Global View of Machine Learning and Forest Fire

Subjects: Meteorology & Atmospheric Sciences
Contributor: Yee Jian Chew , Shih Yin Ooi , Ying Han Pang , Kok-Seng Wong

Utilising machine learning techniques in aiding forest fire detection, analysis, and prediction is not new, and these techniques have been successfully adopted in many other countries as they have been gaining more attention. Hence, this is probably a potential research direction to be delved into in the near future.

forest fire Malaysia review survey fire map wildfire

1. Introduction

Fire is considered an environmental factor in the Mediterranean climate, having played an obvious evolutionary role in the structure and function of Mediterranean climate ecosystems. In the aftermath of wildfires, accelerated erosion occurs [1][2], thus threatening the natural regeneration process. Additionally, it is well-acknowledged that water erosion, biodiversity, and biotic natural capital affect recovery [3][4]. To that end, emergency post-wildfire erosion-mitigation treatments are required to enhance ecosystem sustainability as in highly fire-prone ecosystems featuring losses of biodiversity, ecosystem function, or services following wildfire events occurring with unnaturally high frequencies, the magnitude of extent or intensity can result in land degradation or even the complete transformation of the ecosystem. In addition to their impacts on the carbon cycle, such events, usually called as megafires because of their size, reduce the amount of living biomass, affect species composition, affect water and nutrient cycles, increase flood risk and soil erosion, and threaten local livelihoods by burning agricultural lands and homes. In addition, these fires have devastating impacts on local wildlife, as animals either are unable to escape from the fires or become threatened by the loss of their habitat, food and shelter.

Climate change [5] and the wildland–urban interfaces (WUIs) [6] have increased the frequency and devastating impacts of wildfires. The effects of global climate change have led to a rise in temperature and a fall in precipitation, shaping a prolonged dry and warm period that favours the ignition and spread of wildfires [5]. Radeloff et al. [6] stated that the upsurge of new housing development in WUI areas, specifically near forest regions, generally increases the likelihood of wildfire occurrence. The combination of the aforementioned conditions converts wildfires into megafires. A megafire is an extraordinary fire that devastates a large area. Megafires are notable for their physical characteristics including intensity, size, duration, and uncontrollable dimension, as well as their social characteristics, including suppression cost, damage, and fatalities [7].

Forest fires recur periodically in Malaysia due to many factors, such as human negligence [8][9], topography [10], and meteorology [11]. In the last two years [12][13][14], haze and forest fires caused serious environmental problems in

Malaysia and its neighbouring countries. Forests play a critical role in sustaining the human environment. Most forest fires not only destroy the natural environment and ecological balance but also seriously threaten the security of life and property. Thus, the early discovery and forecasting of forest fires are both urgent and necessary for forest fire control, and they have become one of the nation's interests.

Forest fires and the resultant smoke-haze are not relatively new experiences in Malaysia. Despite improved management, wildfires have not been completely eradicated and seem to be increasing in intensity and periodically recurring due to many factors, e.g., climatic factors, improper peatland management, traditional slash and burn activities, and poor water management. In 2019, haze and forest fires caused a serious environmental problem for Malaysia and its neighbouring countries, including Indonesia, Singapore and Brunei. The forests and peatlands in Pahang caught fire in early February 2019 [15]. In August 2019, the forest fires in Riau shrouded the entire Klang valley with dense haze. Additionally, some major cities and towns in the state of Sarawak, including Kuching, were also affected by the haze resulting from the Kalimantan wildfire. Subsequently, the air quality in Kuala Baram and Miri reached hazardous levels that led to Malaysia activating its National Action Plan for Open Burning and its existing National Haze Action Plan on 14 August 2019. Many states were shrouded, including Pahang, Kuala Lumpur, Negeri Sembilan, Penang, Putrajaya, Selangor, Sabah and Sarawak, by the haze [16][17][18]. Subsequently, 2.4 hectares (ha) of forest were also burned in Johor in August 2019 [19]. Historical data have shown that the incidence of forest fires are more severe in Sabah [20] and Sarawak [9] than in Peninsular Malaysia. The worst fire in Sabah happened from 1983 to 1985 [21] due to the severe drought caused by the El Nino phenomenon [22]. About one million ha in mostly over-logged forests disappeared [20]. An uncontrolled forest fire can alter forest ecosystems and lead to social, economic, and environmental losses. Moreover, pollution from fires leads to respiratory problems in people living hundreds of kilometres away.

