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Advancements in Wildfire Prediction and Detection: A Systematic Review

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Abstract

This comprehensive review provides a detailed analysis of wildfire prediction and detection research, focusing on methodologies, techniques, and challenges in wildfire management. Through a systematic examination of literature, we identify common approaches, key findings, and major challenges in the field. We explore a wide array of methodologies, including machine learning and deep learning techniques, such as decision trees, logistic regression, neural networks, and convolutional neural networks, among others. Additionally, we investigate the integration of emerging technologies like unmanned aerial vehicles (UAVs), satellite imagery, and Internet of Things (IoT) devices into wildfire management systems. The review underscores the importance of interdisciplinary collaboration and stakeholder engagement in addressing socio-ecological challenges associated with wildfires. Furthermore, we highlight the need for continued innovation, data standardization, and knowledge exchange to advance wildfire prediction and detection capabilities.

Keywords: Wildfire detection; wildfire prediction, machine learning, deep learning

1. Introduction

According to recent statistics, wildfires are a major threat to the environment, animals, buildings and people all over the world [1]. The recent years have witnessed a rising incidence and severity of wildfire, making it imperative to understand the factors that could aid in accurate prediction and early detection of such fires [2]. It is crucial to identify fires at their initial stage as well as give accurate prognosis so that actions can be taken before the occurrence of more severe wildfires leading to loss of lives or property. Hence, the application of new technologies like machine learning, deep learning, and remote sensing technologies in the discovery of new techniques for the prediction and early detection of wildfires has become popular [3], [4].

It has been observed that application of machine learning and deep learning algorithms have given improved results in many different fields such as environmental science & natural disaster management [5], [6]. These techniques hold the possibility to process large volume of information of various types such as satellite images, meteorological data, geographical data, historical records of wildfires and other data types to recognize patterns and detect wildfires[6], [7]. Subsequently, enhancements in the sensor systems and data analysis resources have enabled the creation of the real-time wildfire detection with the help of several technologies like autonomous ground-based sensors, UAVs, and WSNs.

There are still some gaps that have been identified in the existing literature and therefore future works in the area of wildfire prediction and detection are as follows [8]: The challenges involve the following: There is a need to enhance the accuracy of the prediction models, ensure that data from different sources are processed and linked, the algorithms that are to be developed are to cover the complexity of the environment, and detection systems are to be fine tuned for the real world environments in the different parts of the world. These challenges call for multi-disciplinary research, development and implementation efforts among scholars, professionals, policy makers and other relevant stakeholders cutting across different fields.

This systematic literature review will therefore attempt to offer a literature review of the current trends in wildfire prediction and detection research. In particular, the current paper aims to discuss the prominent approaches, methods, and models used for wildfire prediction and detection. Besides, we will discuss the limitations of the research, potential issues, and directions for further research in the future. In its research identification and synthesis of previous studies, this review aims to contribute towards developing future research propositions in the area of wildfire prediction and detection.

2. Research Methodology

Thus, the primary objective of this systematic review is to examine the typical methods to use and the barriers that may be encountered in wildfire prediction and detection tasks. This research will be helpful in the future research studies related to the prediction and detection of wildfires. That is why, based on the information presented in Table 1, we will analyze the following research questions (RQs) in this study.

Table 1 Research Questions and Motivations

RQ#	Research Question	Motivation
RQ#1	What are the common techniques used in wildfire detection?	To identify and analyze the prevailing methodologies and models employed for detecting wildfires, which will help in understanding the current state of the art and guide future improvements.
RQ#2	What are the common techniques used in wildfire prediction?	To explore and evaluate the predictive models and algorithms used to forecast wildfire occurrences, providing insights into their effectiveness and areas for enhancement.
RQ#3	What are the challenges faced in wildfire prediction and detection?	To recognize and document the key difficulties and obstacles encountered in both detecting and predicting wildfires, which is crucial for addressing these issues in future research and application development.

2.1.Data Collection

In this study, we gathered articles from multiple primary databases: IEEE, Elsevier, Springer, and others. Our search criteria were designed with the guidance of experts in wildfire prediction and detection, focusing on relevant techniques and models. The screening process followed the systematic review approach outlined by PRISMA, encompassing various distinct phases, which are elucidated below.

Figure 1 Basic Flow of Study

2.2.Search Strategy

Our primary objective was to collect articles related to wildfire prediction and detection. We employed a search strategy that specifically targeted prediction, detection, and other technical keywords related to wildfire research, as detailed below. Notably, we did not employ any population filters, and our search encompassed all relevant fields. In total, our search across the selected databases yielded 979 records that met our criteria.

("wildfire prediction" OR "wildfire detection" OR "forest fire prediction" OR "forest fire detection") AND ("techniques" OR "methods" OR "approaches") AND ("datasets" OR "data sources") AND ("evaluation" OR "metrics") AND ("challenges" OR "issues") AND ("machine learning" OR "deep learning" OR "models") AND ("future work" OR "research directions") AND ("survey" OR "review" OR "state of the art")

2.2.1. Screening

The study screening procedure is essential for guaranteeing the quality and applicability of the included research in a systematic literature review. This entails carefully reviewing the abstracts and titles of the articles found using the search technique to find research that satisfies the predetermined inclusion and exclusion criteria. The principal objective is to curtail the quantity of articles to a reasonable extent while preserving those that offer significant perspectives and data.

We began this investigation with a sizable collection of 979 preliminary works on wildfire prediction and detection that we had collected from a variety of sources. Two writers were in charge of vetting the articles based on predetermined inclusion and exclusion standards (Table 2). A third author helped to address any conflicts or disagreements, which resulted in the improvement of the inclusion/exclusion criteria. With a Cohen's Kappa coefficient of 0.89, the agreement between the two major authors demonstrated almost perfect consistency, suggesting a high degree of dependability in the screening procedure [9]. The steps in the study screening procedure are as follows:

Duplicate Removal: Initially, we identified and removed duplicate records to avoid repetition. We found 104 duplicated texts across the three databases, leaving us with 875 unique records.

Title-Based Selection: Next, we filtered out papers that appeared unrelated based on their titles, reducing the pool to 230 papers.

Abstract-Based Selection: We then examined the abstracts of the shortlisted articles to further refine our selection. This step involved organizing the articles for deeper analysis and considering their research methodologies. As a result, we narrowed down the pool to 87 papers.

Full-Text Analysis: Finally, we conducted a thorough assessment of the empirical quality of the remaining articles. This involved comprehensive text analysis to ensure the studies met our criteria for inclusion. This stage led to the selection of 49 papers from the initial pool of 87 articles.

2.2.2. Eligibility Criteria

The eligibility criteria for selecting research papers in this systematic literature review focus on identifying studies specifically related to wildfire prediction and detection techniques. To ensure relevance and alignment with the review's objectives, studies must have been published in reputable journals or presented at recognized conferences.

Table 2. Inclusion and Exclusion Criteria

Criteria #	Inclusion criteria	Exclusion Criteria
IE1	Studies focusing on wildfire prediction and detection techniques.	Studies not related to wildfire prediction and detection.
IE2	Articles published in peer-reviewed journals, conference proceedings, or reputable sources.	Non-peer-reviewed sources or papers from unreliable or questionable publishers.
IE3	Research papers written in English.	Non-English articles.
IE4	Studies that provide detailed information on the feature extraction techniques, models, or algorithms used for wildfire prediction and detection.	Articles lacking sufficient information on the methodologies or techniques employed.

2.2.3. Primary Selected Studies

We thoroughly reviewed 49 research papers to address the previously outlined research questions concerning wildfire prediction and detection. These papers were sourced from a diverse range of reputable platforms relevant to the field of wildfire research. Our search encompassed well-established databases including IEEE, Elsevier, and Springer, along with respected journals and conferences in the field. Additionally, we extended our search to include other valuable publication channels such as ArXiv and AAAI to ensure a comprehensive examination of the wildfire prediction and detection domain.

3. Forest Fires Prediction and Detection Systems

Machine learning, a subset of artificial intelligence (AI), empowers machines to make choices by learning from data. Numerous researches have explored AI's application across various fields, including the forecast and detection forest fires. Introducing AI into forest fire prediction and detection systems shows great promise. Consequently, extensive research has been conducted on fire occurrence modeling to capitalize on AI's benefits. A wide range of machine learning methods have been used for this challenge. These models also become sub-models of other systems for predicting and detecting forest fires using sophisticated technologies. The tendency of development is aimed at the connection between AI and WSNs, UAVs for automating the process of fire prediction and detection.

