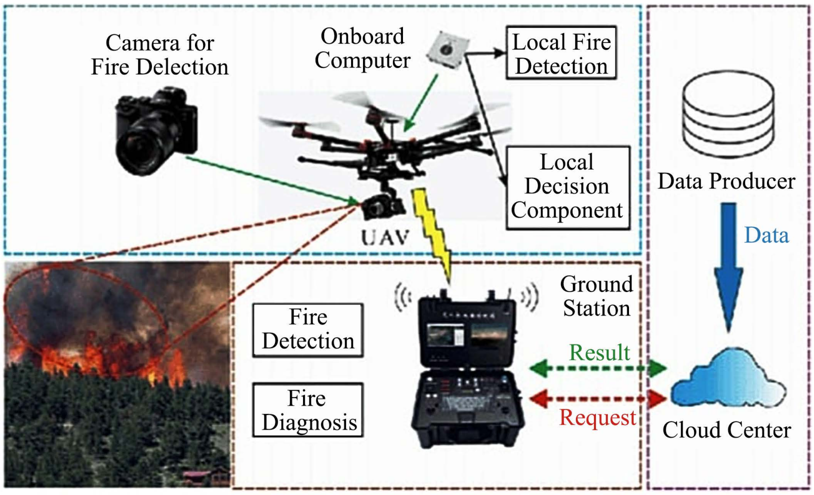

Figure 3. Forest fire detection approach using UAV and YOLOv3 [1].

Figure 4. Demonstrating semantic segmentation [2] of forest fire.

With the help of various sensors that are mounted on top of a UAV, one can detect smoke or changes in temperature and relay this information to a ground station for processing. In addition to various sensors, cameras can be mounted on top of the UAVs to relay real-time scene information to a ground station for further processing. With the help of edge computing technologies, an emerging trend is to analyze the information captured by the sensors and camera using tiny ML devices mounted on the UAV, we can predict the onset of a forest fire. Instead of relaying the captured information to the ground stations, now we can do the analysis using the power available in UAV batteries and predict the onset of forest fires. Upon predicting the adverse incident outcome, an alert can be triggered to the corresponding authorities with the precise location of the forest fire, so that the fire is contained and damage is minimized. **Figure 5** captures an example scenario where UAVs can be controlled remotely from a building and are utilized for detecting forest fires.

With the help of Tiny ML devices, we can now run ML/DL on top of UAVs. Further, UAVs can operate in areas that are difficult or dangerous for humans to access, such as steep terrain or dense forest. Thus, with UAVs, one can get real-time information about forest fires, minimize the risk of damage, navigate difficult or dangerous terrains, and at the same time reduce the risk of injury or death for firefighters and other emergency responders.

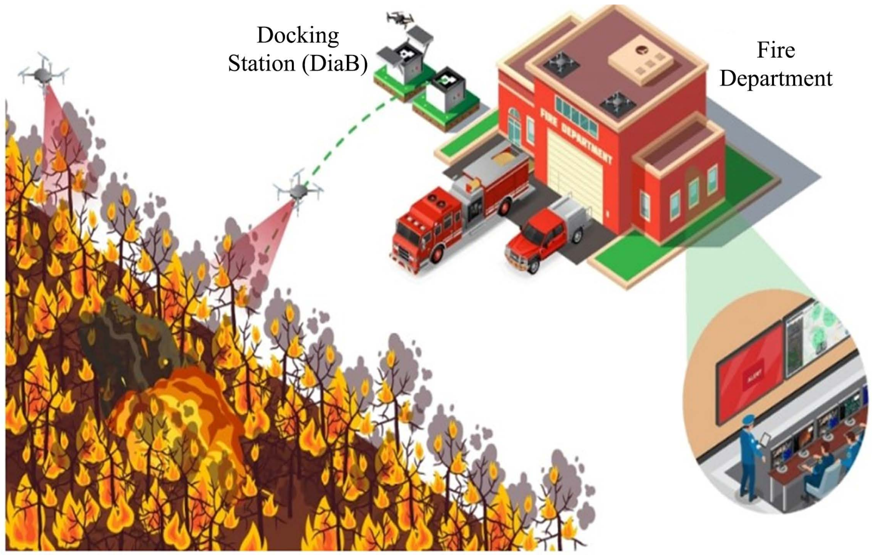

Figure 5. Demonstrating the UAVs usage in detecting forest fires.