From the global perspective, the explosion of machine learning and artificial intelligence had undoubtedly inspired researchers to adopt machine learning and deep learning algorithms to combat the issues of forest fires [23][24]. However, most studies have utilised independent sets of methodology focussing on particular regions, thus preventing the replication of experiments. Since each fire incident may be triggered or promoted by different topologies, climates, weather, forest structures, or landcover conditions [25][26], solutions should be fine-tuned based on the study location to effectively tackle fires.

2. Global View of Machine Learning and Forest Fire

Although traditional fire detection systems such as the CFFDRS [27], FDRS [28], and Slovenia Environment Agency fire detection system [29] have been proven to be very feasible for the task of fire detection, it is plausible to improve their detection and prediction abilities by building machine learning models with a fire database containing the historical fire occurrences and all contributing factors of forest fires.

Bui et al. [30] examined forest fire susceptibility through a hybrid artificial intelligent approach that combined the usage of a neural fuzzy inference system (NF) and particle swarm optimization (PSO) in Vietnam. This hybrid approach was named Particle Swarm Optimized Neural Fuzzy (PSO-NF). The spatial information of tropical forest fire susceptibility was extracted and modelled with the adoption of PSO-NF. The forest fire model was retrieved from NF, and the best parameter values were selected through the PSO. The authors created a GIS forest fire database based on 10 factors associated with forest fires, i.e., slope, aspect, elevation, land use, NDVI, distance to road, distance to residence area, temperature, wind speed, and rainfall. Most of the factors were derived from the Landsat-8 remote sensing data, and the climatic data (i.e., temperature, wind speed and rainfall) were extracted from the National Climatic Data Center (NDCC) [31]. They also compared their proposed algorithm (PSO-NF) with random forest and support vector machine algorithms, and the classification accuracy attained by the PSO-NF (85.8%) surpassed the other two notable classifiers (85.2% and 84.9%, respectively). Later, Bui et al. [32] proposed a new hybrid methodology by amalgamating Multivariate Adaptive Regression Splines (MARS) and Differential Flower Pollination (DFP) into a new methodology named MARS-DFP. DFP was appended to the MARS as a feature extractor to retrieve the spatial patterns of forest fire severity. The proposed algorithm attained a classification accuracy of 86.57%.

Fire kernel density was utilised to detect forest fires by Monjarás-Vega et al. [33], who extracted the spatial patterns of fire occurrence at the regional and national levels in Mexico by utilising geographically weighted regression (GWR) to predict fire density. The fire kernel density was calculated by using two different approaches, which are regular grid density and kernel density, over spatial resolutions ranging from 5 to 50 km on both the dependent and the independent variables captured from human and environmental candidates.

The element of forest fire susceptibility was also exploited by Moayedi et al. [34] in a high fire-prone region in Iran. An ensemble fuzzy method was proposed by aggregating the results retrieved from an adaptive neuro-fuzzy inference system (ANFIS) with genetic algorithm (GA), PSO, and differential evolution (DE) evolutionary algorithms. The GIS forest fire database was built based on 15 ignition factors, i.e., elevation, slope aspect, wind speed, plan curvature, soil type, temperature, distance to river, distance from road, distance from village, land use, slope degree, rainfall, topographic wetness index, evaporation, and NDVI. It should be noted that the authors did not specify the source for each of the mentioned factors. The best performance results were attained by ANFIS-GA, with which the area under receiver operating characteristics (AUROC) was calculated as 0.8503 and the mean squared error (MSE) was calculated as 0.1638.

Instead of predicting forest fire incidents akin to many other works, Sevinc et al. [35] sought to predict the probability of an event that triggered a forest fire by utilising a Bayesian network model. The primary motivation of the authors was to investigate the reason behind each forest fire incident, as the probable causes for almost 54% of forest fires were disclosed to be unknown in the location of study. The empirical testing was conducted in the Mugla Regional Directorate of Forestry area located southwest of Turkey. To assemble the Bayesian network model for each of the causes of fire occurrence, the authors incorporated wind speed, month, distance from settlement, amount of burnt area, relative humidity, temperature, distance from agricultural land, distance from road, and tree species. Sevinc et al. [35] reported an AUC score of 0.91 for hunting, indicating that hunting is the most plausible ignition factor for forest fires that happened between 2008 and 2018.