This section gives an overview of the most widely employed machine learning approaches for modelling forest fires, including ANN, logistic regression, decision trees, and their hybrids. We also extend our focus to the resource that has integrated machine learning techniques such as ANN, decision trees, Bayesian methods, and fuzzy logic with WSN technology.

3.1. Deep Learning Based Forest Fires Prediction and Detection Systems

Artificial Neural Networks (ANNs) [10] are computational structures derived from biological neurons that exist in the human brain. Artificial neurons arranged in layers and coupled by weighted interconnections make up these networks. An ANN's characteristics include parallelism and modularity, noise insensitivity, and the ability to learn from examples and generalize to new, unobserved pattern exemplars.

Because of these features, ANN models can be used in many other domains, including as pattern recognition, medical diagnosis, image processing, signal processing, and financial analysis. The learning mode of neural network models is used to classify them: g. Unsupervised ANNs included Kohonen's Self Organizing Maps (SOMs), Expectation-Maximization clustering neural networks (EM), and Fuzzy C-Means (FCM). Super ANNs, such as Multi-Layer Perceptron (MLP) was utilized with back-propagation network (BPN). This is because the sort of neural network being used, a two-layer network with a competitive learning model called Kohonen's self-organizing feature map, allows for the supply of multiple alternatives to optimize the neural network's performance during training.

The use of ANNs in forest fire forecasting and detection has been extensively documented, either as a stand-alone predictor or as a part of WSN- or UAV-based detection systems. The automatic forest fire detection systems have a new orientation thanks to the integration of additional technologies like WSN and UAV with AI.

The next two sections give a brief on previous work done in development of ANN based forest fire prediction systems and then moves to works done in forest fire detection systems.

3.1.1. Wildfire Prediction

Several types of Artificial Neural Networks (ANNs) [1], [11]–[15] have been incorporated into the forest fire prediction models. For example, Vasilakos et al. [15] developed a back-propagation neural network sensitivity analysis method for designing the Lesvos Island, Greece, fire igniting technique. Using a quantitative method, they assessed the impact of several variables on the likelihood of a fire starting and came to the conclusion that factors such as temperature, humidity, wind speed, and amount of precipitation over the preceding 24 hours might have a significant influence. The 10-hour fuel moisture content had the biggest impact on vegetation and geographical data, but fuel models, aspect, and elevation also had a big impact. The month of the year, closeness to populated areas, landfills, and major roads, and socioeconomic characteristics had the biggest effects on the fire risk index in terms of the number of people living in forests.

A Forest-Fire Susceptibility (FFS) map for Central Portugal was created by Dimuccio et al. [11] by combining ANN modeling with analysis from the Global Information System (GIS). The Landsat Normalized Difference Vegetation Index (NDVI), viewsheds, topographic slope and aspect, road density, precipitation, and population density were among the eight fire-related characteristics that they rated using a frequency-probabilistic technique. These factors were given weights by a back-propagation neural network, which were then combined using GIS to produce the FFS index map. This map was validated against information from burnt zones between 1990 and 2007, showing a 78% agreement. Karouni et al. [13] also explored back-propagation artificial neural networks for fire occurrence prediction. Their 4-input feed-forward network achieved maximum values of approximately 98.9% for precision, 76.9% for specificity, 94.2% for sensitivity, and 93.5% for accuracy. Additionally, this study investigated the use of decision trees.

A other study [14] looked at different machine learning methods to find burned forest patches. MLP, fuzzy logic, support vector machines (SVM), and radial basis function networks (RBFN) were among the models used. Data on topography, climate, and meteorological conditions (temperature, wind speed, and relative humidity) were incorporated into records from 7,920 forest fires that occurred between 2000 and 2009. Clusters of varied sizes of burned areas were found by the approach. With humidity and wind speed, the MLP model achieved success rates of 53.02% and 62.89% for 5 clusters and 3 output clusters, respectively, and an around 65% overall accuracy. The RBFN model performed poorly. Mean Absolute Error (MAE), Mean Absolute Percent Error (MAPE), and Root Mean Square Error (RMSE) were additional metrics used in the model review process. The MLP model's RMSE, MAE, and MAPE were 15.85, 4.11, and 51, respectively, compared to 18.35, 4.05, and 54 for the RBFN model, and 7.33, 3.36, and 69 for the SVM model.

For forest fire prediction systems, deep learning techniques—in particular, Convolutional Neural Networks (CNNs)—have also been studied [16]. For instance, to predict the spread of a fire, Hodges et al. [17] used a Deep Convolutional Inverse Graphics Network (DCIGN). Variables like locations, fuel kinds, and meteorological conditions—primarily wind—were employed in this study. According to the published results, the mean F-measure, sensitivity, and precision were 93%, 92%, and 97%, respectively.

Table 3. Summary of few papers based on deep learning based wildfire prediction systems

Ref	Year	Model	Dataset	Features	Results	Key Finding
[15]	2009	Back-propagation NN	Lesvos Island, Greece	Temperature, humidity, wind speed, precipitation, fuel moisture content, fuel models, aspect, elevation, month, proximity to populated areas, landfills, major roads, socioeconomic characteristics	Quantitative assessment of fire likelihood based on environmental variables	10-hour fuel moisture content, vegetation, and geographical data had the biggest impact on fire likelihood.
[11]	2011	ANN with GIS	Central Portugal	Landsat NDVI, viewsheds, topographic slope and aspect, road density, precipitation, population density	78% agreement with burnt zones between 1990 and 2007	Fire susceptibility map validated with historical data showing significant accuracy.
[13]	2014	Back-propagation ANN	Not specified	Not specified	Precision: 98.9%, Specificity: 76.9%, Sensitivity: 94.2%, Accuracy: 93.5%	High performance in fire occurrence prediction using a 4-input feed-forward network.
[14]	2012	MLP, Fuzzy logic, SVM, RBFN	7,920 forest fires (2000-2009)	Topography, climate, meteorological conditions (temperature, wind	MLP: 53.02% (5 clusters), 62.89% (3 clusters), Overall accuracy: 65%. RBFN performed poorly. Metrics	MLP model was effective in identifying burned area clusters; RBFN

				speed, relative humidity)	(RMSE, MAE, MAPE) for MLP: 15.85, 4.11, 51; RBFN: 18.35, 4.05, 54; SVM: 7.33, 3.36, 69	was less effective.
[17]	2019	CNN	Not specified	Locations, fuel types, meteorological conditions (primarily wind)	Mean F-measure: 93%, Sensitivity: 92%, Precision: 97%	Effective prediction of fire spread using Deep Convolutional Inverse Graphics Network (DCIGN).

3.1.2. Wildfire Detection

Works concentrating on ANN-based forest fire detection systems are summarized in the following synthesis [18]–[24]. For example, Kalabokidis et al. [19] used a variety of data and approaches to create the Auto-Hazard Pro Decision Support System (AHP DSS). They created the Fire Risk Index (FRI), a tool that evaluates the risk of fire caused by human activity in certain places. The system comprises modules for weather forecasting, fire detection, fire danger assessment, fire propagation, and resource dispatching. It does this by utilizing both old and updated models. Kalabokidis et al. improved the weather module by reducing systematic errors in temperature and wind speed using Kalman filtering techniques.

CNN models are frequently used in fire detection systems, especially when trying to identify the presence of fire in images [21][23][24]. Zhang et al. [24] proposed a two-stage classifier: first, a fine-grained patch classifier (NN model) to locate fire patches, and then a global image-level test using a deep CNN. For the SVM-Raw and CNN-Raw patch classifiers, they reported accuracies of roughly 92.2% and 93.1%, respectively. With an accuracy of roughly 94.39%, Muhammad et al. [21] created a fire detection framework for Closed-Circuit Television (CCTV) security cameras with a CNN-based model. CNN, deep NN, and adaptive fuzzy algorithms are all included in the multifunctional AI framework for fire detection that Park et al. [23] presented. Their framework includes IoT data collection, context preprocessing, and context decision blocks, with reported accuracy of approximately 95% and reduced end-to-end delay by 67% compared to legacy systems.

