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A Review of the Scope of AI-Based Early-Fire Detection and Prediction in Forested Areas

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ABSTRACT

Protection of the ecology requires the existence of forests on every continent. They play a significant part in the global carbon cycle and are home to numerous plant and animal species. Because they disturb the local environment, forest fires pose a grave threat to the survival of animals, plants, and even humans in many regions of the world. New technologies and methodologies can be used to identify and anticipate forest fires in advance, enabling authorities to better prepare for and respond to these blazes. For the purpose of recognising and analysing the various tactics, this paper gives an overview of many forest fire prediction and detection approaches and their respective data sets. The causes, frequency, and risk factors of fire are explored, as well as a survey of the various works and technique systems. In this work, we analyse and assess the findings and significant components of the investigations.

Keywords: ***forest fire forecast, rate of forest fire propagation, forest fire detection, deep learning, andYOLOv5.***

INTRODUCTION

Deforestation can have far-reaching repercussions on the Earth's ecological system, as forests are a vital habitat and link in the biological food chain. Long-term human development is dependent on the protection of forests, and forest fire control is a vital aspect of this protection [1]. Wildfires have increased in a number of regions over the past few decades, generating billions of dollars in damages and fatal air pollution. Accurate and effective near-real-time wildfire forecasts that may be utilised to determine firefighting strategies are essential for both emergency fire response and fire risk assessment. Due to the complexity of fire dynamics and systems, it is challenging to forecast and simulate wildfire spread [3].

Wildfire management, mitigation, and evacuation plans must be bolstered by means of early warning and forecasting technologies. In order to disperse resources effectively and extinguish fires as quickly as possible, emergency responses to wildfires rely heavily on accurate estimates of fire behaviour for the following day. The increased availability of remote-sensing data, processing capacity, and advances in machine learning make data-driven approaches to assessing the likelihood of wildfires more practical than ever before. The "Next Day Wildfire Spread" dataset is a large-scale, multidimensional dataset of historical wildfires containing two snapshots of the fire spreading pattern at times t and t+1 [4].

There have been numerous proposals for detecting these forest fires. There are several technologies proposed, including satellites, cameras, wireless sensor networks, and unmanned aerial vehicles (UAV). Others propose detecting flames based on visual attributes such as image identificationand object detection.

LITERATURE SURVEY

Shaoxiong Zheng et al. [1], developed a forest fire prediction model using convolution neural network with the help of deep learning technique like Principal component analysis (PCA) and transfer learning. Based on classic dynamic convolution neural network (DCNN) model, an enhanced version of DCNN model was built and dubbed as "DCN Fire" to accurately assess the risk of a wildfires, where the detection accuracy was 7.41% and the prediction error was 4.8%. When comparing original images with enhanced images, the optimal value for verification accuracy was 98.3%

with a loss rate of 50% and a batch size of 50. Therefore, the model provided the analytical reference for deterring and addressing forest fires due to its speed and accuracy to recognise and classify the risk of a forest fire under natural light conditions.

As a dataset for comparing the study of algorithm implementation performance, 4,000 forest fire risk photographs were captured in Guangdong Longshan and Jiangmen Sihui forest farms in order to compare the results. The image sizes ranged from 200 × 200 through 4000 x 4000 pixels. The image of a flame was split into conventional sizes for model training, and data enhancement was utilised to address the issue of overfitting. The DCN Fire model parameters were optimised in order to achieve verification accuracy with a learning rate of 0.0001, a momentum of 0.90 and 20,000 iterations.

The accuracy over original and enhanced image dataset of DCN_Fire (0.971 and 0.983), 13- layer(0.952 and 0.964), 15-layer(0.968 and 0.971) and 20-layer (0.979 and 0.983) DCCN models was evaluated accordingly. And compared with the accuracy of other models where Kim's CNN model and AlexNet used Softmax classifier with a accuracy of 93.2% and 93.7% respectively. Similarly, Eight- layer CNN + Fisher vector and HOG + SVM used SVM classifier resulting accuracy of 95.1% and 43.3%. While, Deep belief net + neural net used BPNN classifier with a accuracy of 87.7 % . All of these model used the same training and test data sets. As future work, the model can be further improved and the forest danger identification model's network performance can be enhanced.