Table 1 summarises the related works discussed in this section. A thorough review associated with machine learning techniques in the task of forest fire detection or prediction as presented in [23][24].

Table 1. Summary of general machine learning classification techniques used for forest fire detection tasks.

Year of Publication	Reference	Year of Studies	Dataset	Objective
2017	[30]	Lam Dong, Vietnam	GIS database built based on the 10 factors associated with forest fires	To investigate forest fire susceptibility through the combined usage of neural fuzzy inference system (NF) and particle swarm optimization (PSO).
2019	[32]	Lam Dong, Vietnam	GIS database built based on the 10 factors associated with forest fire	To produce a forest fire susceptibility map through a hybrid methodology by combining Multivariate Adaptive Regression Splines (MARS) and Differential Flower Pollination (DFP).
2020	[33]	Mexico	GIS database built based on the 16 factors associated with forest fires	To adopt geographically weighted regression (GWR) to predict fire density.
2020	[34]	Iran	GIS point database utilising 15 forest fire factors	To segregate the location into different fire-prone risks by combining adaptive neuro-fuzzy inference system (ANFIS) with the genetic algorithm (GA), particle swarm optimisation (PSO), or differential evolution (DE).
2020	[35]	Turkey	Table data including fire causes and 9 ignition factors	To investigate the probable causes for the fires by building Bayesian networks for each fire cause along with the ignition factors.

Deep Learning and Forest Fire

Deep learning techniques, which are gaining popularity in recent years, have also been adopted to improve the models in the forest fire domain. Due to their success in the field of image processing and handling spatial information [36], researchers from the fire domain have also exploited similar techniques by utilising satellite remote sensing data, satellite imageries, unmanned aerial vehicle (UAV) images (e.g., drone), and surveillance camera footage.

Zhang et al. [37] proposed a deep convolutional neural network (CNN) to automatically annotate the fire regions in an image by using bounding boxes. To improve the fire patch localisation annotation, the authors designed a two-level (cascaded) CNN where the first CNN model was trained with the full image to identify whether the image contained at least one fire patch and the second CNN model was trained with the fire patches to accurately locate the fire regions in the image. A total of 25 videos from a fire detection dataset [38] were utilised to build their dataset. The authors then extracted one image from every five frames and resized them to 240 × 320, followed by the manual annotations of fire boundaries with 32 × 32 bounding boxes. A subset of the data comprising 178 training images (12,460 patches) and 59 testing images (4130 patches) was used to evaluate the CNN models. A comparison of the performance of the proposed CNN against the support vector machine linear classifier showed that the CNN achieved a detection accuracy of 90.1% and the support vector machine only achieved a detection accuracy of 89% on the testing dataset.

A fine-tuned CNN trained with a CCTV surveillance camera containing 68,457 images was devised by Muhammad, Ahmad and Baik [39]. The proposed algorithm was able to detect fire in images with distinct indoor and outdoor environments. The authors emphasised that the model could process 17 frames/s, and the performance of the model in terms of precision, recall, and f-measure were recorded at 0.82, 0.98, and 0.89, respectively.

Hodges and Lattimer [40] presented a Deep Convolutional Inverse Graphic Network (DCIGN) that combined both CNN and transpose convolutional layers to estimate the spread of wildfires after ignition from 6 h to 24 h. The authors exploited 13 fire attributes, such as aspect, fuel model, slope, moisture, and canopy height, to train the model. A precision of 0.97, sensitivity of 0.92, and f-measure of 0.93 were found when using the proposed technique.

An AlexNet CNN model with modified adaptive pooling combined with traditional image processing was proposed by Wang et al. [41] to automatically locate fire pixels from images obtained from the Corsica Fire Database. The authors stated that the present studies only applied CNN directly to the fire images without considering colour features. Thus, they segregated the fire regions in the images by utilising the colour features before training the CNN model. Subsequently, the best classification accuracy of 90.7% was reported by the authors when they trained and evaluated the model using only the segmented images instead of the full original images.

