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J Wireless Com Network (2023) 2023:112
https://doi.org/10.1186/s13638-023-02320-w

EURASIP Journal on Wireless Communications and Networking

RESEARCH **Open Access**

Drone network for early warning of forest fire and dynamic fire quenching plan generation

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Abstract
Wildfires are one of the most frequent natural disasters which significantly harm the environment, society, and the economy. Transfer learning algorithms and modern machine learning tools can help in early forest fire prediction, detection, and dynamic fire quenching. A group of drones that has high-definition image processing and decision-making capabilities are used to detect the forest fires in the very early stage. The proposed system generates a fire quenching plan using particle swarm optimization technique and alerts the fire and rescue department for a quick action, thereby stop the forest fire at an early stage. Also, the drone network plays a major role to track the live status of forest fire and quenches the fire. ResNet, VGGNet, MobileNet, AlexNet, and GoogLeNet are used to detect the forest fire hazards. The experimental results prove that the proposed technique GoogLeNet-TL provides 96% accuracy and 97% F1 score in comparison with the state-of-the-art deep learning models.

Keywords: Convolutional neural networks, GoogLeNet, Forest fire, Transfer learning, Drone network, Early warning

1 Introduction

India has seen heavy economic losses in few states due to forest fires. Due to increased temperatures and low availability of water, particularly during the summer season, India experienced major forest fire hazards in the last two decades. In Indonesia, the forest fire is becoming very difficult to deal with, hence, many nearby countries like Singapore are joining hands with Indonesia to fight together. In the USA, a mega fire incident happened in California in the year 2018, which affected many people. In the year 2023, a forest fire was reported in Canada. The forest fire incidents are increasing year by year gradually which affects the environment which leads to an unbalanced ecosystem, thereby to the death of flora and fauna.

1.1 Literature survey

An evaluation of the impact of wildfires is required in order to properly create and implement active fire prevention policies. The MCD14ML used in a contextual algorithm to find fires in 1 km pixels. Four fire products, particularly for their ability to detect tiny fires, in mountainous, foggy, and fire-prone areas over subtropical China were examined

[1]. A different method for detecting and monitoring wildland fires by utilizing a dataset of Red Green Blue (RGB) and infrared images captured by drones was proposed and it categorizes the captured photos as the fire or the no-fire by using RGB and thermal images [2]. Thermal infrared imaging offers excellent chances to remotely collect data. The data including fire radiative power, fire line intensity, and spreading rate of fire both in time and space were considered. Software-based video stabilization method was a novel concept created especially for thermal infrared images of forest fires [3].

An adaptive system for identifying forest fire hotspots was proposed, and a contextual test algorithm was applied to specify forest fire points based on a novel technique. The new algorithm was used for monitoring fire disasters because it was quickly and efficiently extracted fire hotspot information and was sensitive to small and low-temperature fires [4]. The ATT Squeeze U-Net combines two popular network architectures: The squeeze-and-excitation block and the U-Net. The squeeze-and-excitation block was incorporated to enhance the feature representation capabilities of the network, allowing it to learn more discriminative features. The U-Net architecture, known for its effectiveness in image segmentation tasks, served as the backbone [5]. Geographic interpolation methods for mapping the daily evolution of fires was done and evaluated the precision of the maps produced by multi-sensor active fire products. The standard active fire products from the visible infrared imaging radiometer suite, the moderate resolution imaging spectroradiometer, and the combined products were used as inputs [6]. A novel hybrid way of clustering the causes of forest fires in Brazil was examined using PCA-DGM, which successfully solved clustering issues with various shapes [7]. Forest fires in the Amazon rainforest result from a combination of two factors, namely natural factors like lightning strikes and human factors including agricultural clearing, deforestation, and climate change effects. The impacts of live fuel moisture content (LFMC) and dead fuel moisture content (DFMC) were explored with a correlation between the parameters. The DFMC played a significant influence in causing the mega fire in California, although the LFMC exhibited the highest link with the occurrence of fire between 2001 and 2018 [8]. One of the most serious disasters that has been primarily kindled by global warming is forest fires. In another study, it was observed that the strength of the tree has significantly decreased, which resulted in an unhealthy forest environment. A system that deployed sensors in the forests monitors the various parameters such as temperature, humidity, and smoke, and then the collected data was transmitted to another layer, where real-time analytics and decision-making took place, which enables the early fire detection and timely alerts [9].

1.1.1 Unmanned aerial vehicles

Unmanned Aerial Vehicles (UAV) are increasingly employed in forest fire fighting. The drones provide critical advantages by accessing remote and hazardous areas, monitoring fire progression, and delivering real-time data to firefighters. Equipped with thermal cameras and sensors, UAV detect hotspots, enabling early intervention which can also carry payloads such as water or fire retardants for precision drops. Additionally, drones aid in search and rescue efforts by locating missing persons in dense forest environments. UAV can capture high-resolution images and it can create accurate maps of the fire perimeter which helps the firefighting teams to visualize the extent and direction of the fire. These maps assist in devising strategies for containing and extinguishing the fire effectively. Utilizing UAV in forest fire detection reduces the need for manned aircraft, minimizing the risk to human pilots. Drones are relatively cost-effective compared to traditional aerial surveillance methods.

In another approach, the use of UAV small cells to enhance or temporarily restore connectivity in ultra-dense cellular networks was investigated. The primary objective was to minimize the overall power consumption of the network by optimizing several key factors including the number of UAV small cells needed, their optimal placement, the user-device associations, and power allocation [10]. Focus on optimizing the position of UAV in communication systems to maximize throughput was addressed by [11] which targeted on optimal UAV placement for maximizing system throughput based on user traffic demands and locations. Two methods, a heuristic and an approximation algorithm, were presented and simulations demonstrated significant throughput improvements [11]. By leveraging the capabilities of UAVs, forest fire detection efforts can be significantly enhanced, leading to quicker response times, and more efficient firefighting operations, ultimately protect the forests and minimizing the extensive damage caused by wildfires [12]. With highly flammable forest areas, Uttarakhand state in India makes up to 5.43% of the Indian forest area. Mapping the burned areas was done using Sentinel-1 Synthetic Aperture Radar and validated the results using Sentinel-2 because COVID-19 interfered with field evaluation and ground truth validation [13]. A secure, energy-efficient multi-layer architecture using reconfigurable intelligent surfaces in integrated terrestrial-aerial networks to combat jamming and eavesdropping attacks was proposed by [14].