Using a multilayer feedforward network (MLFN), Maeda et al. [22] assessed high-risk forest fire recognition in the Brazilian Amazon region. They used 2005 NDVI composite MODIS data to train the model. By using this technique, the ANN received data from each pixel in the multi-temporal satellite pictures. With the temporal and spectral pixel properties, the MLFN then calculated values between 0 and 1 to examine areas in relation to fire danger. The authors summarized the findings of the study in that they attained a global accuracy of about 90% and the MSE value of 0. 07. Notably, this is so because of their simple ANN architecture that has only 4 neurons in the hidden layer, which helped in achieving quick teaching with adequate levels of accurateness.

For the purpose of detecting forest fires, Arrue et al. [18] introduced the FAR system, which combines rule-based systems, ANNs, and infrared image processing. Utilizing input from video and infrared

cameras, meteorological sensors, and geographic information system datasets, the system integrates a sensor interface, image processing, and decision function modules. ANN models, such as BPN, RBFN, and DLVQ, were employed to map the potential for forest fires using infrared imaging data, yielding successful detection and false alarm rates. Previous studies [20][25]–[27] have investigated the application of ANN model integration in Wireless Sensor Networks (WSN) for forest fire detection. For example, Yu et al. [27] used MLP in a WSN for forest fire detection, utilizing node data to estimate the probability of a fire occurring, hence reducing power consumption and extending network lifetime. Hefeeda and Bagheri [26] developed a multi-criteria detection system based on the distance between the sensor nodes and the fire, while Liu et al. [20] created a WSN for detection utilizing the FWI components. Furthermore, to reduce false alarms, Ishii et al. [28] developed an MLP-based system with numerous fire sensor inputs.
However, as Lloret et al. [29] proposed an initial WSN-based forest fire detection system without AI incorporation. They also invented a wireless multisensory network system by using infrared radiation and smoke sensors for the rural and forest areas in Spain where a live view can be seen by the fire fighters through wireless IP Cameras in real time.
These studies altogether prove that the ANN-based methods can be efficiently applied to the forest fire detection in order or independently or integrated into WSN to improve the efficiency of fire detection and further the technology for the better forest and fire management.
UAVs have been considered an innovative tool to detect and monitor forest fires, using progress made in the production of the UAVs and the technologies involved [5], [30]–[33]. When integrated with other machine learning techniques, UAVs are advantageous in that they can provide remote sensing that covers vast and hard-to-reach regions. An excellent overview of UAV types and uses, with references to forestry applications, is presented in [34].
Kinaneva et al. [32] developed a forest fire detection platform utilizing two types of UAVs: a thermal camera mounted fixed wing drone and a thermal camera mounted rotary wing drone. These UAVs recorded data that was analyzed onboard and then the result was sent to a base station for further analysis. It used the neural network model to identify and categorize the presence of smoke in forest images taken by the UAVs. In another study [35], the authors have incorporated UAVs with sensor networks which are based on Long Range (LoRa) digital wireless communication technology called LoRaWAN. Georgiades et al. [30] described an automatic real-time forest fire detection and monitoring system using UAS with optical and thermal payload. It applied ROS for decision making and had automatic detection and control sections as modules. In the same way, in Kinaneva et al. [32], the use of UAVs was adopted for fire detection alongside the use of ANN for forest image classification. Notably, both teams were also involved in the implementation of Interreg Balkan-Mediterranean project “SFEDA.
Sherstjuk et al. [33] presented a system of multiple UAVs for forest fire recognition and monitoring that uses the remote sensing, image processing, and multiple UAVs. Patrolling missions were performed by fixed-wing micro-UAVs while rotary-wing micro-UAVs were carrying out confirmation missions. The system has a good identification rate toward the forest fire event, and it was approximately 92%, and the time taken for the process was less than 2 minutes. The various key findings obtained from the reviewed studies on ANN-based forest fire prediction and detection system are summarized in Table 3 and 4, with details on the type of machine learning applied, dataset used, and main findings reported. Taken together, these studies establish the utility of UAVs and machine learning for forest fire management and monitoring.

Table 4. Summary of few papers based on deep learning based wildfire detection systems

Ref	Year	Model	Dataset	Features	Results	Key Finding
[18]	2000	FAR system (rule-based, ANNs, infrared image processing)	Video, infrared cameras, meteorological sensors, GIS datasets	Infrared imaging data, meteorological data, GIS data	Successful detection and false alarm rates	Effective integration of multiple inputs for forest fire detection
[19]	2012	AHP DSS (variety of models)	Not specified	Weather data, fire detection, fire danger assessment, fire propagation, resource dispatching	Improved accuracy in fire risk evaluation by reducing systematic errors in weather forecasts	Comprehensive decision support system with enhanced weather module using Kalman filtering
[21]	2018	CNN-based model	CCTV security cameras	Image data	Accuracy: ~94.39%	Effective fire detection framework for CCTV using CNN
[22]	2009	MLFN	2005 NDVI composite MODIS data	Temporal and spectral pixel properties	Global accuracy: ~90%, MSE: 0.07	High accuracy in high-risk forest fire recognition using simple ANN architecture
[23]	2019	CNN, deep NN, adaptive fuzzy algorithms	IoT data collection	IoT data, context preprocessing, context decision blocks	Accuracy: ~95%, reduced end-to-end delay by 67%	Multifunctional AI framework for fire detection with high accuracy and reduced delay
[24]	2016	CNN-based two-stage classifier	Image data	Fire patches (fine-grained), global image-level test	SVM-Raw accuracy: ~92.2%, CNN-Raw accuracy: ~93.1%	Effective fire detection using a two-stage CNN classifier
[26]	2005	Multi-criteria detection system	Wireless sensor networks	Distance between sensor nodes and fire	Not specified	Improved detection system by considering sensor node distance

[27]	2006	MLP	Wireless sensor networks	Node data	Not specified	Reduced power consumption and extended network lifetime by using MLP
[5]	2018	UAV-based detection systems	UAV data	Remote sensing, image processing, various UAV payloads	Not specified	UAVs enhance fire detection and monitoring capabilities
[30]	2019	UAS with optical and thermal payloads	UAV data	Optical and thermal imaging, decision making (ROS)	Real-time detection and monitoring	Automatic real-time detection and control system using UAVs
[32]	2019	UAVs with neural network model	UAV data	Thermal camera data, image classification	High identification rate (~92%), process time: <2 minutes	Efficient fire detection and monitoring using multiple UAVs with thermal cameras and neural networks
[33]	2018	Multiple UAV system	UAV data	Remote sensing, image processing	Identification rate: ~92%, process time: <2 minutes	Effective forest fire recognition and monitoring with multiple UAVs
[35]	2018	UAVs with sensor networks	LoRaWAN-based sensor data	Long Range (LoRa) digital wireless communication	Not specified	Enhanced forest fire detection by integrating UAVs with sensor networks

3.2.Development of a Wildfire Prediction System Utilizing Logistic Regression

Logistic regression is a statistical technique frequently used in binary data analysis to predict the probabilities of an event occurring or not and uses a logarithmic transformation to build a relationship between the predictor variables and the given binary response variable. In this approach, the odds of the two possible outcomes are then transformed using logarithm to the base e, known as logistic transformation. It has various uses in the simulation of natural occurrences such as; forest fires and occurs mostly in areas where the probability of occurrence needs to be estimated.

For example, Chang et al., [36] applied logistic regression to forecast forest fire eruption in Heilongjiang province of China. Their study involved the collection on information such as topographical features, vegetation cover, climatic characteristics, climate, and human activities. They obtained the average accuracy of approximately 85. 7% with logistic regression. According to their research, they noted that meteorological conditions, topography, type of fuel, and people's activities were some of the factors that affected the occurrence of forest fires.

Daily minimum temperature, mean wind speed, daily minimum humidity, average mean temperature, and precipitation were seen as variables that have a direct impact on forest fires. According to the study, these factors differed in the extent of effects in various regions. For instance, in Durango State, Mexico, the intensity of terrestrial use, the rate of terrestrial use change, vegetation cover category, and amount of rainfall formed the main predictors of fire incidence; in central Spain's Mediterranean biome, the level of live fuel moisture was a major determinant. The analysis of anthropogenic fires in northeast China revealed tight relation with human action indicators, fuel moisture, and vegetation type in eastern Kentucky, USA, forest fire occurrences are affected by factors such as elevation and slope.