Up until this point, we have discussed the impact of forest fires, the need for containing the fires, ML approaches for detecting the forest fires, and the role of UAVs in early forest fire prediction and detection. In the upcoming sections, we will be discussing the methodology used to identify the scientific corpora related to usage of ML-based technologies and UAVs for the early detection and prediction of forest fires. Further, we will be discussing the key contributions of each paper in detail.

3. Review of Literature

For identifying relevant scientific articles and publications on the topic "Forest Fire Prediction and Prevention using Machine Learning and Deep Learning Models," we compiled a list of keywords. These keywords were used to query the IEEE database to identify relevant IEEE publications on this topic. The following is a list of keywords that are compiled to query the IEEE database:

1) Forest fire;
2) Forest fire detection;
3) Early forest fire detection;
4) Fire management;
5) Wild land fire;
6) Wildfires;
7) Smoke detection;
8) Fire detection;
9) Forest fire prevention;
10) Deep learning;
11) Machine learning;
12) Edge computing;
13) Internet of things;

14) Sensors;
15) Unmanned Aerial Vehicles;
16) UAVs;
17) Drones.

We queried the IEEE Xplore website [4] with the above-mentioned list of keywords to identify the most recent paper publications that contain any of the keywords mentioned in the paper content. These papers range across easy-to-collect information such as taking a picture of a forest region using a drone, to detecting forest fires using sensors for smoke detection and Sentinel-2 [5] satellite imagery data. A concise description of each paper follows.

3.1. A Deep Learning Based Forest Fire Detection Approach Using UAV and YOLO V3

Jiao *et al.*, in "A Deep Learning Based Forest Fire Detection Approach Using UAV and YOLO v3" [6], highlighted that UAVs are largely being used in monitoring forest fire and detection due to their high mobility and their ability to cover areas at different altitudes and locations with relatively lower cost. Citing these advantages with UAVs, Jiao *et al.*, developed a UAV based platform for forest fire detection and later adopted YOLOv3 for UAV-based aerial images using onboard computational power. Despite using a tiny-YOLOv3 with low FPS, their proposed model achieves real-time forest fire detection. Further, Jiao *et al.*, tested their proposed model using 60 images and added an extra CNN layer to improvise the model's performance. The authors did not shed much light on the dataset details, and their results show that the proposed model achieved 82 percent precision and 79 percent recall. By looking at the recall value (less than the precision value), we wonder about false positives produced by the proposed model. We speculate that the model fails to distinguish scenarios such as fog, forest fire smoke, etc. Overall, this paper emphasizes the advantages of utilizing UAVs for forest fire detection and proposes a lightweight YOLOv3-based solution for forest fire detection.

3.2. Wildfire Detection in Aerial Images Using Deep Learning

Hoor *et al.*, in "Wildfire detection in aerial images using deep learning" [7], proposed a YOLOv5-based real-time forest fire detection model, wherein their model will observe frame by frame in a video to detect the forest fire and trigger an alert upon detecting the fire. One of the main highlights of this paper is that the authors trained and tested their proposed model on publicly available datasets, namely the FLAME [8] and FireNet [9] datasets. Further, from an architectural point of view, the authors used Yolov5 to integrate CSPNet with Darknet, forming CSPDarknet. This helps in reducing the model's parameters and the required FLOPs, which improves the inference speed and reduces the model's accuracy. As the resources on a UAV are constrained, the authors made changes to Yolov5 by considering these constraints. The model was evaluated in terms of precision, recall, and F1 score, and the corresponding values were 0.97, 0.92, and 0.94.

