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REVIEW ARTICLE

Machine learning techniques for forest fire prediction: Current trends, challenges and future directions

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Abstract

Forest fires pose a significant threat to ecosystems, biodiversity and human livelihoods, necessitating the development of advanced predictive models for timely intervention. Machine learning (ML) techniques have emerged as effective tools for predicting forest fires by utilizing various environmental, meteorological and topographical datasets. This review explores recent advancements in ML-based fire prediction, highlighting key methodologies such as Random Forest, Support Vector Machines, Neural Networks and hybrid models. The combination of remote sensing data, real-time observation and cloud computing has notably improved the prediction accuracy. Moreover, the growth of Explainable AI (XAI) has enhanced the interpretability of ML models. Despite advancements, challenges such as data imbalances, model generalization issues and computational constraints persist. Future research must focus on refining ML algorithms to improve regional adaptability, integrating climate change forecasts and establishing real-time early warning systems. By bridging the gap between theoretical advancements and practical applications, ML-driven forest fire prediction models can significantly contribute to mitigating the devastating impact of forest fire and enhancing global fire management strategies.

Keywords: forest fire prediction; machine learning; neural network; random forest; support vector machine

Introduction

Forests play a vital role in maintaining ecological balance by supporting biodiversity, regulating water cycles and sequestering carbon (1). Forest fires disrupts these functions, leading to long-term ecological damage, soil degradation and loss of wildlife habitats (2). These fires may originate from natural occurrences like lightning strikes or from human activities like arson, careless burning or ignorance (3). Worldwide, the incidence of forest fires has increased due to extended periods of drought and heat waves caused by climate change (4). In India, forest fires happen annually, particularly in the northern regions of Himachal Pradesh and Uttarakhand (5). Main reasons for the country's forest fires include slash-and-burn agriculture and the expansion of human communities adjacent to forested regions. Insufficient resources for fire prevention and management are the reason for the occurrence of large fires (6). Forest fires significantly contribute to greenhouse gas emissions by releasing large amounts of CO_2 and various pollutants into the atmosphere, thereby exacerbating climate change. These fires lead to considerable economic damage, endanger the safety and lifestyle of the local community and present a major risk to the country's abundant biodiversity and natural ecosystem (7). A United Nations assessment states that the total area of forests worldwide fell from approximately 7000 million hectares in 1900 to 2890 million hectares in 1975. Severe forest fires have affected several countries in Asia, Africa, Europe, North America, South America and Australia (8).

In India, 20.5 % of the country's total land area is covered by forests, which amounts to 67.5 million hectares (India State of Forest Report, 2023). It consists of 41.68 million hectares of deep forest and 25.87 million hectares of open forest, according to previous research studies (9). Forest fires are a major factor contributing to the degradation of India's forests. In tropical deciduous forests, summertime brings more water stress and more fires (10). Although precise data on fire-related losses are limited, estimates indicate that the yearly risk of wildfires affecting forested regions ranges from 33 % in certain states to over 90 % in others (11). According to the Forest Protection Division of the Ministry of Environment and Forests, 3.73 million hectares of Indian forests are lost by fire every year.

Predicting forest fires plays a crucial role in mitigating their harmful impacts. By utilizing advanced technologies and examining data, we can forecast when forest fires may occur and create strategies to minimize their effects. The goal of fire prediction models is to assess the likelihood and potential trajectory of forest fires by utilizing various meteorological and environmental factors (12). It considers the complex relationships among different elements that can significantly affect the start and spread of fires, including fuel moisture content, terrain characteristics, wind patterns and human actions. Nevertheless, there are several challenges in developing reliable and accurate models (10). Additionally, the impact of climate change on fire patterns and the possibility of new fire behaviours involve uncertainties that pose difficulties for existing models to address this problem (13). Despite these obstacles, fire prediction models are still progressing towards goals like early warning systems, efficient resource allocation for fire management and guidance on mitigation and land-use planning. There must be continuous advancements in data gathering, modelling techniques and knowledge of fire dynamics for these models to become more accurate and practical. Current assessments in the geosciences (14), extreme weather prediction (15), forest ecology (16), flood forecasting (17), statistical downscaling (18), remote sensing (19) and water resources demonstrate the efficacy of using Machine Learning (ML) models.

Machine learning techniques such as Random Forests (RF), Support Vector Machines (SVM), Gradient Boosting Machines (example: XGBoost) (20) and deep learning frameworks like Artificial Neural Networks (ANNs) have found extensive application in wildfire prediction (21). These models are particularly adept at handling diverse data sources, which encompass satellite imagery, meteorological information, vegetation indices and historical records of fires (22). These models are highly significant because they can provide crucial insights to decision-makers, researchers and professionals involved in fire management (14). This article aims to highlight contemporary trends by evaluating the most recent advancements in ML algorithms utilized for forest fire prediction, emphasizing their advantages, limitations and possible applications. Furthermore, the analysis explores potential research directions aimed at enhancing the effectiveness and reliability of ML-based forest fire prediction systems. The review aims to bridge the gap between theoretical advancements in ML and their practical applications in forest fire management. Data obtained from the Scopus database reveals that a significant number of research papers on forest fire prediction began to emerge around 2017 (Fig. 1). Following that period, the volume of publications has steadily increased, with many appearing as research articles and conference papers (Fig. 2).

Fundamentals of forest fires and predictive factors

Understanding their causes and contributing factors is essential for effective prevention and management. Wildfires, commonly known as forest fires, are uncontrolled fires that occur in forested or plant-rich areas (23). The start and spread of forest fires depend on three fundamental elements known as the "fire triangle": fuel, oxygen and heat (24). When these factors align under suitable environmental conditions, a fire can spark and rapidly expand. Forest fires can be caused by both natural events and human activities (25). Natural events such as lightning strikes are responsible for many ignitions in isolated regions, alongside occurrences like volcanic eruptions and spontaneous combustion due to elevated temperatures (26). Conversely, human activities play a significant role in forest fire incidents and include practices like agricultural burning, leaving campfires unattended, tossing away cigarettes and intentional arson (27). The behaviour of a forest fire is influenced by several factors. The speed at which fire spreads is influenced by wind velocity, the type of combustible materials present and the landscape of the area (23). The intensity or the quantity of energy released during the burning process, is dependent on the fuel availability and current environmental conditions (28). Finally, the fire's direction is greatly affected by wind direction and the terrain features, which are crucial in determining the fire's movement. Predicting forest fire involves understanding the interaction between environmental, meteorological, topographical, vegetation and anthropogenic factors (Fig. 3). These factors influence both the chances of fire igniting and its spread. Remote sensing and sensor networks enable the real-time collection of these factors and providing critical inputs for ML models to predict and assess forest fire risk.