Moreover, the application of Geographic Information Systems (GIS) has been examined for the purpose of creating the maps of forest fire risk, as well as, using the logistic regression models [8], [37]–[40]. For instance, De Vasconcelos et al. [39] came up with a model for estimating the probabilities of wildfire ignition in the central region of Portugal. Logistic regression analysis was used by their study in conjunction with a multilayer feed-forward neural network in which the genetic algorithm was adopted as the learning rule. Using database including the ignition dates, location, causes, land use and burn areas, the authors reached the maximum possible overall accuracy of approximately 78%. 13% for ignition and 63% for no ignition with a logistic regression model and approximately 75 percent using CART. 7% for ignition and 87/100 for extinctions) Access to and use of this work are unlimited; however, the authors have requested to be informed of any duplication, republication or systematic distribution of this work. 8% for no ignition with the result from neural network. These results showed the extent to which both methods can give reasonably accurate predictions.

A model based on logistic regression was presented by Catry et al. [37] to predict the spatial patterns of ignitions with an emphasis on human actions and their presence. Explanatory variables such population density, proximity to highways, type of land cover, and elevation were included in their analysis. Using this model in conjunction with Geographic Information Systems (GIS), they created a map of Portugal's ignition risk. The reported accuracy rates for accurately predicted eruptions were roughly 78.2%, and for correctly predicted no-ignitions, they were 82.7%. The most significant factor in determining the patterns of ignition was found to be population density, which was followed by the kind of land cover, elevation, and proximity to highways.

Vega-Garcia et al. [8] went into comparison studies that looked at the effectiveness of the two models in relation to the widely used Artificial Neural Networks (ANNs) and logistic regression for forest fire detection and prediction [39][8]. Using GIS data, De Vasconcelos et al. [39] concentrated in particular on Alberta's Whitecourt Provincial Forest. They discovered that forest managers typically go for the ease of use of logistic regression, even though ANNs are more complicated and frequently seen as opaque. However, ANNs are better at handling strong correlations among input variables, while logistic regression is limited by things like serial correlations in the data. Both approaches produced accuracies that were comparable despite these variations. About 85% of accurately anticipated no-fire and 78% of correctly forecasted fire were reported by the ANN-based model. Nevertheless, De Vasconcelos et al. acknowledged limitations in their model, notably a number of wrong alarms and the inability to predict fire occurrences outside the fire season.

In order to model the risk of human-caused fire occurrence in five ecoregions in Spain, Padilla and Vega-Garcıa [41] used logistic regression. The daily meteorological data, regional features, and historical reports of daily fire incidents between 2002 and 2005 were all used in their analysis. Frequently used fire weather indices from the Canadian forest fire weather index system were among the variables. They discovered that the Fine Fuel Moisture Code (FFMC) and the Fire Weather Index (FWI) were both significant and were among the top three most relevant variables. The evaluation results showed that the area under the receiver operating characteristic curve (AUC) values ranged from 0.52 to 0.86, while the total percentage of accurately projected fires ranged from 47.4% to 82.6% among 53 models.

Table 5. Summary of few papers based on logistic regression based wildfire prediction systems

Ref	Year	Model	Dataset	Features	Results	Key Finding
[36]	2013	Logistic Regression	Heilongjiang province, China	Topographical features, vegetation cover, climatic characteristics, human activities	Accuracy: ~85.7%	Meteorological conditions, topography, type of fuel, and human activities significantly affect forest fire occurrence
[37]	2009	Logistic Regression	Portugal	Population density, proximity to highways, type of land cover, elevation	Accuracy: ~78.2% (ignition), ~82.7% (no-ignition)	Population density, type of land cover, elevation, and proximity to highways are significant predictors of ignition patterns
[39]	2001	Logistic Regression, Multilayer Feed-Forward NN	Central Portugal	Ignition dates, location, causes, land use, burn areas	Accuracy: ~78.13% (logistic regression), ~75% (CART)	Logistic regression and ANN models can provide reasonably accurate predictions for wildfire ignition
[8]	1996	Logistic Regression, ANN	Alberta's Whitecourt Provincial Forest	GIS data, meteorological data, regional features, historical fire reports	Accuracy: ~85% (no-fire), ~78% (fire) for ANN	Logistic regression is easier to use, but ANNs handle strong correlations better; both methods produce comparable accuracies
[41]	2011	Logistic Regression	Spain (five ecoregions)	Daily meteorological data, regional	AUC: 0.52 to 0.86, accuracy:	Fine Fuel Moisture Code (FFMC) and Fire Weather Index

				features, historical daily fire incident reports	47.4% to 82.6% among 53 models	(FWI) are significant predictors of human-caused fire occurrence

3.3.Development of a wildfire Prediction System Utilizing Decision Tree

The decision tree [41] stands as a supervised learning algorithm renowned for its efficacy in predictive modeling. It was originally designed by J. Quarry as the Iterative Dichotomiser (ID3), then it was developed into the C4. 5 algorithm. Another important enhancement of decision tree learning is the so-called Classification and Regression Tree (CART) by L. Breiman et al [42] where the classification as well as regression problems can be solved in a unified way. In decision tree, the solutions can be foreseen, described, and categorized and thus, the trees in which the inner nodes are tests on attributes, the branches are outcomes of tests, and the leaves are decisions or classes.

The most important amongst them is the root node of a decision tree, which always forms the crucial split. This tree has an inherent capability to be explained in terms of IF-ELSE rules, which makes application of the tool more comprehensible to the user. Decision tree methodologies have applicability in independent tree models as well as within the groups of trees in an ensemble where two or more decision trees are used for better performance. The most commonly used DT ensembles are Boosting DT, Bagging DT, and Random Forest (RF) [43] algorithms.

The algorithms of decision tree learning and their boosting methods have proven to be quite effective in different fields because of their ability to resist the noise, their ability to work with redundant attributes and at the same time learn with high generalization ability. It is possible to point out their potential possibilities of usage in ecological setting and demonstrate that some of them like predicting and detecting forest fires, for instance, are extremely important.

3.3.1. Wildfire Prediction

Stojanova et al. [44] exemplify the application of decision tree (DT) and its ensemble methods in forecasting forest fires. They conducted an assessment of forest fire occurrences in Slovenia, employing both decision tree algorithms and logistic regression. Utilizing three datasets encompassing GIS data, multi-temporal MODIS data, and meteorological ALADIN data, the authors demonstrated that bagging DT yielded superior results in terms of accuracy, precision, and Kappa statistics, particularly for the continental Slovenia dataset. The reported accuracies stood at approximately 81.2% for DT, 84.9% for bagging DT, and 84.4% for boosting DT. Additionally, the authors explored fire outbreak risk estimation [45], comparing the predictive performance of various data mining techniques. Their findings highlighted the DT ensembles as delivering the best performances.

Three forest fire susceptibility maps were presented by Pourtaghi et al. [46] using three different machine learning techniques: Random Forest (RF), Boosted Regression Tree (BRT), and Generalized Additive Model (GAM). In the Minudasht Township, Golestan Province, Iran, topographical, meteorological, and geological data were used to assess these models. The MODIS satellite photos, historical records, and national reports were utilized by the authors to create their dataset of fire locations and occurrences. The findings showed that the forecast accuracy for BRT was roughly 80.74%, for RF it was 72.79%, and for GAM it was 87.70%. Notably, this study found that the most influential elements in the occurrence of forest fires were annual temperature, slope degree, distance to highways, annual rainfall, and land use.

Two models for factors impacting fire occurrence identification and probability modeling in the European Mediterranean region (Portugal, Spain, France, Italy, and Greece) were presented in the study reviewed in Oliveira et al. [47]. These models are based on the Multiple Linear Regression (MLR) and the random forest. The prediction power and variables chosen by each technique of the two models were compared by the authors. The comparison revealed that the RF model outperforms the MLR in terms of predictive power; this is because the MLR does not take into account the non-linear correlations between the variables. The dependent variable and the predictors did, however, have a positive association, according to the MLR.