3.3. Fire Hotspots Mapping and Forecasting in Indonesia Using Deep Learning Algorithm

Sri Listia Rosa *et al.*, in "Fire Hotspots Mapping and Forecasting in Indonesia Using a Deep Learning Algorithm" [10], implemented a Long Short-Term Memory (LSTM) algorithm for forecasting the fire hotspot number. The authors used the MODIS data available in NASA Earth Data. The proposed model achieved more than 95 percent accuracy with an error of 4.56 percent. We believe if we can predict possible hotspots in the future and monitor them with UAVs for forest fire detection, we can expand our focus on these concentrated regions to prevent fire mishaps.

3.4. Forest Fire Prediction Using Machine Learning Techniques

Preeti *et al.* in "Forest Fire Prediction Using Machine Learning Techniques" [11], conducted a comparison study of various ML models such as Decision Tree, Random Forest, Support Vector Machine, and Artificial Neural Networks (ANN), for predicting forest fires. One of the best things about this paper is that the authors collected meteorological data from Kaggle and preprocessed the data to identify the hotspot's location based on the meteorological data available in the dataset. Though the authors have not explicitly mentioned the dataset details, they mentioned the term Montesano in the European Republic and based on this information, the forest fire area dataset was the best match on Kaggle [12]. Further, the authors neatly depicted the preprocessing steps and comparison study results but on the whole, there is no novelty in modeling as this is a comparison study of existing models for forest fire prediction.

3.5. A Real-Time Forest Fire Recognition Method Based on Rshufflenetv2

Li *et al.* in "A Real-Time Forest Fire Recognition Method Based on R-shufflenetv2" [13], proposed a forest fire recognition model based on R-shufflenetv2. Per the authors, R-shufflenetv2 is composed of a series of R-shufflenetv2 units and is an improved version of shufflenetv2. The authors comprehensively explained the architecture of the RshufflenetV2 model and highlighted the differences between the original shufflenetv2 and the R-shufflenetv2 and how Rshufflenetv2 can improve accuracy. The authors used the FLAME dataset [8] to train the models and eventually highlighted that R-shufflenetv2 performed better than the original shufflenetv2 and achieved real-time fire detection with a recognition speed of 31 FPS. One of the main drawbacks of this paper is that the authors have not compared the results of R-shufflenetv2 with YOLO models. There are a lot of YOLO model variants that are deployed on resource-constrained UAVs, but the authors did not draw comparisons with those models. Any time saved is precious in preventing the spread of forest fires, and if a strong comparison was conducted between the R-shufflenetv2 prediction time and resource consumption with YOLO models that would have made a great case study.

3.6. Detection of Forest Fire Using Support Vector Machine in Comparison with Random Forest to Measure Accuracy, Precision and Recall

In the paper "Detection of Forest Fire Using Support Vector Machine in Comparison with Random Forest to Measure Accuracy, Precision, and Recall" [14], Susmitha *et al.* reviewed the performance of a novel linear support vector machine approach for forest fire detection in comparison with the Random Forest algorithm. Though the authors mentioned that the dataset is available on the UCI data repository, they did not provide any links to the dataset. We tried searching for the dataset, but it is hard to find. This research paper aims to compare accuracy, precision, and recall values. Eventually, the authors concluded that novel linear SVM is a better algorithm than random forest as it has higher precision, recall, and accuracy scores.

3.7. Forest Fire Prediction for NASA Satellite Dataset Using Machine Learning

Monika *et al.* in the "Forest Fire Prediction for NASA Satellite Dataset Using Machine Learning" paper [15] investigated the use of ML algorithms such as Decision Tree (DT), Random Forest (RF), Logistic Regression, and Gradient Boosting Classifier for predicting forest fires using satellite data. This study aims to predict the risk of forest fires using satellite data from NASA's Moderate Resolution Imaging Spectroradiometer (MODIS) dataset. The study concludes that the boosting classifier gives the highest accuracy of 96 percent among all the other methods on the MODIS dataset and 98 percent on the VIIRS-NPP datasets.

3.8. SpotFire: An Intelligent Forest Fire Detection System Design with Machine Learning

Revathi *et al.*, in "Spotfire: An Intelligent Forest Fire Detection System Design with Machine Learning" [16], proposed a sensory unit capable of performing regular assessments of a location. The authors opted for a spherical design for the sensory unit, such that the sensor unit can withstand any outside forces and has the characteristics to guard against damage from the hard circumstances present in tropical forests.