1.1.2 Internet of Things

The Internet of Things (IoT) is a transformative technology that connects physical objects to the digital world, enabling data-driven insights and automation across various domains. IoT refers to a network of interconnected devices, sensors, and objects that can communicate and share data with each other over the Internet. These devices are embedded with sensors, and connectivity capabilities enables them to collect, transmit, and receive data to perform various tasks and enhance efficiency in various domains, including environmental monitoring, health care, and agriculture. IoT devices can transmit alerts to a central monitoring system as soon as abnormal conditions are detected which enables rapid response and reduces the time between fire detection and firefighting efforts. IoT devices use a variety of communication protocols, such as Wi-Fi, Bluetooth, ZigBee, and cellular networks, to transmit data to central hub.

The image analysis is used to detect fire, alerts authorities through IoT devices, which trigger the preventive measures like sprinklers and fire extinguishers [15]. An IoT-based system for managing and detecting peatlands was installed near Malaysia's Raja Musa Forest Reserve in Kuala Selangor. The viability of the data of IoT systems was confirmed by examining the correlation between the collected data and the data from the Malaysian meteorological department. Ground water level was utilized to develop the drought code rather than temperature and rainfall measures. The field measurements of ground water level from multiple sites in a tropical peatland forest are collected and compared the predictions of the machine learning models with the ground truth measurements and analysed the accuracy and reliability of the predictions [16]. Rate-splitting multiple access for multicast communication in a satellite and aerial-integrated network catering to IoT device connectivity demands was proposed by [17] which optimizes spectral efficiency while minimizing interference and hardware complexity using an iterative penalty function-based algorithm. Simulations validated its effectiveness over benchmark methods.

1.1.3 Wireless sensor networks

A review of different types of sensors, such as temperature, smoke, and flame sensors, and how effectively the sensors detect fire-related phenomena were discussed. Also, the role of efficient communication protocols, data fusion techniques, and energy efficiency considerations in designing efficient Wireless Sensor Network (WSN)-based fire detection systems were addressed [18]. A set of data mining techniques including support vector machines and random forests were tested, and various techniques such as data fusion, anomaly detection, and quicker decision-making based on the collected sensor data were discussed for efficient management of firefighting resources, including prioritizing targets for air tankers and ground crews [19]. In [20], the random events that happen simultaneously were frequently reported by several nodes. The node's relative proximity to the event determines how well it can detect the events. The four specified parameters for which fuzzy field values were obtained for each variable via a membership function.

1.1.4 Drone path planning

Drones are increasingly being used in forest firefighting efforts due to their ability to provide valuable data and support to firefighting teams. Drones can carry payloads like water or fire retardant containers, which can be released at precise locations to combat the fire. Extended flight times allow drones to remain in the air for longer periods, providing continuous support to firefighting efforts. Drone network is capable of detecting the forest fire from the air and so it cannot be destroyed by the forest fire. The Particle Swarm Optimization (PSO) is a population-based metaheuristic optimization algorithm inspired by the social behaviour of bird flocking or fish schooling. It aims to solve optimization problems by iteratively improving a population of candidate solutions called particles. A novel optimization algorithm called the two-stage multi-swarm particle swarm optimizer was presented with application for both unconstrained and constrained global optimization problems. The two-stage process involved a global exploration stage and a local exploitation stage [21]. A novel algorithm called modified PSO with effective guides was implemented to improve exploration and exploitation capabilities which guides the particles based on historical information and the global best position enhances its performance in finding high-quality solutions for complex optimization problems [22]**.** Forest fire data is obtained for various countries including India, Amazon region in Brazil, USA, and Australia [23–26]. Ant Colony Optimization (ACO) leverages the principles of swarm intelligence and pheromone communication to efficiently navigate complex problem spaces and had demonstrated its effectiveness in solving a wide range of optimization problems. Artificial Bee Colony Optimization

(BCO) is a nature-inspired optimization algorithm inspired by the foraging behaviour of honeybee colonies to find high-quality solutions in various domains [27].

1.1.5 Deep learning-based approaches

A novel prediction approach provides the ability to decide what steps to be taken to reduce the harmful effects of wildfire causes based on its estimated scale in the fire's early stages. The data were split into training and testing sets following feature normalization and multi-collinearity testing. A Back Propagation Neural Network (BPNN), a Recurrent Neural Network (RNN), and Long Short-Term Memory (LSTM) were used for creating prediction models using the meteorological elements as input data. The LSTM method had the highest accuracy. In order to avoid the forest fire incidents, early detection of forest fire smoke is essential. Long-range wildfire smoke typically moves slowly. A unique attention-enhanced bi-directional LSTM network for video-based forest fire smoke recognition was proposed. The temporal attention subnetwork and the spatial features extraction network provided the highest accuracy and resulted in the fewest false alarms for a variety of settings [28].

Transfer learning (TL) uses pre-trained accurate models. A TL model which successfully solves a particular problem, can also be used to solve another related problem. The advantage of TL is, the time to train the TL model is comparatively low. The potential of TL in boosting the training progress of deep reinforcement learning was explored and the researchers tested the TL in OpenAI Gym games, such as SpaceInvaders and AirRaid. It was found that TL not only reduces the time taken for training but also leaded to better performance [29]. The idea of transferring deep features learned for image classification that predicted object location in tracking frames was done which improved tracking performance in accuracy and speed, with real-time capabilities [30]. A synthetic way to increase the size of the imagery dataset was developed and offered a new framework for automatically detecting dead trees from aerial pictures using a retrained mask region-based convolutional neural network (CNN) method with TL strategy. A framework that utilized CNN to analyse aerial images and classify them into different forest health categories was presented. Datasets of aerial photography were analysed and evaluated in eight fine-tuned models. By training the model on a large dataset of labelled images, the system was able to assess the health status of the forest [31].