The mean reduction in accuracy (IncMSE) was employed by Oliveira et al. [47] as a variable significance metric in the random forest model. The variables Total_prec_fireseason (93.31% Avg % IncMSE) and Total_prec_nofireseason (179%) were found to be highly significant. As for variable selection, MLR used the percentage of the "lmg" metric; Total_prec_nofireseason (48.19) and Total_prec_fireseason (22.15) showed up as significant variables. Interestingly, out of the eight variables taken into consideration, off-season precipitation was found to be the most important variable in both models.

In order to create tailored models at various spatial observation scales, Lozano et al. [48] assessed the Classification and Regression Tree (CART) algorithm for modeling the risk of fire occurrence. Their study used Landsat imagery to estimate the vegetation health and type, as well as environmental characteristics like accessibility, fire history, and topography. The total accuracy that was reported was 88.39%.

As shown by Prasad et al. [49], statistical techniques such as Regression Tree Analysis (RTA), Bagging Trees (BT), Random Forest (RF), and Multivariate Adaptive Regression Splines (MARS) have found use in ecological prediction beyond the prediction and detection of forest fires. Their research centered on forecasting the distributions of tree species in the eastern United States in relation to various climatic circumstances.

Table 6. Summary of few papers based on decision tree based wildfire prediction systems

Ref	Year	Model	Dataset	Features	Results	Key Finding
[44]	2016	Decision Tree (DT), Bagging DT, Boosting DT	GIS data, MODIS data, ALADIN data	Topography, vegetation, meteorology	Accuracy: ~81.2% (DT), ~84.9% (Bagging DT), ~84.4% (Boosting DT)	Bagging DT yielded superior accuracy, precision, and Kappa statistics for the continental Slovenia dataset.
[45]	2012	Various data mining techniques	Not specified	Not specified	Not specified	DT ensembles delivered the best performances for fire

						outbreak risk estimation.
[46]	2016	Random Forest (RF), Boosted Regression Tree (BRT), Generalized Additive Model (GAM)	Minudasht Township, Golestan Province, Iran	Topographical, meteorological, geological data	Accuracy: ~80.74% (BRT), ~72.79% (RF), ~87.70% (GAM)	Annual temperature, slope degree, distance to highways, annual rainfall, and land use were the most influential factors.
[47]	2012	Multiple Linear Regression (MLR), Random Forest (RF)	European Mediterranean region	Meteorological data, fire occurrences	RF outperformed MLR in predictive power; significant variables included Total_prec_fireseason and Total_prec_nofireseason	RF model better captures non-linear relationships; off-season precipitation was the most important variable.
[48]	2008	Classification and Regression Tree (CART)	Landsat imagery, environmental data	Vegetation health, type, accessibility, fire history, topography	Total accuracy: 88.39%	CART algorithm effectively modeled fire occurrence risk at various spatial observation scales.
[49]	2006	Regression Tree Analysis (RTA), Bagging Trees (BT), Random Forest (RF), Multivariate	Eastern United States	Climatic conditions, tree species distributions	Not specified	Statistical techniques are useful for ecological prediction beyond forest fire detection and prediction.

		Adaptive Regression Splines (MARS)				

3.3.2. Wildfire Detection:

It's important to remember that, although the decision tree (DT) method and its ensembles are frequently used for fire prediction, their use in fire detection is much more restricted than that of logistic regression. The topic of DT-based forest fire detection systems has not received much attention in the literature. Giuntini et al. [2], for example, incorporated the DT algorithm into a Forest Fire Detection (FFD) system that was based on a Wireless Sensor Network (WSN). Their suggested model used a fault-tolerant, self-organizing WSN architecture to detect wildfires, and it evaluated three decision tree components using the forest fires dataset from the UCI machine learning library. In a similar vein, Maksimovic´ and Vujovic´ [50] investigated data mining methods in WSN-based fire detection systems, encompassing the DT algorithm. They found that classifiers like the one-level decision tree (OneR) yielded acceptable results, particularly with small datasets.

Table 7. Summary of few papers based on decision tree based wildfire detection systems

Ref	Year	Model	Dataset	Features	Results	Key Finding
[2]	2017	Decision Tree (DT)	Forest fires dataset (UCI library)	Various sensor data	Not specified	DT algorithm used in a fault-tolerant, self-organizing WSN architecture for wildfire detection.
[50]	2013	Decision Tree (DT), One-level Decision Tree (OneR)	Not specified	Not specified	Acceptable results, particularly with small datasets	OneR classifier yielded acceptable results for WSN-based fire detection systems.

4. Other Machine Learning Algorithms for Wildfire Prediction and Detection Systems

Researchers have attempted alternative approaches for the prediction and detection of forest fires in addition to the well-known machine learning techniques like ANNs, logistic regression and DT. This section discusses several methods for forecasting and spotting forest fires utilizing additional machine learning techniques like SVM, Gradient Boosting Machine (GBM), Bayesian, and fuzzy logic.

4.1.Development of a Wildfire Prediction System Utilizing SVM

Cortez and Morais [51] presented an analysis of using support vector machine (SVM) for burned area prediction based on meteorological data from the northeast of Portugal. Their dataset included climate parameters such as temperature, rainfall, relative humidity, and wind speed. Hence, while the SVM method was efficient when it came to the identification of small fires, the method had its drawbacks when it came to the detection of large fire. MAD and RMSE were used to measure the overall performance and yielded values of about 13. 07 for MAD and 64. 7 for RMSE. Similarly, O¨zbayog˘lu and Bozer [14] employed SVM for identifying burned forest areas, achieving RMSE, MAE, and MAPE values of about 7.33, 3.36, and 69, respectively.

Habiboglu et al. [52] presented a different kind of video-based fire detection system that uses an area covariance matrix technique and SVM as the classifier. Ten negative and seven positive videos were included in the collection. The maximum true detection rate of the SVM model—especially when using the Radial Basis Function (RBF) kernel—was roughly 96.6%, whereas the linear kernel produced a yield of about 90.9%. The study demonstrated the effectiveness of the temporally extended covariance matrix approach, which can handle 20 frames (320 x 240 pixels) per second and integrates color, spatial, and temporal information.

4.1.Development of a Wildfire Prediction System Utilizing Gradient Boosting Machine

GBM effectively predicts wildfire outbreaks by aggregating predictions from weak learners into a robust model. Hyperparameter tuning in GBM enhances its capability to detect complex wildfire patterns.

Recent studies have investigated various aspects of forest fire prediction and management, particularly in different regions of China using GBM. Xu et al.,[53] focused on the formation of forest fire boundaries in Yangyuan County, Sichuan Province, analyzing key factors such as topography, vegetation, climate, and human activity. Their study utilized a matched case-control conditional light gradient boosting machine (MCC CLightGBM) to analyze environmental models, revealing optimal sampling distances for boundary prediction. Similarly, Shi & Zhang [54] developed a forest fire susceptibility model using the LightGBM algorithm, incorporating eight variables from diverse factors like topography and human activity. Comparing with logistic regression (LR) and random forest (RF) models, the LightGBM model showcased superior performance metrics, emphasizing the importance of temperature as a driving factor for fire occurrence. Furthermore, Jing et al., [55] employed the LightGBM model to predict forest fire occurrences in Southwestern China, considering 16 variables including climate and human factors. Despite demonstrating high predictive accuracy, the study's geographic specificity may limit the generalizability of its findings to other regions. These studies collectively underscore the significance of advanced machine learning techniques in forest fire prediction and management, offering valuable insights for future research and practical applications.

4.1.Development of a Wildfire Prediction System Utilizing KNN

K-Nearest Neighbors (KNN) is utilized in forest fire prediction due to its simplicity and effectiveness in identifying patterns based on the similarity of neighboring data points, making it suitable for analyzing spatial relationships in wildfire-prone areas.

In recent studies, Muslim Karo Karo et al., [56] focus on classifying wildfire types in Indonesia using three algorithms: K-Nearest Neighbour (K-NN), Naïve Bayes, and Iterative Dichotomise 3 (ID3). Leveraging data from the Global Forest Watch (GFW) platform, they employ feature selection to enhance classification accuracy. The ID3 algorithm stands out with notable performance metrics, achieving an accuracy of 65.83% and a promising 2-5% improvement through feature selection. However, the reliance on a single dataset source and the study's context-specific findings may limit broader applicability beyond Indonesia. Conversely, Rosadi et al., [57]explore machine learning methods for predicting forest fire occurrences in peatlands, highlighting classical and advanced classification techniques like support vector machine (SVM), k-Nearest Neighborhood (kNN), Logistic Regression (logreg), Decision Tree (DT), Naïve Bayes (NB), and AdaBoost (DT based). Despite limited studies on peatland fire modeling in Indonesia, their research underscores the effectiveness of machine learning in this domain. Nonetheless, the study's reliance on provincial data might constrain its generalizability to other regions.