Attributes such as CO level, light intensity, temperature, and humidity are captured using the sensory unit. Further, the authors have proposed a novel hybrid classifier using a random forest with a linear regression model. Overall, in this paper, the authors have demonstrated novelty in both the sensory unit design and the machine learning algorithm, but they did not compare the performance of their proposed model with any other existing models. The authors reported that they used a dataset from Kaggle [17] and obtained an accuracy of 98.76 percent.

3.9. Deep Learning-Based Automated Forest Health Diagnosis from Aerial Images

In "Deep Learning-Based Automated Forest Health Diagnosis from Aerial Images," Chiang *et al.* suggested that an important portent of forest fire is the condition of forests [18]. This aspect is really interesting, as none of the above-mentioned papers cover this point. The idea of this paper is to implement automated dead tree detection from aerial images using a retrained Mask RCNN (Mask Region-based Convolutional Neural Network) approach with a transfer learning scheme. The authors have collected data using aerial photography from the Wood of Cree in Scotland. Further, the authors have expanded the dataset using synthetic data generation techniques. Next, the authors have used eight different pre-trained nets to compare the model performance, such as ImageNet with ReLU, ImageNet with Leaky ReLU, and COCO with ReLU. Finally, the authors concluded that the mean average precision score using a masked R-CNN approach is the best, which is 54 percent in dead tree detection from aerial images. In our opinion, this paper seems to be quality research as it emphasizes an important point, talks about data collection, and does some qualitative comparison analysis.

So far, most of the above-mentioned papers are aimed at triggering an alert upon detecting forest fires. But none of those papers discussed in detail how to minimize false alarms.

3.10. Wildfire Detection and Avoidance of False Alarm Using DenseNet

In "Wildfire Detection and Avoidance of False Alarm Using DenseNet" [19], Sridhar *et al.* discussed this important aspect. The authors used DenseNet for the detection of wildfires and to eliminate false alarms by using a mixed dataset that includes fire-like objects and non-fire objects. The authors have created their own dataset by scraping the internet using various search engines for images with and without fire. Further, with DenseNet, the authors demonstrated 90 percent accuracy in classifying images with forest fires. An important aspect that is lacking is that they did not offer much insight on how they are minimizing the false positives from a model perspective but rather focused more on having a large dataset. Also, the authors did not conduct any comparison studies.

3.11. Lightweight Forest Fire Detection Based on Deep Learning

In [20], the authors focused on developing a DL model for forest fire detection with an emphasis on detection speed as well as suitability of the models for embedded devices. The authors utilized the YOLOv4 model with a lightweight model, MobileNet. In addition to utilizing the MobileNet, the authors incorporated depth-wise separable convolution. Both of these changes were made to ensure that their proposed model achieves better results in a time-efficient manner. In the authors' own words, the following are the contributions made by the authors in this research paper: As per the authors, most of the existing forest fire datasets only contain images with obvious flames, and the number of images that contain inapparent flames is not sufficient. Further, the authors have highlighted that the presence of red leaves in these images may lead to false positives as the red colors are closer in color scale to those of the forest fires. Hence, the authors have developed a dataset from scratch by addressing these real-time issues. Apart from creating a new dataset, the main goal of the authors was to propose a lightweight model, YOLOv4Light, for forest fire detection by utilizing MobileNet and separable convolutions. Lastly, the authors captured the relationship between light and smoke to avoid false positives due to the presence of leaves in red.

Though the authors highlighted the reasons for creating a new dataset, they have not open-sourced the dataset. This is one of the drawbacks of this paper if one is trying to reproduce the proposed model results. Further, the authors compared the proposed YOLOv4 Light with Fast-RCNN, YOLOv3, and YOLOv4 models. It is interesting to see that the YOLOv4 model performed better than all the models (even the proposed model) on fire detection, but in the rest of the scenarios, such as red leaf, smoke detection, etc., the proposed YOLOv4 Light model performed slightly better than the YOLOv4 model. Nonetheless, the experimental evidence that YOLOv4 is performing better than the proposed model on fire detection. We believe that if one were to compromise on the detection accuracy and emphasize more on the detection speed, the proposed model could be utilized given the fact that it has a faster frame per second value than the other models. Also, it would be interesting to study the performance of a similar lightweight architecture on the YOLOv7 model to see if this helps improve the model's performance on fire detection tasks.