Zhang et al. [42] adopted 14 influencing fire factors—elevation, slope, aspect, average temperature, average precipitation, surface roughness, average wind speed, maximum temperature, specific humidity, precipitation rate, forest coverage ratio, NDVI, distance to roads, and distance to rivers—to train a CNN algorithm to forecast a spatial prediction map. Data from 2002 to 2010 collected from the Yunnan Province of China were used in the research. The authors also applied feature selection techniques such as multicollinearity analysis and information gain ratio to evaluate the importance of each fire attribute. Additionally, an oversampling technique was employed to resolve the issue of the imbalance class while proportional stratified sampling was also utilised to fairly compare the performance of the CNN with other benchmark classifiers such as random forest, support vector machine, multi-layer perceptron (MLP), and kernel logistic regression. The authors reported that a high AUC of 0.86 was attained by the proposed CNN.

To benefit from the real-time aerial images captured from UAVs, a low-power CNN deep learning algorithm based on YOLOv3 was devised by Jiao et al. [43] to improve the accuracy and speed of detection. The authors utilised the UAVs' internal computing resources to determine whether any fire pixels were detected from studied footage. They justified that the transmission of a large amount of data from the UAVs to the cloud services was not feasible. At the same time, contents in the videos or images may be susceptible to privacy issues. To resolve these concerns, only the results (i.e., fire or no fire detected) were sent from the UAVs to the cloud services. It should be highlighted that the YOLOv3 model was trained on a desktop computer before embedding it onto the UAVs for evaluation and testing purposes. A precision of 0.82, recall of 0.79, and f1-score of 0.81 were achieved by the proposed model.

Ban et al. [44] proposed a deep learning framework based on a CNN to automatically identify burnt regions by training the model with the Sentinel-1 Synthetic Aperture Radar (SAR) images. The experiments were conducted based on two fire incidents in Canada and one fire incident in America. The authors emphasised the feasibility of SAR images in wildfire monitoring as SAR is an active sensor that can produce microwave signals and receive the returned signals (i.e., backscattered). In other words, SAR does not need to rely on the availability of sunlight, so it can capture all images during the day and night-time. By training the CNN model with SAR images containing the VV and VH polarisation, the model was able to detect the progression of wildfires in all three of the study locations. When comparing the proposed CNN against the traditional log-ratio method, Ban et al. [44] reported a considerable improvement in terms of the Kappa metrics, which were improved by 0.11, 0.27, and 0.30 for the three respective incidents.

Similar to the work of Jiao et al. [43], Wang et al. [45] developed a lightweight YOLO and MobileNetv3 integrated with a pruned network and knowledge distillation process to improve the speed and accuracy of real-time detection on a UAV. They pretrained their models with the MSCOCO dataset before training the models utilising a fire dataset. A total of 1069 fire and 775 non-fire images were supplied to allow the model to learn the characteristics of fire regions. The proposed model was able to achieve a recall of 98.41%, precision of 88.57%, and accuracy of 96.11%. While the performance of the proposed model was on par with other baseline models, the authors emphasised that the proposed technique was able to reduce the inference (i.e., testing) time required from 153.8 ms (YOLOv4 model) to 37.4 ms (proposed model). This was enabled by tremendous reductions in model parameters resulting in an approximate 95.87% inference time reduction compared with the YOLOv4 model.

Table 2 summarises all the deep learning algorithms adopted in the forest fire domain. Among the eight pieces of literature reviewed in this section, five studies utilised images from UAV or CCTV to perform image recognition and three studies exploited the availability of remote sensing information to perform relevant fire detection tasks.

Table 2. Summary of deep learning techniques in forest fire detection tasks.