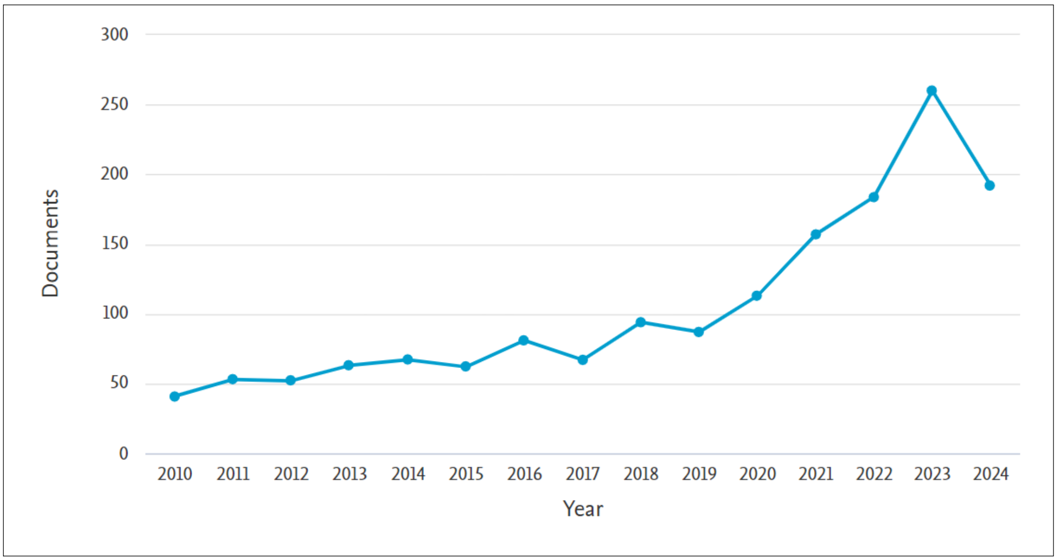

Fig. 1. Total number of documents published by year wise.

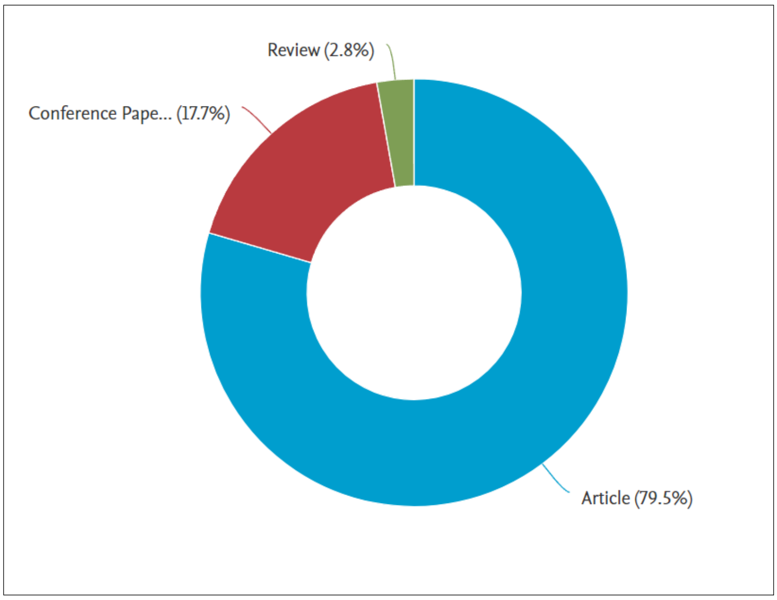

Fig. 2. Types of documents published.

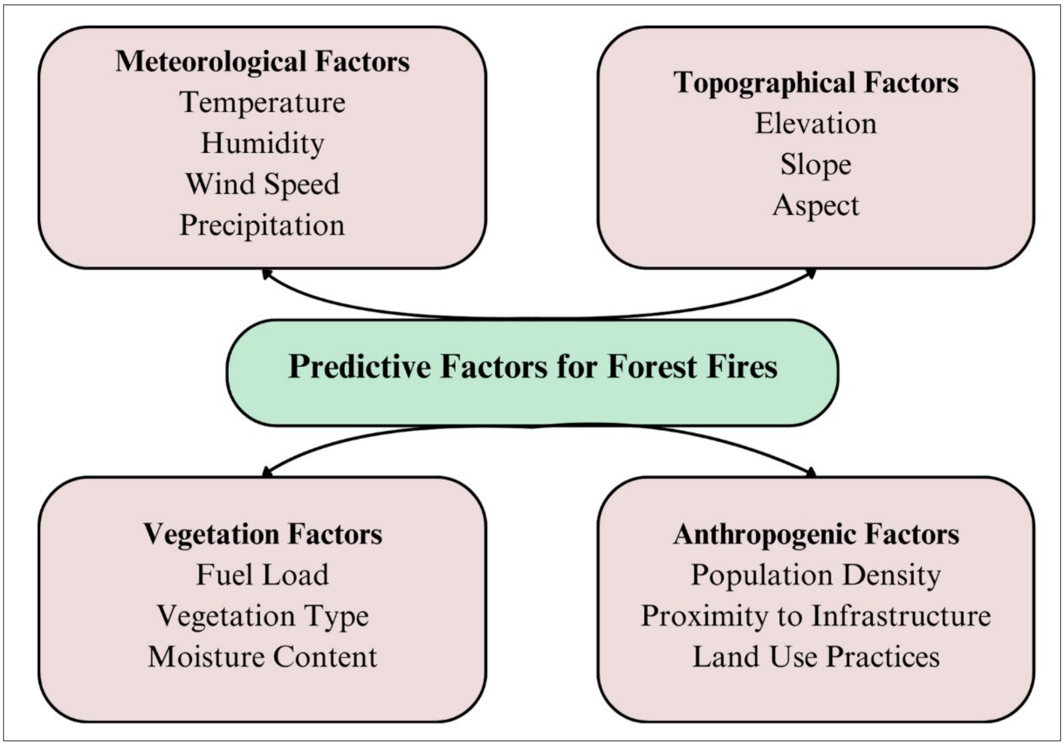

Fig. 3. Predictive factors for forest fires.