3.12. Forest Fire Detection Method Based on Deep Learning

In the "Forest Fire Detection Method Based on Deep Learning" [21] research paper, Wenjie Wang *et al.* too focused on developing a lightweight real-time fire detection technology by leveraging the YOLO model. Given the fact that conventional fire warning systems suffer from relatively low sensitivity and accuracy, the main emphasis of this research is to detect the forest fire accurately in the budding stage itself. One of the interesting aspects of this research paper is that the authors clearly highlighted the problems with existing technology in forest fire monitoring, such as weak generalization performance, complex models, and difficult landing. The contributions of the authors in this research paper are a lightweight YOLOv5 model with the aim to reduce the amount of calculation in the flame detection network, improve the detection speed, and have the ability to run on small embedded devices. For experimental evaluation of the proposed model, the authors collected the training dataset through a network and manually labeled the images. For drawing comparisons on the proposed model's performance, the authors utilized various versions of YOLOv5, such as YOLOv5s (small), YOLOv5m (medium), YOLOv5l (large), and YOLOv5Xl. The mean Average Precision (mAP) and speed of the proposed model are better than all the variants of the YOLOv5. Though the authors clearly mentioned the need for research in forest fire detection, the paper did not explain much about the proposed model. Further, there is no information given on the availability of the dataset. Lastly, like [20], it would be a really interesting line of work to test both these [20] and [21] lightweight model proposals on the YOLOv7 model.

3.13. Early Forest Fire Segmentation Based on Deep Learning

In their paper "Early Forest Fire Segmentation Based on Deep Learning," Li *et al.* [22] proposed an early forest fire segmentation algorithm based on DL, named F-Unet. The core idea of this research paper is a feature fusion network to improve the segmentation accuracy of the model. The authors tested the proposed F-Unet on the FLAME dataset and demonstrated that the proposed model can significantly improve fire segmentation precision. This paper clearly highlights the advantages of opting for DL-based models for forest fire segmentation compared to traditional methods such as histogram-based segmentation, the Otsu method, etc. Further, the authors explain the inspiration for designing the F-Unet. The proposed feature fusion network idea was inspired by the bidirectional feature pyramid network (BIFPN) and utilizes the optimization principle of BIFPN. Further, the authors clearly established the evaluation criteria, which are mean pixel accuracy (MPA) and mean intersection over union (MIoU). The authors also provided in-depth analysis on both the qualitative and quantitative fronts to demonstrate the experimental evidence of F-Unet efficiency. In terms of both MPA and MIoU, F-Unet achieves better performance than the other models used for comparison. However, the segmentation speed of F-Unet is not on par with that of the other models used for comparison. From both [20] and [21] research papers, it can be seen that there is a need for lightweight and efficient models, and we believe if further research is done to optimize these attributes while retaining either the same or better MPA and MIoU metrics, F-Unet can be a great model for early forest fire segmentation as it can help firefighters get information on fire area, spread direction, and so on [22]. Lastly, the authors used a publicly available dataset called FLAME [23].

3.14. Early Forest Fire Region Segmentation Based on Deep Learning

In "Early Forest Fire Region Segmentation Based on Deep Learning," Wang *et al.* [24] have proposed a novel forest fire monitoring framework based on convolutional neural networks. The core idea of this research paper is that the forest fire area is very small and hard to detect using traditional methods for the "early" detection of forest fires. The proposed method involves the utilization of dilated convolutions, which are a special type of convolution layer. The fact that the dilated convolutions support exponentially expanding receptive fields without losing coverage or resolution will help in aggregating information at multiple scales. In fact, this multi-scale context aggregation approach followed in this research improved the forest fire segmentation. The authors tested this proposed approach on multiple CNN frameworks, such as SqueezeNet, Highway B, ResNet-56, and ResNet-110. Of these four models, the authors identified that the SqueezeNet model yielded better accuracy. Overall, this paper has novelty as it talks about increasing the receptive field in an image by using the Convolution Operation. Lastly, another interesting feature of this paper is that the authors tested the proposed technique of using dilated convolutions in real-time settings to effectively monitor and detect early forest fires.