4.2.Development of a Wildfire Prediction System Utilizing Naïve Bayes and Markov Models

In order to evaluate the selection and ranking of biotic, abiotic, and human factors impacting wildfire activity in Swaziland, Dlamini [58] created a Bayesian Belief Network (BBN) model. Dlamini reported sensitivity, specificity, and Area Under the Curve (AUC) values of roughly 0.96, 0.72, and 0.96, respectively, using the MODIS active fire dataset from 2001 to 2007. Land cover, elevation, mean annual rainfall, and mean annual temperature were found to be the most relevant elements in the occurrence of wildfires in Swaziland.

Borges and Izquierdo [59] suggested an alternative method that uses Bayesian classifiers to model the probability of fire incidence using vision (color). In order to determine the incidence of a fire, their model assessed variations in parameters such as color, area size, region coarseness, boundary roughness, and skewness in video frames. Findings showed false-negative and false-positive rates of roughly 0.028% and 0.68%, respectively, indicating that the system is suitable for automatic event retrieval and real-time fire detection in newscast footage. Bahrepour et al. [60] used data mining techniques to examine datasets and extract important aspects for the identification of homes and wildfires in Wireless Sensor Networks (WSN). Distributed neural networks and naive Bayes classifiers were utilized to attain detection accuracies of over 81% for residential fires and over 92% for wildfires.

Similarly, Saoudi et al. [61] utilized a naive Bayes classifier for forest fire detection in a multi-sensor WSN, achieving a precision of approximately 94%. Meanwhile, Mahmoud and Ren [62]combined image processing techniques for video-based fire detection, achieving recall, precision, and F-score values of about 93.13%, 92.59%, and 92.86%, respectively, with a false detection rate below 40%. Breejen et al. [63] proposed an autonomous ground-based forest fire detection system using temporal difference of smoke plumes against natural background, with performance validated using black and white video cameras.

Furthermore, Toreyin et al. [64] introduced a Markov model-based fire detection system that mimics flame flicker processes in color video by using hidden Markov models. Their tests showed a decrease in false alarms when compared to techniques that only used color information and motion detection, and they processed 320 x 240 images in roughly 10 milliseconds.

4.3.Development of a Wildfire Prediction System Utilizing Fuzzy Logic

The fuzzy logic technique was first presented by Zadeh [65]. It offers an alternative to the binary truth values of classical logic for handling ambiguous and uncertain material by allowing truth values to vary between 0 and 1. This approach has been used in a number of domains, such as home fire monitoring [66][67] and forest fire modeling and detection [50][68][69]. A fuzzy logic-based system for home monitoring and fire detection employing Wireless Sensor Network (WSN) technology was presented in Saputra et al. [67]. Using fuzzy rule techniques, the system used data from CO, temperature, humidity, and smoke sensors to calculate fire probability estimates. For a test on thirty sample data, the reported error ratio was roughly 6.67%. A hybrid model for fire prediction was suggested by Chen et al. [66], combining fuzzy logic with a multi-layer neural network (3-layer BP NN). Utilizing neural networks and expert database units inside a multi-sensor data fusion framework, the model reduced communication and saved energy by combining data features through a fuzzy inference approach to forecast the likelihood of a fire.

In a similar vein, Manjunatha et al. [68] looked into a fuzzy rule-based approach for cluster head data fusion. Through integration of temperature, humidity, light intensity, and CO sensor data, the system was able to identify events with minimal false alarms and transmission costs. A comparison study of several data mining approaches in WSN-based fire detection systems was given by Maksimovic´ and Vujovic´ [50]. They discovered that while classifiers like OneR or Fuzzy Unordered Rule Induction Algorithm

(FURIA) produce decent results with smaller datasets, neural network classifiers perform better with larger datasets. The compatibility of the dataset and the application determine which algorithm is best.
Key findings from research on fire prediction and detection systems using machine learning algorithms other than ANNs, logistic regression, and DT are compiled in Table 8. This includes the type of machine learning applied, the dataset used, and the primary published results.

Table 5. Summary of few papers based on other and fuzzy logic based wildfire prediction systems

Ref	Year	Model	Dataset	Features	Results	Key Finding
[51]	2007	Support Vector Machine (SVM)	Meteorological data from northeast Portugal	Temperature, rainfall, relative humidity, wind speed	MAD: 13.07, RMSE: 64.7	SVM efficient for small fire identification, less effective for large fire detection
[14]	2012	Support Vector Machine (SVM)	Not specified	Not specified	RMSE: 7.33, MAE: 3.36, MAPE: 69	SVM effective in identifying burned forest areas
[52]	2012	Support Vector Machine (SVM)	Video data	Area covariance matrix, color, spatial, temporal information	True detection rate: 96.6% (RBF kernel), 90.9% (linear kernel)	SVM with RBF kernel highly effective for video-based fire detection
[53]	2022	MCC CLightGBM, MCC CRF	Digital Linear Strip Dataset using ArcGIS	Topography, vegetation, climate, human activity	MCC CLightGBM: AUC of 0.86 and 0.88, F1-score of 0.78 and 0.73, and ACC of 81.83% and 84.87	Fire boundaries are most likely to form near roads, populated areas, and significant topographic relief
[54]	2022	LightGBM	Subtropical National Forest Park in Jiangsu, China	Topographic factors, climatic factors, human activity factors, vegetation factors	Acc: 88.8%	LightGBM outperformed LR and RF in predicting fire susceptibility, with temperature identified as the main driving factor of fire.
[55]	2022	LightGBM	Nearly 20 years of forest fire	Climate, vegetation,	Acc: 79.9%	The LightGBM model

			data in Southwestern China	human factors, topography		effectively predicts forest fires in Southwestern China, with high accuracy and robustness
[56]	2022	KNN,NB, ID3	Global Forest Watch (GFW) platform	Latitude, Longitude, Brightness temperature, Scan size in pixels	KNN Accuracy: 55.4%	Feature selection positively impacts model performance by 2-5%
[57]	2020	KNN, SVM, DT, NB	data from South Kalimantan Province	Topographical and meteorological	KNN Acc: 95%	kNN demonstrates high prediction accuracy, but generalizability beyond South Kalimantan Province may be limited.
[58]	2010	Bayesian Belief Network (BBN)	MODIS active fire dataset (2001-2007)	Land cover, elevation, mean annual rainfall, mean annual temperature	Sensitivity: 0.96, Specificity: 0.72, AUC: 0.96	Identified key factors influencing wildfire occurrence in Swaziland
[59]	2010	Bayesian Classifiers	Vision (color) data	Color, area size, region coarseness, boundary roughness, skewness	False-negative rate: 0.028%, False-positive rate: 0.68%	Effective for automatic event retrieval and real-time fire detection in video footage
[60]	2010	Naive Bayes, Distributed Neural Networks	WSN data	Not specified	Detection accuracy: >81% (residential fires), >92% (wildfires)	High detection accuracy for both residential and wildfires using data mining techniques in WSN
[61]	2016	Naive Bayes	Multi-sensor WSN data	Not specified	Precision: ~94%	High precision for forest fire

						detection in multi-sensor WSN
[63]	1998	Autonomous ground-based system	Black and white video data	Temporal difference of smoke plumes	Not specified	Validated performance in detecting forest fires using temporal difference of smoke plumes
[64]	2005	Markov Model-based System	Color video data	Flame flicker processes, color information, motion detection	Processed 320 x 240 images in ~10 ms, reduced false alarms	Effective in mimicking flame flicker processes and reducing false alarms in video-based fire detection
[67]	2017	Fuzzy Logic-based System	WSN data	CO, temperature, humidity, smoke sensor data	Error ratio: ~6.67%	Effective home monitoring and fire detection using fuzzy logic and WSN technology
[66]	2003	Hybrid Model (Fuzzy Logic + Multi-layer NN)	Multi-sensor data	Data features, fuzzy inference	Reduced communication, saved energy	Hybrid model effective for fire prediction by combining fuzzy logic and neural networks in a multi-sensor data fusion framework
[68]	2008	Fuzzy Rule-based Approach	Sensor data	Temperature, humidity, light intensity, CO sensor data	Not specified	Identified events with minimal false alarms and transmission costs using a fuzzy rule-based approach
[50]	2013	Various (OneR, FURIA,	Not specified	Not specified	Not specified	Neural network classifiers perform better with larger