Zechuan Wu et al. [2], established a model for forestry management to control and predict fire spread using Artificial Neural Network (ANN) in multidimensional physical and environmental variables. This model, which combines Heilongjiang's cellular automata and Wang Zhengfei's model for comparison with the ANN model, is applicable only for affected forest areas between 1 ha and 100 ha. The model was found to have an average accuracy of 0.8502, with a sensitivity of 0.9526 and an F- measure of 0.8985. After gaining a greater understanding of the propagation behaviours of fire cover, the model quickly generates a profile of fire peak intensity. Which aids forest managers and firefighting agencies in planning their operations and strategies effectively.

The study was undertaken in the province of Heilongjiang in China, which has 8.46 million hectares of forest regions, and was divided into several 500 × 500 m grids to anticipate the spread of forest fires. The Heilongjiang Forestry Bureau supplied historical forest fire disturbance datasets between 2002 and 2020. The dataset includes the incidence time, extinguishing time, geographic location information, the forest fire's source, and its area. And the moderate-resolution imaging spectroradiometer (MODIS) photos were downloaded from the MODIS series satellite products, which feature four 500 x 500 m scenes per day. The input data for model training comprised environmental parameters, including humidity, temperature, precipitation, wind speed and wind direction for the appropriate area, as well as the terrain's slope, aspect, and elevation. For the development of the forest fire spread model, the Boruta feature-screening method was utilised to extract features, and ANN was employed to train the model.

A method based on hybrid of Wang Zhengfei's model and CA is also proposed for comparing prediction accuracy with a created ANN model, which has superior prediction accuracy due to multidimensional combustion performance and diverse environmental parameters. Future progress can be made by examining the temporal and spatial distribution of forest microclimate-related elements in depth, analysing the rule of coordinated changes, and merging microclimate components for model simulation and training. In addition, reliable fuel models can be connected to evaluate the model calibration procedure.

Sibo Cheng et. al. [3] suggested a wildfire prediction system based on machine learning and reduced order modelling techniques that employs a convolutional autoencoder for parameter identification and a data assimilation-dependent inverse strategy to reduce order space. The training dataset was generated via a physics-based fire simulator that forecasts the burned area at various time steps with a cheap computational cost. These forward and inverse modelling approaches are then integrated with real-time observations for more accurate future predictions.

MODIS and Visible Infrared Imaging Radiometer Suite (VIIRS) satellite pictures acquired in California during the Chimney Fire (2016) and Ferguson Fire (2017) validated the data generated by the cellular automata fire simulator for training and testing (2018). The relative reconstruction error was developed in order to assess the reconstruction accuracy of various Reduced Order Models (ROMs). As the autoencoder was exclusively trained on simulated data, the reconstruction errors of satellite images were found to be larger than those of test data, and both the prediction models and the ROMs' adaption to satellite images were unsatisfactory.

This constraint can be overcome by employing fire prediction models on a worldwide scale with sparser grids, which trades off predicting precision for generalizability. Future research could concentrate on learning from more complicated fire simulations to enhance forward and inversemodelling.

Fantine Huot et. et al. [4] proposed a decade of historical remote sensing wildfire datasets aggregated using Google Earth Engine (GEE) throughout the United States from 2012 to 2020 to predict the spreading of wildfires using machine learning models, which can be used as a benchmark for developing wildfire propagation models with a one-day lead time. This dataset combines 2-D fire data with many explanatory variables (e.g., topography, vegetation, weather, drought index, and population density) aligned over 2-D regions, providing machine learning models with a large number of features. In order to determine the efficacy, the dataset was applied to a neural network, and the performance of two machine learning models—logistic regression and random forest—was evaluated. A neural network has the largest area under curve (AUC) at 28.4%, followed by a random forest at 22.5% and logistic regression at 19.0%. Precision and recall for the positive class were 33.6% and 43.2%, respectively, for the neural network.

The data were extracted as 64 km x 64 km regions with a 1 km resolution to capture all typical active fire sizes at different locations and periods when wildfires occurred, as well as to provide two samples of the fire spreading pattern at time t and time t+1 day. The dataset consists of 18545 samples, with 58% of these examples resulting in an increase in fire size from t to t+1, 39% in a decrease in fire size, and 33% in a steady fire size.