3.15. Prediction of Forest Fire Using Machine Learning Algorithms: The Search for the Better Algorithm

In [25] "Prediction of Forest Fire Using Machine Learning Algorithms: The Search for the Better Algorithm," Rakshit *et al.* have worked on identifying the best classification model that predicts forest fires with greater accuracy. The authors employed various standard ML algorithms such as SVM, KNN, Decision Tree, Naive Bayes, etc. The dataset utilized for comparing these techniques is the meteorological data collected from Montesinho Natural Park, Portugal. Upon searching the internet for this dataset, it appears that it is available to the public on Kaggle [26]. The authors evaluated the mentioned models across various metrics such as the area under the receiver operator characteristic curve, F1-Score, precision, and recall. Though the AUC metric for Naive Bayes is higher than others, based on the F1-score, the Precision and Recall Values Decision Tree is the best-performing model. Though this is a comparative study paper, it would have been better if the authors had considered the latest techniques, such as DL-based classifiers such as LSTM-based classifiers or fully connected classifiers, to compare the model's performance.

3.16. Deep Learning Based Forest Fire Detection and Alert System

In "Deep Learning-Based Forest Fire Detection and Alert System" [27], Mohnish *et al.* proposed a deep learning-based Convolutional Neural Network (CNN) model to detect forest fires. The authors conducted an end-to-end study that includes phases such as image collection, pre-processing, and image classification. The authors used the CNNs for feature extraction and fed these obtained features into detecting forest fires. Further, the authors have implemented a hardware setup using a Raspberry Pi, which sends fire detection alerts as an email, buzz, and LCD display. The authors created the dataset from open-source websites, and the dataset size is around 2500 fire images and 2500 non-fire images. The main drawback is that this model is more like a proof of concept on how to detect and send forest fire alerts and does not include any comparative studies that talk about how the proposed model fares against existing techniques. Rather, this paper is focused on how to detect and send alerts with a DL model trained on limited data and the Raspberry Pi module.

4. Datasets

The following are the list of publicly available datasets that were used in the research papers identified as part of this survey:

4.1. FLAME Dataset

FLAME is one of the fire image datasets that was collected from drones during the burning of piled detritus in an Arizona pine forest [8] and [23]. This dataset covers video recordings as well as thermal heatmaps captured by infrared cameras. These images and videos are then annotated and labeled frame-wise, which would aid upcoming researchers in easily applying the fire detection and modeling algorithms. **Figure 6** contains sample images taken from the FLAME dataset.

4.2. FLAME2 Dataset

Though none of the above research papers were based on this dataset, it is interesting for the researchers that the Flame dataset now has a second version. Flame 2 is an extension to the FLAME dataset, and this dataset gives additional information to the main dataset's aerial imagery, the supplementary dataset covers information regarding weather, the burned area plan, a geo referenced RGB point of the pre-burned area, an RGB orthomosaic, as well as links to its further information [28]. **Figure 7** shows the sample images from the FLAME2 dataset.