1.1.6 Analysis of forest fire events across various countries

The forest fire incidents are increasing year by year gradually which affects the environment that leads to an unbalanced ecosystem, thereby to the death of flora and fauna. A set of guidelines for effective data visualization to visualize forest fire patterns, distribution, and trends were explored to enhance the understanding of forest fire data and decision-making processes [32, 33]. The count of fire spots reported in Amazon for the period 1999–2019 shows that the October–November–December season has more fire spots as shown in Fig. 1, and fire spots are on the rise from August month onwards till the end of the year.

In Indonesia, the forest fire is becoming very difficult to deal with, hence, many nearby countries like Singapore are joining hands with Indonesia to fight together.

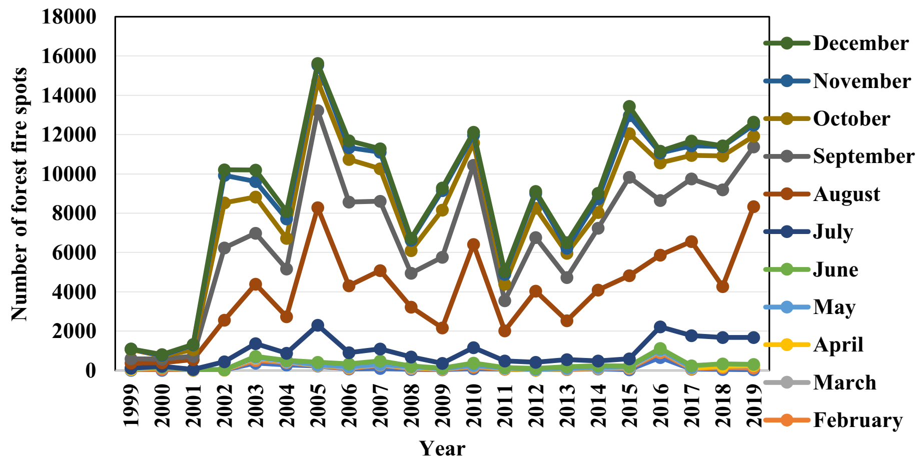

Fig. 1 Number of fire spots located in the Amazon forest area during year 1999–2019

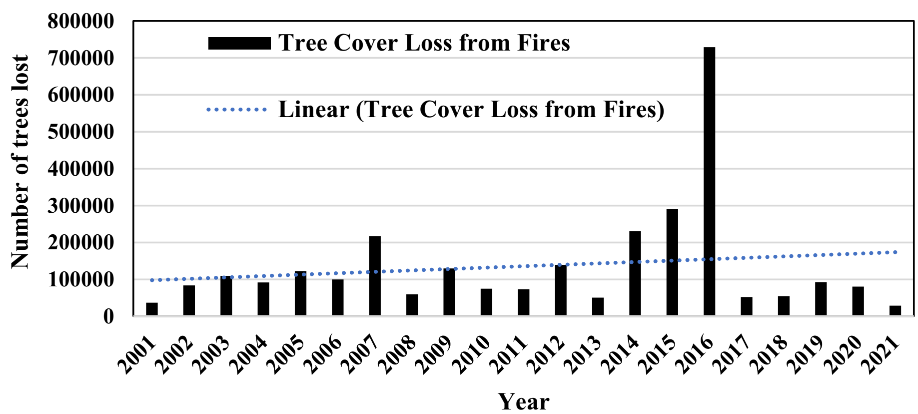

Fig. 2 Number of trees lost due to forest fire in Indonesia during 2001 to 2021

Figure 2 shows the loss of trees due to the forest fire for the past 20 years (2001–2021) in Indonesia and it is evident that, from the year 2014 to 2016, Indonesia had seen the biggest forest fire hazards and as a result of which, a lot of trees were lost during that time. There had been a decline in the number of trees lost, from the year 2019.

In the USA, a mega fire incident happened in California in the year 2018, which affected many people. In the year 2023, a forest fire was reported in Canada. India has seen heavy economic losses in few states due to forest fires. Due to increased temperatures and low availability of water, particularly during the summer season, India experienced major forest fire hazards in the last two decades.

Figure 3 showcases the number of forest fire events that occurred during the period of 2017–2021 in India. In 2021, India went through more number of forest fires when compared to the previous years.

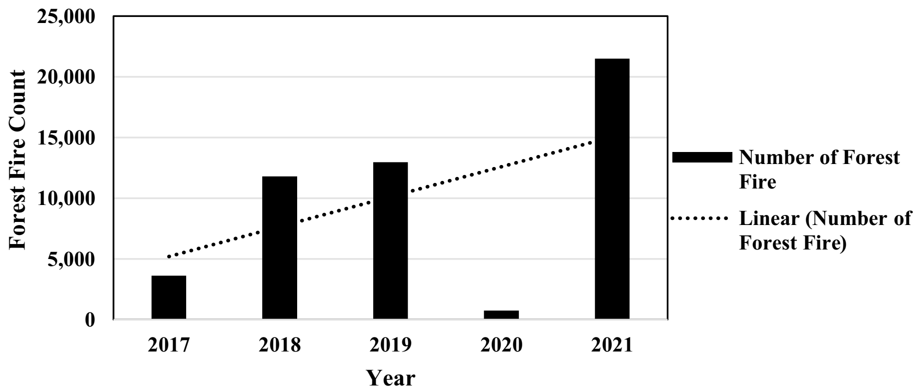

Fig. 3 Forest fire event analysis in India from year 2017 to 2021

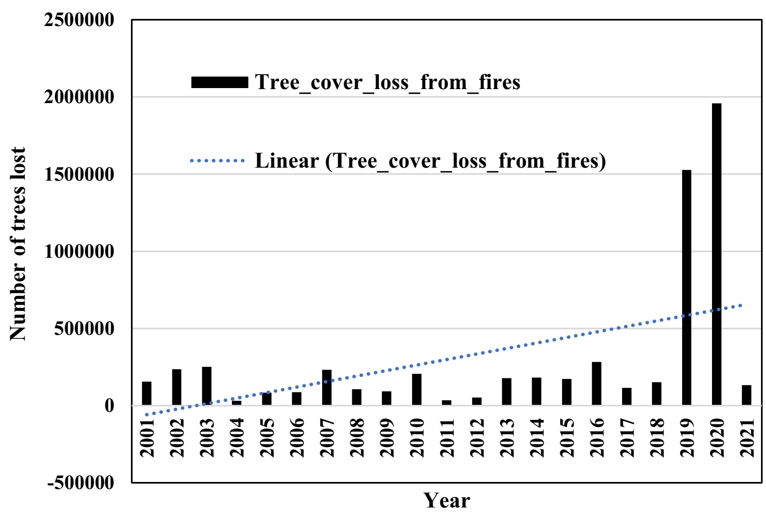

Fig. 4 Number of trees lost due to forest fires in Australia from the year 2001 to 2021