Year of Publication	Reference	Dataset	Objective	Algorithm
2016	[37]	Image: unmanned aerial vehicle (UAV)	Establish computer vision/image recognition	Full image and fine-grained patch fire classifier with deep convolutional neural networks (CNNs)
2018	[39]	Image: CCTV surveillance camera	Establish computer vision/image recognition	Fine-tuned CNN

Year of Publication	Reference	Dataset	Objective	Algorithm
2019	[40]	Remote sensing data consists of 13 fire-influencing attributes	Estimate the spread of wildfires	Deep Convolutional Inverse Graphic Network (DGIGN)—Deep CNN and transport CNN
2019	[41]	Image: Corsica Fire Database	Establish computer vision/image recognition	Conventional image processing, AlexNet CNN, and modified adaptive pooling
2019	[42]	Remote sensing data containing 14 fire-influencing factors	Classify fire pixels	Feature selection: multicollinearity analysis/information gain ratio and CNN
2019	[43]	Image: UAV	Establish computer vision/image recognition (real-time)	Low-power YOLOv3 CNN
2020	[44]	Satellite Image: SAR Image (Sentinel-1 Synthetic Aperture Radar)	Establish automatic burnt region detection	CNN
2021	[45]	Image: UAV	Establish computer vision/image recognition	Lightweight YOLO and MobileNetV3 with pruned network and knowledge distillation

References

1. Stefanidis, S.; Alexandridis, V.; Spalevic, V.; Mincato, R.L. Wildfire Effects on Soil Erosion Dynamics: The Case of 2021 Megafires in Greece. Agric. For. 2022, 68, 49–63.
2. Efthimiou, N.; Psomiadis, E.; Panagos, P. Fire Severity and Soil Erosion Susceptibility Mapping Using Multi-Temporal Earth Observation Data: The Case of Mati Fatal Wildfire in Eastern Attica, Greece. Catena 2020, 187, 104320.
3. Stefanidis, S.; Alexandridis, V.; Ghosal, K. Assessment of Water-Induced Soil Erosion as a Threat to Natura 2000 Protected Areas in Crete Island, Greece. Sustainability 2022, 14, 2738.
4. Köninger, J.; Panagos, P.; Jones, A.; Briones, M.J.I.; Orgiazzi, A. In Defence of Soil Biodiversity: Towards an Inclusive Protection in the European Union. Biol. Conserv. 2022, 268, 109475.
5. Goss, M.; Swain, D.L.; Abatzoglou, J.T.; Sarhadi, A.; Kolden, C.A.; Williams, A.P.; Diffenbaugh, N.S. Climate Change Is Increasing the Likelihood of Extreme Autumn Wildfire Conditions across California. Environ. Res. Lett. 2020, 15, 94016.
6. Radeloff, V.C.; Helmers, D.P.; Kramer, H.A.; Mockrin, M.H.; Alexandre, P.M.; Bar-Massada, A.; Butsic, V.; Hawbaker, T.J.; Martinuzzi, S.; Syphard, A.D. Rapid Growth of the US Wildland-Urban Interface Raises Wildfire Risk. Proc. Natl. Acad. Sci. USA 2018, 115, 3314–3319.