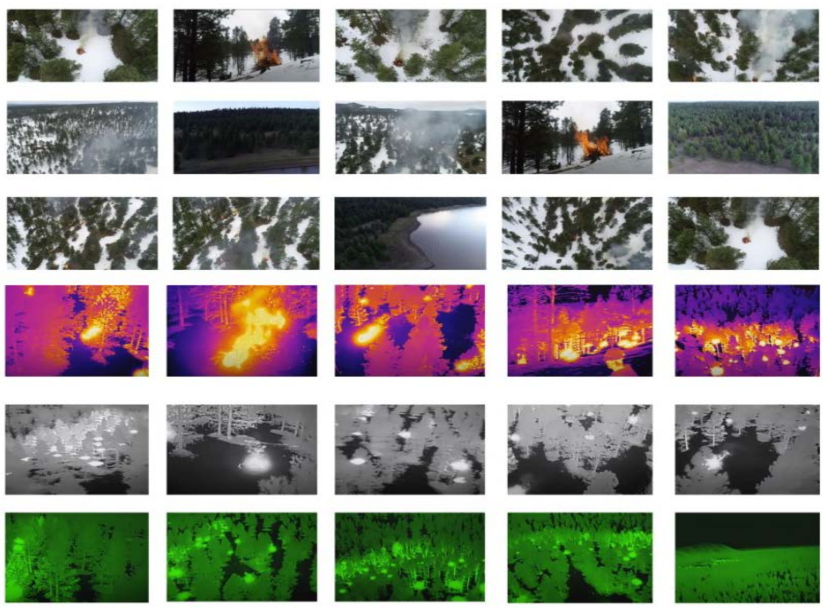

Figure 6. FLAME dataset sample images.

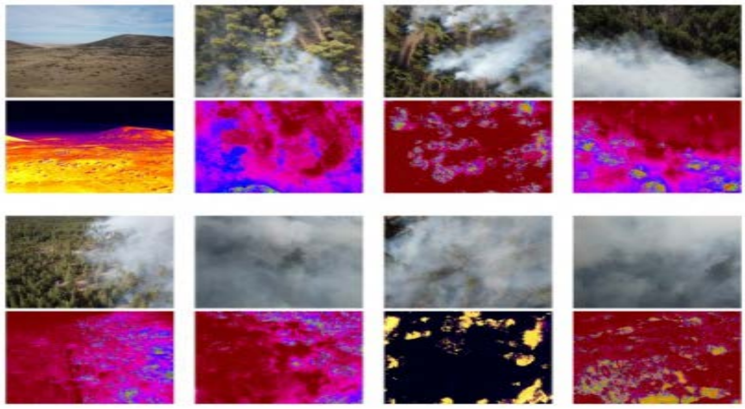

Figure 7. FLAME2 dataset sample images.

4.3. Montesinho Forest Fire Dataset

This dataset covers 517 forest fire cases from the Montesinho natural park in Portugal [12] [17] [26].

It records the weekday, month, and coordinates of the burned area and also includes meteorological data such as humidity, wind, rain, and temperature. The workflow reads the given data and trains the associated model based on the spatial, temporal, and weather variables. This model is then fed to the burned area for predictions based on its current coordinates and time, where the forest fire happened. The force sent to the incident is applied for evaluating prediction.

4.4. MODIS Datase

This instrument is functioning on both the Aqua and Terra spacecraft. It has a swath width of 2300 km and views the entire surface of the Earth every two days. The detectors measure their 36 spectral bands between 0.4 and 14.37 μm, and thus they acquire data at mainly three spatial resolutions of 250 m, 500 m, and 1000 m. This data is then fed to a ground station in New Mexico. Then this data is provided to the EOS Data and Operations System (EDOS), located at the Goddard Space Flight Center.

4.5. FireNet Dataset

Fire disasters are hazardous as they result in the loss of property and lives. So, it is therefore vital to find fast and possibly portable ways to detect fire. FireNet is one of the custom-compiled fire datasets, which was now utilized in the described research paper by Arpit *et al.* The dataset is always available for download.

4.6. Fire Detection Dataset

The Fire Detection Dataset has a collection of datasets that include videos for smoke and fire detection. It was composed of a total of 31 videos, both captured in real-world environments and available for downloading from the web. The dataset is divided into two main parts: the first part includes 14 videos characterized by information about the fire and the second part consists of the remaining

17 videos that do not have any event of interest; in specific, this portion involves critical situations traditionally considered to be fire, such as red-colored objects moving in the scene, clouds, or smoke. This dataset is publicly available, and Figure 8 shows the examples from the Fire Detection Dataset.