The overall risk of forest fires is determined by the combination of various factors. Weather conditions such as extended periods of drought increase the likelihood of fires by drying out vegetation, making it more susceptible to ignition (29). The geography plays an important role as it influences wind currents that can carry embers across large areas, promoting fire spread (30). Human activities, including agricultural practices such as shifting cultivation and careless actions such as campfires, substantially increase the risk of forest fires, especially in areas that are already vulnerable to natural fires. Identifying these predictive factors is crucial for developing precise models that forecast fire risks (31). ML techniques have proven to be powerful tools in this regard, as they analyse historical data from multiple variables to predict future fire events effectively (32). For example, remote sensing technologies utilize satellite imagery to monitor moisture levels in vegetation, while statistical models investigate the relationships between previous weather trends and fire occurrences (33). More sophisticated techniques, such as RF and ANN, combine various variables to provide extremely accurate spatial predictions, which facilitates enhanced risk management and prevention strategies (34).

Overview of machine learning in forest fire prediction

Machine learning is a branch of Artificial Intelligence (AI) that allows systems to learn from data and enhance their performance without being explicitly programmed (35). In the realm of predictive analytics, ML utilizes both historical and real-time data to uncover patterns, predict outcomes and improve decision-making processes (36). Predictive analytics encompasses techniques like statistical modelling and data mining employs ML algorithms to examine the relationships between different variables and accurately predict future occurrences. This ability makes ML essential for predicting forest fires, where the intricate interactions of meteorological, topographical and vegetation factors need to be analysed to evaluate fire risks (37). The importance of ML in predicting forest fires lies in its ability to tackle significant challenges such as non-linearity and high dimensionality in the data (38). Traditional approaches often rely on static models or rules derived from expert knowledge, which frequently struggle to capture the intricate and unpredictable aspects of wildfire dynamics. In contrast, ML models can analyse extensive datasets from multiple sources, including satellite imagery, weather data and historical fire records (13). For example, supervised learning techniques can identify areas vulnerable to fires by leveraging labelled historical data, while unsupervised learning can uncover hidden patterns within unlabelled information (39). Moreover, reinforcement learning improves decision-making by optimizing resource allocation for firefighting efforts. In comparison to traditional statistical techniques, ML marks a significant evolution in predicting forest fires (40). Traditional models are limited by their dependence on predefined assumptions and narrow datasets, which frequently results in overly simplistic predictions (41). The adaptability of ML enables it to capture intricate relationships without needing specific programming or assumptions regarding the underlying data distribution. Furthermore, advanced ML techniques such as neural networks and ensemble techniques can integrate multimodal data, such as thermal images and humidity levels (42). This flexibility not only enhances accuracy but also facilitates real-time risk evaluation, establishing ML as an essential resource for proactive forest fire management. The commonly used ML algorithms and their specific use cases in forest fire prediction are given in Table 1. An analysis of the existing literature reveals a clear trend in the application of specific ML models. This is visually represented by a word cloud generated using frequency-based word cloud analysis (Fig. 4). This figure illustrates the frequency of ML algorithms employed in forest fire prediction research. The size of each algorithm's name corresponds to its relative prevalence in the literatures. Prominent techniques include RF, Logistic Regression, ANN, Convolutional Neural Networks (CNN), Support Vector Machines and Decision Trees, indicating their widespread use in addressing prediction challenges. The major reasons for the RF and Logistic regression being dominant are their ability to handle non-linear features and binary outcomes effectively. Additionally, the inclusion of terms such as "Boosting," "Ensemble Learning," and "Hyperparameter

Table 1. Common ML algorithm and their specific use cases

ML algorithm	Specific use case in forest fire prediction	References
Regression models	Predicting the size and intensity of forest fires based on environmental factors	(71)
Decision Trees (DT)	Identifying high-risk fire-prone areas by analysing key variables such as vegetation type and topography	(72)
Random Forests (RF)	Classifying regions with varying fire susceptibility by combining multiple decision trees for robust predictions	(73)
Support Vector Machines (SVM)	Predicting small-scale fire occurrences by analysing meteorological patterns and vegetation indices	(74)
Clustering techniques	Detecting spatial and temporal patterns of forest fires to identify hotspots and seasonal trends	(75)
Artificial Neural Networks (ANN)	Modelling nonlinear relationships between variables like fuel moisture, wind speed and fire spread dynamics	(76)
Convolutional Neural Networks (CNN)	Analysing satellite imagery to detect thermal anomalies and classify regions based on fire risk	(77)
Hybrid models	Combining regression models with neural networks for improved accuracy in predicting fire susceptibility values across diverse datasets	(78)
Ensemble models	Integrating multiple ML algorithms like RF, SVM and ANN to enhance predictive accuracy and reliability	(72)