7. Buckland, M.K. What Is a Megafire? Defining the Social and Physical Dimensions of Extreme US Wildfires (1988–2014). Ph.D. Thesis, University of Colorado, Boulder, CO, USA, 2019.
8. Abdullah, M.J.; Ibrahim, M.R.; Abdul Rahim, A.R. The Incidence of Forest Fire in Peninsular Malaysia: History, Root Causes, Prevention and Control. Prev. Control. Fire Peatl. 2002, 27–34.
9. Chandrasekharan, C. The Mission on Forest Fire Prevention and Management to Indonesia and Malaysia (Sarawak). Trop. For. Fire. Prev. Control. Rehabil. Trans-Bound. Issues 1998, 14, 1–79.
10. Setiawan, I.; Mahmud, A.R.; Mansor, S.; Shariff, A.R.M.; Nuruddin, A.A. GIS-grid-based and Multi-criteria Analysis for Identifying and Mapping Peat Swamp Forest Fire Hazard in Pahang, Malaysia. Disaster Prev. Manag. An. Int. J. 2004, 13, 379–386.
11. Patah, N.A.; Mansor, S.; Mispan, M.R. An Application of Remote Sensing and Geographic Information System for Forest Fire Risk Mapping. Malays. Cent. Remote Sens. 2006, 54–67.
12. Bernama 80 Hektar Hutan Simpan Kuala Langat Terbakar. Available online: https://www.bharian.com.my/berita/kes/2020/04/679541/80-hektar-hutan-simpan-kuala-langat-terbakar (accessed on 2 August 2021).
13. Bernama Lebih 40 Hektar Hutan Simpan Kuala Langat Selatan Terbakar. Available online: https://www.bharian.com.my/berita/nasional/2021/03/791876/lebih-40-hektar-hutan-simpan-kuala-langat-selatan-terbakar (accessed on 2 August 2021).
14. Berita Harian Kegiatan Memancing Disyaki Punca Kebakaran Hutan. Available online: https://www.bharian.com.my/berita/wilayah/2020/03/670625/kegiatan-memancing-disyaki-punca-kebakaran-hutan (accessed on 2 August 2021).
15. Tang, K.H.D. Climate Change in Malaysia: Trends, Contributors, Impacts, Mitigation and Adaptations. Sci. Total Environ. 2019, 650, 1858–1871.
16. Alagesh, T.N. 40 ha of Pahang Forest, Peat Land on Fire. New Straits Times, 26 February 2019. Available online: https://www.nst.com.my/news/nation/2019/02/463995/40ha-pahang-forest-peat-land-fire-nsttv(accessed on 28 August 2022).
17. Then, S. Forest Fires Flare up Again in Parts of Sarawak. The Star. 17 July 2019. Available online: https://www.thestar.com.my/news/nation/2019/07/17/forest-fires-flare-up-again-in-parts-of-sarawak (accessed on 28 August 2022).
18. Tay, R. The Haze Is Making a Comeback in August, and Some Malaysian Regions Are Already Affected. 2 August 2019. Available online: https://web.archive.org/web/20190823091814/https://www.businessinsider.my/the-haze-is-making-a-comeback-in-august-and-some-malaysian-regions-are-already-affected/ (accessed on 28 August 2022).

19. Then, S. More Hotspots in Kalimantan May Bring Widespread Transboundary Haze to S'wak. The Star. 18 August 2019. Available online: https://www.thestar.com.my/news/nation/2019/08/18/more-hotspots-in-kalimantan-may-bring-widespread-transboundary-haze-to-s039wak (accessed on 28 August 2022).
20. Beaman, R.S.; Beaman, J.H.; Marsh, C.W.; Woods, P. V Drought and Forest Fires in Sabah in 1983. Sabah Soc. J. 1985, 8, 10–30.
21. Woods, P. Effects of Logging, Drought, and Fire on Structure and Composition of Tropical Forests in Sabah, Malaysia. Biotropica 1989, 21, 290–298.
22. Cane, M.A. Oceanographic Events during El Nino. Science 1983, 222, 1189–1195.
23. Abid, F. A Survey of Machine Learning Algorithms Based Forest Fires Prediction and Detection Systems. Fire Technol. 2020, 57, 559–590.
24. Bot, K.; Borges, J.G. A Systematic Review of Applications of Machine Learning Techniques for Wildfire Management Decision Support. Inventions 2022, 7, 15.
25. Chuvieco, E.; Salas, J. Mapping the Spatial Distribution of Forest Fire Danger Using GIS. Int. J. Geogr. Inf. Sci. 1996, 10, 333–345.
26. Cochrane, M.A. Fire Science for Rainforests. Nature 2003, 421, 913–919.
27. Dymond, C.C.; Field, R.D.; Roswintiarti, O. Using Satellite Fire Detection to Calibrate Components of the Fire Weather Index System in Malaysia and Indonesia. Environ. Manag. 2005, 35, 426–440.
28. De Groot, W.J.; Field, R.D.; Brady, M.A.; Roswintiarti, O.; Mohamad, M. Development of the Indonesian and Malaysian Fire Danger Rating Systems. Mitig. Adapt. Strateg. Glob. Chang. 2007, 12, 165.
29. Stojanova, D.; Panov, P.; Kobler, A.; Džeroski, S.; Taškova, K. Learning to Predict Forest Fires with Different Data Mining Techniques. In Proceedings of the Conference on Data Mining and Data Warehouses (SiKDD 2006), Ljubljana, Slovenia, 17 October 2006; pp. 255–258.
30. Bui, D.T.; Bui, Q.-T.; Nguyen, Q.-P.; Pradhan, B.; Nampak, H.; Trinh, P.T. A Hybrid Artificial Intelligence Approach Using GIS-Based Neural-Fuzzy Inference System and Particle Swarm Optimization for Forest Fire Susceptibility Modeling at a Tropical Area. Agric. For. Meteorol. 2017, 233, 32–44.
31. National Centers for Environmental Information Daily Weather Records|Data Tools|Climate Data Online (CDO)|National Climatic Data Center (NCDC). Available online: https://www.ncdc.noaa.gov/cdo-web/datatools/records (accessed on 5 April 2021).
32. Bui, D.T.; Hoang, N.-D.; Samui, P. Spatial Pattern Analysis and Prediction of Forest Fire Using New Machine Learning Approach of Multivariate Adaptive Regression Splines and Differential