Once trained, the ML model can be used to anticipate the size of flames the following day and be beneficial for allocating resources for combating fires. However, MODIS data limitations the ML model's prediction resolution, as its fire detection method is conservative, especially at night or when there is cloud cover. To get around this, uncertain labels are added, which the ML model ignores in order to account for this pixel, however fire-spreading labels will still exhibit bogus patterns. Furthermore, this dataset can be increased to a worldwide scale or span a more extensive time period. Similarly, the proposed workflow and approach can be adapted to other difficulties, such as assessing the likelihood of regions being affected by droughts, hurricanes, and other occurrences from past remote-sensing data.

Alya Faryanti Purbahapsari et al. [5] suggested a geospatial artificial intelligence (GeoAI) strategy for detecting forest fire hotspots in advance. The dataset of forest and land fires is derived from the Lapan WebGIS platform (http://modis-catalog.lapan.go.id/) using satellite image processing of Terra MODIS, Aqua MODIS, S-NPP VIIRS, NOAA-20 VIIRS, and Landsat-8 OLI for fires that occurred in 2017–2019. By studying the spatial and temporal patterns of the hotspots, the ST-DBSCAN clustering method is utilised to identify forest and land fires, while CNN detects fire and smoke in eachcluster of multispectral footage.

The GeoAI has been developed to automate and accelerate the forest and land fires investigation process for the Directorate General of Law Enforcement Ministry of Environment and Forestry (DGLE MoEF). It has the ability to find hotspots in an average of 7.5 minutes, whereas manual hotspot finding can take anywhere from 1 to 5 hours, depending on the operator's skill. Additionally, it automatically clusters hotspots, validates forest and land fires, and calculates the burn area.

The GeoAI model under DGLE MoEF has exceptional potential to accelerate forest and land fire analysis, eliminate human error, and improve efficiency in early detection and law enforcement implementation; however, it is still in development and requires further enrichment in terms of datasets,variables, features, verification, and validation results.

Md. Abdur Rahman et. et al. [6] suggested a fire detection model based on a vision-based system using computer vision, which includes background reduction, colour extraction, spatial wavelet analysis, and support vector machines (SVM) to operate in real time. The model is trained using both fire and non-fire video datasets gathered by the Signal Processing Lab at Bilket University, consisting of 500 wavelet energies extrapolated from the actual fire video and 500 moving pixels that appeared to be fire but were not fire.

When a fire is detected, an alarm system automatically sends an SMS or email to the local fire department, where a pipeline model is constructed. Due to the constant movement of the fire, background subtraction is utilised initially in this proposed method, followed by colour segmentation in the specified region, wavelet analysis to discriminate genuine fire from fire-like objects, and SVM to identify the actual fire and set the alert accordingly. This SVM pipeline model demonstrated an average accuracy of 93.33% on a random sample while detecting 6.67% false positives in two fire-color motion videos, as compared to other SVM methods, which achieved an accuracy of 90.4% (SVM + motion detection + colour detection) and 92.6% (SVM + LAB histogram, SURF texture descriptor). The accuracy can be improved by incorporating high-resolution cameras, and the detection time can be decreased by utilising a powerful CPU with a real-time processing library such as OpenCV. However, the performance accuracy in real-time fire detection satisfies the standards for forest management and industrial application, thereby contributing to the prevention of losses.

Wahyono et. al. [7] suggested a real-time procedure for an early warning system to detect forest fires utilising motion feature analysis and colour probability with frame evaluation using the intersection over union (IoU) ratio. In this architecture, fire is categorised based on colour, shape, and movement at specified areas, which are then represented by colour probability in the segmentation step, a colour histogram in the classification stage, and image moments in the verification stage.

In the VisiFire dataset, which contains films with resolutions ranging from 400 x 256 to 1600 x 1200 at frame rates between 15 and 29.97 FPS, the performance of the proposed framework yielded a 0.8997 true-positive rate and an average processing time of 21.70 FPS. The methodology begins with the formation of a colour probability using the Gaussian Mixture Model and Expectation Maximization (GMM-EM) methods, followed by the training of a model on a dataset where machine learning strategies (SVM and RF) are applied to classify the images, which are then validated by examining the motion of fire regions.