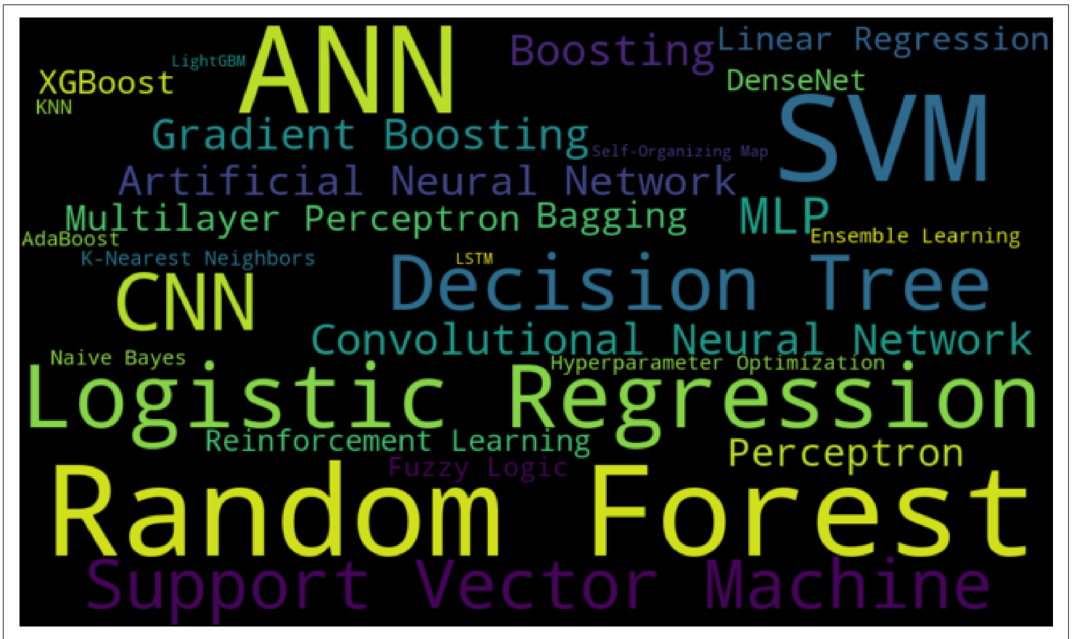

Fig. 4. Word cloud visualization of ML techniques used in forest fire prediction.

Optimization" highlights the trend toward advanced model architectures and fine-tuning strategies aimed at improving predictive performance. The word cloud provides a concise visual summary of the diverse landscape of ML algorithms currently applied in forest fire prediction. Also, a wide range of datasets, augmentation techniques and evaluation metrics have been used across various studies to improve the performance of forest fire prediction models. An overview of commonly used data sources is provided in Table 2 and various data augmentation techniques is explained in Table 3. A different step involved in data preprocessing is shown in Fig 5. Additionally, the performance metrics used for evaluating these models are summarized in Table 4.

Machine learning techniques for forest fire prediction

As forest fire becomes increasingly common and widespread, researchers are utilizing ML techniques to gain insights into the contributing factors. Researchers have explored different approaches for using ML in forest fire prediction, such as integrating it with traditional techniques or other strategies. Forest Fire Spread Behaviour Prediction (FFSBP) model integrates Cellular Automata (CA) with the Wang Zhengfei model (a model that predicts forest fire spread velocity and direction) along with ensemble machine learning to estimate the burned area (48). CA was selected due to its capacity to simulate fire spread dynamics, while ensemble learning improves the prediction accuracy. The model was evaluated using data from the "3.29 Forest Fire" in China to validate fire spread. Additionally, fire data from Montesinho National Forest Park, Portugal, was used to predict the burned area. Results indicate that the FFSBP model estimated a burned area of 286.81 hectares with a relative error of 28.94 %, surpassing the performance of the Farsite and Prometheus models. The FFSBP model, which employs XGBoost, LightGBM and GBoost, provided reliable predictions for burned areas, particularly for small and medium-sized fires (49). The research concludes that the FFSBP model significantly improves prediction regarding fire spread and damage, offering essential insights for firefighting and forest management practices. The RF algorithm combined with remote sensing is employed to assess forest degradation in Ukraine during the wartime period of 2022–2023 (50). Random Forest was chosen for its high accuracy in land cover classification and its ability to process large satellite datasets effectively. They have analysed deforestation patterns using Landsat 8 satellite imagery and the Hansen Global Forest Change dataset. The results indicate significant forest loss in areas affected by the conflict, with 807.56 km^2 lost in 2022 and 771.81 km^2 in 2023. The study concludes that deforestation caused by war is a critical environmental issue, emphasizing the importance of AI-driven early warning systems to monitor and alleviate ecological damage in areas impacted by conflict. A data-driven forest fire spread prediction model was developed using a Spatiotemporal Graph Neural Network (STGNN) (51). This method was chosen to overcome the issues of accuracy and transferability limitations of traditional wildfire models by integrating both spatial and temporal factors influencing fire spread. The model was trained on a dataset of European wildfires from 2016 to 2022, featuring satellite-derived burned area perimeters, meteorological data (ERA5-Land), fuel types, land cover and topography. The result showed that neither the Portugal model nor the Mediterranean model reached high accuracy levels (IoU: 0.37 and 0.36, respectively), but the Mediterranean model exhibited superior generalization across various regions. The research concludes that, despite limitations in accuracy, STGNN offer opportunities for enhancing forest fire prediction by identifying generalized spread patterns, although the quality of data remains a major challenge. AutoST-Net, a spatiotemporal deep learning framework designed for predicting forest fire spread, which combines a 3D Convolutional Neural Network (3DCNN) with a Transformer (52). This approach was chosen to capture both local (short-range) and global (long-range) spatiotemporal relationships, which improves prediction accuracy over traditional models. The model was trained on a forest fire dataset from Sichuan and Yunnan, China. Dataset was obtained through Himawari-8 satellite and Google Earth Engine (GEE) and includes various factors such as weather,

Table 2. Data sources for forest fire prediction

Data source	Description	Use case in forest fire prediction
Satellite imagery		
MODIS (43)	Provides daily global coverage of vegetation indices, land surface temperature and active fire locations	Detecting active fires and mapping burned areas using thermal infrared bands
Landsat (44)	Offers high-resolution imagery for assessing vegetation health and changes in land cover over time	Monitoring long-term changes in vegetation and identifying areas prone to forest fire
Sentinel (45)	Provides multispectral imagery with high temporal and spatial resolution for vegetation analysis	Generating vegetation indices (e.g., NDVI) to assess fuel availability
Meteorological data		
Ground stations	Collects localized data on temperature, humidity, wind speed and precipitation	Incorporating real-time weather variables into ML models to predict fire ignition probability
Weather models	Provides global forecasts of meteorological conditions at high resolutions	Using forecasted weather data to predict fire spread dynamics over several days
Topographical data		
Digital Elevation Models (DEMs)	Offers elevation data to model slope, aspect and elevation	Calculating slope steepness to predict uphill fire spread rates
GIS-based topographical layers	Integrates DEMs with other spatial datasets to create comprehensive maps of terrain features	Identifying areas with steep slopes or specific aspects that are more prone to fires due to preheating effects
Fuel data		
Vegetation maps	Classifies land cover types based on satellite imagery or field surveys	Classifying regions based on fuel type to estimate fire susceptibility
Biomass inventories	Quantifies the amount of combustible material available in a given area	Estimating potential fire intensity by analysing biomass density