Figure 4 shows the loss of trees due to forest fires during 2001–2021 in Australia and it is linearly increasing year by year, except few years like 2008, 2011, and 2017. The year 2019 and 2020 had seen more of such disasters than previous years.

Figure 5 shows the number of forest fires in the USA from 1990 to 2021. It is clear that the number of forest fire hazards is comparatively less in the recent decade. The existing models are having few drawbacks such as static fire detection, less accuracy, and communication failure due to loss of components that are destroyed by fire. Even though many WSN-based implementations for forest fire detection are there in literature, the drawback is, the WSN will be destroyed in case forest fire that quickly destroys the infrastructure. So, there arises a need for a network that is not affected by fire and also to monitor the forest in real time. In this paper, TL-based techniques are used to detect forest fire. A dynamic fire quenching plan is generated for real-time forest fire quenching, and the TL models are used to detect the forest fire early.

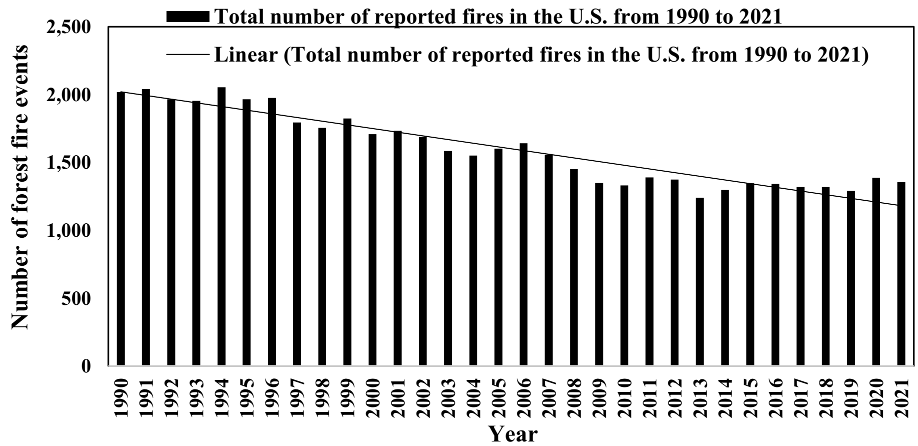

Fig. 5 Forest fire in the USA during the year 1990 to 2021

2 Experimental methods

VGG19Net is a deep CNN (DCNN) that has been widely used for various image classification tasks. It is characterized by its deep learning architecture, which consists of 19 convolutional layers, followed by fully connected layers for classification. VGG19Net [34] processes images of size 224 × 224 pixels, and the input images are modified accordingly. The input images are transformed using scaling, cropping, and flipping. After initializing the weights of the model with the pre-trained weights, fine-tuning is performed to adapt the model to the new task which involves updating the weights of the last few layers. GoogLeNet [35] is designed to achieve high accuracy while minimizing the number of parameters in the network.

The drone network is capable of detecting the forest fire from the air and so it cannot be destroyed by the forest fire. The drones have high-resolution camera and thermal imaging camera along with a computing node that runs the TL-based image processing model. The proposed system uses state-of-the-art CNN-based image processing and video processing for forest fire detection. Fire risk alarm is useful which provides early warning and it alerts the government and fire agencies. Forest fire early warning notifications are given to respective forest fire and rescue services departments. The drones have high-resolution camera and thermal imaging camera along with a computing node that runs the transfer learning-based image processing model. This data helps firefighting teams assess the fire's size, direction, and intensity. Drones can carry various sensors, including gas sensors, to detect changes in air quality caused by smoke and hazardous gases which is critical for assessing the safety of firefighting personnel. Thermal cameras on drones can detect hotspots and the fire's heat signature even in low-visibility conditions. Geographic Information System (GIS) capabilities enable drones to create detailed maps of the fire's perimeter, helping firefighters plan containment strategies. With respect to India, forest fire database from forest survey of India, and Indian Council of Forestry Research and Education dataset of forest fire points in India which includes information on the location and timing of forest fires.

2.1 Proposed early warning system for forest fire detection

GoogLeNet is used for forest fire detection in the proposed methodology. The images are resized to a standard size and normalized the pixel values. A new classification layer that is specific to forest fire detection is added. Further, the weights of the initial layers are fixed, which detects the low-level features and updates the weights of the later layers that detects the high-level features such as smoke and fire.

Other models such as ResNet, AlexNet, and MobileNet are modified similarly to make it ready for forest fire detection. The work flow diagram is shown in Fig. 6, and the proposed forest fire detection methodology is explained in algorithm 1. The water bodies in the forest area are marked as vertices in the graph, and the connectivity between vertices are represented as weighted edges. Floyd–Warshall algorithm is used to find the shortest path to water resources. The runtime of proposed algorithm 1 is $O(n^3)$. The proposed algorithm operates on live data and takes decision to control the forest fire. The state of the art image processing techniques ensure that the forest fire or smoke is detected immediately and hence it is useful in real-time use.