		Neural Networks)				datasets, OneR and FURIA produce good results with smaller datasets

5. Discussion

5.1.Focus Wise Publication Trends

Exploring the publication trends in the detection and prediction of forest fires is an excellent way to determine the preference toward deep learning and machine learning approaches. Deep learning shows slightly more preference for fire detection with 13 articles, followed by machine learning with 12 articles. This preference is because deep learning models like CNNs and RNNs have better abilities than their simpler counterparts in processing complex data patterns. On the other hand, a notable area of interest is fire prediction, which has a significantly higher number of machine learning-based papers (14) as compared to deep learning papers (5). This is most probably due to the fact that, generally, the machine learning algorithms like SVM, decision trees and random forests are more appropriate for the diverse datasets and modeling of the environmental features that are more appropriate in the case of a fire occurrence. The models of machine learning are also more efficient in interpretation which helps in the understanding of fire threats and formulation of solutions.

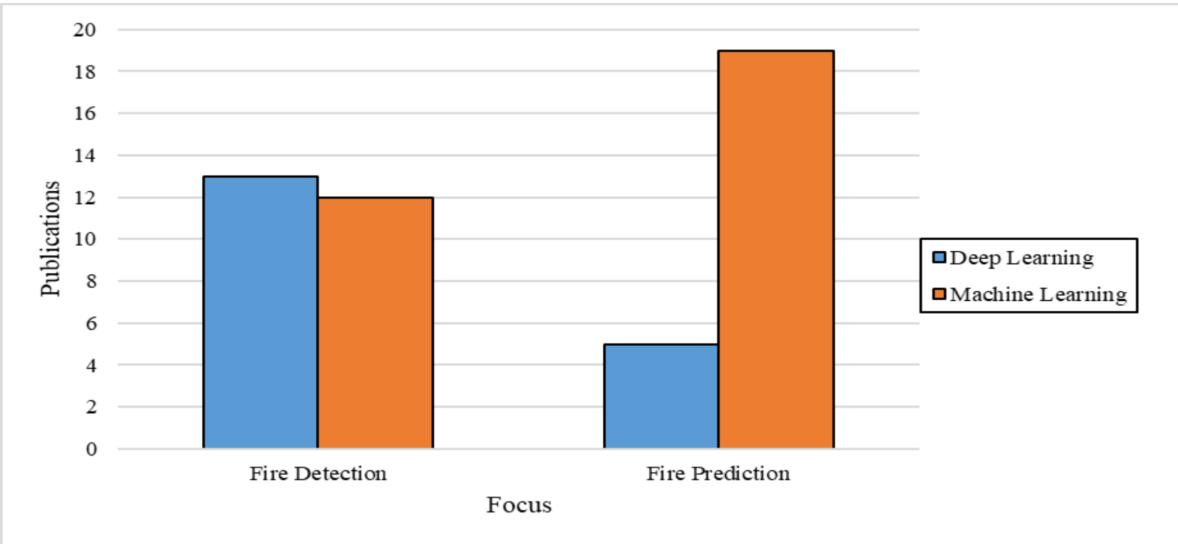

Figure 2. Focus wise Trends in Wildfire Prediction and Detection

5.2.Common Models

Deep learning and machine learning are two vast categories of algorithms widely employed in the forest fire detection and prediction area, as each of them is applicable to different portions of the general problem. Of all the deep learning models, Biomedical text mining writes that neural networks (NNs) are the most popular, featured in 10 publications as a model that can find intricate patterns in the data. The most used techniques with four citations are multi-layer perceptron (MLP) and convolution neural network (CNN): MLP for classifying data and CNN for working with images.

In conclusion, the most conventional methods used in machine learning are DTs and LR, and they are

mentioned in 5 papers. DTs are preferred for their manufacturability as well as the capability to work with data of various kinds, while LR works better in case of binary classification. Other classifiers that can be classified as less popular but still rather significant include Naive Bayes (NB) classifiers and fuzzy logic systems which have been applied in 4 articles at most. NB classifiers work well especially when dealing with large volume of data, and fuzzy logic systems when dealing with uncertainty.
Among three publications about the RF, the ensemble learning is their advantage and SVMs in three publications are good at dealing with high-dimensional space. The Markov model is mentioned in 2 publications; this approach is suitable for modeling time-series data.
These models are a set of models that are chosen depending on the complexity of the tasks and the need for interpretability and high accuracy in their solution. While DL models such as NNs and CNNs have been used for detection due to the large and diverse nature of datasets, ML models such as DTs, LR, and NB perform well in terms of interpretability and have efficient prediction capabilities.

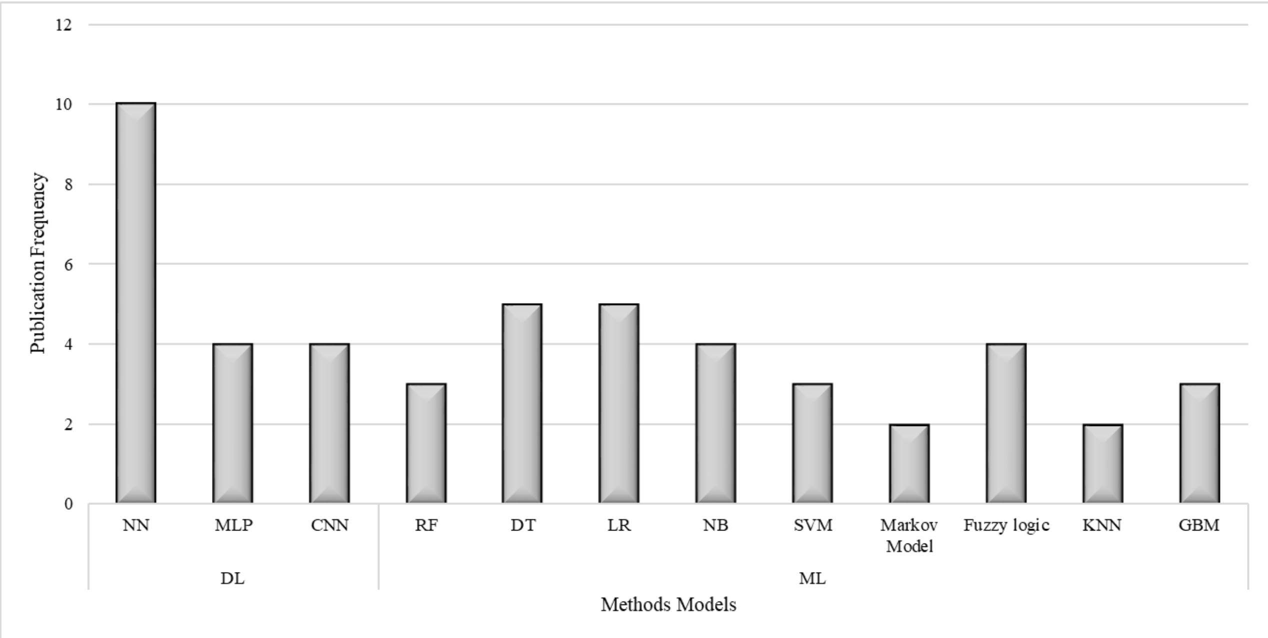

Figure 3. Common Methods in Wildfire Detection and Prediction

5.3.Evolution

The progression of methods like machine learning (ML) and deep learning (DL) in the area of forest fire detection and prediction also exhibits the enhancement of models in the technological field. The initial machine learning methods include logistic regression and artificial neural networks (ANNs), pioneering the use of the predictive models which was seen in the work done by Vega-Garcia et al. [8] in 1996. The application of these models showcased the possibility of using ML in analyzing the complexities of fire emergence through structured data and comparatively basic models.
Subsequently, from the early 2000s onwards, there was an introduction of more powerful models of ML. For example, De Vasconcelos et al. [39] in their 2001 study, used multilayer feed-forward neural networks combined with logistic regression to enhance the predictivity assessment. At the same time, mathematical decision tree-based and fuzzy logic systems were developed for both fire prediction and detection with the flexibility and interpretability of the models in handling a number of environmental inputs. The 2005

study by Prasad et al. [49] exemplifies the use of multiple regression and tree-based techniques, emphasizing the growing trend of ensemble learning to enhance model performance.