This approach's shortcoming is that it cannot identify forest fires caused by smoke or haze because it relies on the visual appearance of fire. Additional sensors such as a thermal camera, a temperature sensor, or a humidity sensor can be employed to overcome this problem. In addition, it continued to produce false positives, which have an impact on fire detection handling and necessitate additional study to eliminate these false positives. The most difficult aspect of integrating the module isphysically attaching the camera.

Teo Khai Xian et al. [8] used YOLOv5 to develop a forest fire detection algorithm that can analyse images captured by unmanned aerial vehicles (UAVs). This algorithm was then converted into an optimised model that can run on an embedded board, removing the need for trained personnel to operate and monitor UAVs for fire detection. YOLOv5 is an evolution of YOLO (You Only Look Once), a PyTorch- and CSPDarknet53-based object detection tool. The dataset used to construct the algorithm is received from Mohnish Sai Prasad, which contains 5000 forest fire and non-forest fire photos, and a smaller dataset is downloaded from Google Images for testing purposes. The dataset is preprocessed and divided into 80/20 groups, then augmented with additional data to prevent overfitting.

Transfer learning is then used to construct the method, which consists of YOLOv5 and a PANet network for enhancing information flow. A focus layer is utilised to decrease memory and the number of layers while accelerating forward and backward propagation. Open Vino (Open Visual Inference and Neural Network Optimization) is an open-source toolkit for the optimization and deployment of visually oriented AI systems. This toolkit, in conjunction with the Intel Movidius Neural Compute Stick 2 (NCS 2), enables inference at the edge without an internet connection. The results demonstrate that the method has a high MAP, larger than 97%, with reasonable inference times, indicating that the constructed model has a great deal of promise.

Jingjing Qian et al. [9] introduced a Y4SED forest fire identification algorithm to identify forest fire sources in various scenarios, where the algorithm merges Yolov5-S and EfficientDet-D2, trains and predicts the dataset in parallel, and uses a weighted box fusion algorithm (WBF) to process the prediction results to obtain the fusion frame, which effectively solves the problem of missing detection in forest fire identification. Both models were trained with 300 iterations in 12 batches using the SGD optimizer for Yolov5 and AdamW for EfficientDet-D2.

The dataset is gathered from the open-source website BoWFire and the forest fire photographs on the internet using a web crawler; it contains numerous fire images and images with fire disruptors (sun). The dataset was manually filtered to provide a set of 2,976 forest fires.

For assessing the model Microsoft COCO standard, the most authoritative standard in the field of target recognition was used, with the IOU precision criterion set at 0.5. (AP). Comparing experimental findings with Yolov5 and EfficientDet, the suggested Y4SED enhanced detection performance by 2.5–4.5%, with an average accuracy of 87%.

Mohnish S et al. [10] developed a CNN-based deep learning approach for detecting forest fires, using a Raspberry Pi hardware setup to display detection accuracy and notify the proper department. After preprocessing the forest fire photos, the dataset was trained and verified in the CNN model, which is then executed on the Raspberry Pi. If a forest fire is spotted, a buzzer and an email are sent. The dataset is derived from an open-source website and contains 2500 fire and non-fire forest photos, which are then preprocessed and divided into a training and validation set. The model was trained with 15 epochs of 100 batches of 16 samples each. Image classification utilises five sets of convolution and max pooling layers, with the filter size of the convolution layer ranging from 32 to 256, followed by flattening the image and connecting it to a neural network of 128 neurons, which is then connected to a single neuron with a sigmoid activation function. Inoder is utilised to counter overfitting dropout.

On the validation dataset, the model's overall accuracy is determined to be 92.20 percent. Using the Global Positioning System, the effort can be escalated to pinpoint the precise location of the fire (GPS). This research is limited by the fact that the model has not been tested on real-time data or video and requires additional validation on real-time videos.