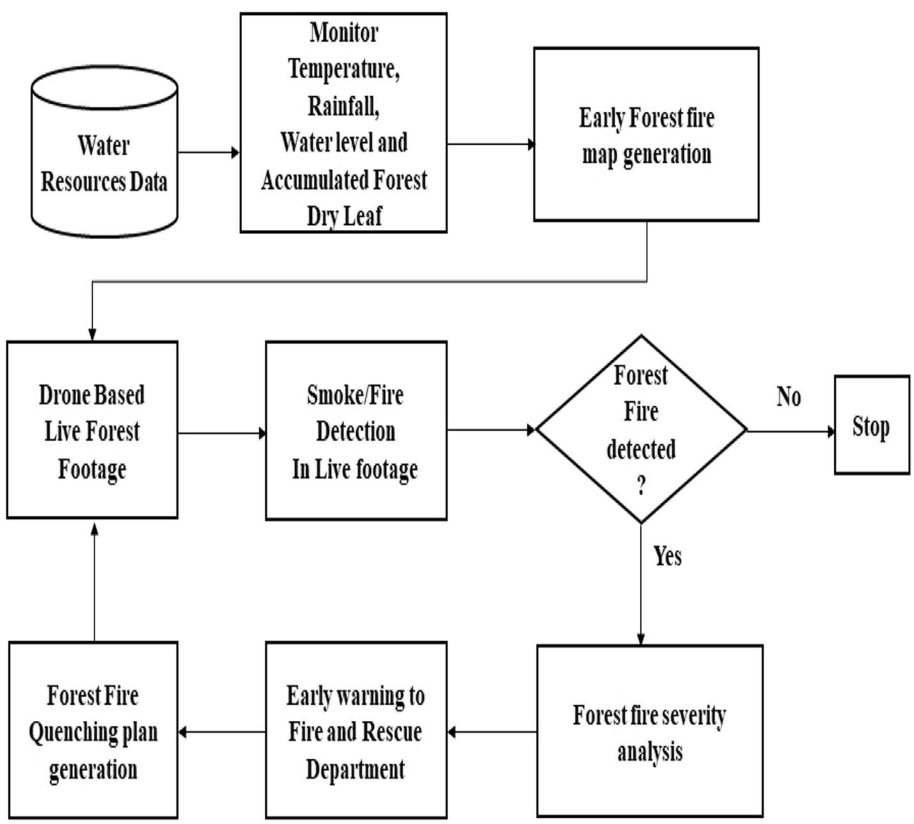

Fig. 6 Work flow diagram for TL-based early forest fire detection and dynamic fire quenching system

Algorithm 1 TL-based forest fire early detection and dynamic quenching plan generation

Input : Forest location, Forest water body graph (G), Rainfall, Temperature, Wind data, and TL models.

Output : Forest fire quenching plan generation and early warning of forest fire

BEGIN

1. Get drone live images for the given forest area.
2. Apply TL model for smoke and fire detection in drone images.
3. IF smoke or forest fire is detected or high risk is assessed THEN
   a. Perform fire severity analysis
   b. Generate a dynamic fire quenching plan on the graph G, using shortest path to water resources
   c. Share the fire quenching plan with the fire and rescue team
   d. Leading drone finds the forest fire location and establishes the communication with nearby drones. Remaining drones use particle swarm optimization technique to locate the forest fire and quench the same.
   e. Monitor and update the fire quenching plan based on the effectiveness of the response
   END IF
4. IF no fire is detected or the forest fire risk is low THEN
   Continue monitoring and update fire risk assessment
   END IF

END

2.2 Dynamic forest fire quenching plan

In case of forest fire, fire quenching plan is generated with respect to the given location, the nearby water bodies are listed using the shortest path algorithm. Furthermore, other backup locations where water available are also shown. Once a fire is located, PSO