A major change of approach began in the mid 2000s through the increased computational capacity and the access to large data sets in using the deep learning methodologies. Deep neural networks, CNNs and other similar architectures came onto the platform due to their high accuracy in handling multidimensional data such as satellite imagery and sensor networks. For instance, the study conducted by Manzoor et al. [27] in 2006, proposed a multi-criteria detection system with aid of Deep learning and was able to demonstrate the efficiency of deep learning in complicated pattern recognition.

Deep learning persisted and progressed, with new uses of CNN based classifiers and back-propagation neural networks being applied in the late 2000s and early 2010s. Web based articles such as those of Cheng et al. [26] in 2005 and Yao et al. [22] in 2009 discussed the use of CNNs for fire detection based on the fact that CNNs have high accuracy in processing visual data. At the same time, detailed models like SVM and Bayesian classifiers were becoming more defined in their functionalities for certain tasks, as observed in the 2007 and 2010 studies by Cortez and Morais [44] and Dlamini [58].

Starting from the year 2012, there are papers which integrate the ideas of machine learning and deep learning with an indication that both the fields would be complementary. Some of the relevant works highlighted in section 'Machine learning and fire detection' by Saoudi et al. [61] and Chen et al. [66] attempted to incorporate fuzzy logic with neural networks to construct solid framework for the management of uncertainties in fire detection and prediction. Furthermore, deep learning methods, including multi-layer perceptron (MLPs) and convolutional neural networks (CNNs), kept on developing for usage in the subsequent detection methods and real-time monitoring devices such as UAV-based systems by the late 2010.

Since 2018, world saw further development of more elaborate model and UAV-based detection system using deep learning as discussed in the subsequent section. These models included various sensors and used developed neural network to give accurate and fast detection of fire. This period also saw researchers experiment on the use of ensemble learning techniques, and using multiple models to improve predictive accuracy and robustness, as presented by authors like Oliveira et al [39] and Stojanova et al [36].

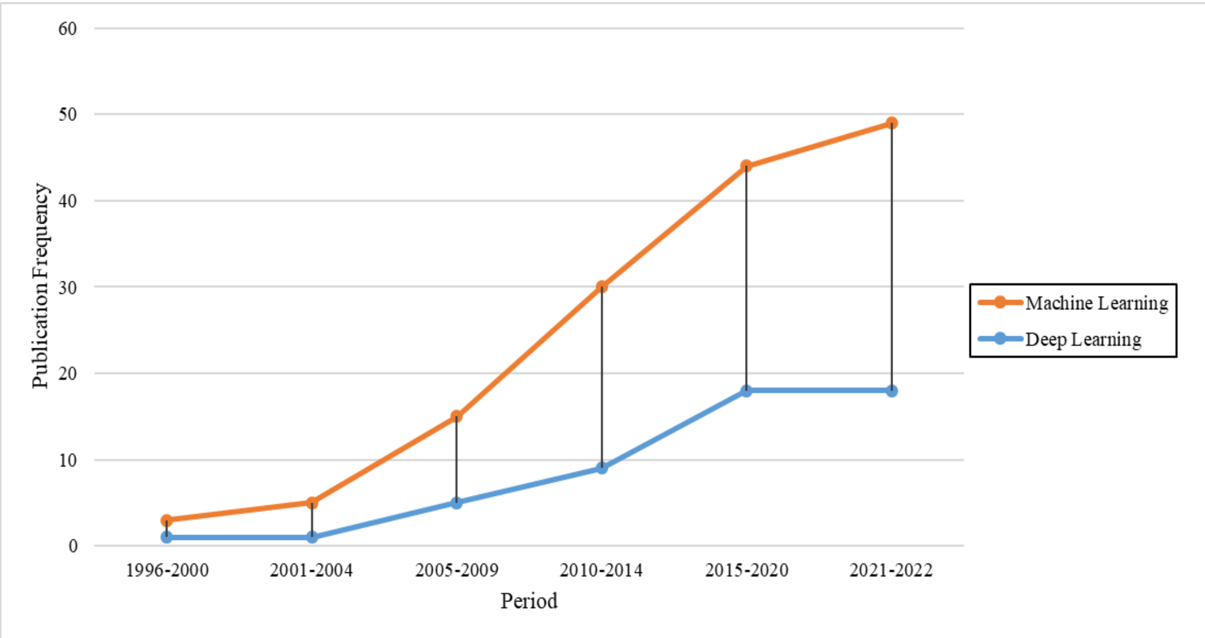

Figure 4. Evolution of Wildfire Detection and Prediction Methods

5.4.Challenges

Nevertheless, there are several issues that re still actual in the sphere of wildfire prediction and detection considering contemporary technologies and research. One big issue is the high degree of endliness of the factors that play a role in the behavior of fire or wildfire. Some factors influencing forest fires include weather conditions, physical terrain, vegetation cover, and human activities; these factors are complex and therefore I finding good models that can predict the occurrence of fires are a challenge [2]. Further, since wildfires are constantly changing their spatial extent and intensity over time, timely monitoring and detection becomes difficult especially in remote or remote areas where there could be few permanent infrastructures for surveillance.

Another challenge is how to aggregate and analyze data coming from different sources or inherent to such objects [37]. Frequently used approaches for the wildfire index prediction and detection involve various sort of information: satellite images, meteorological information, geographic information and statistical data on previous wildfires. Despite that, to combine and analyze such heterogeneous sources of information and turn them into useful patterns and findings, it is necessitated to apply highly developed algorithms and computational capacities. Besides, data quality and its presentation in the right time and with a high degree of accuracy in big datasets and data incoming from different sources creates extra difficulties.

Additionally, certain aspects such as the scalability and the interoperability of the systems used in the wildfire predictions and detection are also a constrain to its deployment and operationalization[40]. A majority of these systems is designed based on the restriction of geographical location or climate, and thus have certain restrictions on their usage. In the same way, several compatibility challenges may emerge when using different detection systems or when sharing information among the multi-sectoral and multi-organizational wildfire response teams.

Other considerations that relate to ethical and social concerns are also important considerations to make when guaranteeing wildfire prediction and detection[70]. The issues of privacy, ownership of data, and fair treatment due to the bias of algorithms are some of the delicate questions that need to be discussed and solved in the process of the more proper use of the technologies. Therefore, there is a need to embrace community involvement, indigenous people’s participation and other peoples who participate actively in Wakhande so as to consider cultural values, their kindred preferences and promote project ownership in wildfire management plans.

6. Conclusion and Future Directions

This systematic review paper offers a thorough examination of the current landscape of wildfire prediction and detection research, delving into various methodologies, techniques, and challenges inherent in wildfire management. Through a systematic analysis of existing literature, we've identified common approaches, highlighted key findings, and outlined major challenges confronting the field. Looking ahead, several promising avenues for future research and development emerge. Foremost among these is the imperative for continued innovation in predictive modeling techniques, aiming to enhance accuracy, scalability, and real-time capabilities. This entails integrating advanced machine learning algorithms like deep learning and ensemble methods, alongside the development of hybrid models that harness diverse data sources and sensor technologies. Moreover, emerging technologies such as unmanned aerial vehicles (UAVs), satellite imagery, and Internet of Things (IoT) devices hold significant potential in augmenting wildfire monitoring and detection capabilities. Future research endeavors should focus on integrating these technologies into existing wildfire management systems, emphasizing interoperability, data fusion, and decision support. Interdisciplinary collaboration and stakeholder engagement are essential to addressing the multifaceted socio-ecological challenges associated with wildfires. Engaging with local communities, indigenous groups, and other stakeholders is crucial for co-designing and implementing wildfire management strategies that are culturally sensitive, inclusive, and equitable. Lastly, sustained investment in data collection, sharing, and standardization efforts is paramount to enhancing the quality, availability, and accessibility of wildfire-related data. Establishing open-access repositories, standardized data formats, and data sharing protocols will facilitate collaboration and knowledge exchange among researchers, practitioners, and policymakers, ultimately advancing our collective understanding and management of wildfires.

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