Table I Summary of Study on System for Detecting and Predicting Forest Fires

REFERENCE	METHODS	TYPE OFDATASET	EPORTED RESULTS	TASK
Shaoxiong Zheng et al. [1]	Dynamic Convolution Neural Network (DCCN), Principal Component Analysis (PCA) and Transfer Learning	4000 forest fire risk images of Guangdong Longshan and Jiangmen Sihui forest farms	Verification accuracy of Optimal value is 98.3% and loss rate 50%	Improved traditional dynamic convolution neural network to build forest fire prediction model
Zechuan Wu et al. [2]	Artificial Neural network, Combination of Heilongjiang's cellular automata and Wang Zhengfei's model	Satellite images from MODIS of Heilongjiang Forestry from 2002 to 2020	Average accuracy is 85.02% , Sensitivity is 95.26 % and F-measure is 89. 85%	Using ANN in multidimentional physical and environmental variables for forestry management to control and predict forest fire
Sibo Cheng et.al. [3]	Reduced-order modelling: PCA, Convolution and Singular Value Decomposition Autoencoding; Forward Problem: Machine learning Prediction :- RandomForest Regression, KNN and Multilayer preception; Inverse Problem: Latent data assimilation technique and Hyperparameter tuning	Cellular automata fire simulator and Satellite Images	A space-wide prediction accuracy of at least 95% with an error rate ofless than 5%	Reconstruction of satellite pictures based on observationsfor the Chimney and Ferguson region
Fantine Huot et.al. [4]	Neural Network, Random Forest andLogistic Regression	Historical remote sensing wildfire dataset aggregated using Google Earthengine across united state from 2012 to 2020	AUC of neural network is 28.8%, random forest 22.5% and logistic regression 19.8%	The dataset served as a baseline for the forecast and spread offorest fires using AI and ML.
Alya Faryanti Purbahapsari et.al. [5]	ST-DBSCAN clustering algorithmand Convolution Neural Network	Satellite image data on forest andland fires from 2017 to 2019	Finds hotspot in average time of 7.5 minutes	Early detection of forest fire hostpotusing GeoAI
Md. Abdur Rahman et. al.[6]	Background subtraction, color- based segmentation, spatial wavelet analysis for colour variation, and SVM classification	Fire and non firevideo dataset	Average accuracy of SVM pipeline is 93.33%	Vision based fire detection system which automatically sends SMS/Email tonearby fire bigrade

Wahyono et. al.[7]	Model of GaussianMixture with Expectation Maximization (GMM-EM)	VisiFire dataset containing videosof the resolution from 400 x 256 to 1600 x 1200 at a frame rate from 15to 29.97 FPS	Prediction accuracy is89.97%	Early warning systemof forest fire detection using motion feature analysis and color probability with frame evaluation using intersection over union (IoU) ratio
Teo Khai Xianet.al [8]	Transfer Learning, YOLOv5, PANet	Mohnish Sai Prasad’s dataset	Mean average precision is 97%	Yolov5 with the PANet network is
	Network	that contains both 5000 fire and nonfire images		used to increase information flow, while OpenVino isutilised to optimiseand implement AI solutions with a visual focus.
Jingjing Qian et.al.[9]	YOLOv5-S and EfficientDet-D2	BoWFire dataset	Predicted accuracy is 87%	Fuses Yolov5-S and EfficientDet-D2 predict and train the dataset in parallel utilising the weightedbox fusion approach to analyse the prediction results for the fusion frame (WBF).
Mohnish S et. al.[10]	CNN and Global Positioning System(GPS)	Dataset is createdfrom opensource website that consists of 2500 fire and non fire images	Predicted accuracy is 92.02%	Implement the forest fire dectction based on CNN in RaspberryPi which displays theaccuracy and send notification to concern department

CONCLUSION

Forest fires can burn homes, animal habitats, and wood, spewing carbon dioxide into the atmosphere. Wildfires must be spotted early and contained to avoid their unchecked spread. For predicting and detecting forest fires, numerous artificial intelligence (AI) techniques, such as machine learning and deep learning algorithms, are offered. It has been demonstrated that remote sensing data is most useful in fire modelling systems, and that neural network-based relapse-based approaches are often employed for identification and forecasting.

YOLOv5s with EfficientDet-D2 is the most effective object recognition technique, with an accuracy of 87%, according to this research evaluation. We also discovered that machine learning may be used to forecast the spread of forest fires by analysing data from the "Next Day Wildfire Spread" video collection, which includes remote sensing data.

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