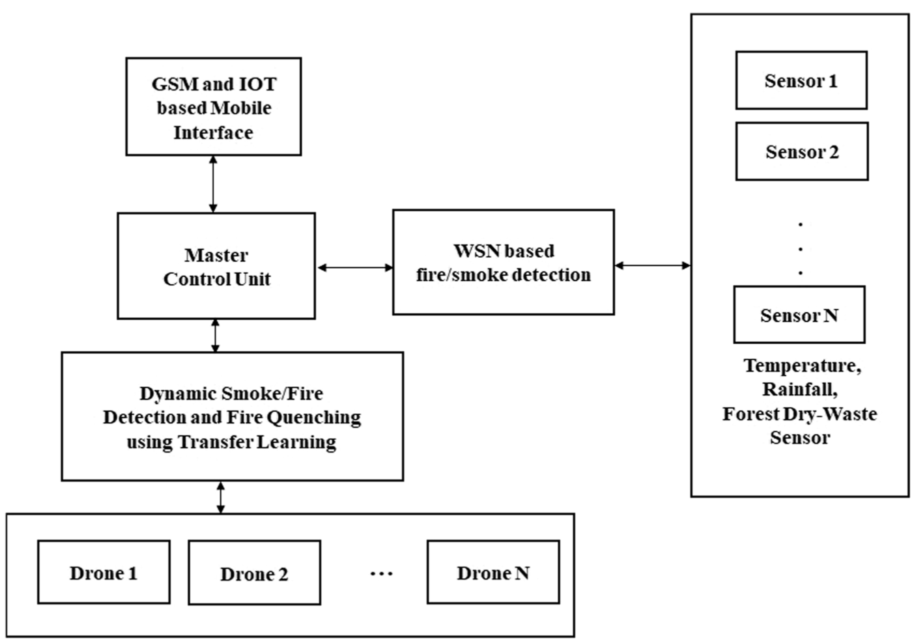

Fig. 7 Proposed early forest fire detection and dynamic fire quenching system

technique is used to find the best possible fire quenching plan. Once the leading drone is reaching the nearest point to fire, it establishes the communication with nearby drones and then other drones reach to the fire location and quench the same. The algorithm 2 explains the steps for early detection of forest fires. The runtime of algorithm 2 is $O(n^3)$. The forest fire alarm is the early warning signal that alerts the fire and rescue department. The necessary actions are initiated by the officers and the effectiveness of the operations are monitored by a master control unit. Figure 7 explains the overall architecture of the proposed methodology that considers physical parameters such as temperature, rainfall, amount of dry waste accumulated in the forest, wind speed, and heatwave information and uses TL-based DCNN for smoke and fire detection.

```
Algorithm 2   Early forest fire detection and forest fire risk alarm generation

Input   :   Forest Sensor data, Wind speed, Accumulated forest dry leaf, Temperature data,
            Rainfall data, Number of Days (N), Forest area to be covered, TL models, Heatwave data
Output  :   Generation of forest fire risk alarm
BEGIN
    1. Pre-process the sensor data
    2. IF the station's maximum temperature is <=40 degree Celsius AND
            Departure from normal temperature is 5 to 6 degree Celsius, THEN
            Generate forest fire risk alarm
       END IF
    3. IF the station's minimum temperature is >40 degree Celsius AND
            Departure from normal temperature is 4 to 5 degree Celsius, THEN
            Generate forest fire risk alarm
       END IF
    4. Analyse the amount of accumulated dry leaf and the heat wave possibility
    5. IF forest dry leaf waste is beyond the safety limits OR
          The heat wave is possible within N days OR
          Dry leaf burning point temperature is reached in the current forest area THEN
            Generate forest fire risk alarm
       END IF
    6. IF wind speed is favourable for the spreading of forest fire THEN
            Generate forest fire risk alarm
       END IF
    7. IF a forest fire risk or forest fire spread alarm is generated THEN
             Call TL-based forest fire early detection and quenching plan generation
       END IF

    8. IF the given forest area has no forest fire risk, THEN
            Report the status to the master control unit and generate stop signal
       END IF
    9. IF any problem is reported in drone operation THEN
            Generate stop signal and report
       END IF
END
```

In case fire or smoke is detected, it immediately communicates to the fire rescue team. Furthermore, the proposed system performs fire severity analysis based on the wind speed and direction, it finds the projected path in which fire spreads and generates the fire quenching map dynamically pointing out the nearby water resources.

This map also helps to plan the evacuation of people and forest animals which minimizes the damage due to forest fire. If the fire is very severe to handle, it alerts the next-level disaster management and recovery team for instant action. It is found that the proposed system is able to quickly find the best plan and the alternate plans with minimal time and hence it is suitable for real-time use. For very dangerous forest fires, anti-fire chemicals can be sprayed using helicopters or drones. Since the fire is detected early and quenched early, it helps to save the environment and thereby protecting the flora and fauna. A total of ten thousand images related to Indian forest fire events are considered for training and testing. A confusion matrix is used as a measure of the performance of classification algorithms which has four important results, namely true positive (TP), true negative (TN), false positive (FP), and false negative (FN) as shown in Table 1.

The vital parameters are calculated using the following formulas.

$$\text{Precision} = \frac{\text{TP}}{\text{TP} + \text{FP}} \tag{1}$$

$$\text{Recall} = \frac{\text{TP}}{\text{TP} + \text{FN}} \tag{2}$$

$$\text{Accuracy} = \frac{\text{TP} + \text{TN}}{\text{Total}} \tag{3}$$

$$\text{F1 Score} = \frac{(2 * \text{Precision} * \text{Recall})}{(\text{Precision} + \text{Recall})} \tag{4}$$

$$\text{True Positive Rate} = \frac{\text{TP}}{\text{TP} + \text{FN}} \tag{5}$$

$$\text{False Positive Rate} = \frac{\text{FP}}{\text{FP} + \text{TN}} \tag{6}$$

3 Results

The TL-based image processing techniques are tested for accurately detecting the forest fire. The machine learning algorithm and DCNN that are modified with TL implementations are compared and the best one is found out and the results are shown in Table 2 and Fig. 8. The F1 score is a metric commonly used to evaluate the performance of binary classification models. It provides a balance between precision and recall, which are two essential evaluation metrics for binary classifiers. The F1 score takes into account both FP and FN and provides a single metric to assess the model's overall performance.

From the accuracy, precision, recall, and F1 score, it is clear that the proposed GoogLeNet-TL methodology performs better. The Receiver Operating Characteristic (ROC)

Table 1 Confusion matrix

Confusion matrix	Predicted values	
Actual values	**Fire**	**No Fire**
Fire	True positive	False positive
No Fire	False negative	True negative

Table 2 Classification metrics for forest fire detection

Algorithm	TP	TN	FP	FN	Accuracy	Precision	Recall	F1
ResNet-TL	5123	3114	527	1236	0.82	0.85	0.9	0.81
VGGNet-TL	5591	2419	1183	807	0.80	0.85	0.82	0.87
MobileNet-TL	6617	1917	744	722	0.85	0.9	0.89	0.9
AlexNet-TL	6073	1987	1219	721	0.81	0.86	0.83	0.89
GoogLeNet-TL	8011	1589	152	248	0.96	0.98	0.98	0.97

curve is a graphical representation of the performance of a binary classification model across various discrimination thresholds. It is a fundamental tool used to assess and compare the accuracy and performance of different classifiers or models. The ROC curve is created by plotting the True-Positive Rate (TPR) against the False-Positive Rate (FPR) at various threshold values.

The ROC curve is drawn for the set of the algorithms used and it is shown in Fig. 9. It is clear that, GoogLeNet-based TL model has very good performance followed by MobileNet-based TL model. Along with PSO, ACO, and BCO are tested for measuring the performance metrics. The best path taken by the drones using ACO is shown in Fig. 10.

The trajectory of 10 drones using PSO is shown in Fig. 11, and the cost function is shown in Fig. 12. It is very clear that the PSO is very quickly reduces the cost function to zero. Total distance travelled by drones and total time taken are analysed, and the results prove that PSO is suitable for forest fire quenching. Here, 10 m per second speed is the speed of the drone for calculating the time taken. The results are shown in Figs. 13 and 14.