Flower Pollination Optimization: A Case Study at Lao Cai Province (Viet Nam). J. Environ. Manag. 2019, 237, 476–487.

33. Monjarás-Vega, N.A.; Briones-Herrera, C.I.; Vega-Nieva, D.J.; Calleros-Flores, E.; Corral-Rivas, J.J.; López-Serrano, P.M.; Pompa-García, M.; Rodríguez-Trejo, D.A.; Carrillo-Parra, A.; González-Cabán, A. Predicting Forest Fire Kernel Density at Multiple Scales with Geographically Weighted Regression in Mexico. Sci. Total Environ. 2020, 718, 137313.
34. Moayedi, H.; Mehrabi, M.; Bui, D.T.; Pradhan, B.; Foong, L.K. Fuzzy-Metaheuristic Ensembles for Spatial Assessment of Forest Fire Susceptibility. J. Environ. Manag. 2020, 260, 109867.
35. Sevinc, V.; Kucuk, O.; Goltas, M. A Bayesian Network Model for Prediction and Analysis of Possible Forest Fire Causes. For. Ecol. Manag. 2020, 457, 117723.
36. Jiao, L.; Zhao, J. A Survey on the New Generation of Deep Learning in Image Processing. IEEE Access 2019, 7, 172231–172263.
37. Zhang, Q.; Xu, J.; Xu, L.; Guo, H. Deep Convolutional Neural Networks for Forest Fire Detection. In Proceedings of the 2016 International Forum on Management, Education and Information Technology Application, Guangzhou, China, 30–31 January 2016; Atlantis Press: Amsterdam, The Netherlands, 2016.
38. Bilikent SPG Computer Vision Based Fire Detection Dataset. Available online: http://signal.ee.bilkent.edu.tr/VisiFire/ (accessed on 5 November 2021).
39. Muhammad, K.; Ahmad, J.; Baik, S.W. Early Fire Detection Using Convolutional Neural Networks during Surveillance for Effective Disaster Management. Neurocomputing 2018, 288, 30–42.
40. Hodges, J.L.; Lattimer, B.Y. Wildland Fire Spread Modeling Using Convolutional Neural Networks. Fire Technol. 2019, 55, 2115–2142.
41. Wang, Y.; Dang, L.; Ren, J. Forest Fire Image Recognition Based on Convolutional Neural Network. J. Algorithms Comput. Technol. 2019, 13, 1748302619887689.
42. Zhang, G.; Wang, M.; Liu, K. Forest Fire Susceptibility Modeling Using a Convolutional Neural Network for Yunnan Province of China. Int. J. Disaster Risk Sci. 2019, 10, 386–403.
43. Jiao, Z.; Zhang, Y.; Xin, J.; Mu, L.; Yi, Y.; Liu, H.; Liu, D. A Deep Learning Based Forest Fire Detection Approach Using UAV and YOLOv3. In Proceedings of the 2019 1st International Conference on Industrial Artificial Intelligence (IAI), Shenyang, China, 23–27 July 2019; pp. 1–5.
44. Ban, Y.; Zhang, P.; Nascetti, A.; Bevington, A.R.; Wulder, M.A. Near Real-Time Wildfire Progression Monitoring with Sentinel-1 SAR Time Series and Deep Learning. Sci. Rep. 2020, 10, 1322.
45. Wang, S.; Zhao, J.; Ta, N.; Zhao, X.; Xiao, M.; Wei, H. A Real-Time Deep Learning Forest Fire Monitoring Algorithm Based on an Improved Pruned + KD Model. J. Real-Time Image Process.

2021, 18, 2319–2329.