Table 3. Data augmentation techniques

Category	Technique	Description	Use case in forest fire prediction
Synthetic data generation (46)	SMOTE (Synthetic Minority Oversampling Technique)	Generates synthetic samples for underrepresented classes	Balancing datasets where fire occurrences are less frequent compared to non-fire
	GANs (Generative Adversarial Networks)	Produces realistic synthetic data by learning patterns from existing datasets	Generating high-resolution satellite imagery for regions with limited historical data
Spatial augmentation (47)	Rotation and scaling	Rotates or scales images to simulate different perspectives or resolutions	Enhancing CNN performance by diversifying training datasets with rotated satellite thermal images
	Cropping and patching	Divides large images into smaller patches for localized analysis	Training ML models on specific high-risk zones identified through MODIS or Sentinel imagery
Temporal augmentation	Time shifting	Adjust timestamps to create new time-series sequences	Generating additional weather patterns by shifting historical meteorological data
	Interpolation	Fills gaps in time-series datasets using linear or spline methods	Creating continuous weather profiles from intermittent ground station readings
Image based augmentation	Geometric transformations	Flips, crops, rotates, or zooms images randomly	Improving model generalization by introducing variations in satellite image orientation and scale
	Color space transformations	Alters RGB channels, contrast, or brightness of images	Simulating different lighting conditions to improve fire detection accuracy in varying environments
	Random erasing	Delete part of an image to simulate occlusions or missing data	Training models to handle incomplete satellite imagery caused by cloud cover or sensor errors

Table 4. Performance evaluation and metrics used for forest fire prediction models

Metric	Task type	Use case in forest fire prediction
Mean Absolute Error (MAE)	Regression	Evaluating the average difference between predicted and actual fire intensity and size
Root Mean Squared Error (RMSE)	Regression	Assessing the magnitude of prediction errors in fire intensity, emphasizing larger errors
Mean Absolute Percentage Error (MAPE)	Regression	Evaluating the average percentage difference between predicted and actual fire metrics
Accuracy	Classification	Evaluating overall model performance by measuring the proportion of correctly predicted instances
Precision	Classification	Evaluating the accuracy of positive fire occurrences by determining the proportion of correctly predicted positive cases compared to all anticipated positive instances
Recall (sensitivity)	Classification	Assessing the model's ability to detect all actual fire occurrences, minimizing false negatives
F1-Score	Classification	Balancing precision and recall to evaluate model performance on imbalanced datasets
AUC-ROC	Classification	Comparing model performance by evaluating their ability to distinguish between fire-prone and non-fire-prone areas
Confusion matrix	Classification	Analysing specific prediction errors such as false positives and false negatives to identify model weaknesses
Intersection over Union (IoU)	Spatial overlap	Evaluating the overlap between predicted and actual fire areas to assess spatial accuracy
Sorensen-Dice Coefficient	Spatial overlap	Measuring the similarity between predicted and actual fire regions, focusing on spatial overlap
Kappa statistics	Spatial evaluation	Measuring agreement between predicted and observed spatial distributions of fires
Spatial resolution accuracy	Spatial evaluation	Assessing how well models predict fire-prone areas at different spatial scales
Time-series analysis	Temporal evaluation	Evaluating model performance over different time periods to ensure consistency in predictions
Lagged predictions	Temporal evaluation	Evaluating the accuracy of models in forecasting fires weeks or months ahead to support proactive planning.

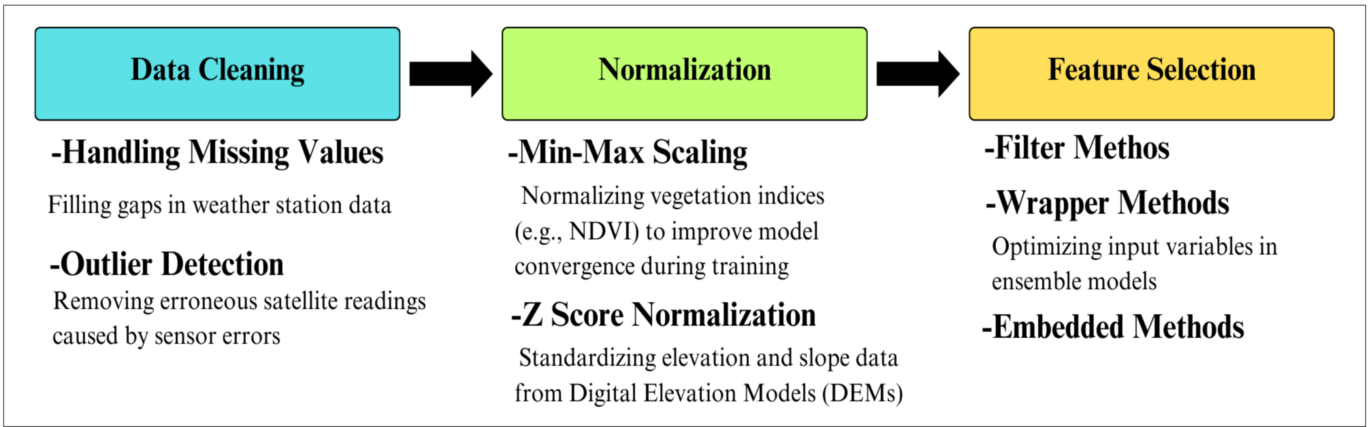

Fig. 5. Data preprocessing techniques.