4 Conclusion and future work

The proposed method is very helpful to prevent forest fire at a very early stage. The proposed TL-based forest fire quenching plan helps to protect the environment, ecosystem and thereby the economic state of the country. Five state of the art image processing techniques modified with TL algorithms are used to detect the forest fire events in India. The GoogLeNet-based TL provides high accuracy and F1 score than all other models which generates fire quenching plans based on shortest path to water resources and also notifies the next level disaster management teams based on the fire severity. The proposed model helps to save the ecosystem, protects nature, and ensures a pollution-free

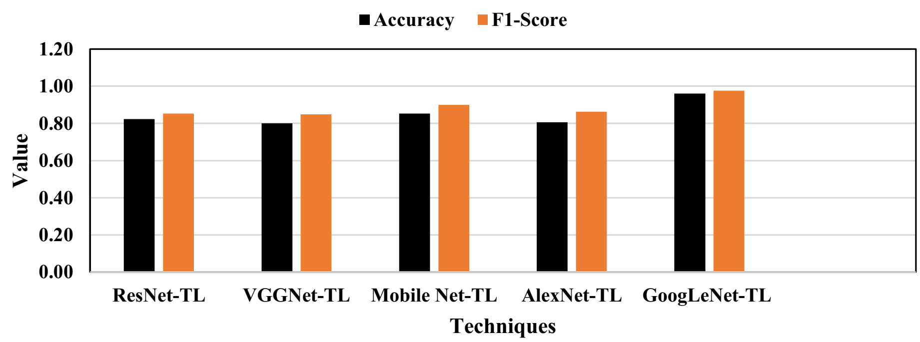

Fig. 8 Comparison of accuracy and F1 score for various TL-based algorithms for forest fire detection in India