5. Comparison of Machine Learning Techniques

To mitigate forest fires, it is essential to find a solution to detect and predict forest fires, and we came up with one of the potential solutions for implementing ML and found a handful of techniques related to ML/DL algorithms. Figure 9 shows the comparative study done on different algorithms and evaluated based on their precision, resolution, and accuracy. From the table, it is evident that the YOLO algorithm works better with lightweight embedded systems and yields much more efficient results. For predicting forest fires, it is essential to spot the hotspot regions and also to diagnose the health condition of the forest.

VIDEO	RESOLUTION	FRAME RATE	FRAMES	FIRE	EXAMPLE
Fire 1	320 × 240	15	705	Yes	
Fire 2	320 × 240	29	116	Yes	
Fire 3	400 × 256	15	255	Yes	
Fire 4	400 × 256	15	240	Yes	
Fire 5	400 × 256	15	195	Yes	
Fire 6	320 × 240	10	1200	Yes	

Figure 8. Fire detection dataset sample.

PURPOSE	METHOD USED	DATASET	RESULT	DRAWBACKS
Light weight model for FFD	UAV & YOLOV3 YOLOV5	FLAME FIRE Net	P: 82% R: 79% P: 97% R: 92%	False Positives
Hotspot mapping & Forecasting (Indonesia)	LSTM Algorithm	MODIS	A > 95% Error: 4.56%	
Fire Detection	SVM	UCI Data Repository	Novel Linear SVM is better (P, R, A)	
Fire Detection using YOLOV5 family with embedded device	YOLOV5S YOLOV5M YOLOV5L YOLOV5XL		Increased detection speed and precision with variants	No information about dataset used; No comparison with last model (YOLOV7)
Fast Detection	R-ShufflenerV2 ShufflenerV2	FLAME	R-ShufflenerV2 has better recognition speed of 31 FPS	No comparison with other models
Fire Detection	Sensory Unit + Linear Regression Model	Kaggle	98.7% Accuracy	No comparison
Fire Detection Avoidance of False Alarm	CNN (DenseNet)	Mixed dataset with fire-like and non fire-like objects	90% Accuracy	Focused only on collecting large datasets
Fast detection speed suitable for embedded devices	YOLOV4 Fast RCNN YOLOV3	Real-time dataset (small flames, red leaves, smokes, fgs)	YOLOV4 (better) Avoided false positives	
Forest Fire Segmentation	CNN(FUnet) Compared with traditional methods	FLAME	Better Segmentation Accuracy Funet (MPA)	
Region Segmentation	CNN (dilated convolution) SqueezeNet Highway B ResNet-56 ResNet-110		Increased Segmentation Accuracy SqueezeNet gives better result	
Hotspot Identification	Decision Trees Random Forest SVM ANN	Kaggle (meteorological data)	Identified accurately	
Forest health Diagnosis	Masked RCNN Image Net with ReLu Image Net with leaky ReLu Coco with ReLu	Data from aerial photography	Masked RCNN (better precsion) 54% dead tree detection	

Figure 9. Comparison of different ML technique.

6. Conclusion and Future Work

Forest fires pose a significant threat to the environment, economic and human health. It is of vital importance to detect and contain the forest fires at the earliest. The focus of this survey paper was to identify various modes of research that were conducted in detection and prediction of forest fires using the ML, DL and UAVs. With the increase in the availability of vast amounts of data, and evolving technologies to generate and process data, evolving hardware such as UAVs and edge computing devices are being leveraged for early fire detection and prevention.

In the future, it is best if several benchmark datasets are created for tabular, image, and video data analysis for early forest fire detection and prevention. Further, there is an ever-increasing demand for edge computing, and we believe research on this front should be carried out to test the efficiency of UAVs in processing the data on the fly and triggering an alert for adverse events. Further, in the field of computer vision, vision transformers are gaining prominence, and it is worth exploring these models for the detection of forest fires and comparing their performance with that of CNNs to evaluate the best models in terms of false alarms. Lastly, YOLO family models are evolving with each passing day, and it is best to do a comprehensive review of YOLO versions to see which version is better for preparing lightweight architectures that need to be mounted on UAVs for real-time scene processing.

Conflicts of Interest

The authors declare no conflicts of interest regarding the publication of this paper.

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