terrain and vegetation. AutoST-Net outperformed existing models like RF, CNN-LSTM and 3DUnet, by achieving a Mean Intersection over Union (MIou) of 82.98 % and an F1-score of 80.50 %. The study concludes that AutoST-Net considerably improves fire spread prediction, aiding in emergency response and forest management, although its accuracy is still influenced by the quality of the data and regional adaptability. The deep learning model named CNN-BiLSTM, which combines CNN and Bidirectional Long Short-Term Memory (BiLSTM), is designed to predict forest fire spread in near-real time (53). CNN is utilized to capture spatial relationships, whereas BiLSTM addresses temporal dynamics, resulting in improved prediction accuracy. The model was trained on Visible Infrared Imaging Radiometer Suite (VIIRS) active fire data, along with environmental factors such as temperature, wind speed, precipitation, soil moisture, land cover and topographical data. The results indicate that CNN-BiLSTM surpassed conventional models like LSTM and CNN-LSTM, achieving an F1-score of 0.64 and an IoU of 0.53 on the validation dataset. MA-Net, a deep learning model designed to predict the spread of forest fire by integrating multimodal geospatial and meteorological data (42). MA-Net was chosen for its effectiveness in image segmentation and ability to capture spatial dependencies in forest fire spread (30). The model was trained on 947 fire incidents across northern Russian regions using remote sensing datasets such as MODIS (54), Copernicus DEM, ERA5-Landand WorldPop. It achieved an F1-score of 0.67 for predictions made over three days, with wind direction and land cover identified as the most influential factors. The study concludes that MA-Net provides promising results for short-term fire spread forecasting, which can aid emergency response efforts. Table 5 summarizes the various ML techniques for forest fire prediction.

Trends in forest fire prediction research

Spatiotemporal prediction models

Forest fire prediction research has evolved significantly, driven by advancements in ML, Remote Sensing (55) and Data Analytics. A major trend in this area is the development of spatiotemporal prediction models. These models integrate spatial characteristics such as types of vegetation and landforms, along with temporal elements like weather conditions and seasonal changes. Recently introduced models, such as AutoST-Net, merge 3DCNN with transformers to effectively analyse spatiotemporal information (52). It utilizes the transformer's attention mechanisms to optimize feature extraction and boost accuracy. Similarly, spatiotemporal knowledge graphs (STKG) integrate diverse multi-source data to forecast fires by mapping out spatial and temporal connections (56). These models are utilized for predicting the dynamics of fire spread, identifying areas at high risk and examining the effects of climate change on fire behaviour (57).

Integration of remote sensing and ground-based data

Remote sensing satellites like MODIS provide extensive spatial data for detecting fire across large regions. Whereas ground-based sensors provide more localized insights such as temperature, humidity and smoke for early fire detection (58). MODIS and Sentinel satellites deliver information on vegetation indices, thermal anomalies and land surface temperature, while high-resolution images from Landsat help track long-term changes in plant health (59). Ground-based weather stations gather real-time meteorological information, including temperature, humidity, wind speed and precipitation. The integration of these datasets allows ML models to better predict fuel moisture levels and map fire-prone areas with increased precision. This integration enhances the accuracy of predictions by utilizing the advantages of both data types.

Development of real-time prediction systems

These systems utilize real-time data from satellites, Internet of Things (IoT) devices and weather models (60). Deep learning techniques such as CNN analyse real-time satellite images to detect active fires and thermal irregularities. IoT-enabled sensors deliver localized environmental information for immediate risk assessment (61). Real-time systems enhance early warning mechanism, facilitating rapid decision -making for the allocation of firefighting resources and evacuation strategies (62). This functionality is crucial for minimizing response times and alleviating the effects of fires.

Use of cloud computing and big data analytics

Cloud computing enables the storage and analysis of large datasets necessary for predictive modelling. Services like GEE merge satellite images with analytical tools for extensive large scale analysis (63). Cloud-based ML platforms support the scalable development of predictive models by utilizing diverse datasets. Big data techniques like ensemble methods integrate several ML algorithms to boost prediction accuracy (64), while transfer learning leverages pre-trained models to adjust predictions for different regions or conditions. These technologies improve the efficiency of ML models in managing complex datasets, facilitating precise predictions over broad geographic areas.

Explainable AI (XAI) for forest fire prediction

XAI methods focus on enhancing the transparency of ML models by offering insights into their decision-making mechanisms (65). Predictions related to forest fires often involve critical decisions, understanding the rationale behind a model's fire prediction is crucial for establishing trust. XAI tools such as SHAP (Shapley Additive Explanations) and LIME (Local Interpretable Model-Agnostic Explanations) emphasize the role of specific features (like temperature or vegetation moisture) in shaping predictions. This transparency fosters greater confidence among stakeholders by explaining predictions to policymakers, fire-fighters and community members. It also aids in improving the model by identifying which features are most responsible for errors or uncertainties. By incorporating these trends, researchers can create resilient systems that substantially reduce the risks associated with forest fires.

Challenges and limitations

Predicting forest fires using ML encounters several challenges and limitations that hinder the development of reliable and generalizable models. A primary challenge is the lack of data and imbalanced datasets, where the number of non-fire incidents significantly exceeds that of actual fires because they are infrequent. This imbalance results in skewed models that struggle to identify rare fire incidents, leading to a high