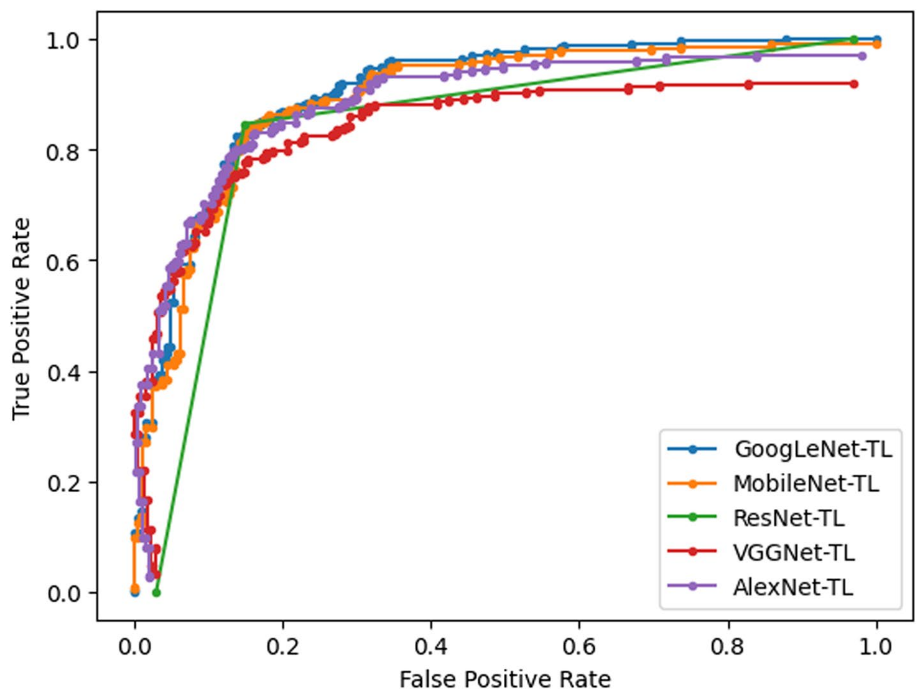

Fig. 9 Receiver Operating Characteristics for various algorithms

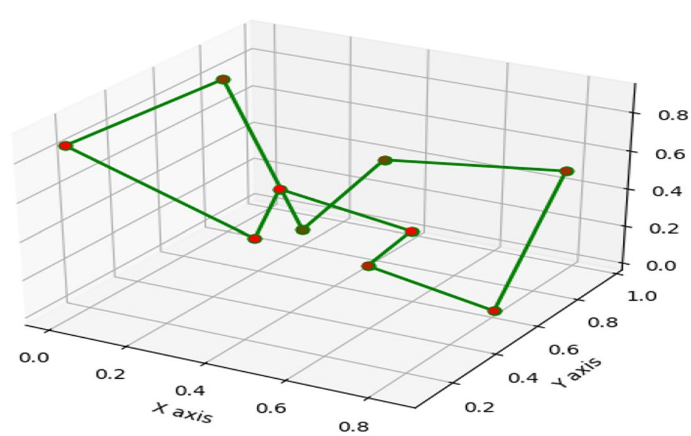

Fig. 10 Best path taken by drones when ACO is used for forest fire quenching

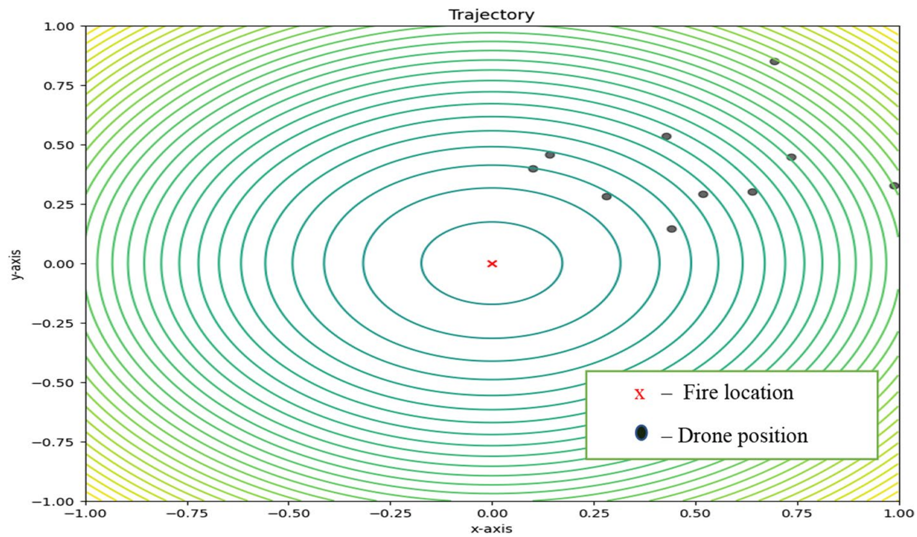

Fig. 11 PSO Trajectory obtained for 10 drones

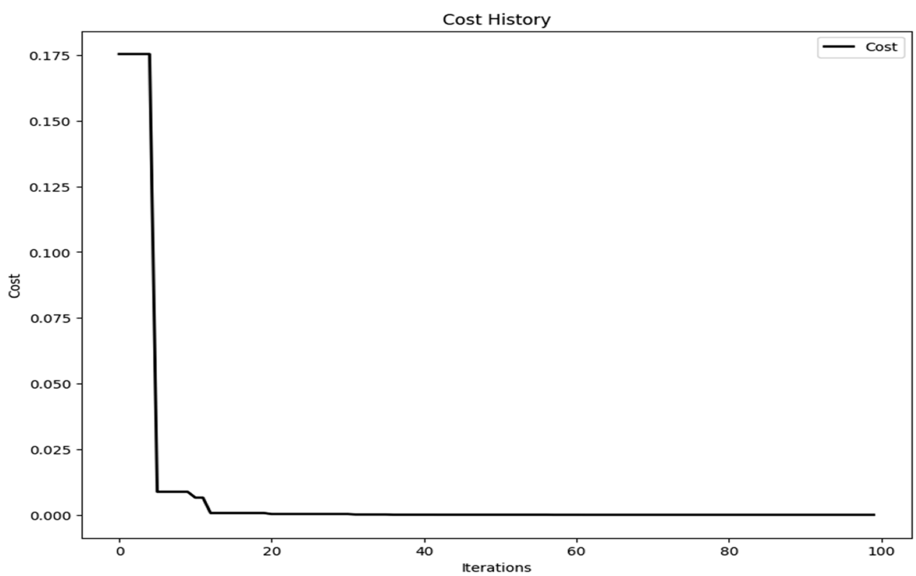

Fig. 12 PSO cost function

environment, thereby bringing prosperity to the people. The proposed system can be used for other countries with little modifications. As a future enhancement, an army of drones with anti-fire chemical spraying facilities can be used that leads to a better way to protect the forest. The drone network can also be extended to support intrusion detection and surveillance.

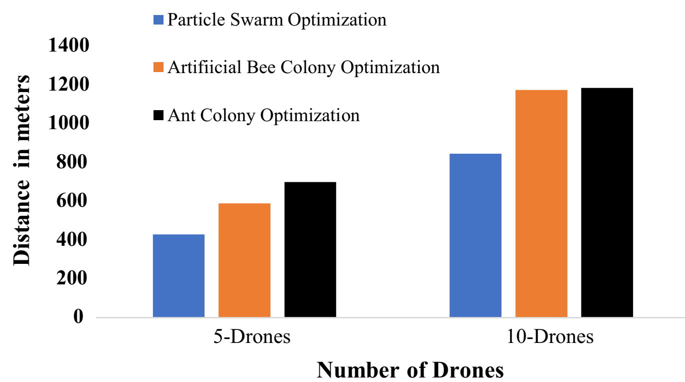

Fig. 13 Total distance travelled by all drones for forest fire quenching

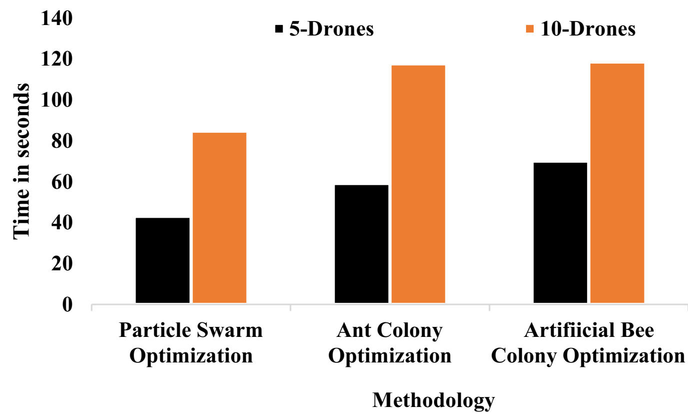

Fig. 14 Total time taken by all drones for forest fire quenching

Abbreviations

ACO	Ant Colony Optimization
BCO	Artificial Bee Colony Optimization
BPNN	Backpropagation neural network
CNN	Convolutional neural networks
DCNN	Deep convolutional neural networks
DFMC	Dead fuel moisture content
FP	False positive
FN	False negative
FRP	Fire radiative power
IOT	Internet of Things
KNN	K-nearest neighbour
LFMC	Live fuel moisture content
LR	Logistic regression
LSTM	Long short-term memory
PSO	Particle Swarm Optimization
RNN	Recurrent neural network
ROC	Receiver Operating Characteristic
TL	Transfer learning
TP	True positive
TN	True negative
UAV	Unmanned aerial vehicles
WSN	Wireless sensor networks

Acknowledgements
The authors thank the Big Data Analytics Research and Development laboratory, Department of Computer Technology, MIT Campus, Anna University for providing the infrastructure support to carry out the research. One of the authors Dr. C. Valliyammai, is thankful to the Science and Engineering Research Board, Department of Science Technology, Government of India for the award of SERB–POWER (Promoting Opportunities for Women in Exploratory Research) Fellowship

(File No. SPF/2021/000068) and providing technical support to carry out this work. The authors would like to thank the respected editors and the reviewers for their helpful comments.

Author contributions
CV has contributed to the research paper by setting the overall goal and drafted the idea for proposed architecture and helped choose the set of algorithms for the project. SM has contributed for the research by gathering the required data and by implementing the idea in python and performed result analysis. SM has written the manuscript, and CV has reviewed and provided critical inputs to improve the manuscript.

Funding
This article has not received any funding support.

Availability of data and materials
All the data used in this research are publicly available.

Declarations

Competing interests
The authors declare that they have no conflicts of interest to report regarding the present study.

Received: 19 May 2023 Accepted: 17 October 2023
Published online: 04 November 2023

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