Table 5. Machine learning models used in forest fire prediction

Methodology	Dataset	Results	Conclusion	Reference
Spatio-temporal clustering, Genetic Algorithm (GA) for feature selection, Histogram Gradient Boosting (HistGB) for prediction	NASA FIRMS (VIIRS) wildfire data (2000–2022), geospatial features from GEE, meteorological data from ERA5, topographical and vegetation data	HistGB achieved an average accuracy of 94 % for wildfire occurrence prediction, with a False Alarm Rate (FAR) of 4 %. For burnt area and fire duration, the model outperformed baseline methods but showed higher errors for larger fires and longer durations	The proposed framework improves wildfire prediction in Alaska by integrating spatio-temporal clustering and ensemble learning, helping risk assessment and fire management. However, data resolution and model generalization require further enhancements for predicting large and long-duration fires.	(79)
RF and eXtreme Gradient Boosting (XGB)	2015–2022 fire data from NASA FIRMS (VIIRS), topographic data (SRTM), land cover (MoFor/KLHK), meteorological data (CHIRPS, MODIS LST) and environmental variables (NDVI, NDMI, soil moisture)	XGB outperformed RF with an accuracy of 94.73 %, recall of 99.9 % and F1-score of 97.29 %.	The study identified key fire factors and developed vulnerability maps for Kalimantan, Sumatra and Papua, aiding fire prevention strategies.	(80)
RF, SVM, Gradient Boosting Trees (GBT), Convolutional Neural Networks, K-nearest Neighbour (kNN)	- Meteorological data: Bureau of Meteorology (BOM), Australia - Topographic data: Geoscience Australia, NASA (MODIS - Aqua/Terra satellites) - Active Fire Point Data: NASA FIRMS (MODIS) - Historical fire data: Black Summer Bushfire Disaster (2019-2020)	- Topographical classification: kNN achieved the highest accuracy (97.15 %) and perfect recall (1.0), outperforming other models. - Meteorological classification: RF performed best with 90.61 % accuracy. - Regression models: RF regressor had the best performance for both topographical and meteorological data.	The study demonstrated that ML models significantly improve forest fire prediction, with kNN and RF showing the highest accuracy. NDVI, precipitation and wind speed were the most influential factors.	(81)
Multi-Layer Perceptron Neural Network (MLP NN) with Virtual Sensors using Polynomial Regression for data augmentation	- Physical sensors data: 15 physical sensors measuring temperature, humidity, light intensity, smoke and sound (recorded at 10-second intervals) - Virtual sensors data: Generated using polynomial regression to enhance model training	- Prediction accuracy improved with virtual sensors - Best accuracy observed with 15 physical + 30 virtual sensors - Some scenarios (e.g., "Fire Increasing") saw accuracy improvements up to 46.15 %, while others experienced minor declines	Integrating virtual sensors with physical sensors enhances forest fire prediction accuracy. This method expands monitoring coverage without incurring additional hardware expenses.	(82)
Convolutional Neural Network, U-Net and Autoencoder	Publicly available satellite data from Landsat, Sentinel-1 and Sentinel-2 (2018–2020). Additional geospatial and meteorological data from GEE were included.	CNN achieved the highest fire detection accuracy of 82 %, outperforming U-Net and Autoencoder. CNN also demonstrated better generalization across different wildfire scenarios.	The potential of deep learning for real-time wildfire detection, with CNN providing the best results. Future research should focus on improving segmentation accuracy and integrating additional environmental factors to enhance predictive performance.	(83)
RF and Fuzzy Analytic Network Process (FANP)	- Fire data (2001–2020): MODIS Collection 6.1 (NASA FIRMS) - Environmental data: Rainfall, temperature, humidity, NDVI, land cover, wind speed - Human activity data: Distance to settlements, roads - Topographic data: Elevation, slope, aspect (SRTM, GIS sources)	- FANP achieved higher accuracy (AUC = 88.5 %) compared to RF (AUC = 81.4 %) - Fire-prone zones were identified in the western and southern regions of Wuyishan National Park - Areas classified as fire risk “level 3+”, which covered 98.44 % of past fires, while “level 4+” covered 65.63 %	FANP is more effective for small-scale fire risk zoning compared to RF, offering better accuracy and decision support for forest fire management in ecologically sensitive areas.	(22)
RF, SVM, MaxEnt	Various geospatial and meteorological datasets, including remote sensing data and historical fire occurrences.	- RF performed best with an AUC of 0.91, Accuracy of 0.8694 and F1-score of 0.9176. - SVM had an Accuracy of 0.8756 and AUC of 0.87. - MaxEnt showed the lowest performance with an AUC of 0.84.	The study highlights the superiority of the RF model for forest fire prediction, demonstrating higher accuracy and reliability compared to SVM and MaxEnt.	(84)
Integrated ML Framework (Weighted Ensemble of RF, XGBoost, CatBoost, SVM and KELM)	- Forest fire data (2003–2016): Global Fire Atlas - Climate data: NOAA (temperature, humidity, wind speed, air pressure, rainfall) - Topographic data: SRTM (altitude, slope, aspect, TWI) - Vegetation data: NDVI from GEE - Socioeconomic factors: Population density, distance to industrial/ residential areas, roads and rivers	- Integrated model achieved accuracy of 86.02 %, AUC of 0.772 and sensitivity of 92.34 %. - Fire risk map successfully classified areas into five fire risk levels. - High-risk areas were mainly in the northwest, northeast and southern regions.	The weighted ensemble model outperformed individual models in fire risk prediction and mapping, offering a scalable and adaptable framework.	(85)
One-Class ML Models: One-Class SVM, Isolation Forest, AutoEncoder, Variational AutoEncoder (VAE), Deep Support Vector Data Description (DeepSVDD), Adversarially Learned Anomaly Detection (ALAD)	- California (2012-2016): 7,335 wildfire incidents from MODIS, NOAA, US Census Bureau - Western Australia (2001-2020): 33,300 wildfire events from Department of Biodiversity, Conservation and Attractions - Meteorological Data: Temperature, humidity, wind speed, precipitation - Topographical & Vegetation Data: Elevation, NDVI, Live Fuel Moisture Content (LFMC)	- OCSVM (PyOD) performed best, achieving 99 % accuracy, precision, recall and F1-score. - One-class models outperformed two-class ML models (SVM, RF, XGBoost, ANN).	One-class ML models demonstrate high accuracy for forest fire prediction, outperforming conventional binary classification methods. The study also developed a web-based tool using a Flask REST API to deploy the best -performing model for real-time wildfire risk assessment.	(86)

RF	- Fire severity data (2002–2020): Monitoring Trends in Burn Severity (MTBS) and Utah Fire Atlas - Environmental & Topographic Data: Elevation, slope, vegetation type, canopy fuels - Weather Data: Energy Release Component (ERC), temperature, precipitation	- RF achieved an out-of-bag R^2 of 67.1 % and classification accuracy of 85 %. - Burn severity was highest in productive vegetation and high-elevation areas.	The study confirms that vegetation productivity, fuel availability and topography are key wildfire burn severity predictors.	(87)
Prophet, ARIMA, Simple Linear Regression, Polynomial Regression, Support Vector Regression, Decision Tree regression, RF regression	Fire Incident Data (2016-2022): Open dataset from Smart Dublin, including annual logs of fire incidents from Dublin Fire Brigade (85,813 entries).	- Prophet achieved the highest R^2 (0.91), effectively capturing trends, seasonality and holiday effects. - ARIMA performed well (R^2 = 0.84) but was less flexible.	Prophet outperformed other models in forecasting Dublin fire incidents, providing transparent and interpretable predictions using Explainable AI (XAI).	(88)
RF and Support Vector Regression (SVR)	- Fire Data: Wildfire occurrence and burn severity from MTBS - Hydrological Data: Stream temperature and turbidity from USGS NWIS (2007–2024) - Climate Data: Air temperature, precipitation, discharge from PRISM and MACA downscaled climate models	- RF outperformed SVR for stream temperature prediction (R^2 = 0.98, RMSE = 0.88°C)	ML effectively predicts post-wildfire water quality changes, aiding climate-resilient water management.	(89)
YOLOV9-CBM (Enhanced YOLOV9 with C3-SE module, BiFPN and MPDIoU loss function)	CBM-Fire Dataset - A custom dataset with 2,000 fire and smoke images collected and labelled for training, validation and testing.	- Recall increased by 7.6 %, MAP improved by 3.8 % over YOLOV9. - Outperformed YOLOV3, YOLOV5, YOLOV8, SSD and faster R-CNN in detection accuracy.	YOLOV9-CBM significantly improves fire detection accuracy and efficiency, making it effective for both forest and urban fire monitoring.	(90)

rate of false negatives (66). Although techniques for generating synthetic data, such as SMOTE and GANs have been used to tackle this challenge, they frequently introduce noise and fail to capture the complexities of real-world situations. Another limitation stems from the complex and nonlinear interactions among factors like fuel type, weather conditions, topography and human activities. For example, while wind speed can enhance fire propagation on steep terrain, the moisture content in vegetation can hinder ignition even in dry conditions (13). Simplistic models like logistic regression often neglect to incorporate these complex dynamics, resulting in prediction inaccuracies. The generalizability of ML models across regions is another critical concern. Models that are trained on data from a specific geographic location may not perform well when they are used in other areas because of variations in vegetation types, climatic conditions and landscape characteristics (67). For instance, a model created for forests in Canada might inaccurately predict fire risks in Mediterranean environments due to differences in fuel types and weather patterns. Approaches like transfer learning (68) and domain adaptation have demonstrated potential in overcoming this challenge, but they need more refinement. Moreover, the computational requirements of contemporary ML models pose a considerable barrier to implementation. Deep learning techniques, including CNN and transformers, require significant computational power when trained on extensive datasets (69). This becomes particularly problematic for real-time prediction systems that depend on quick processing of data streams from satellites or the Internet of Things (70). Although cloud computing platforms like GEE have addressed some of these issues by offering scalable resources, they also present challenges related to cost and accessibility. Another persistent limitation is the uncertainty in predictions, which arises from the chaotic nature of wildfires and limitations in input data quality. Incomplete meteorological data or low-quality satellite images lead to inaccuracies in predictions. Moreover, numerous ML models function as "black boxes," which complicates the ability of stakeholders such as policymakers or emergency responders to have confidence in their results. XAI approaches, such as SHAP or LIME, strive to mitigate this problem by offering clarity on feature significance and decision-making pathways, but these methods are still evolving. Climate change has created new difficulties by altering historical patterns of fire behaviour. Increased temperatures, extended drought periods and shifting precipitation patterns have led to a rise in the frequency and intensity of fires in various regions, making historical data less dependable for training ML models. Integrating climate forecasts into ML models is essential, but it adds complexity due to uncertainties associated with climate simulations.

Conclusion

Machine learning has revolutionized forest fire prediction by utilizing sophisticated algorithms, real-time data and computational resources to improve fire risk assessment and early warning systems. The ability of ML models to analyse extensive amounts of environmental, meteorological and topographical data has significantly improved predictive accuracy, supporting proactive wildfire management. The implementation of hybrid models, deep learning architectures and ensemble methods has further reinforced prediction capabilities, providing powerful solutions for detecting fires and estimating their spread. Furthermore, the integration of remote sensing, IoT and cloud computing enables scalable and real-time fire monitoring for rapid response and resource allocation. As climate change alters forest fire dynamics, future studies should incorporate climate forecasts into ML models for improved long-term predictions. ML techniques must adapt to shifting weather patterns, increasing fire frequencies and evolving vegetation characteristics. Developing region-specific ML models will improve generalizability and accuracy. The implementation of transfer learning and domain adaptation strategies can improve model applicability, allowing predictive models trained in one region to be effectively applied to another. The increasing adoption of XAI offers valuable opportunities for enhancing trust in ML-based fire prediction systems. Another important area for future research is the creation of integrated early warning systems that utilize real-time data from satellite imagery, weather monitoring stations and IoT-enabled ground sensors. Big data analytics and cloud-based computing enable continuous, high-resolution monitoring of fire-prone areas. Collaboration among AI experts, climatologists, ecologists and governmental organizations is crucial for effective ML-based forest fire prediction. Decision-makers ought to promote the use of AI-driven tools by funding, data-sharing and establishing policy frameworks for real-time fire management. Future research should also explore the ethical considerations and data privacy issues related to large-scale fire monitoring systems. As ML continues to evolve, the incorporation of multimodal datasets such as social media reports, aerial drone imagery and data provided by citizens can drastically improve fire prediction abilities. These alternative data sources can complement conventional meteorological and remote sensing data, improving situational understanding and promoting community involvement in fire prevention initiatives. Ultimately, the future of ML-based forest fire prediction relies on the seamless fusion of AI, remote sensing, real-time data analytics and climate science. By overcoming current challenges and adopting interdisciplinary strategies, researchers can develop fire prediction models that are more precise, interpretable and scalable, ultimately aiding in the reduction of forest fire and promoting global environmental sustainability.

Authors' contributions

RS carried out the original draft preparation as well as the supervision. MV -prepared the review part, methodology and resources. MK performed the -writing, editing and validation of the review part. KB, KA, MS carried out writing and editing of the review part. All authors read and approved the final manuscript.

Compliance with ethical standards

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